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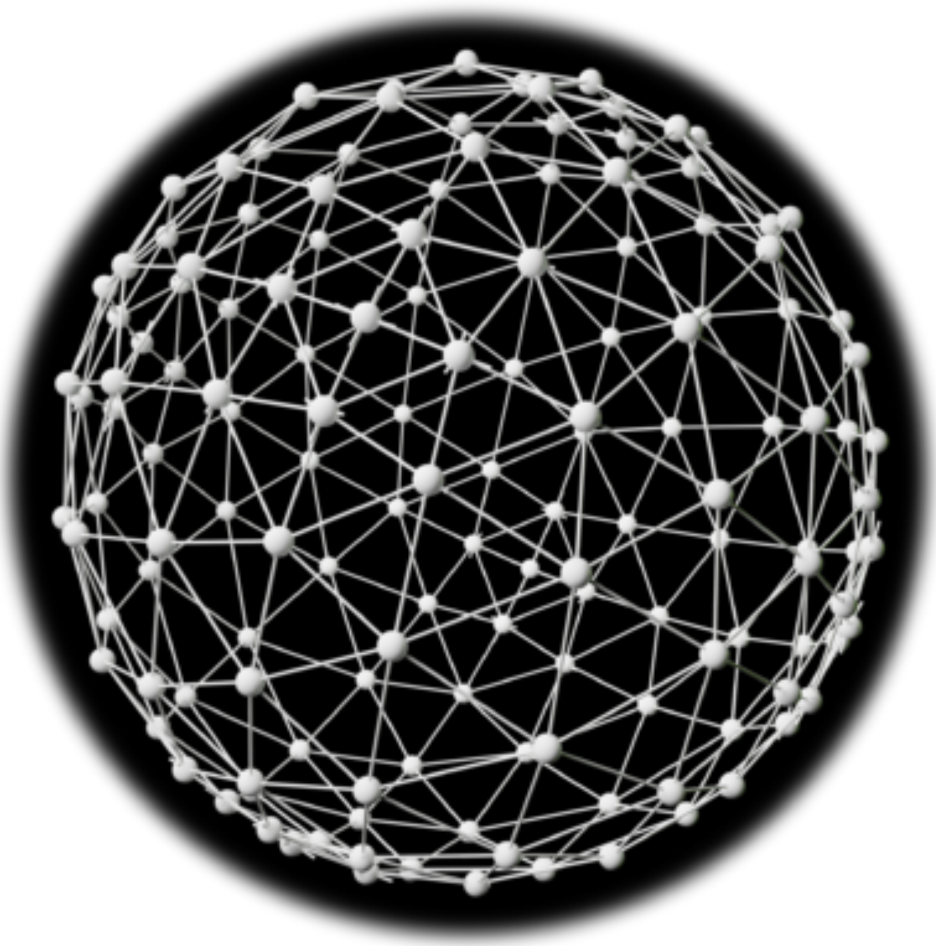


D02. Study on informed public policy-making on base of policy modelling and simulation

Data analytics for Member States and Citizens – ANNEX Special study: Predictive Models Tackling the COVID-19 Epidemics

18 May 2020 (Final draft)

Predictive Models Tackling the COVID-19 Epidemics

1.1 Introduction

One of the unexpected effects of the lockdown was the widespread attention dedicated to epidemiological curves and exponential models. Topics which looked like obscure, boring and highly specialistic became popularized under concept like “flattening the curve”. Indeed, predictive models about the spread have become a strategic asset for understanding and managing the crisis. Having accurate estimates of how the epidemics is evolving, and more importantly, predictions about how it will evolve in the future under different types of lockdown measures, became a fundamental asset not only for ensuring public health, but also for saving the economy. Their importance became clear when the update to the model produced by the Imperial College (as new data became available) led to a complete reversal of policy in the UK and the US. Indeed, accurate models are necessary to move beyond a open/closed model towards a smarter and more nuanced policy approach, or as one popular social media post put it, to move from the “hammer” to “the dance. Every country is using different models to manage the crisis, and many research departments are producing theirs. But how are these models developed, concretely? What predictions do they offer? What data do they use? How influential are they in defining policy choices, and most importantly, are best performing countries using better models? This piece provides an overview of the different models adopted across countries, and tries to extract lessons to be learnt for the future. The findings show that different models have been used for different purposes. For instance, agent based models can be used to assess the impact of mitigation measures, while fitting curve can be used to estimate the magnitude of epidemic dimensions such as the number of deceased and the number of infected individuals. As the saying goes, all models are wrong, but some are useful. And useful they were indeed, as the more data are available, the better are the estimates. Further, several models are able to predict the extent to which mitigation measures affect epidemic and healthcare dimensions, thereby providing tools to the policy makers. On the other hand, having more advanced and sophisticated models is not the magic wand that decides the fate of a country. Indeed, many experts declare that “The mathematical side is pretty textbook”. Other related measures are at least as important. First, high quality data. Models are built on estimates, and early stage models were wildly wrong because of the incorrect estimated data put in stemming from assumptions driven by necessity. In fact, when scarce data was available for a single location, models had to be calibrated using data from locations where the epidemics was ongoing. For instance, for the series of Imperial College models, critical assumptions concerned the value of R (reproduction rate), the rate of death, the length of incubation, and the period in which infected and asymptomatics can be infectious. As for a model developed by the University of Oxford, a critical assumption was the suggestion that the infection has reached the UK by December or January, and the figure that only one in 1,000 infections will need hospitalization is removed from reality. This is questionable, as on March 24 (at the time of release of the model) more than one in 1,000 people have already been hospitalised in the Lombardy region of Italy, despite stringent control measures being implemented. But the crucial info hidden from both teams of modellers regards the number of people that have been infected without showing symptoms, and for which a reliable test would be a game changer for modellers as it might significantly alter the predicted path of the pandemics. In fact, it appears that the mortality rate is much lower than official numbers suggest, as many people are infected without knowing it and they do not get tested. By the same token, some countries have better data because of their existing data infrastructure. For instance, Germany has a register of ICU which updates occupancy data on a daily basis. And the main limitations underlying all models is that we don't know how many people are infected in the first place. Secondly, models need to be used properly. They are not commodity that provide a number which the policy makers use to take decisions. There needs to be a full understanding of the subtleties involved, the levels of uncertainty, the risk factors. In other words, you need in-house data and model literacy embedded in the policy making process, in house. You can't outsource that. Indeed, a recent report for the US highlighted the limitations of a process that involved experts on an ad hoc, on demand basis, leaving much arbitrariness to the process: "Expert surge capacity exists in academia but leveraging those resources during times of crisis relies primarily on personal relationships rather than a formal mechanism." On a similar token, in the UK, a recent article pointed out that experts involved in the SAGE were too "narrowly drawn as scientists from a few institutions". By the same token, there was insufficient in house capacity to manage this input: In the US, "there is currently limited formal capacity within the federal government", while in the UK, "the criticism levelled at the prime minister may be that, rather than ignoring the advice of his scientific advisers, he failed to question their assumptions".[1] Further, it is important to ensure transparency in the modelling assumptions, as using models based on assumptions in absence of hard data can lead to over interpretation and exaggeration in the magnitude of the outbreak. Therefore, assumptions must be transparent and clear to the reader and the policy maker in order to be aware of the caveats. Moreover, researchers should perform extensive validation and sensitivity analysis exercises by using different modelling and estimation techniques. By the same token, models should be developed in collaboration with policy makers and practitioners, as in the case at hand, the joint elaboration of simulations and scenarios by policy makers and scientists helps in producing models that are refined to tackle the containment policies adopted. And the researchers/ IT vendors should develop easy to use visualization to help policy makers and citizens to understand the impact of containment policies: interactive visualization is instrumental in making evaluation of policy impact more effective. A final point is to consider carefully the sources of uncertainty in the model, whether statistical (e.g. confidence intervals), parametrical (e.g. the rate of transmission), concerning measurements (e.g. data on fatality), or of a more conceptual level (e.g. assuming a representative agent).

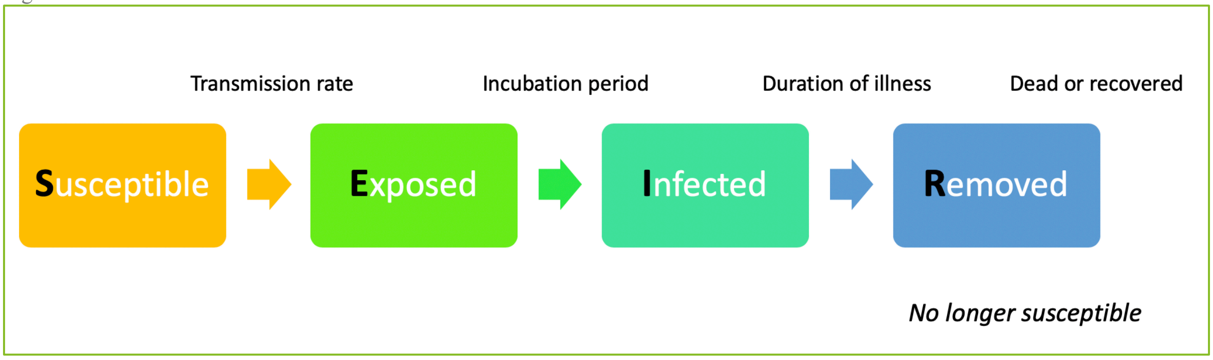
But we must not forget perhaps the most important variable: the quality of the health service itself. For instance, Germany has by far the largest number of ICU beds per head.

[1] The quotes come from https://mobile.reuters.com/article/amp/idUSKBN21P1VF?__twitter_impression=true and https://www.centerforhealthsecurity.org/our-work/publications/2020/modernizing-and-expanding-outbreak-science-to-support-better-decision-making-during-public-health-crises

1.2 Overview of the models

Several countries are making extensive use of predictive models to forecast the severity of the COVID-19 outbreak and its impact in terms of population affected and strain over the healthcare system. Computer simulations are becoming an increasingly important part of policymaking. However, as they are based on information that is oftentimes estimated or assumed, it is important to be aware of the limitations and possible lack of robust forecasts. The simplest epidemics models (called SIR[2]) aim to understand how an individual passes from being susceptible (S) to the virus, have become infected (I); and then either recover (R) or die. A bit more advanced modelling technique (see the flow in Figure 1) adds the individuals exposed (E) to the virus[3,4].

Figure 1 – Flow of SEIR Model



Some information can be merely assumed at the start of an epidemic, such as the proportion of infected people who die, and the basic reproduction number (R0), which is the number of people to whom one infected person will transmit the virus. In the same way, also some other parameters have to be assumed, such as the presence or not of natural immunity inside a population. More advanced models make use of stochastics rules, for instance attributing a probability lower than one that someone in the I group infects an S person when they meet, and also the behaviour of agents is modelled in different ways. Most models make use of equations to sort individuals into strata, while others adopt an agent based approach in which each individual moves around and acts according to their own specific rules, and therefore are able to include in the analysis social factors (such as social distancing and travelling), as well as healthcare resources. Further, there are epidemiological models based on mobility matrices (origin-destination) and demographic profiles to understand the extent and direction of the spread of the epidemic, thanks to which it can help to make decisions on the distribution of resources and on hospital logistics, as well as displacement analysis models between municipalities and between geographic areas of the country to identify groups of users with similar displacement patterns, and effectiveness models of lockdown measures, aimed at monitoring the behavior of groups of users before and after the adoption of restrictive measures for mobility. The choice of the model depends on the specific issue at hand: for instance,

2 https://www.nature.com/articles/d41586-020-01003-6?fbclid=IwAR0WqP_6AH7myk9YJGFeqw0lXlD2KiBPScEX_WQdzrW67n41krXaZYkTV0Q#ref-CR1
3 https://www.thelancet.com/journals/lancet/article/PIIS0140-6736(20)30260-9/fulltext
4 https://cmmid.github.io/topics/covid19/current-patterns-transmission/wuhan-early-dynamics.html

when testing the effects of social distancing on infection rates, there is no need to use an agent based model as everybody is compelled to behave in the same way, i.e. staying at home.

In total, our analysis depicts a total of 28 different models, 19 of which are used in policy making as reported by the general press as well as by the fact that authors are members of the teams of advisors working for several governments. Further, almost all of the models are published and available for scrutiny (apart from 4, more on that below), while obviously the results of all models are public and available. The study of the models focusses on 6 European countries plus the US: France, Germany, Italy, Spain, United Kingdom, and United States. Most of the models use data collected from the same country, while other integrate the dataset with data from international repositories (e.g. ECDC, WHO, Johns Hopkins CSSE). Interestingly, the models introducing mobility of citizens across regions and countries re-use data on citizens movement collected for other purposes, such as daily origin-destination traffic flows from the Official Aviation Guide (OAG) and International Air Transport Association (IATA) databases, ground mobility flows collected from statistics offices, and mobility data provided by Cuebiq, a location intelligence and measurement company.

From the analytical point of view, the relative majority of models are Susceptible-Exposed-Infected-Recovered (SEIR) models, while there are some spatial epidemic models and some pure statistical models based on maximum likelihood methods and Monte Carlo Markov Chains. Finally, there are strategic models that encompass multiple scenarios assessing the impact of different interventions are able to capture some uncertainty underlying the epidemic outbreak and the behaviour of the population and are the foundation for policy making activity.

As regards the topic of the models, we can distinguish four of them:

- Estimating epidemic variables, such as numbers of infected individuals, number of deceased, and reproduction number (17 models);
- Estimating healthcare variables, such as number of Intensive Care Units Necessary (12 models);
- Assessing the impact on mitigation actions, such as enforcement of lockdowns and social distancing (16 models);
- Assessing the spread of the epidemic model and/or the extent of the mobility of the population (9 models).

A brief illustration of the surveyed models is presented in Table 1.

Table 1 – Brief illustration of the surveyed models

Country	**Total**	**Published**	**Officially used in policy**	**Estimating epidemic variables**	**Est. healthcare**	**Mitigation actions**	**Mobility**
US	6	6	5	2	2	1	4
UK	5	5	5	3	3	4	1
DE	4	4	3	2	0	4	2
IT	6	4	1	4	2	3	1
ES	4	4	2	3	3	2	1
FR	3	3	3	2	3	2	0
Total	28	26	19	16	13	16	9

1.2.1 Predictive Models used in US and the UK

A number of leading scientists are supporting the decision making process of the White House Coronavirus Task Force by providing results analysis based on predictive epidemic models. One of the primary models used by the White House response team is provided by the Institute for Health Metrics and Evaluation University of Washington (**IHME**)[5][6]. As already mentioned, most epidemiological models look at different populations that interact in an outbreak, which are the people susceptible to infection (S), those who are infectious (I) and those already infected who go on to die or recover (R). The IHME model embraces an entirely different statistical approach, taking the trending curve of deaths from China, and "fitting" that curve to emerging death data from US cities and counties to make its forecasts. The first release of the model predicted a bed excess demand of 64,175 and 17,380 of ICU beds at the peak of COVID-19. Further, the peak ventilator use is predicted to be 19,481 in the second week of April, while the total estimated deaths were 81,114 over the next 4 months. Then, the estimates were amended downwards by predicting the death of 60.400 individuals by August, with a peak on the 12th of April. As for the UK, the model predicted 66,314 fatalities, more than Italy (a total of 23,000) and Spain (19,209).[7] These numbers are consistently lower than other estimates. As transparently recognized by the authors, only one location (Wuhan) has had a generalized epidemics, and therefore modelling the US fitting curve on such location is difficult, especially because the timing and extent of social distancing is difficult to mimic. When more US data will be available, the more will become more precise. Further, even though the model takes into account age structure, some other factors are not modelled, such as the prevalence of multi and co-morbidities, chronic lung disease, use of public transport, pollution and population density. On the top of that, the reduction in healthcare quality due to overload is not explicitly taken into account. Other experts consider the estimations to be overly optimistic[8]. In fact, it is argued that actions taken in the US are less drastic than in China, and that while most models assume that social distancing will only slow or reduce transmission, the IHME model assumes that policies such as social distancing are extreme effective at stopping transmission and put the epidemics under control.

Along the same lines, as argued by Siegenfeld, Shen and Bar-Yam[9], the interventions in the US are basically of four typologies: school closures, non-essential business closures, travel restrictions including public transportation closures, and stay-at-home recommendations. It is unlikely that implementing even all four of these measures will yield results like those reported by China, given the multiple steps taken in China's lockdown, many of which have not yet been implemented in the US, such as mandatory masks in public places and quarantine of all suspected cases collectively.

Summarizing, the precision of the IHME model depends a lot on the availability of data as well as on the assumption regarding the extent of interventions. The IHME is planning to continually update its model using new data, so the model will become more accurate over time. In some countries like

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[5] https://covid19.healthdata.org/united-states-of-america

[6] https://www.medrxiv.org/content/10.1101/2020.03.27.20043752v1.full.pdf

[7] IHME uses data from the Data Repository by Johns Hopkins CSSE https://github.com/CSSEGISandData/COVID-19

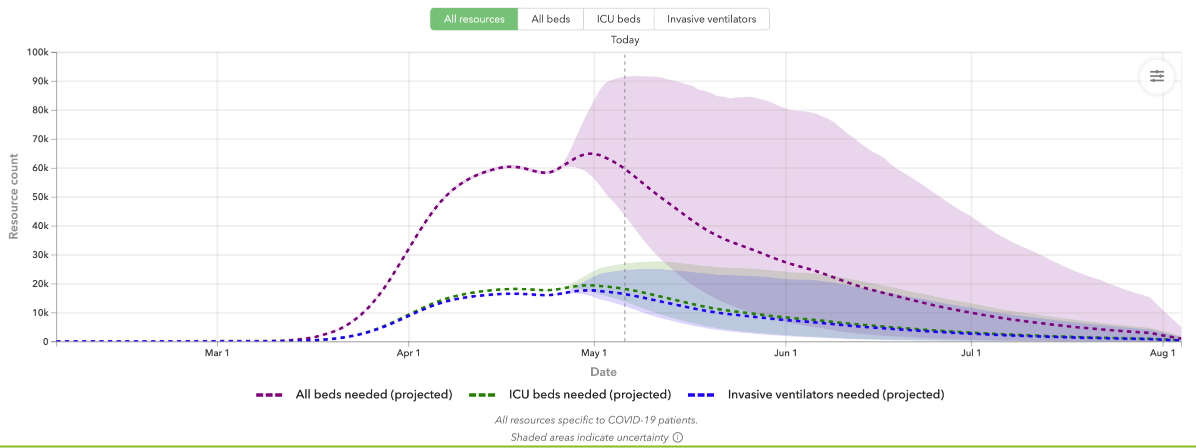
[8] https://www.vox.com/future-perfect/2020/5/2/21241261/coronavirus-modeling-us-deaths-ihme-pandemic

[9] https://necsi.edu/comment-on-forecasting-covid-19-impact-on-hospital-bed-days

Italy, for which there is a large amount of data on fatality rates for COVID-19 over time, the accuracy of IMHE is higher. On the other hand in countries such as UK there is a limited timeframe of COVID-19 fatalities and so less data with which to estimate future trends, and therefore the IHME has a widest range of possible outcomes (14,572 to 219,211 deaths in the UK at the time of writing).

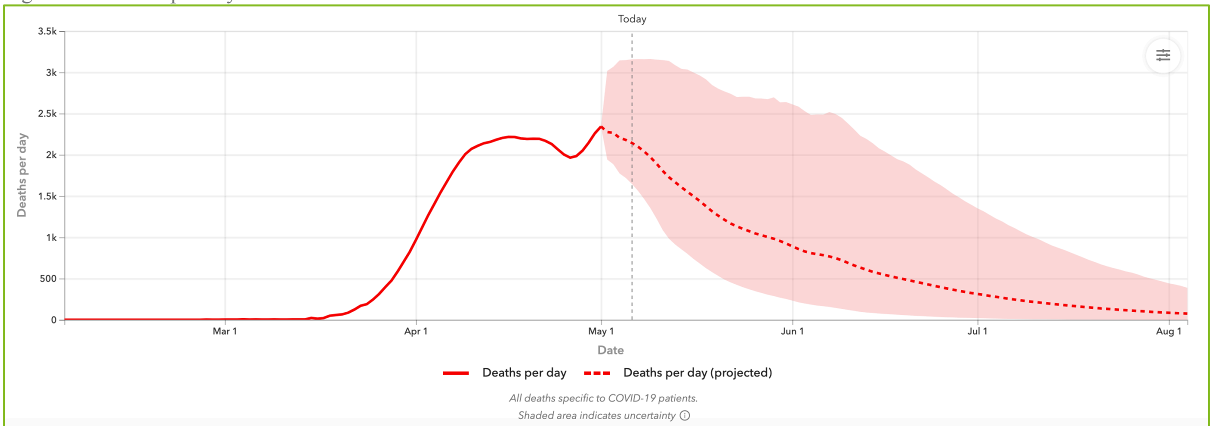
At any rate, as of May 6th 2020, examples of projections based on IHME are depicted in the following Figures Figure 2, Figure 3 and Figure 4.

Figure 2 - Hospital Resource use



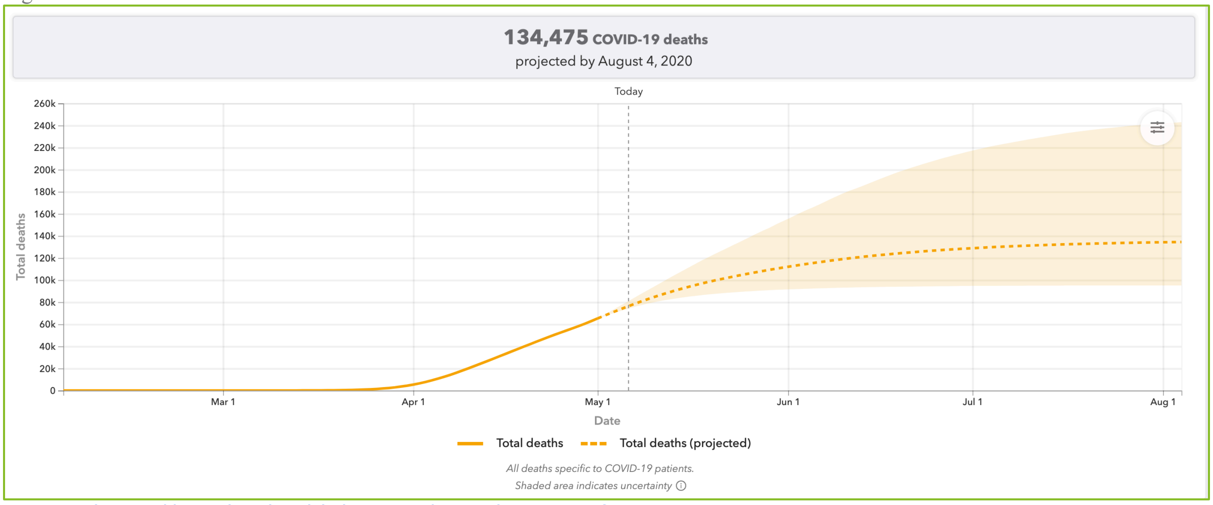
Source: https://covid19.healthdata.org/united-states-of-america

Figure 3 – Deaths per day in US



Source: https://covid19.healthdata.org/united-states-of-america

Figure 4 – Total deaths in US



Source: https://covid19.healthdata.org/united-states-of-america

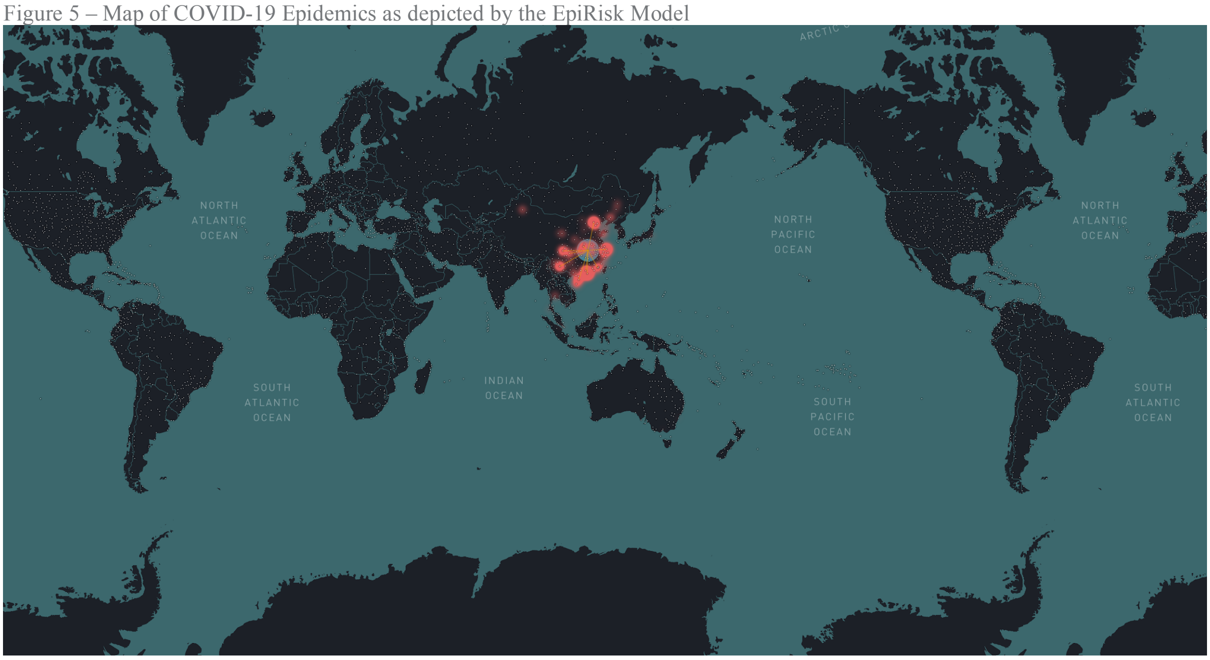
Based on the IHME, other historical model projections for a given country or region (based on data scraping from the John Hopkins dashboard[10] and the IHME website[11]) are produced by the **Los Alamos National Labs**[12][13]. Specifically, they estimate at US state level the number of cases and deaths elaborating two processes: the first process is a statistical model of how the number of COVID-19 infections changes over time, while the second process maps the number of infections to the reported data. Regarding the first process, they model the growth of new cases as the product of a dynamic growth parameter and the underlying numbers of susceptible and infected cases in the population at the previous time step, scaled by the size of the state's starting susceptible population. To model new deaths in the population, they assume that a fraction of the newly generated cases will die and get that fraction from observations. The model can be used to produce short- and long-term forecasts that can help guide situational awareness about what may happen in the near-future. In the model there are two main sources of uncertainty: the primary source of forecast uncertainty is how the growth parameter might change in the future; the second is measurement uncertainty, assumed to scale with the number of reported cases and deaths.

Another leading team stems from the collaboration between Northeastern University and ISI Foundation building on the Global Epidemic and Mobility Model (GLEAM) project, an individual-based, stochastic, and spatial epidemic model used to analyze the spatiotemporal spread and magnitude of pandemic outbreaks. The modeling effort produced is based on data on incubation period, methods of transmission, contagiousness and virulence, transportation, human behaviour and social interactions, availability of medical resources in different areas. As for transportation, the model also includes mobile phone data to track changes in people's movement to better understand the effects of various social distancing policies. Further, simple models typically show the start of an epidemic as an exponential curve based on the basic reproductive number, which in reality is not constant and depends on social networks, such as workplaces, households, and communities, and layered

10 https://coronavirus.jhu.edu/map.html
11 http://www.healthdata.org/covid/data-downloads
12 http://www.covid-projections.com/
13 https://covid-19.bsvgateway.org/#link%20to%20forecasting%20site

them into a larger model. Based on their model, the research team has developed a tool, EpiRisk, aimed at investigating the effectiveness of travel bans. Specifically, the model has been used to achieve situational awareness, then it has been applied to understand how interventions like travel restrictions affect the transmission of the disease. An example of the map of COVID-19 Epidemics as depicted by the EpiRisk Models is provided in Figure 5.

Figure 5 – Map of COVID-19 Epidemics as depicted by the EpiRisk Model



Source: www.epirisk.net

Based on the number of infected, the computational model estimates two quantities:

- The probability of "exporting" a given number of cases n from the origin of the disease outbreak;
- Probability that a single infected individual is traveling from the index areas to that specific destination.

As for the data, the airline transportation ones are based on origin-destination traffic flows from the database of the air travel intelligence company OAG.[14] Furthermore, commuting flows are derived by the analysis and modeling of data of over 78,000 administrative regions worldwide and 5,000,000 commuting patterns.

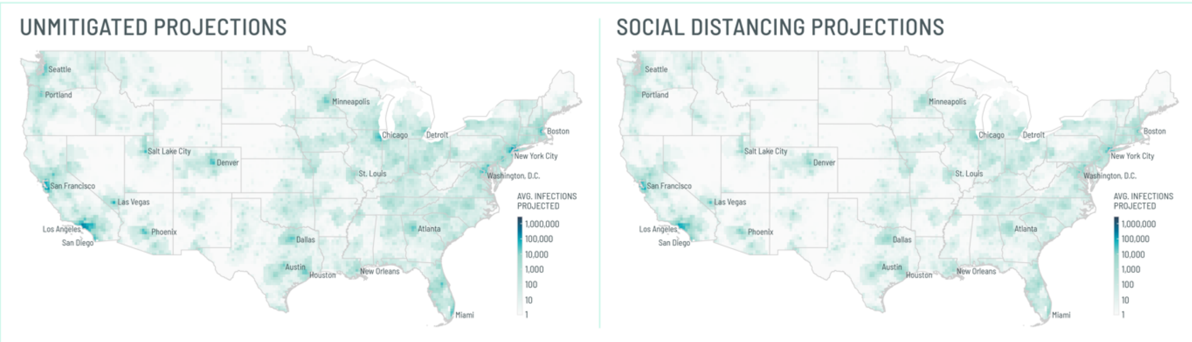
Another application of the GLEAM models stems from the collaboration between Northeastern University, Fred Hutchinson Cancer Research Center, University of Florida, NIH Fogarty Center, ISI Foundation, and the Bruno Kessler Foundation.[15] The model generates an ensemble of possible epidemic projections described by the number of newly generated infections, times of disease arrival in different regions, and the number of traveling infection carriers. The model points to the days around April 8, 2020 as the peak time for deaths in the US. Based on the last projections, a total of 89795 COVID-19 deaths (range of 63719 to 127002) are currently projected through May 18, 2020. The model uses real-world data where the world is divided into subpopulations centered around

14 https://www.oag.com/

15 https://covid19.gleamproject.org/

major transportation hubs (usually airports). The airline transportation data encompass daily origin-destination traffic flows from the Official Aviation Guide (OAG) and International Air Transport Association (IATA) databases (updated in 2019), whereas ground mobility flows are derived from the analysis and modeling of data collected from the statistics offices of 30 countries on five continents. The unmitigated and social distancing projections of the model are available in the following figure Figure 6.

Figure 6 - Unmitigated and social distancing projections



Source: https://covid19.gleamproject.org/

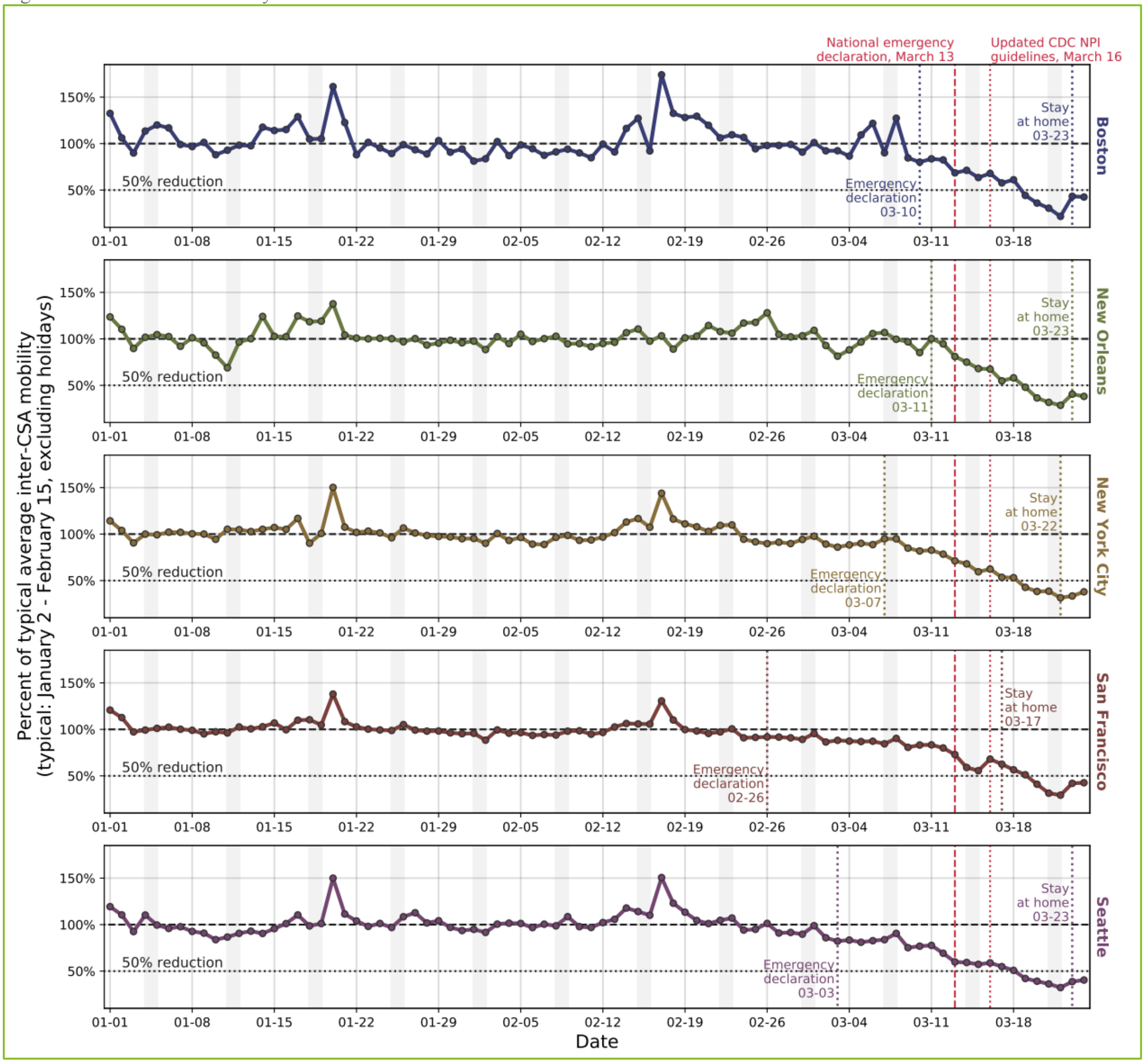
Some other models investigate the effectiveness of social distancing. For instance, **Bakker et al**.[16] make use of mobility data from January 1st 2020 to March 25th 2020 to figure out how has social distancing policy changed mobility and social behavior, how social distancing behavior differs across the physical space of New York City, and how social distancing behavior differs across demographic groups. Mobility data is provided by Cuebiq, a location intelligence and measurement company, and they consist in supplied anonymized records of GPS locations from users who opted-in to share their data anonymously across the U.S. The researchers find that the instance travelled everyday dropped by 70 percent, the number of social contacts in places decreased by 93%, and that the number of people staying home the whole day has increased from 20% to 60%. Very interestingly, they found that the relative differences between different demographic groups for what concerns mobility and social contacts have been dramatically reduced. Finally, they found that supermarkets and grocery stores came to be the most common locations where social contact takes place.

A similar model has used data from Cuebiq to build a preliminary understanding of the effect of work from home policies, mobility restrictions, job loss, and shelter-in-place orders on **urban and inter-urban mobility**.[17] Very interestingly, the model provides an estimation of the decrease in mobility across the U.S. Census Bureau Combined Statistical Areas of Boston, New Orleans, New York city, San Francisco and Seattle (see Figure 7).

[16] http://curveflattening.media.mit.edu/Social_Distancing_New_York_City.pdf

[17] https://www.mobs-lab.org/uploads/6/7/8/7/6787877/assessing_mobility_changes_in_the_united_states_during_the_covid_19_outbreak.pdf

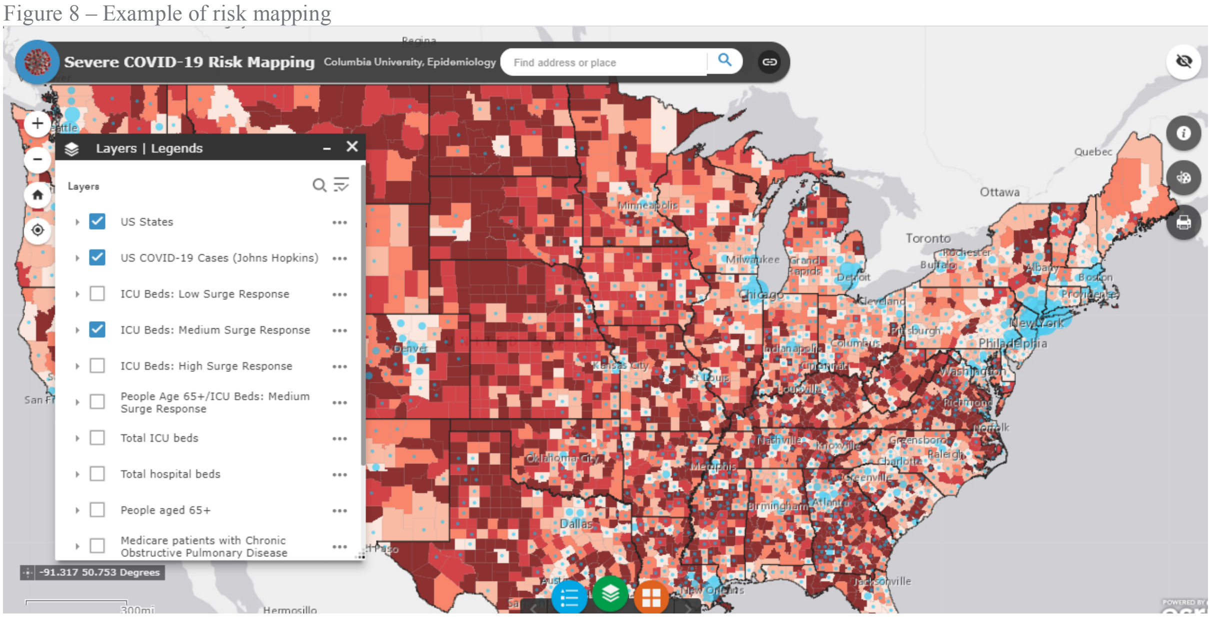
Figure 7 – Decrease in mobility across US Census Areas



Source: https://www.mobs-lab.org/uploads/6/7/8/7/6787877/assessing_mobility_changes_in_the_united_states_during_the_covid_19_outbreak.pdf

A final series of models by **Columbia University** in collaboration with Charles Branas in the Department of Epidemiology and colleagues from Patient Insight, the Mount Sinai Health System and MIT, has been used to provide an estimation of the stress on the healthcare system at county level due to the COVID-19 epidemics. Specifically, the team provides an estimate of the number of hospital critical care beds, including ICU beds and other hospital beds used for critical care purposes, that could be made available by hospitals in response to patient surges. Three scenarios of intensity of hospital response were created, taking into account existing ICU bed availability, currently occupied ICU beds that can be made available, other beds such as post-anesthesia care unit bed, operating room beds, and step-down beds that could be converted to critical care beds for COVID-19 patients and the possibility of having two patients use one ventilator in ICU. All civilian acute medical-surgical tertiary care hospitals and long-term acute care hospitals hospitals for which data were available in the US are included. The mapping tool can also display high risk groups such as individuals 65 years and older, Medicare patients with chronic obstructive pulmonary disease, Medicare patients with diabetes, Medicare patients with coronary artery disease and Medicare patients with chronic kidney disease. Specifically, an example of the risk mapping is provided below (Figure 8).

Figure 8 – Example of risk mapping



Source:
https://columbia.maps.arcgis.com/apps/webappviewer/index.html?id=ade6ba85450c4325a12a5b9c09ba796c

An online interactive COVID-19 mapping tool is also available on the Columbia website.[18] The simulations displayed in the mapping tool are based on a model[19] simulating the COVID-19 transmission dynamics for all US study counties over the period from February 21, 2020 to April 2, 2020, using an iterated filter-ensemble adjustment Kalman filter framework.[20,21,22] This combined model-inference system estimated the trajectories of susceptible, exposed, documented infected, and undocumented infected populations in each county while simultaneously inferring model parameters for the average latent period, the average duration of infection, the transmission reduction factor for undocumented infections, the transmission rate for documented infections, the fraction of documented infections, and the previously mentioned travel multiplicative factor. To account for delays in infection confirmation, the research team employed a time-to-event observation model using a Gamma distribution with a range of reporting delays and different

[18] https://columbia.maps.arcgis.com/apps/webappviewer/index.html?id=ade6ba85450c4325a12a5b9c09ba796c
[19] http://www.columbia.edu/~jls106/branas_etal_preprint.pdf
[20] E. L. Ionides, C. Bretó, A. A. King, Inference for nonlinear dynamical systems. Proc. Natl. Acad. Sci. U.S.A. 103, 18438–18443 (2006).
[21] A. A. King, E. L. Ionides, M. Pascual, M. J. Bouma, Inapparent infections and cholera dynamics. Nature 454, 877–880 (2008).
[22] S. Pei, F. Morone, F. Liljeros, H. Makse, J. L. Shaman, Inference and control of the nosocomial transmission of methicillin-resistant Staphylococcus aureus. eLife 7, e40977 (2018).

maximum seeding. Finally, the log-likelihood was used to identify the best fitting model-inference posterior.[23][24]

The model shows that an estimated 77,588-278,850 total critical care beds were available in the US, depending on the level of hospital surge response preparations. Maps of the US showed differences between the 21-day and 42-day projections as more counties outside the Northeast and urban areas, such as in the South, began to exceed their critical care bed capacity limits. Further, the model shows that 185,192 deaths in the Northeast and 33,986 deaths in the Midwest could be averted by reducing contact with actions such as social distancing, as well as that as many as 104,120 deaths could be averted through an aggressive critical care surge response. Such response includes high clearance and preparation of ICU and non-ICU critical care beds and extraordinary measures like using a single ventilator for multiple patients.

The datasets used include:

- The 2020 Centers for Medicare & Medicaid Services (CMS), Health Care Information System (HCRIS) Data File, Sub-System Hospital Cost Report (CMS-2552-96 and CMS-2552-10);
- The 2018 American Hospital Association (AHA) Annual Survey;
- The 2020 US DHHS Health Resources and Services Administration, Area Health Resources Files (AHRF);
- The 2017-2019 CMS Medicare Provider of Services file, Medicare Cost Report, Hospital Compare Files.

Another set of models that has been used both by the UK and the US governments as a basis for policy making has been developed by Neil Ferguson and his team at **Imperial College** London. Specifically, the Imperial College Response Team released on March 16 an individual-based simulation model[25][26] in which individuals reside in areas defined by high-resolution population density data and get into contacts with other individuals in the household, at school, in the workplace and in the wider community. Data on distribution size of households and age are taken from the census, while a synthetic population of schools distributed proportional to local population density is derived from data on average class sizes and staff-student ratios.

The model uses commuting distance to locate workplaces, and general data on the distribution of workplace size. In the model the transmission occurs through contact between infected and susceptible individuals randomly or at work/school/in the household. According to their model, there are two main policy strategies: mitigation, aimed at slowing the epidemic spread in order to reduce peak healthcare demand while protecting those most at risk of severe disease from infection; and

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[23] Hick, J.L., Einav, S., Hanfling, D., Kissoon, N., Dichter, J.R., Devereaux, A.V., Christian, M.D. and Task Force for Mass Critical Care, 2014. Surge capacity principles: care of the critically ill and injured during pandemics and disasters: CHEST consensus statement. Chest, 146(4), e1Se16S.

[24] Branas CC, Nance ML, Elliott MR, Richmond TS, Schwab CW. Urban–rural shifts in intentional firearm death: different causes, same results. American journal of public health. 2004 Oct;94(10):1750-5.

[25] https://www.imperial.ac.uk/media/imperial-college/medicine/sph/ide/gida-fellowships/Imperial-College-COVID19-NPI-modelling-16-03-2020.pdf

[26] The analysis is based on an agent-based model built in 2005 to see what would happen in Thailand if H5N1 avian flu mutated to a version that could spread easily between people available at https://www.ncbi.nlm.nih.gov/pubmed/16079797?dopt=Abstract

suppression, which is aimed to reduce case numbers to low levels and maintaining that situation indefinitely. The model shows that social distancing measures applied to the population as a whole have the largest impact, and that has the potential to suppress transmission (below the threshold of R=1) if combined with other intervention such as home isolation of cases and school and university closure.

The model considers five main scenarios:

- Case isolation at home;
- Voluntary home quarantine;
- Social distancing of those over 70 years;
- Social distancing of the entire population;
- Closure of schools and universities.

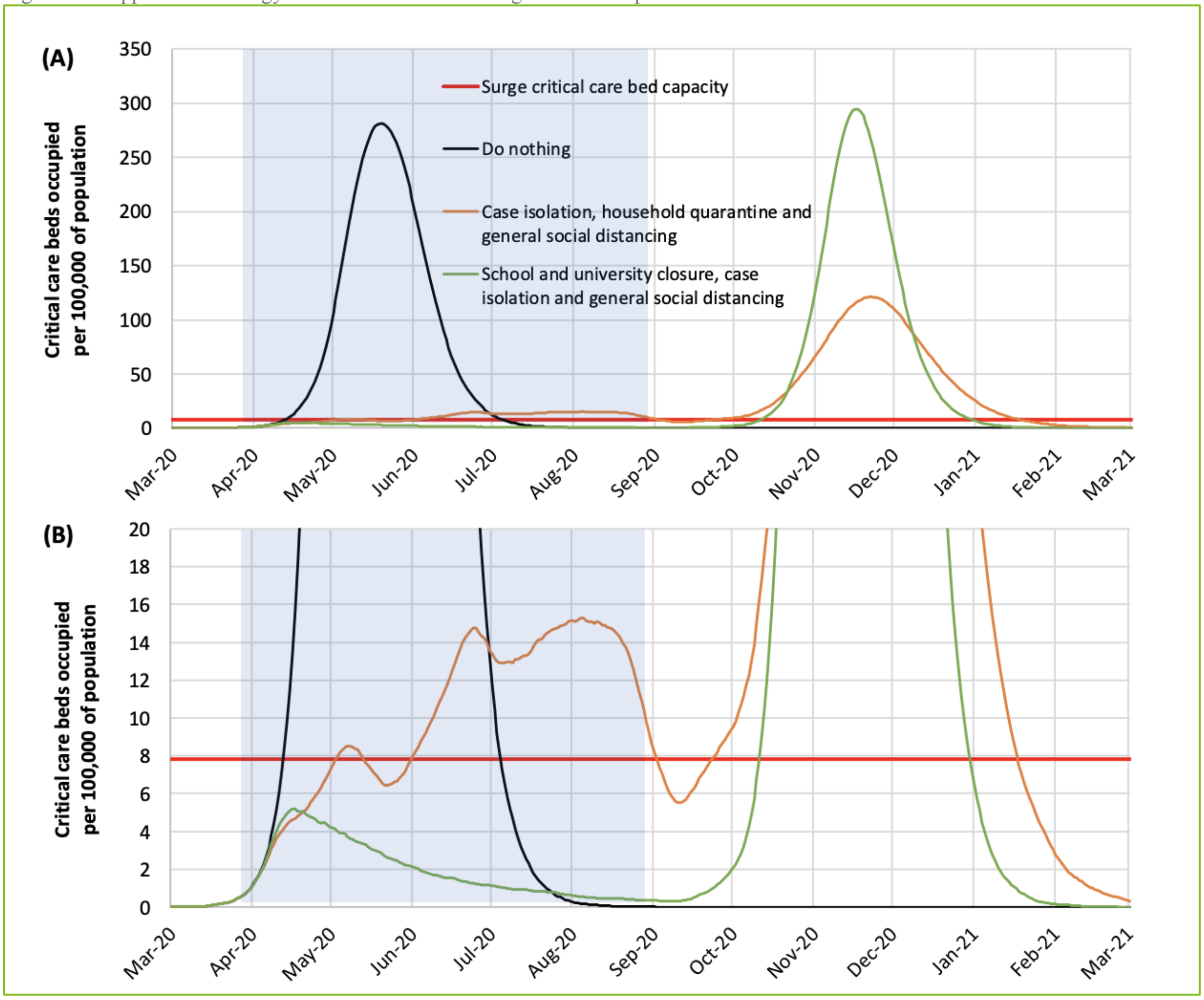
As already mentioned, forecasts are affected by assumptions and data availability[27]. In March 16 2016 update the model by the Imperial College reported up to 500K deaths in the UK and up to 2.2 million deaths in the US in case of no action by the government nor population. Further, the estimated figure that 15% of hospital cases would need to be treated in an ICU was then updated to 30%, arguing that the British ICU capacity (4K beds) would be overwhelmed. This prompted the policy response of the UK government, which initiated social distancing measures. But, as already mentioned, the model is based on a series of assumptions. For instance, it was assumed in the 16 March release that 0.9% of patients affected would die, that R0 was between 2 and 2.6, and that incubation was 5.1 days. Further, it was assumed that an individual is infectious for 4.6 days after being infected, and that asymptomatic can be infectious for 12 hours. However, as researchers discover more about the virus, they are updating many key variables, including R0. For instance, in the models released by the Imperial College on the 26th and 30th of March the value of R0 has been updated respectively between 2.4 and 3.3 and between 3 to 4.7. And in any case, the worst case scenario would take place only if the governments would not implement any mitigating action. In fact, in the best case scenario of a reproduction number of 2 and isolation of people with symptoms, home quarantine, and early implementation of school closures, together with social distancing, deaths in the UK will be just 5,600, so much that on the 25th of March Ferguson declared to be "reasonably confident" that total deaths in the United Kingdom will be held below 20,000.[28][29] But how does R0 change? The first value of R0 considered was based on fits to the early growth-rate of the epidemic in Wuhan. However, Ferguson observed a rate of growth of the epidemics in Europe faster than expected looking at the early data from China, and therefore revised the estimate of the reproduction number, implying that the virus has spread more quickly than expected. This boosts the evidence to support intensive social distancing measures, because the higher the reproduction number is, the more intensive the controls need to be to mitigate the epidemic. The difference might

[27] https://nucleardiner.wordpress.com/2020/03/21/the-imperial-college-modeling-of-the-coronavirus/
[28] https://media.nature.com/original/magazine-assets/d41586-020-01003-6/d41586-020-01003-6.pdf
[29] https://parliamentlive.tv/Event/Index/2b1c71d4-bdf4-44f1-98fe-1563e67060eehttps://parliamentlive.tv/Event/Index/2b1c71d4-bdf4-44f1-98fe-1563e67060ee

be due to the fact that the true number of infections in UK and the rest of Europe is much larger than the official numbers reflect, because many people with mild or nonexistent symptoms will not seek medical treatment or testing. In this regard, a reliable test to see who has been infected without showing symptoms would be a game changer for modellers, and might significantly alter the predicted path of the pandemic. Other assumptions that can be contested are the rate of death, the length of incubation, and the period in which infected and asymptomatics can be infectious.

An example of the forecasts of the critical care bed occupied per 10,000 of population provided by the model based on the March 16 update is depicted in Figure 9, in which the red line is the estimated surge ICU bed capacity in UK, the black line shows the unmitigated epidemic, the orange one shows a containment strategy (i.e. case isolation, household quarantine and social distancing), and the green shows a suppression strategy (closure of schools and universities, case isolation and social distancing) beginning in late March 2020.

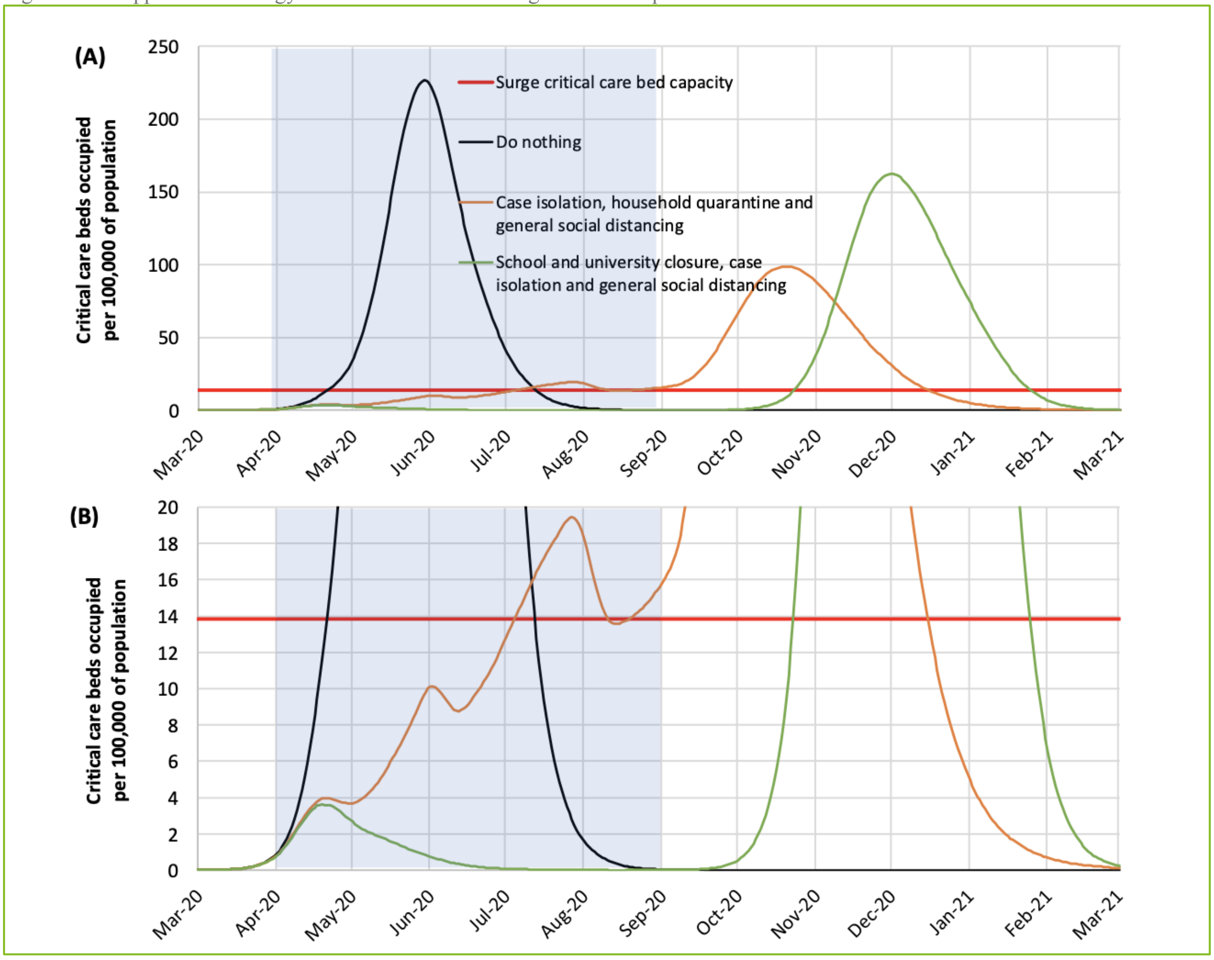
Figure 9 - Suppression strategy scenarios for GB showing ICU bed requirements



Source: https://www.imperial.ac.uk/media/imperial-college/medicine/sph/ide/gida-fellowships/Imperial-College-COVID19-NPI-modelling-16-03-2020.pdf

An example of the forecasts provided by the model based on the March 16 update for UK is depicted in Figure 10.

Figure 10 - Suppression strategy scenarios for UK showing ICU bed requirements



Source: https://www.imperial.ac.uk/media/imperial-college/medicine/sph/ide/gida-fellowships/Imperial-College-COVID19-NPI-modelling-16-03-2020.pdf

On the other hand, the global projections released on March 26 are based on an equation based approach.[30] There the population is divided into four groups: susceptibles (S), infected (I), either recover (R) or die, and those who have been exposed, but who are not yet infectious (E), postulating the mpact of an unmitigated scenario in the UK and the USA for a reproduction number R0 of 2.4 up to 490,000 deaths and 2,180,000 deaths respectively, , and estimate that in the absence of interventions, COVID-19 would have resulted in 7.0 billion infections and 40 million deaths globally this year.

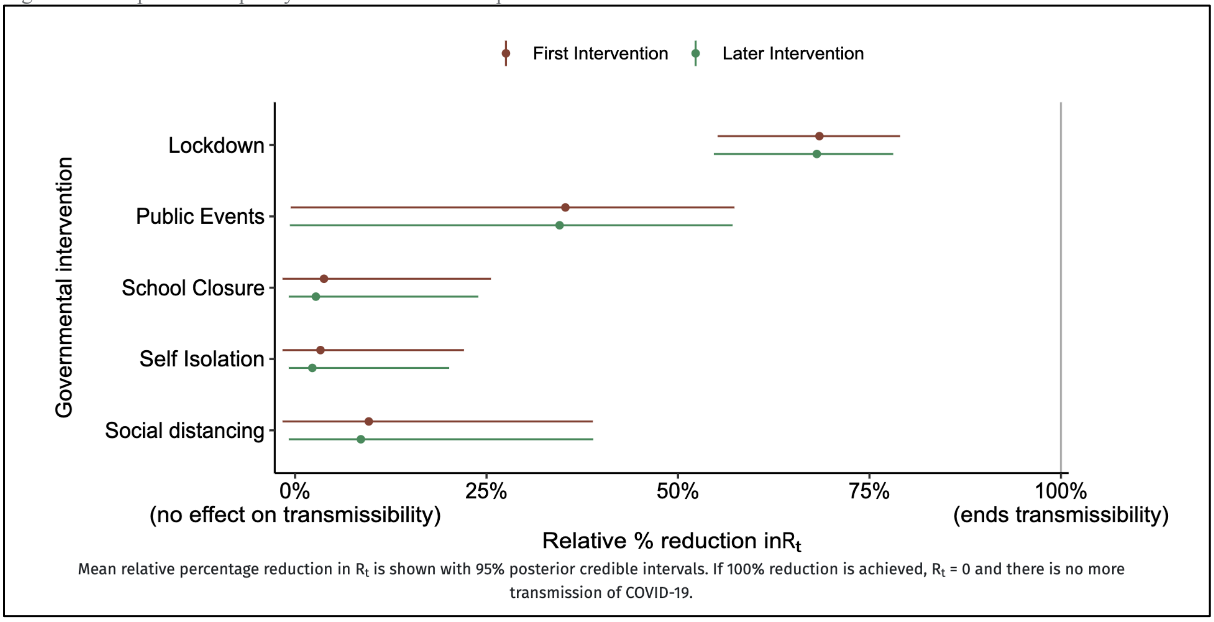
Finally, on the March 30[31] release the modellers adopted a semi-mechanistic Bayesian hierarchical model to attempt to infer the impact of policy interventions across 11 European countries. They assume that the reproductive number is an immediate response to the interventions being implemented rather than broader gradual changes in behaviour. It is important to notice that one of the key assumptions of the model is that each intervention has the same effect on the reproduction number across countries and over time. In this way the researchers are able to leverage on a higher amount of data. Their estimate that the intervention has averted 59,000 deaths up to

[30] https://www.imperial.ac.uk/media/imperial-college/medicine/sph/ide/gida-fellowships/Imperial-College-COVID19-Global-Impact-26-03-2020v2.pdf

[31] https://spiral.imperial.ac.uk:8443/handle/10044/1/77731

31 March across all 11 countries, that between 7 and 43 million individuals have been infected, and that the proportion of the population infected to date is the highest in Spain followed by Italy and lowest in Germany and Norway, reflecting the relative stages of the epidemics. Specifically, they estimated that in Italy and Spain, respectively 38,000 and 16,000 deaths have been avoided. More in depth, the Imperial College team has estimated the estimated impact of interventions on the reproductive number, as displayed in Figure 11.

Figure 11 – Impact of the policy intervention on the reproductive number



Source: https://spiral.imperial.ac.uk:8443/handle/10044/1/77731

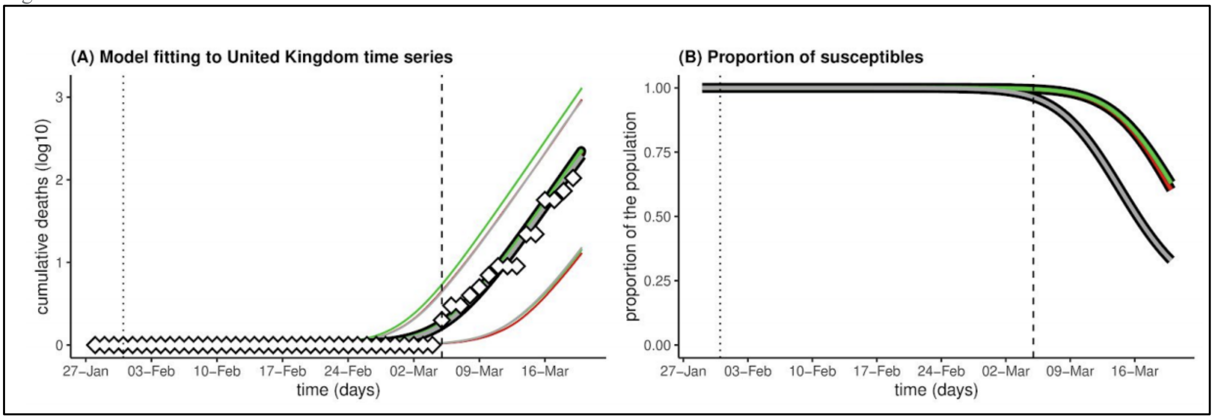
Another model that has been discussed at length is the one developed by the university of **Oxford (UO)**[32]. Specifically, the researchers calibrated a susceptible-infected-recovered (SIR) model to data on cumulative deaths from the UK and Italy, building on the assumption that such deaths are well reported events that occur only in a vulnerable fraction of the population. The authors also assume estimates of critical epidemiological parameters such as the basic reproduction number (R0), infectious period and time from infection to death, probability of death in the vulnerable fraction of the population. This with the aim to assess the sensitivity of the system to the actual fraction of the population vulnerable to severe disease and death. The estimations of the model for the UK and Italy are reported in the figures below. Results are given for three scenarios: R0 = 2.25 and p=0.001, R0 = 2.25 and p= 0.01 (green), and R0 = 2.75 and p=0.01[33] (red). In the part (A) the model shows reported (diamonds) and model (lines) cumulative death counts. In part (B) the model shows the mean proportion of the population still susceptible to infection. In parts (A-B) the vertical lines mark the date of the first confirmed case (dotted) and date of first confirmed death (dashed). The chart shows that in R0 scenarios, by the time the first death was reported (05/03/2020), thousands of individuals would have already been infected with the virus. By 19 March, approximately 36% (R0=2.25) and 40% (R0=2.75) of the population would have already been exposed. Running the same model with R0=2.25 and the proportion of the population at risk of severe disease p being

[32] https://www.medrxiv.org/content/10.1101/2020.03.24.20042291v1

[33] Proportion of the population at risk of severe disease

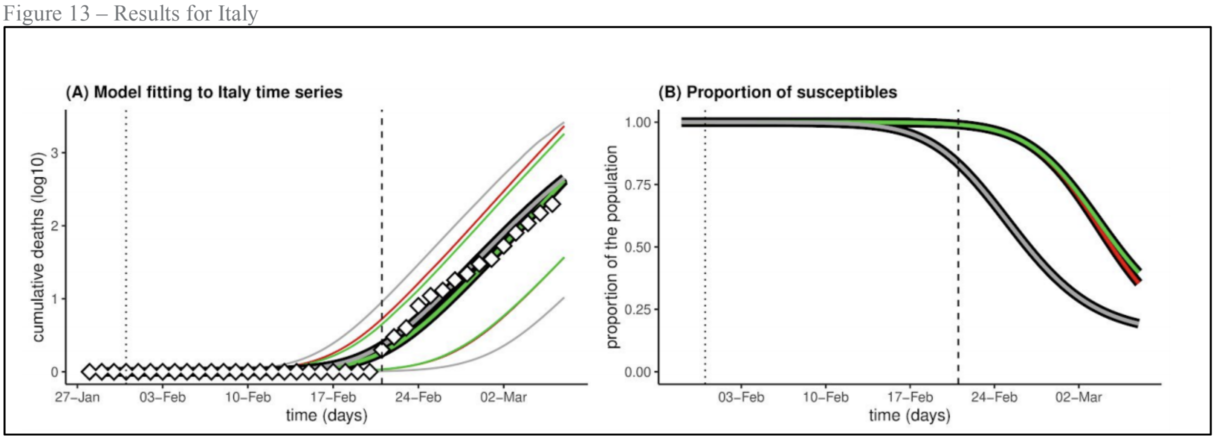
distributed around 0.1%, states that places the start of transmission at 4 days prior to first case detection and 38 days before the first confirmed death and suggests that 68% would have been infected by 19 March (see Figure 12 and Figure 13).

Figure 12 – Results for UK



Source: https://www.medrxiv.org/content/10.1101/2020.03.24.20042291v1.full.pdf

Figure 13 – Results for Italy



Source: https://www.medrxiv.org/content/10.1101/2020.03.24.20042291v1.full.pdf

In summary, the model suggests that the new coronavirus may already have infected far more people in the UK than scientists had previously estimated (maybe half of the population), and that thereby the mortality rate from the virus is much lower than what is generally thought to be, as the vast majority of infected individuals develop mild symptoms or not at all. The model suggests that the infection has reached the UK by December or January, and that therefore people started to be infected in huge numbers before the first official case was reported. Clearly the model presents a very different view from the one produced by the Imperial College one. In fact the Oxford model puts the focus on herd immunity, and concludes that the country had already acquired substantial herd immunity through the unrecognised spread of Covid-19 over more than two months. In any case, the Oxford team is not critic with the measures of social distancing put into place by the UK government, which will reduce the number of people becoming seriously ill and relieve severe pressure on the NHS during the peak of the epidemic. And the UK has abandoned the herd immunity policy after its scientific advisers said this would swamp the National Health Service with critically ill patients.

However, also this model is criticized as far as its assumptions are concerned. First of all, the assumption that the infection has reached the UK by December or January it is not shared by most epidemiologists. Further, the figure that only one in 1,000 infections will need hospitalization is removed from reality, as on March 24 (at the time of release of the model) more than one in 1,000 people have already been hospitalised in the Lombardy region of Italy, despite stringent control measures being implemented (population of Lombardy: 10,060,574; hospitalised: 10,905; hospitalisation rate per 1,000 population: 1.08; deaths: 4,178; deaths per 1,000 population: 0.42).[34]

As we have seen, the results of the model forecasts are influenced by the underlying assumption and data availability. But the crucial info hidden from the modellers regards the number of people that have been infected without showing symptoms, and for which a reliable test would be a game changer for modellers as it might significantly alter the predicted path of the pandemics. In fact, it appears that the mortality rate is much lower than official numbers suggest, as many people are infected without knowing it and they do not get tested. As suggested by three federal public health officials the "overall clinical consequences of COVID-19 may ultimately be more akin to those of a severe seasonal influenza (which has a case fatality rate of approximately 0.1 percent) or a pandemic influenza (similar to those in 1957 and 1968) rather than a disease similar to SARS or MERS, which have had case fatality rates of 9 to 10% and 36%, respectively."[35] This view was also argued by a study estimating that in China that 86 percent of all infections were undocumented in the early stages of the epidemics, and therefore the actual number of infections was roughly six times as high as the official number.[36] This would imply lower estimates for mortality also in case of the US.

Another modelling team consulted by the UK government works at the **London School of Hygiene and Tropical Medicine**.[37] The team used population contact patterns for United Kingdom based self-reported contact data from over 36,000 volunteers that participated in the citizen science project BBC Pandemic. The team leveraged on the data collected to generate fine-scale age-specific population contact matrices by context (home, work, school, other) and type (conversational or physical) of contact. The matrices have then been used to evaluate social distancing and population mixing reduction strategies (e.g. school closures and smart working). The analysis of the team have also focussed on the impact of social distancing and travel restrictions, as well as on the necessity to focus on risk groups, i.e. those are the ones who get the vaccines or the expensive treatments. In this regard, a potential strategy for COVID-19 is to try to cocoon those most affected, meaning complete isolation of the elderly population from our society as much as possible.[38] The same team has also assessed the effect of control strategies to reduce social mixing on outcomes of the COVID-19 epidemic in Wuhan[39]. Specifically, the research team has built an age-specific and location-specific transmission model to assess progression of the Wuhan outbreak under different scenarios of school and workplace closure, showing that changes to contact patterns are likely to have

[34] https://www.ft.com/content/ebab9fcc-6e8d-11ea-9bca-bf503995cd6f

[35] https://www.nejm.org/doi/full/10.1056/NEJMe2002387

[36] https://science.sciencemag.org/content/early/2020/03/24/science.abb3221

[37] https://www.medrxiv.org/content/10.1101/2020.02.16.20023754v2.full.pdf

[38] https://www.dw.com/en/coronavirus-code-computer-modeling-could-help-fight-the-virus/a-52795025

[39] https://www.thelancet.com/action/showPdf?pii=S2468-2667%2820%2930073-6

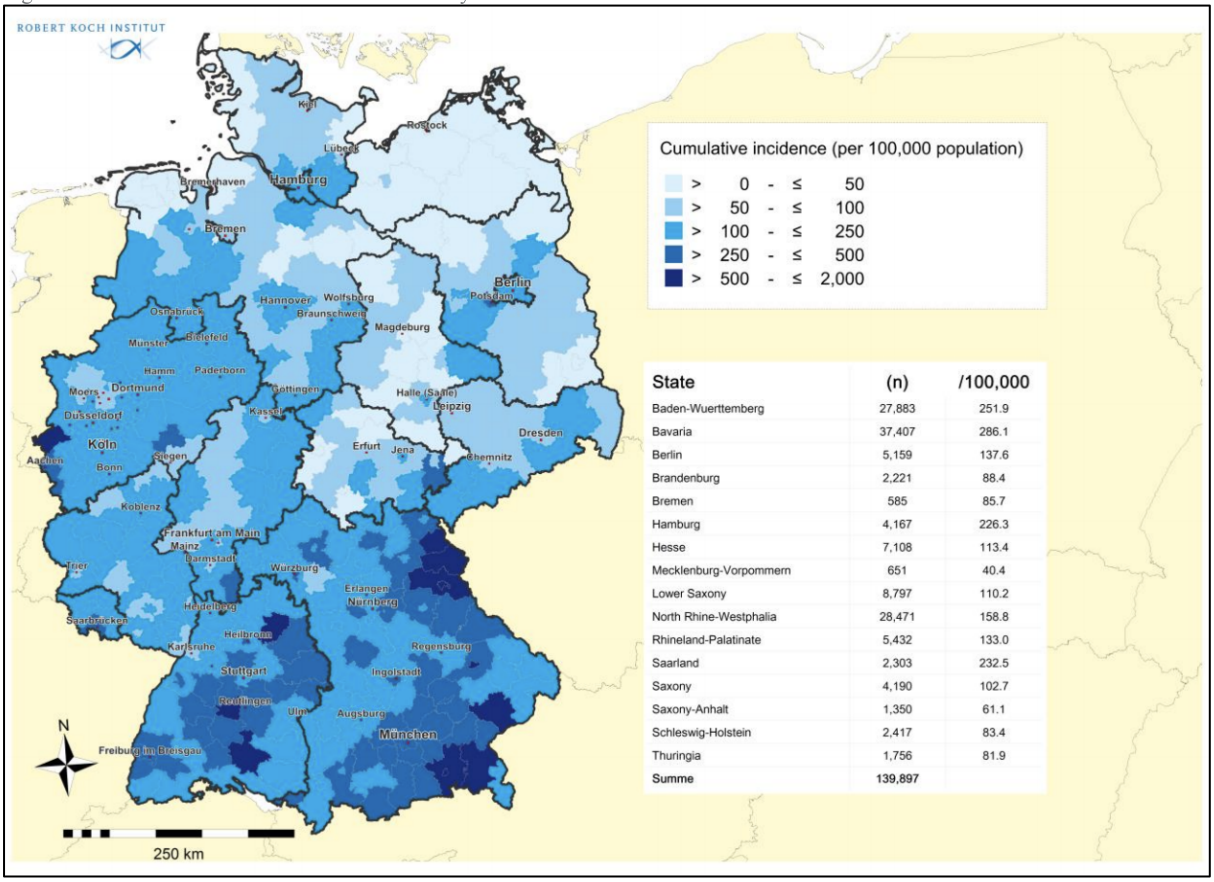
substantially delayed the epidemic peak and reduced the number of COVID-19 cases in Wuhan. Furthermore, the authors show that if these restrictions are lifted in March 2020, a second peak of cases might occur in late August 2020, and if the restrictions were to be delayed by 2 months, also the peak would be delayed. In summary, the research shows that the measures put in place to reduce contacts in school and work are helping to control the COVID-19 outbreak by affording health-care systems time to expand and respond, and especially that authorities need to carefully consider epidemiological and modelling evidence before lifting these measures to mitigate the impact of a second peak.

1.2.2

1.2.3 Predictive Models used in Continental Europe

The German disease and epidemic control is advised by the **Robert Koch Institute (RKI)** within the scope of a national pandemic plan. RKI is a German federal government agency and research institute responsible for disease control and prevention. The RKI is a federal government agency and research institute responsible for disease control and prevention, subordinate to the Federal Ministry of Health. The RKI provides daily updates on the situation of the COVID-19 outbreak, as well as projections and predictions on the future development of the epidemics. Specifically, the RKI provides a dashboard with the number and geographical distribution of active cases, critical cases, deaths and recovered patients, as well as a daily report. As the RKI is public, the common barrier to data innovation stemming from the difficulty in getting modelers to speak to policy makers is mitigated. This is a major factor in the success of German mitigation strategy. An example of the charts produced by the dashboard is depicted in Figure 14.

Figure 14 – Cumulative incidence of COVID-19 by lander



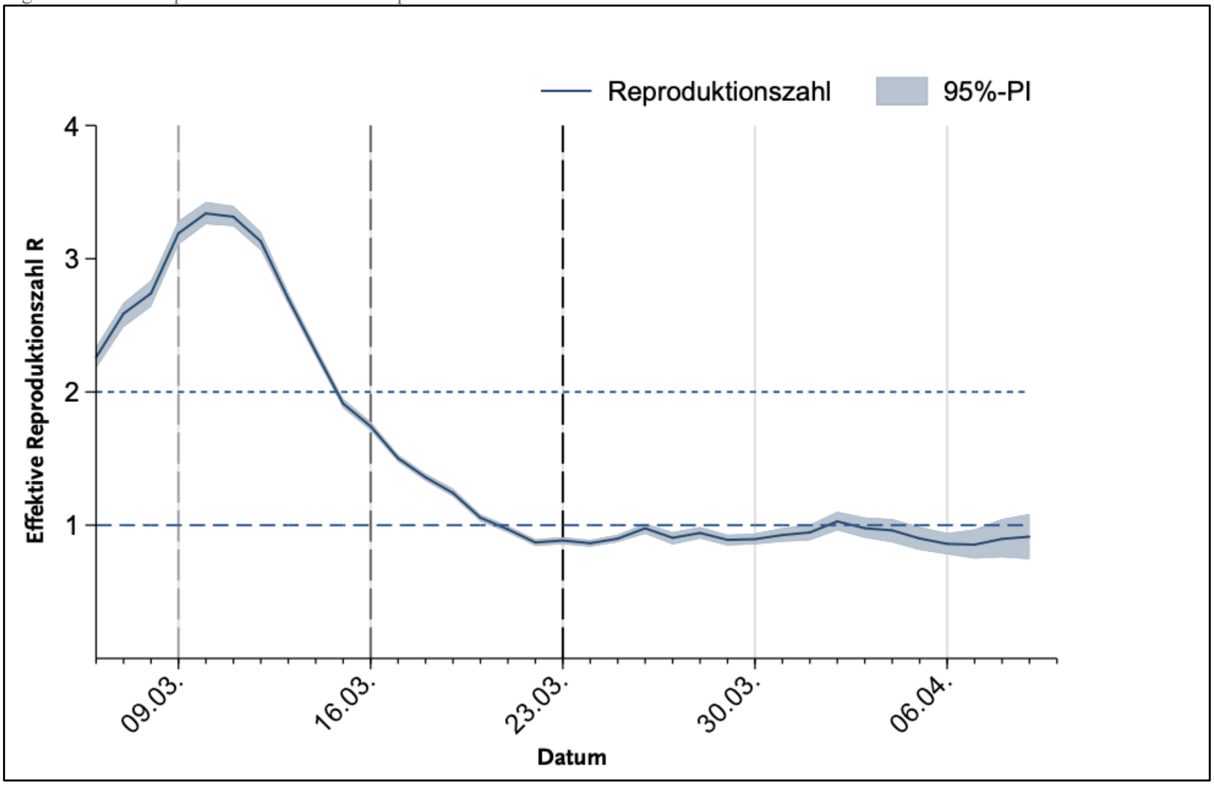
State	(n)	/100,000
Baden-Wuerttemberg	27,883	251.9
Bavaria	37,407	286.1
Berlin	5,159	137.6
Brandenburg	2,221	88.4
Bremen	585	85.7
Hamburg	4,167	226.3
Hesse	7,108	113.4
Mecklenburg-Vorpommern	651	40.4
Lower Saxony	8,797	110.2
North Rhine-Westphalia	28,471	158.8
Rhineland-Palatinate	5,432	133.0
Saarland	2,303	232.5
Saxony	4,190	102.7
Saxony-Anhalt	1,350	61.1
Schleswig-Holstein	2,417	83.4
Thuringia	1,756	81.9
Summe	**139,897**	

Source: https://experience.arcgis.com/experience/478220a4c454480e823b17327b2bf1d4

What is very interesting, the RKI makes available on an almost daily basis the estimation of the reproduction number, R, which is the mean number of persons infected by a case.[40] The current estimate is R= 0.8 and is based on current electronically notified cases (18/04/2020, 12:00 A.M.) and an assumed mean generation time of 4 days. The development of the effective reproduction number R for an assumed generation time of 4 days is depicted in Figure 15.

[40] https://www.rki.de/DE/Content/Infekt/EpidBull/Archiv/2020/Ausgaben/17_20_SARS-CoV2_vorab.pdf?__blob=publicationFile

Figure 15 - Development of the effective reproduction number R



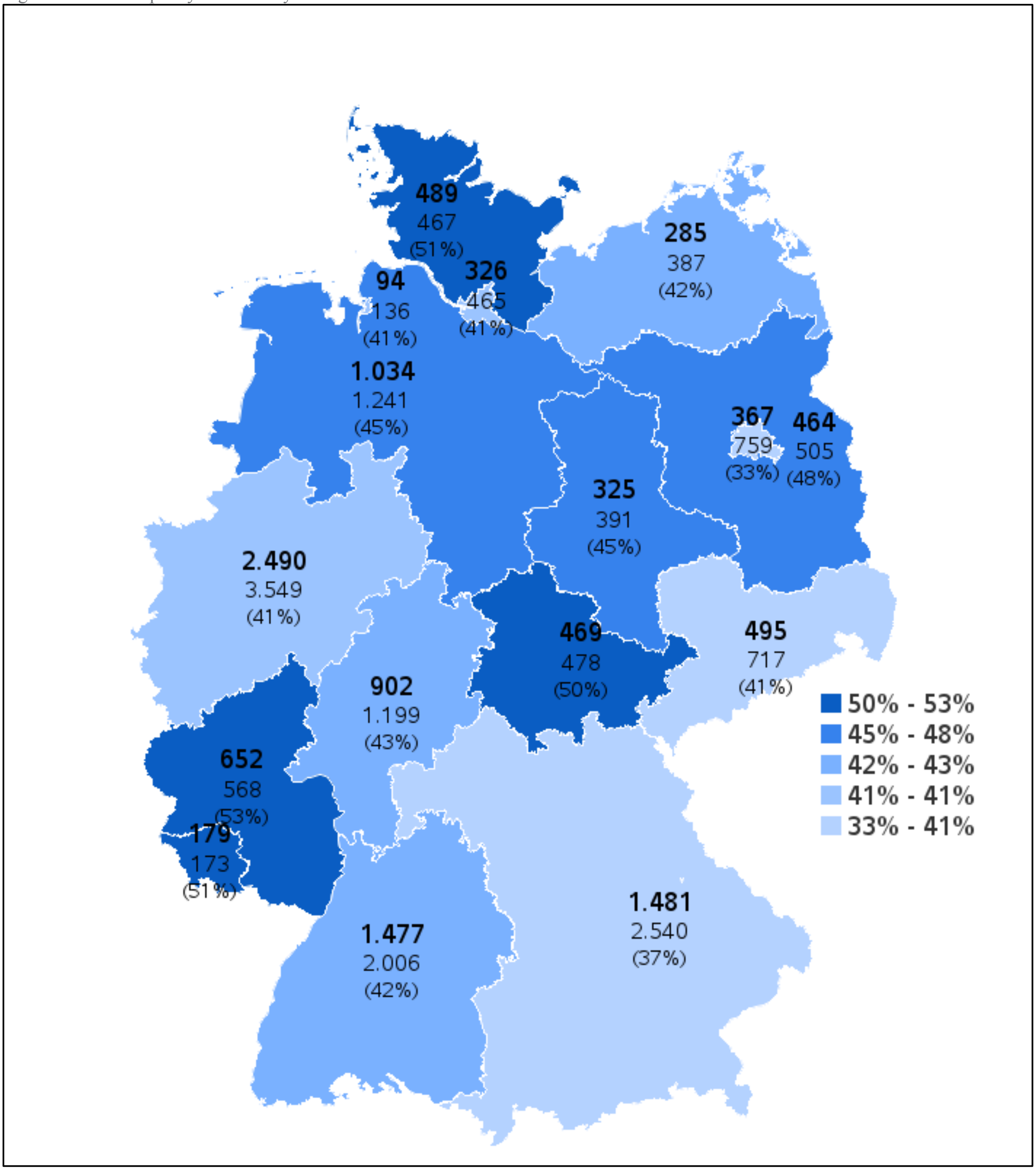
Source:
https://www.rki.de/DE/Content/Infekt/EpidBull/Archiv/2020/Ausgaben/17_20.pdf?__blob=publicationFile

The vertical lines represent the policies carried out by the Federal Government, i.e. the cancellation of major events in different federal states (with more than 1,000 participants) on March 9 2020, the Federal-State Agreement on guidelines against the spread of the coronavirus on March 16 2020, and the nationwide extensive ban on contacts on March 23 2020. There is a clear decrease in the number over time.

Another interesting aspect is the Intensive Care Register, which to the best of our knowledge is a case unique to Germany. The German Interdisciplinary Association for Intensive and Emergency Medicine (DIVI), the RKI and the German Hospital Federation (DKG) have established the register to document the capacities for intensive care as well as the number of COVID-19 cases treated in participating hospitals. Specifically, the DIVI intensive care register documents the number of available intensive care beds in the reporting hospitals on a daily basis. What is very interesting about the register, and what makes it very precise, is the fact that a hospital location can have several reporting areas: this gives the hospital locations the opportunity to report directly from individual wards / departments.[41] A map view with the number of free and occupied intensive care beds & share of free beds in the total number of intensive care beds (Figure 16).

[41] https://www.intensivregister.de/#/intensivregister

Figure 16 – ICU capacity in Germany



Source: https://www.intensivregister.de/#/intensivregister

Another interesting collaborative effort is carried out by RKI together with the the Research on Complex Systems Group (ROCS) at the Institute for Theoretical Biology and IRI Life Sciences at Humboldt University of Berlin. The core of the data used come from RKI together with data from the worldwide air transportation network (WAN).[42] This network has 3893 nodes (airports) that are connected by 51476 directed links (flight routes). Each link is weighted by the traffic flux between

42 http://rocs.hu-berlin.de/corona/docs/analysis/importrisk/

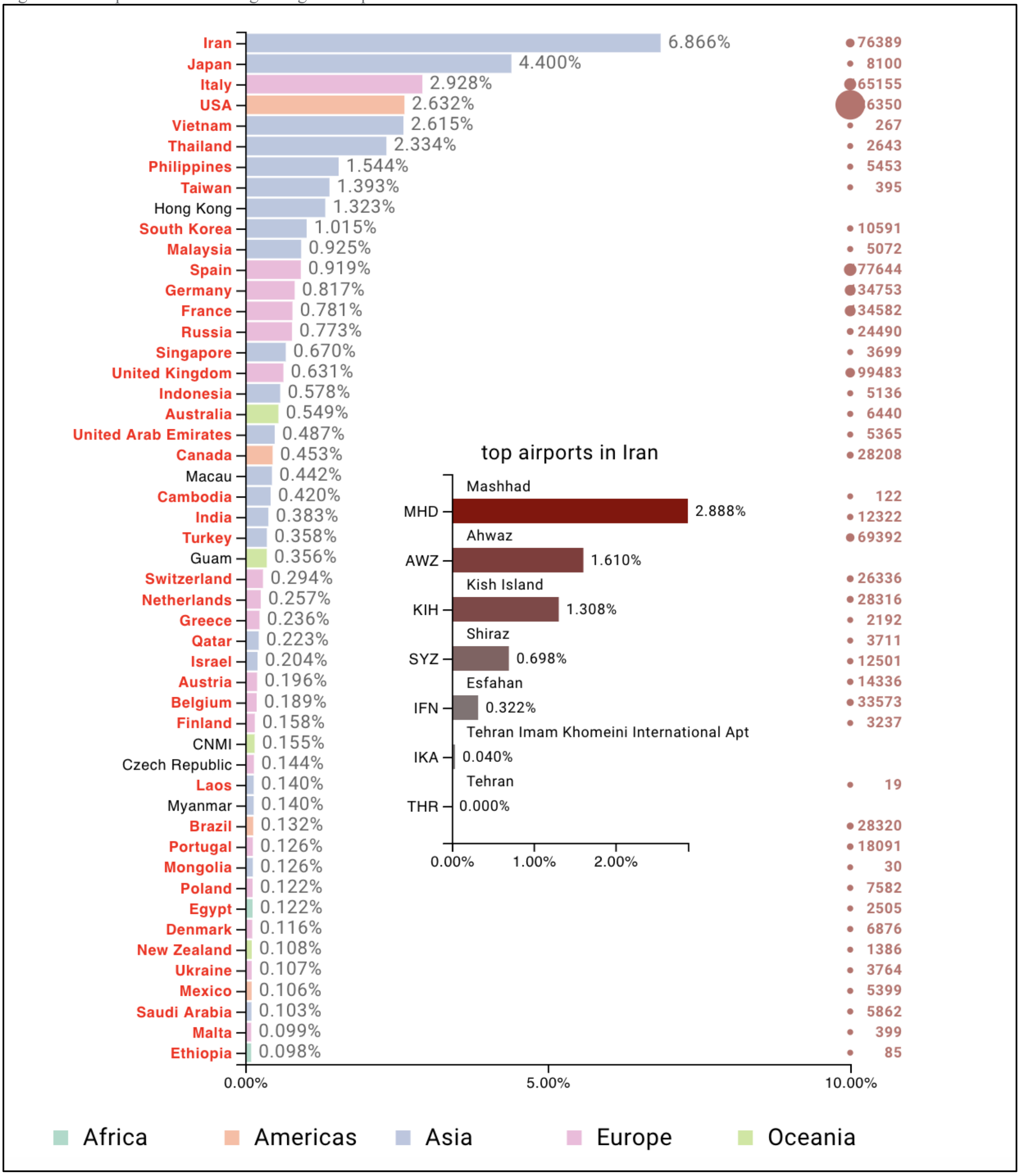
nodes, i.e. the average number of passengers that travel each route per day.[43] Specifically, the team employs a SIR-X model, in which the transmission rate changes over time, inspired by the assumption that susceptible individuals are continuously removed from the transmission process due to interventions such as social distancing, public shutdowns, quarantines, and curfews.[44] This is complemented by an import risk model, which displays the likelihood of importing a case from an affected location to an airport or country distant from the outbreak location. This model is used to assess the If an infected individual boards a plane at airport A in an affected region, the relative import risk P(B|A) at airport B quantifies the probability that airport B is the final destination for that individual (irrespective of non-direct travel routes).

Say, 1000 infected individuals board planes at Hangzhou Airport. An import risk of 0.2% in Germany means that, of those 1000 individuals, only 2 are expected to have Germany as their final destination. By mean of the model it has been possible to describe the situation at the start of the pandemic (see Figure 17).

[43] The underlying network theoretic model is based on the concept of effective distance and is an extension of a model introduced in the 2013 paper The Hidden Geometry of Complex, Network-Driven Contagion Phenomena, D. Brockmann & D. Helbing, Science: 342, 1337-1342 (2013).

[44] SIR-X model is described in detail here: Effective containment explains sub-exponential growth in confirmed cases of recent COVID-19 outbreak in China, B. F. Maier & D. Brockmann, Science, eabb4557, DOI: 10.1126/science.abb4557, (2020)

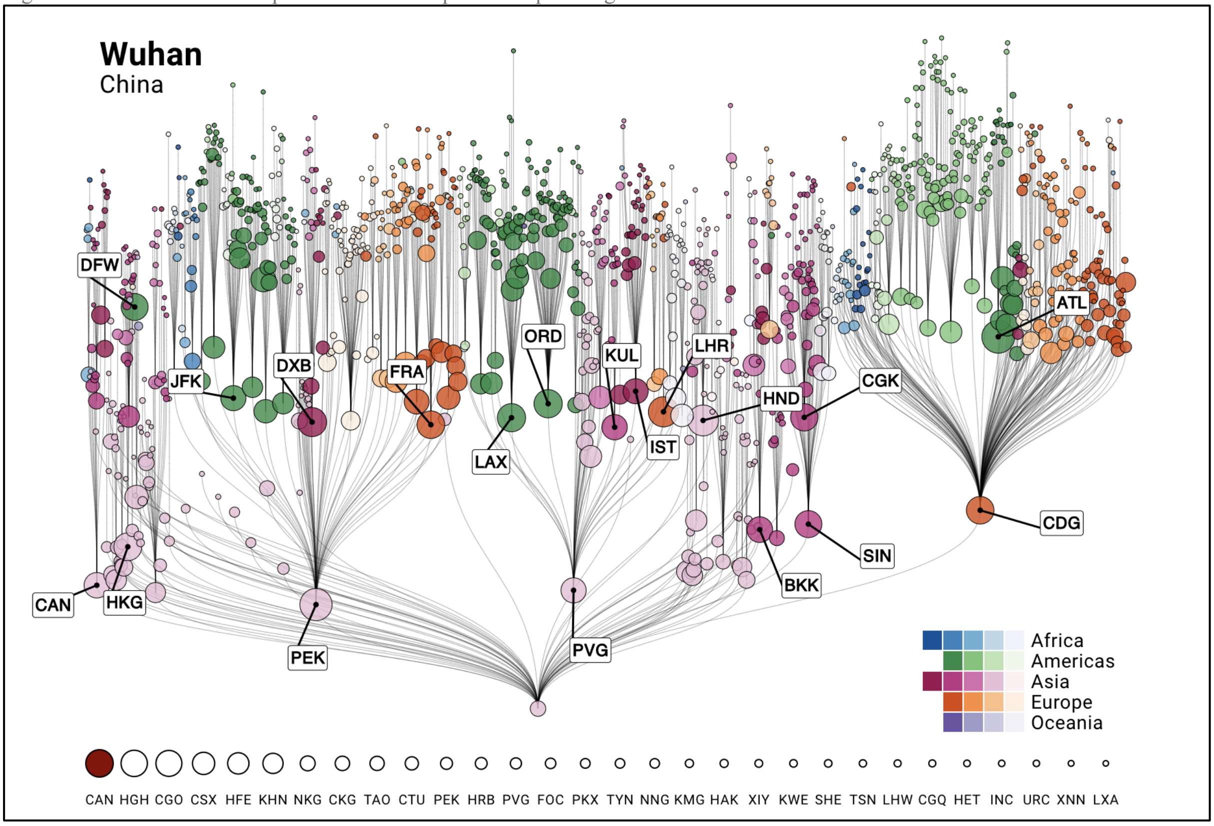
Figure 17 – Import risk at the beginning of the pandemics



Source: http://rocs.hu-berlin.de/corona/docs/analysis/importrisk/

Current import risk estimates for the top 50 countries (excluding Mainland China) at highest risk of importation. The national import risk is the cumulative import risk of all airports in that country. Countries with confirmed cases of COVID-19 at the time are depicted in red; the current number of cases per country are listed on the right-hand side. The import risk model also provides information on the most probable spreading routes from a location in the affected region, i.e. root node in the air transportation network. Figure 18 provides an understanding of the distribution of import risk and the most probable spreading routes from a selected set of airports in affected regions in Mainland China.

Figure 18 - Distribution of import risk and most probable spreading routes



Source: http://rocs.hu-berlin.de/corona/docs/analysis/importrisk/

The tree represents the most probable spreading routes from the root node to all other airports in the network, while the vertical length between nodes represents the effective distance between airports.

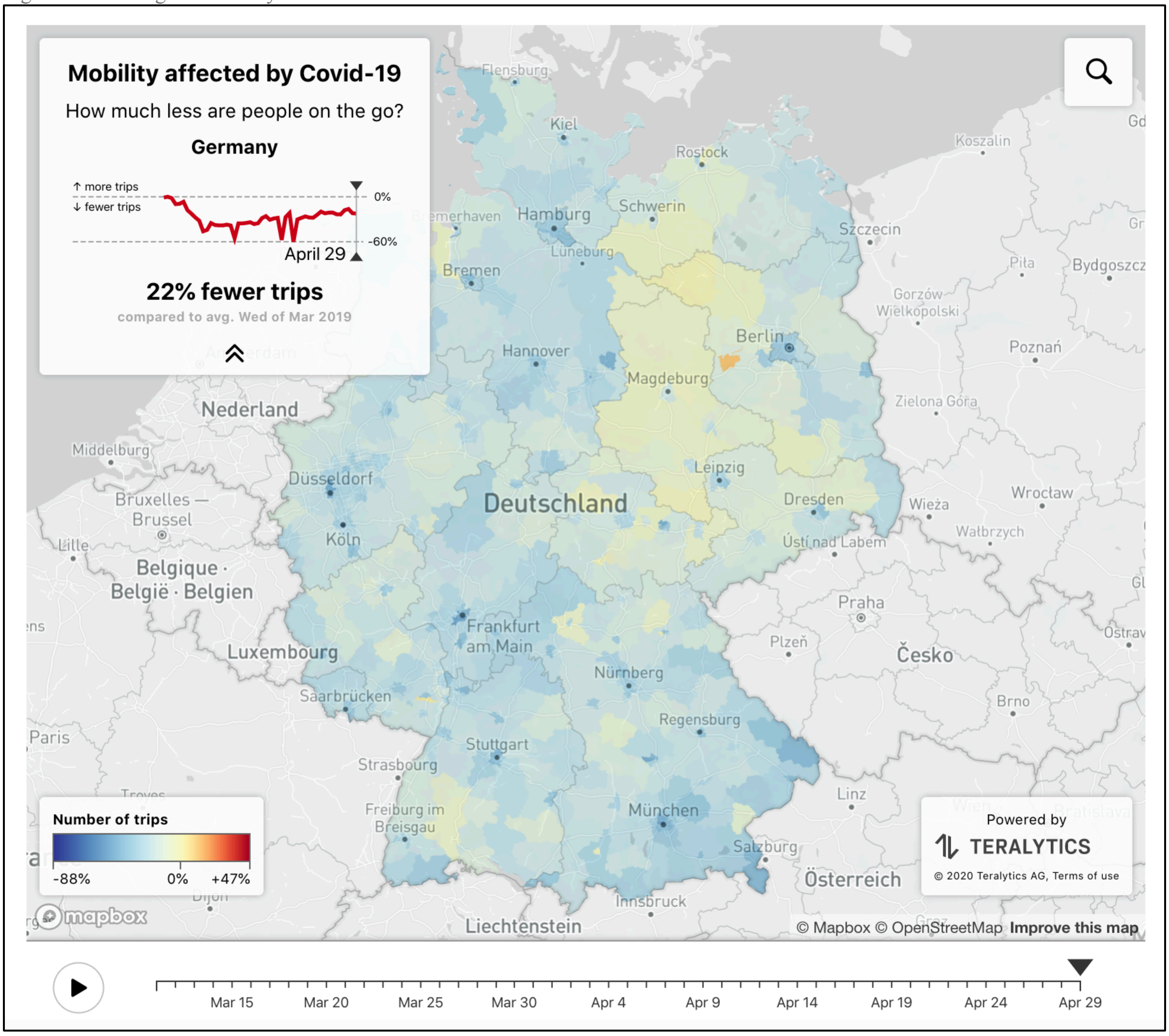
Along the same line the COVID Mobility Project[45] provides a general picture of mobility reduction in Germany due to Covid-19 mobility restrictions. Specifically, the model depicts three phases:

- Initial drop in mobility: mobility fell to -39% below normal in mid-March 2020, after the majority of restrictions in Germany took effect.
- Slow recovery of mobility: in late March mobility slowly increased and finally plateaued at -27% in the second week of April. As restriction policies hardly changed during this time, this increase might be attributed mostly to a relaxing of self-imposed, individual mobility restrictions, paired with increased mobility due to warmer weather.
- Beginnings of an opening: starting April 20th, some mobility restriction policies have been lifted. We observe an immediate increase in mobility to -21% in the week starting April 20th.

Mobility flows of this kind are collected by many mobile phone providers. The team uses data from the German Telekom, which is distributed by the company Motionlogic, as well as data from Telefónica, which is analyzed and aggregated by the company Teralytics. This kind of data is commercially available and is used, for example, by public transportation companies, for predicting traffic or to improve road infrastructure. The live mobility monitor is depicted in Figure 19.

[45] http://rocs.hu-berlin.de/covid-19-mobility/mobility-monitor/

Figure 19 – Change in mobility due to COVID-19



Source: http://rocs.hu-berlin.de/covid-19-mobility/mobility-monitor/

Finally, a team of researchers (**Hartl et al.**) has measured the impact of the German public shutdown on the spread of COVID-19 by making use of data from Johns Hopkins University (2020), which links data from the Robert Koch Institute, the World Health Organization, and the European Centre for Disease Prevention and Control. Specifically, the researchers tested for a trend break in the cumulated confirmed Covid-19 cases by means of maximum likelihood.[46][47] They carried out a first estimation finding a trend break around 20 March.[48] Their finding is that confirmed Covid-19 cases in Germany grew at a daily rate of 26.7% until 19 March. From March 20 onwards, the growth rate drops by half to 13.8%, which is in line with the lagged impact of the policies implemented by the German administration on 13 March and implies a doubling of confirmed cases every 5.35 days. Before 20 March, cases doubled every 2.93 days. In their update of the model they test the impact

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[46] Bai, J (1997), "Estimation Of A Change Point In Multiple Regression Models", The Review of Economics and Statistics 79(4): 551–563.

[47] Bai, J and P Perron (1998), "Estimating and Testing Linear Models with Multiple Structural Changes", Econometrica 66(1): 47–78.

[48] https://cepr.org/sites/default/files/news/CovidEcon1%20final.pdf

of the 22 March policies.[49] From 30 March on, the estimated average growth rate is 5.8%, so that the cases double every 12.20 days, therefore the containment policies are being effective.

The Italian response to COVID-19 is supported by several teams of experts, among which the Task Force for the Covid-19 Emergency established by the Italian Ministry for Technological Innovation and Digitization, and the data utilised are those of the Italian Civil Protection, which in turn are the result of the data collection effort through the Italian integrated COVID-19 surveillance system and aggregated at the national, regional and provincial level. There is no specific and explicit information regarding which models are used by the Italian authorities to take their decisions. According to confidential sources, the Italian National Institute of Health and the Italian Scientific and Technical Committee, in agreement with the Italian Ministry of Health and Italian Civil Protection, are collaborating with Bruno Kessler Foundation in developing the models used by the Italian authorities in taking their policy decisions. The model will be available only when published.

At any rate, on the basis of the modelling effort, members of the Italian Scientific and Technical committee and the Italian National Institute of Health have carried out an assessment of the risks of epidemic spread for COVID-19 disease associated with various scenarios of the release of the lockdown introduced on 11 March on the national territory. Some anticipated results according to which restarting all the sectors without teleworking and with schools open, the country would need 151 thousand intensive care units already in June and a number of hospitalizations, by the end of the year, equal to 430,866.[50]

Some other results obtained suggest that:

1. The reopening of schools would significantly increase the risk of a new epidemic wave with potentially very critical consequences on the stability of the national health system;
2. For all reopening scenarios in which an increase in community contacts is expected, transmissibility crosses the epidemic threshold, thus triggering a new epidemic wave;
3. In most re-opening scenarios of the professional sectors (in the presence of closed schools), even if transmissibility exceeds the epidemic threshold, the expected number of intensive therapies at the peak it would be lower than the current availability of beds at national level (about 9000);
4. If the widespread adoption of personal protective equipment reduces the transmissibility by 15%, the scenarios reopening the commercial sector to the community could allow containment below the threshold epidemic only managing to limit transmission in the community for over 60 years old;
5. If the widespread adoption of personal protective equipment reduces the transmissibility by 25%, the scenarios the reopening of the commercial sector and of the restaurant sector to the community could allow containment below the threshold only managing to limit the transmission in the community over 65 years.

Further, researchers from the **COVID-19 working group, National Institute of Health, Bruno Kessler Foundation and Cyprus University of Technology** have estimated the reproductive

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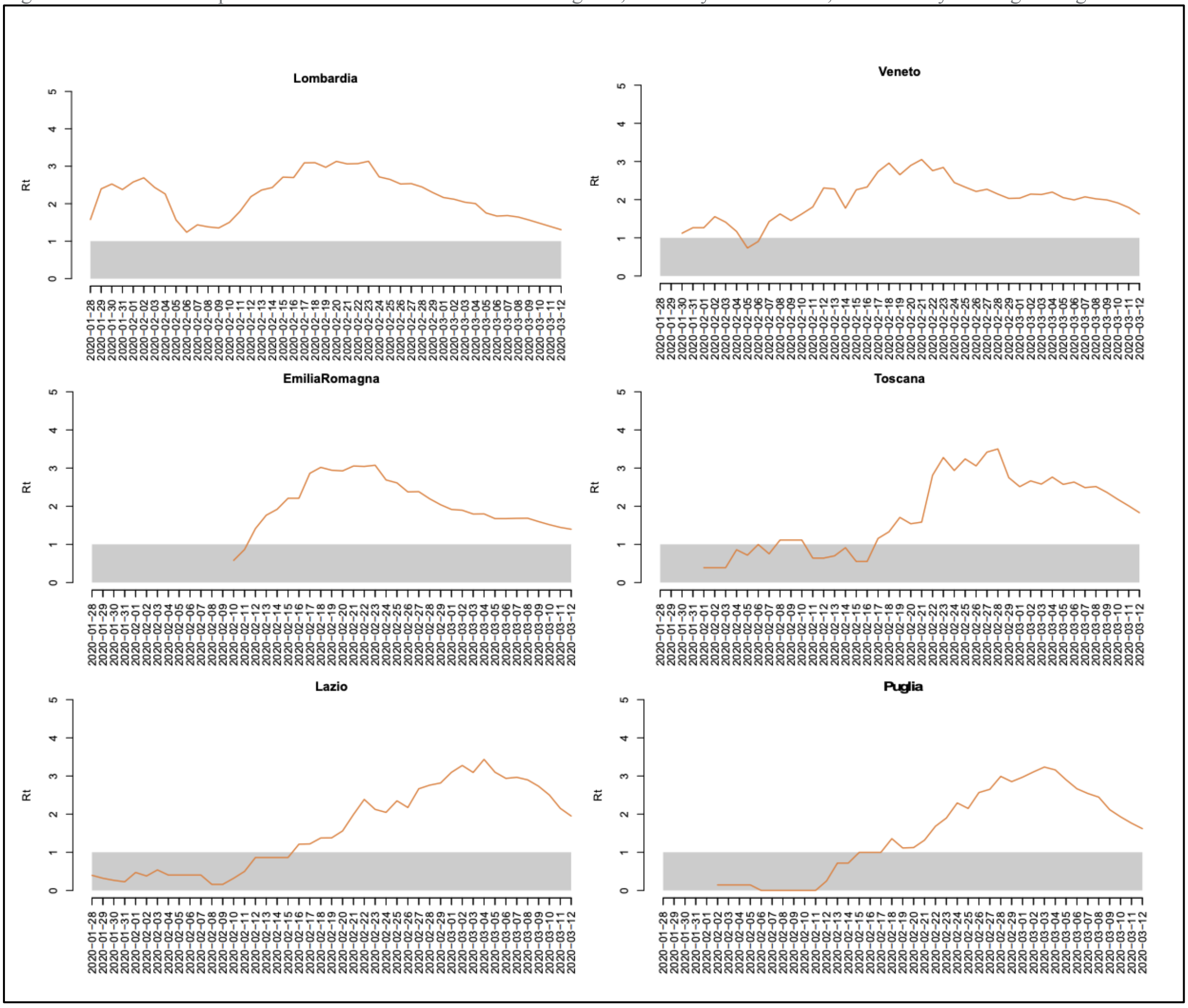
49 https://voxeu.org/article/measuring-impact-german-public-shutdown-spread-covid-19

50 https://drive.google.com/file/d/1pe1gEp4-UAPxLW_vnqntAa4AT5D_nyR1/view

numbers one month into the epidemic.[51] Specifically, they analysed data from the national case-based integrated surveillance system of all COVID-19 infections as of March 24th 2020, collected from all Italian regions and autonomous provinces in order to provide a descriptive epidemiological summary on the first 62,843 COVID-19 cases in Italy as well as estimates of the basic and net reproductive numbers by region. Estimates of R0 varied between 2.5 in Toscana and 3 in Lazio, with epidemic doubling time of 3.2 days and 2.9 days, respectively. The net reproduction number showed a decreasing trend starting around February 20-25, 2020 in Northern regions. Initially R0 was at 2.96 in Lombardia, which explains the high case-load and rapid geographical spread observed. As it can be seen from Figure X, In Lombardia, the Rt started to oscillate reaching maximum values around 3 over the week from February 17 to 23. Starting from February 24, with the enforcement of a quarantined area around the most affected municipalities of the region, Rt was estimated to follow a constantly decreasing trend. The second and third most affected regions in February (Veneto and Emilia Romagna) show an increasing trend of Rt until about February 24. On the other hand, in Tuscany, Lazio, and Apulia are located, the epidemic spread was largely undetected until early March, and after an initial increase, Rt remained nearly constant at values around 2.5-3 until March 4-8, when physical distancing measures began being implemented (Figure 20).

[51] https://www.medrxiv.org/content/10.1101/2020.04.08.20056861v1.full.pdf

Figure 20 - Estimated reproduction number in selected Italian regions, February-March 2020, over a 4-day moving average



Source: https://www.medrxiv.org/content/10.1101/2020.04.08.20056861v1.full.pdf

Overall the reproductive number in Italian regions is currently decreasing, supporting the importance and effectiveness of combined non-pharmacological control measures. Along the same line, researchers and consultants to the Italian Government from the National Observatory on Health in the Italian Regions have estimated the timing according to which the number of new cases in each Italian region will amount to zero. Specifically, they find that the regions with zero new cases will be Basilicata and Umbria on April 21st, while the last will be Tuscany on May 30th.[52]

The impact of containment measures is assessed by another research team by Signorelli et al.[53] that concludes that suspending flights from China and air-ports' checkpoints with thermos-scan did not have a significant effect in containing the epidemic, the implementation of a "red zone" in Lombardy effectively contained the spread of the infection within that area, even though it did not have the same effect in the neighboring provinces (Bergamo, Brescia, and Piacenza); the failure to establish a second "red zone" near Bergamo in the Municipalities of Alzano and Nembro despite the proposal of local authorities (on March 3rd), led to a dramatic out-break with

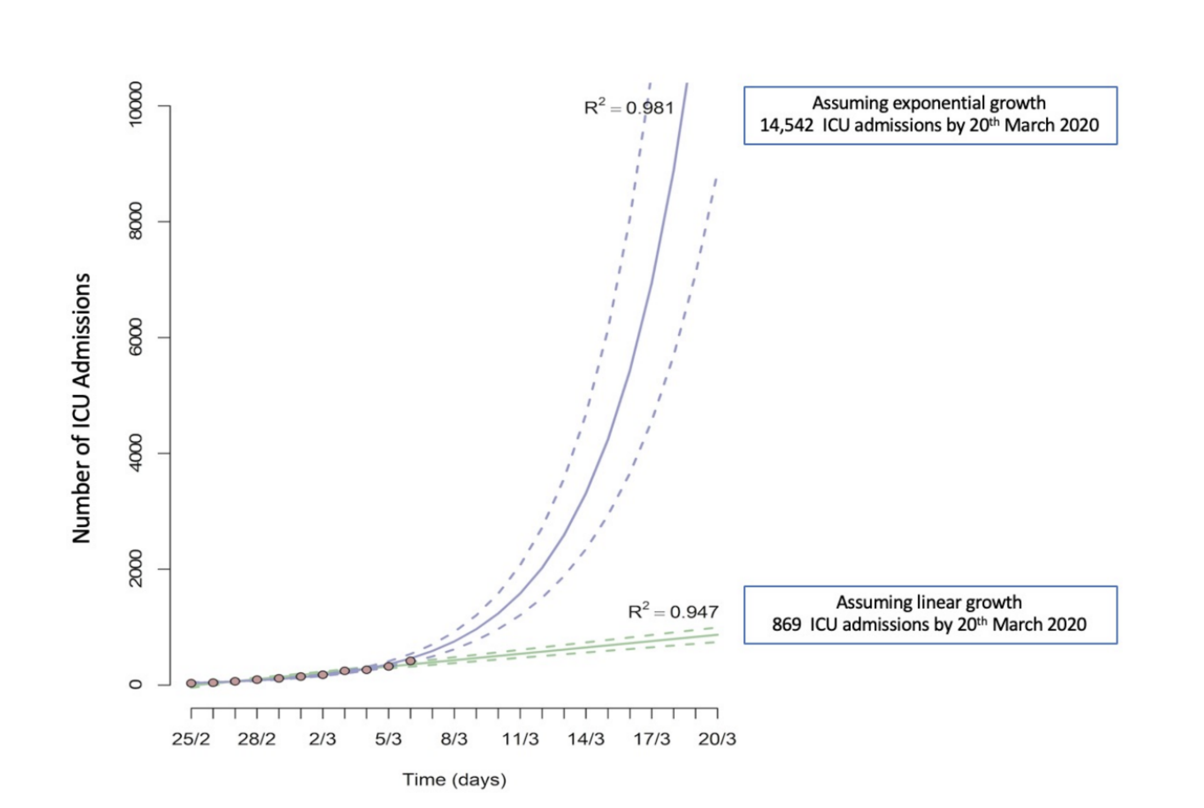
[52] https://www.osservatoriosullasalute.it/wp-content/uploads/2020/04/new-19-aprile-Definitivo-CS-COVID-19-Osservatorio.pdf

[53] https://www.mattioli1885journals.com/index.php/actabiomedica/article/view/9511/8735

about 10,000 cases in Bergamo with over 1,000 death toll and similar figures in the neighbouring areas (Brescia and Piacenza); and finally that General mitigation measures seem to be effective to flatten the epidemic curve of new notified infections.

An Italian team of researchers (**Grasselli et al.**) was the first to address the consequences of the COVID-19 outbreak on critical care capacity outside China.[54] The article shows that despite prompt response of the local and regional ICU network, health authorities, and the government to try to contain the initial cluster, the surge in patients requiring ICU admission has been overwhelming. Therefore, other health care systems should prepare for a massive increase in ICU demand during an uncontained outbreak of COVID-19. This experience would suggest that only an ICU network can provide the initial immediate surge response to allow every patient in need to be cared for. In Figure 21 a linear and an exponential model were fitted to the number of ICU admissions to March 20, 2020.

Figure 21 - Linear and an exponential model fitted to the number of ICU admissions



Source: https://jamanetwork.com/journals/jama/fullarticle/2763188

The predicted number of ICU admissions on March 20, 2020, was estimated to be 869 with the linear model and 14,542 with the exponential model.

Another interesting case is the **COVID-19 Mobility Monitoring project**, which is an on-going project work carried out through a Data Collaborative between the ISI Foundation and Cuebiq Inc, aimed to analyse anonymized location data to understand the effect of mobility restrictions and behavioral changes on the current international COVID-19 outbreak.[55] In their last exercise, they

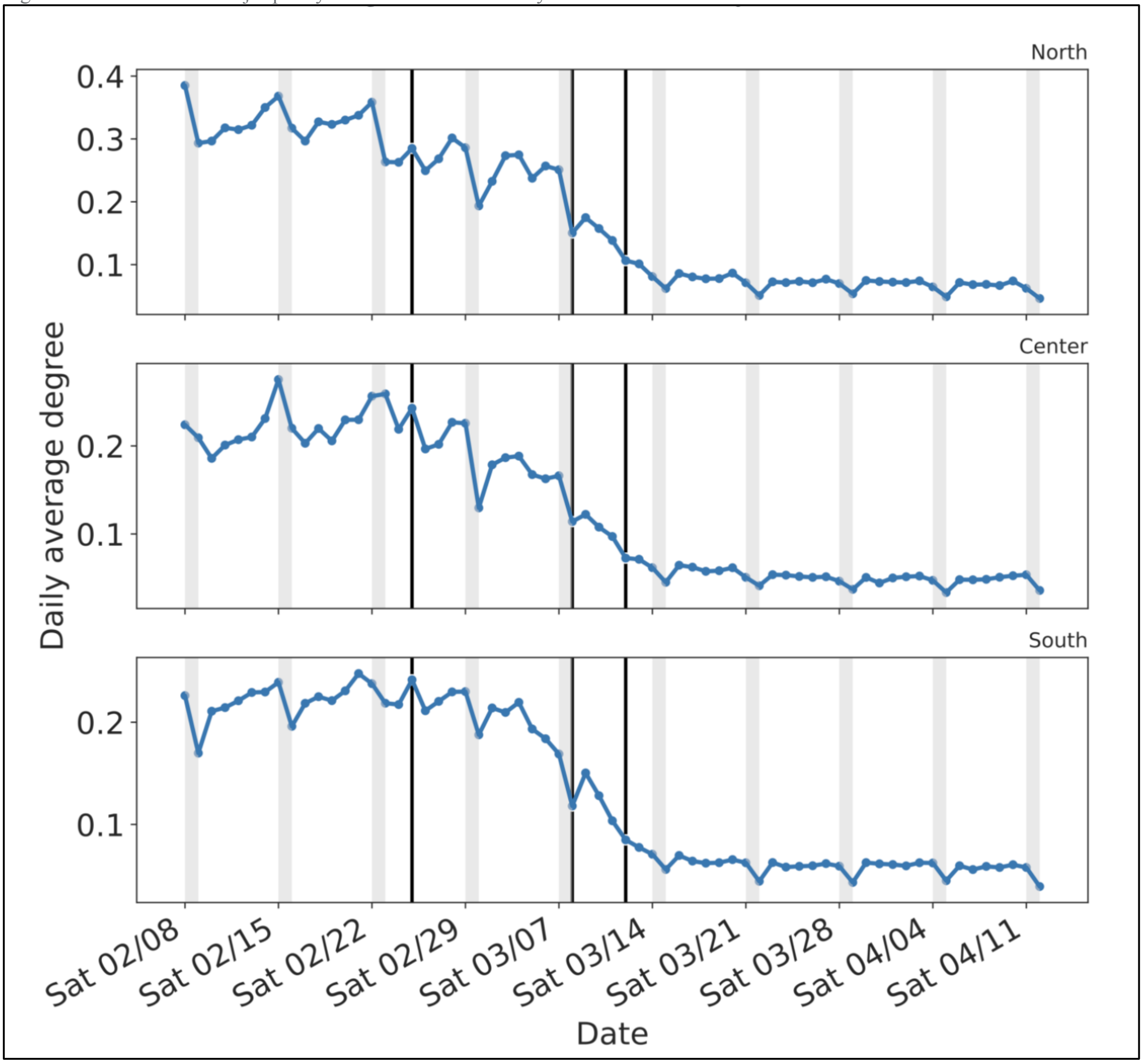
[54] https://jamanetwork.com/journals/jama/fullarticle/2763188

[55] https://covid19mm.github.io/

quantitatively assess the impact of non-pharmaceutical interventions like mobility restrictions and social distancing, to better understand the ensuing reduction of mobility flows, individual mobility changes, and impact on contact patterns, leveraging on the aggregated and privacy-safe mobility data provided by the Cuebiq programme Data for Good.[56] Specifically, they investigate the number of unique contacts made by a person on a typical day, and evaluate the effect of interventions on the social mixing of our users' sample by defining a proxy of the potential encounters each user could have in one hour. In order to do that, the researchers build a proximity network among users based on the locations they visited and the hour of the day when these visits occurred. The network is built by asserting the proximity between any two users in the same province who were seen within a circle of radius R = 50 m in a 1-hour period. The results of the exercise show that on April 12, Easter Day, the average degree of all users was 86% lower than the pre-outbreak averages in the North, 83% in the Center and 82% in the South and the Islands. In conclusion, in the past 4 weeks, the adherence to the mobility restrictions imposed since March 12 has remained high and constant all over the country. Specifically, in Figure 22 vertical lines highlight the start of three major interventions by the government: school closure and mobility restrictions imposed on Lombardy, Veneto, Piedmont, Emilia-Romagna, Liguria and Friuli on February 25, 2020; lockdown of the Lombardy region and additional provinces in Piedmont, Veneto, Emilia-Romagna, Marche on March 8, 2020; national lockdown on March 12, 2020.

[56] https://covid19mm.github.io/in-progress/2020/04/17/third-report.html

Figure 22 – Effect of the major policy interventions on mobility

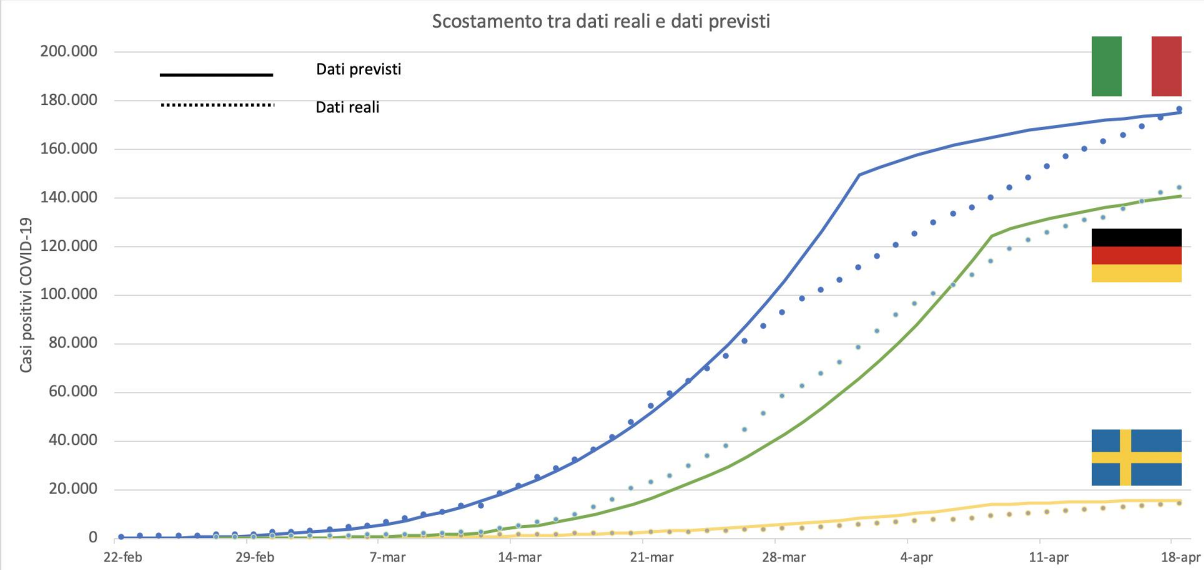


Source: https://covid19mm.github.io/in-progress/2020/04/17/third-report.html

Another Italian based team (**PREDICT COVID-19**) has developed a predictive model on the development of positive and dead cases due to COVID-19.[57] The study assumes that the first 17 days of infection are those that determine the slope of the curve, the duration of the epidemic depends on when the daily peak is reached which depends in turn on the containment strategies, and the curve can be divided into two different sections, before and after daily peak. The model, which is applicable at every level (city, province, region, country, macro-area, continent, etc.) shows that although the peak is close, in some regions the positive cases are underestimated, and also that containment strategies are working. As it can be seen from Figure 23 below, the model seems to be very precise in its predictions.

57 https://www.predictcovid19.com/model.html

Figure 23 – Prediction of the development of new cases and deaths



Source: https://www.predictcovid19.com/model.html

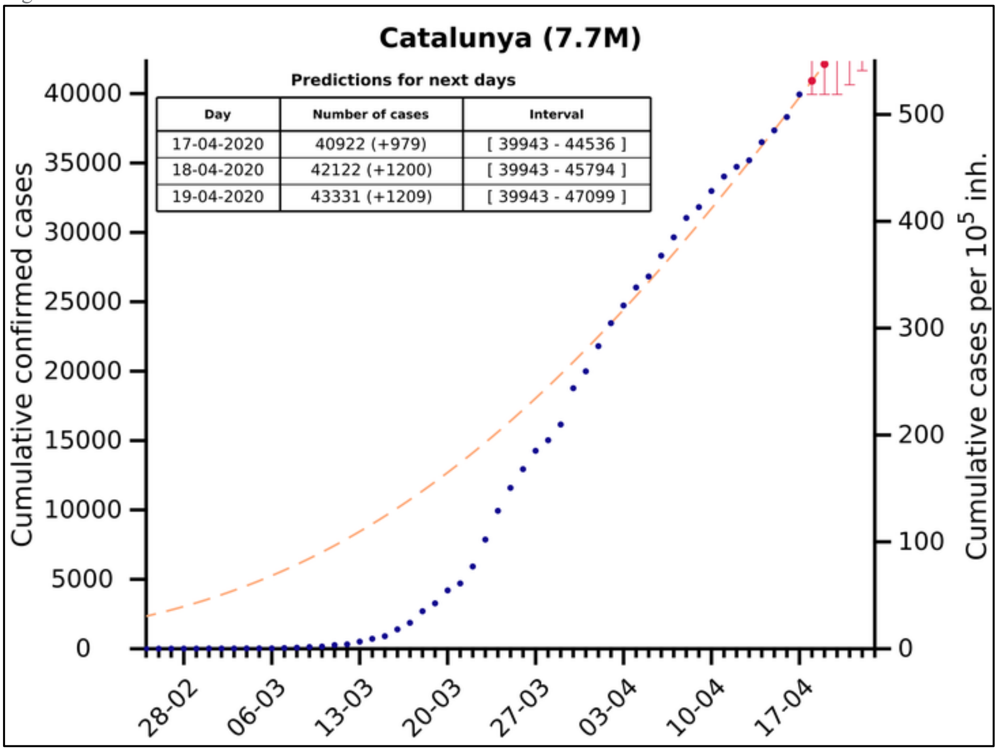
Also for what concerns the Spanish government there is no much explicit information about the models that are used by the government for policy making aimed to mitigate the COVID-19 outbreak. One of the advisors to the Spanish emergency departments is **Juan Luis Fernández Martínez**, a professor of applied mathematics from the University of Oviedo who has developed a short term prediction tool predicting how many patients will need to be admitted in intensive care units.[58] His model uses data at regional level from Asturias, Cantabria and Castile Leon, together with data from the Spanish ministry of health since March 18th, and the estimations issued by Johns Hopkins University. Other models adopted include the one by Polytechnic University of Catalonia, which employs an empirical model verified with the evolution of the number of confirmed cases in previous countries where the epidemic is close to conclude, including all provinces of China.[59] The model permits the evaluation of the quality of control measures made in each state and a short-term prediction of tendencies. Specifically, the model and predictions are based on two parameters: the rate at which the specific propagation rate slows down and the final number of expected cumulative cases. The model is then fit to countries and regions with at least 4 days with more than 100 confirmed cases and a current burden of more than 200 cases with forecasts of up to 3 days. The predicted period of a country depends on the number of datapoints over this 100 cases threshold:

- Group A - countries that have reported more than 100 cumulated cases for 10 consecutive days or more - 3 days prediction;
- Group B - countries that have reported more than 100 cumulated cases for 7 to 9 consecutive days - 2 days prediction;
- Group C - countries that have reported more than 100 cumulated cases for 4 to 6 days - 1 day prediction.

58 https://healthcare-in-europe.com/en/news/predicting-the-future-of-the-covid-19-pandemic-with-data.html
59 https://biocomsc.upc.edu/en/covid-19/Methods.pdf/view

The data sources of the model are World Health Organization (WHO) surveillance reports[60], the European Centre for Disease Prevention and Control (ECDC)[61] and the Spanish Ministry of Health.[62] The short term predictions for Catalonia, Spain and European Union are depicted in figures Figure 24Figure 25 and Figure 26.

Figure 24 – Prediction for Catalonia



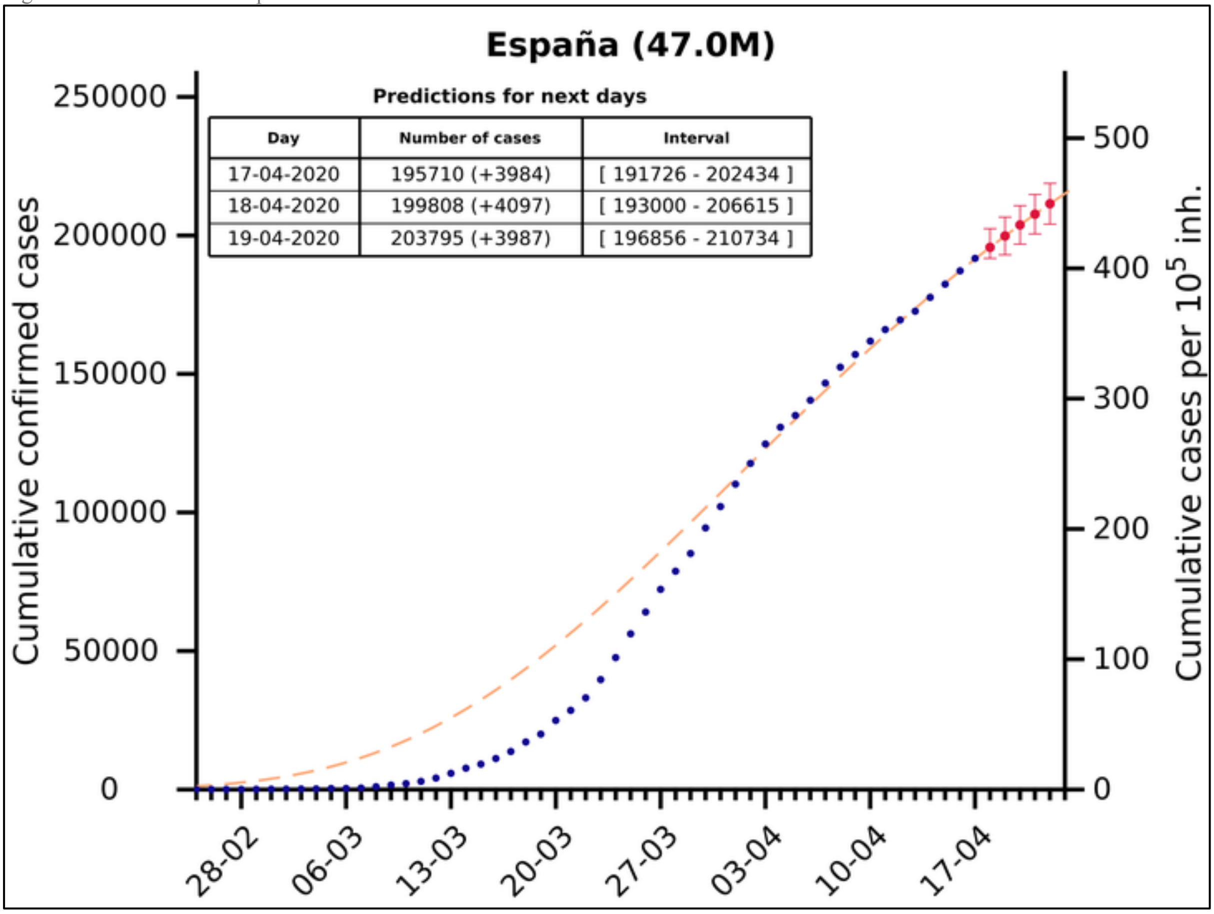
Source: https://biocomsc.upc.edu/en/covid-19/Methods.pdf/view

60 https://www.who.int/emergencies/diseases/novel-coronavirus-2019/situation-reports

61 https://www.ecdc.europa.eu/en/geographical-distribution-2019-ncov-cases

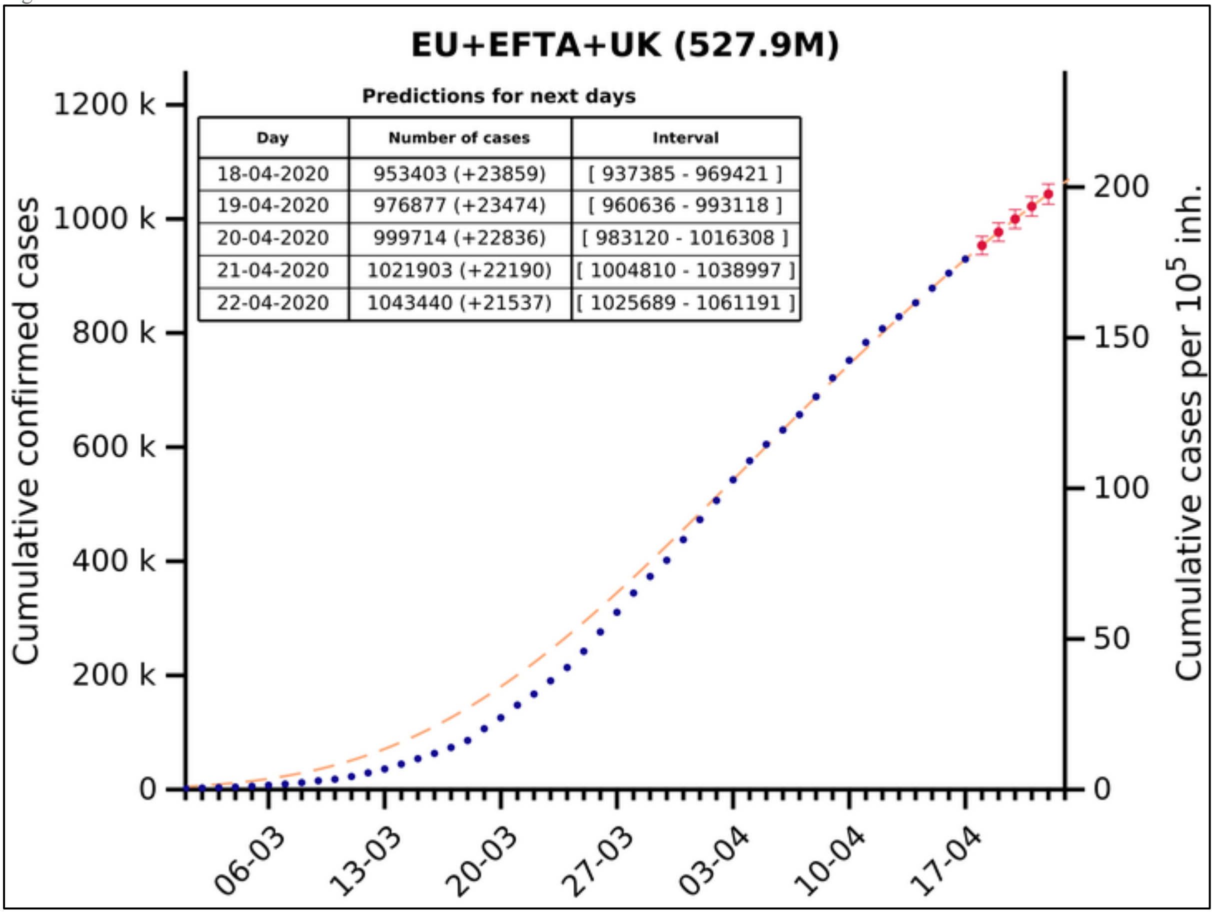
62 https://www.mscbs.gob.es/profesionales/saludPublica/ccayes/alertasActual/nCov-China/situacionActual.htm

Figure 25 – Prediction for Spain



Source: https://biocomsc.upc.edu/en/covid-19/Methods.pdf/view

Figure 26 – Prediction for EU/EFTA/UK

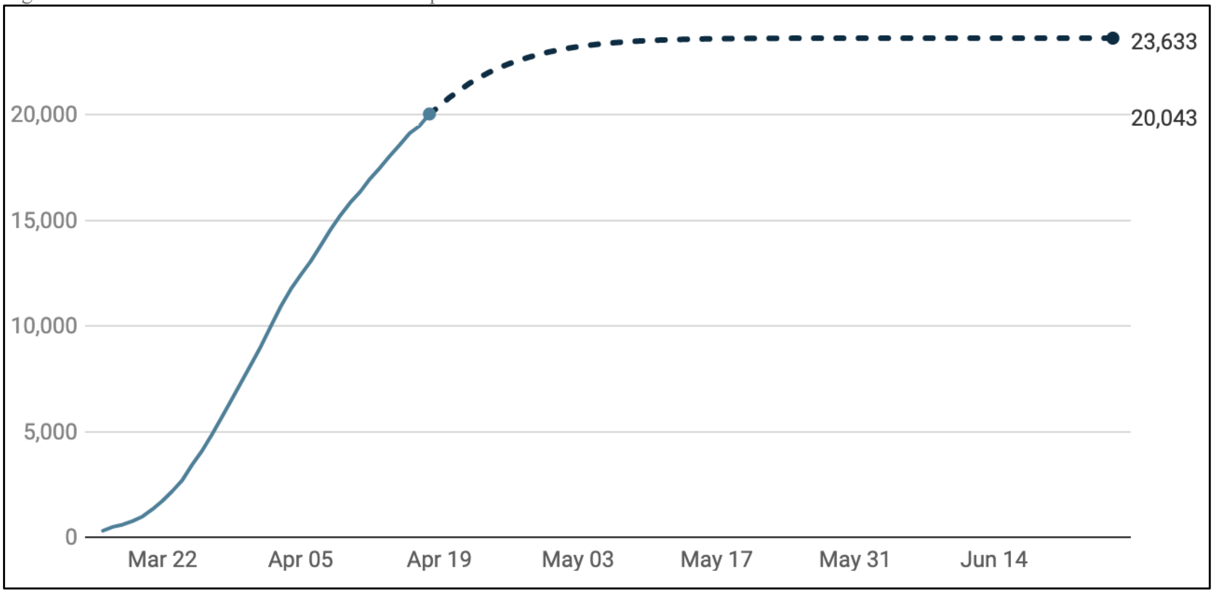


Source: https://biocomsc.upc.edu/en/covid-19/Methods.pdf/view

Another interesting modelling exercise is carried out by **Inverence**[63], which has developed predictive models based on Bayesian time series analysis building on data released by Spain's Ministry of Health. The modelling strategy considered the number of daily ICU admissions in every region and linking it, via a transfer function, to the number of deaths, assuming that the number of ICU admissions is a good indicator of the number of infected individuals in critical condition. The regional models are then combined with a nation-wide model to produce consistent forecasts that consider the covariance structure of all different forecasts. Later on, the research team has developed models for the number of infected cases, based on a dynamical transmission rate model, which allows to understand in a straightforward way the effect of public authorities' actions, which are aimed precisely at reducing this transmission rate. These models for total detected cases have then been coupled to transfer functions for deaths, recoveries, hospitalizations, and ICU admissions. The modelling activity produced a series of forecasts, out of which some examples are provided in the figures Figure 27Figure 28 and Figure 28.

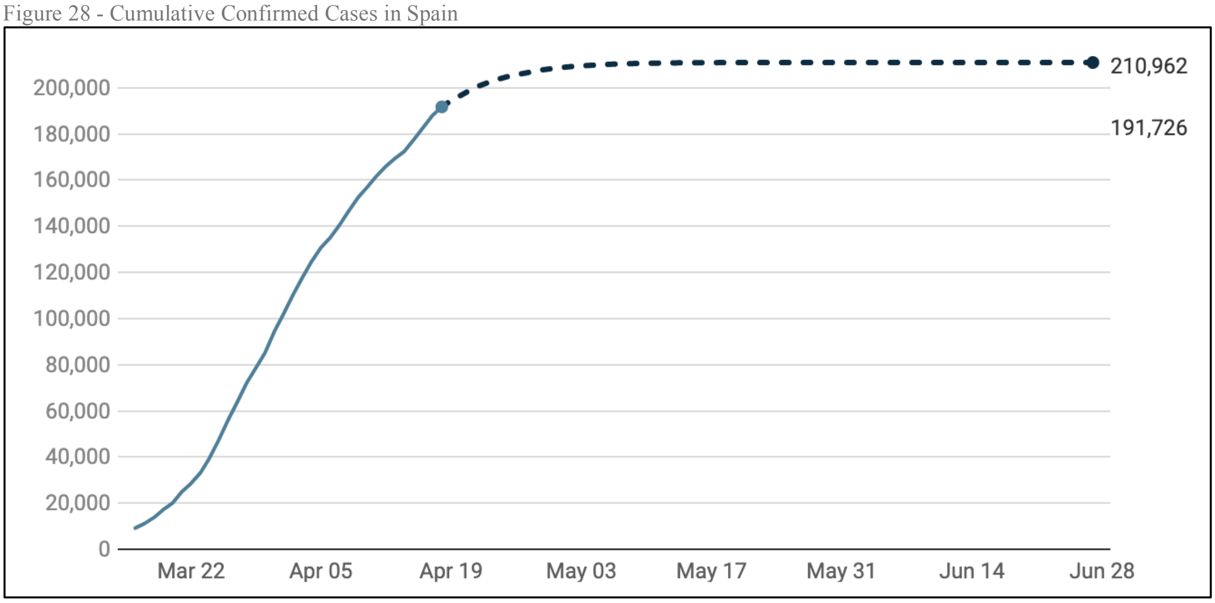
[63] https://covid19.inverence.com/

Figure 27 - Cumulative Number of Deaths in Spain



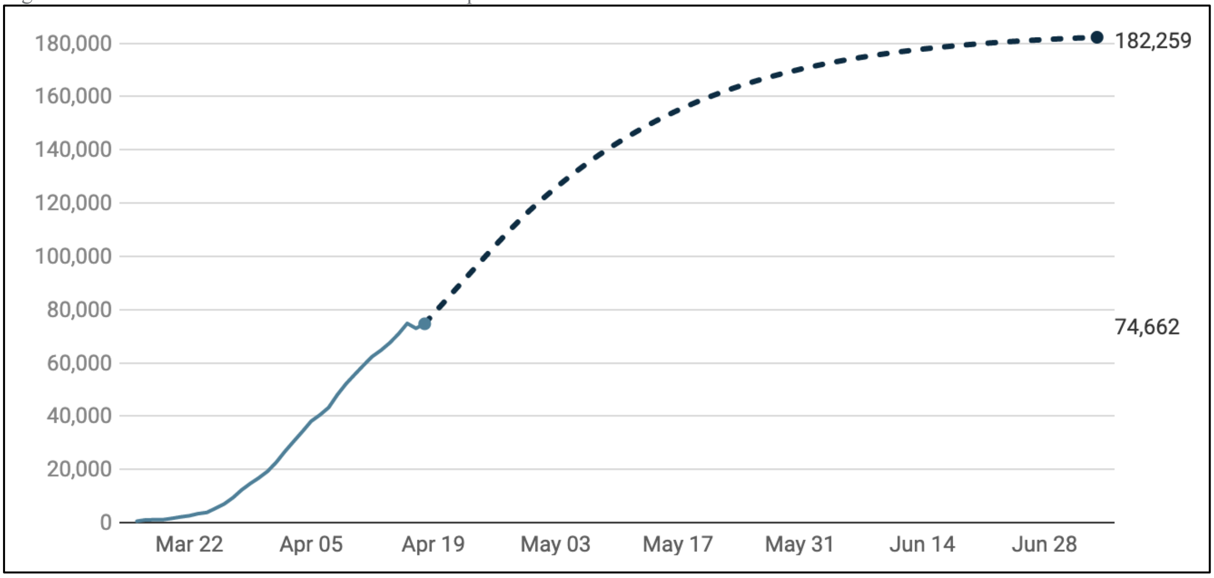
Source: https://covid19.inverence.com/#articulos

Figure 28 - Cumulative Confirmed Cases in Spain



Source: https://covid19.inverence.com/#articulos

Figure 29 - Cumulative Confirmed Recoveries in Spain



Source: https://covid19.inverence.com/#articulos

A final interesting and advanced modelling approach implemented by the University of Zaragoza[64] to describe the propagation of COVID–19 in Spain. The research team adapted a Microscopic Markov Chain Approach (MMCA) metapopulation mobility model to capture the spread of COVID-19 that stratifies the population by ages, and accounts for the different incidences of the disease at each strata. The model is used to predict the incidence of the epidemics in a spatial population through time, permitting investigation of control measures. Specifically, the model makes use of the estimates of the epidemiological parameters and the mobility and demographic census data of the Spanish national institute of statistics (INE) to define human behavior features such as age strata, age-structured contact patterns, the urban demography, and daily recurrent mobility flows. In this application, the model is used to evaluate different containment policies and shows that at the current stage of the epidemics the application of stricter containment measures of social distance are urgent to avoid the collapse of the health system. Furthermore, it also shows that the complete lockdown appears as the only possible measure to avoid the collapse.

As for France, **Massonnaud and his team**[65] have developed a deterministic SEIR model for hospital areas with predictions at one month and 17 five-year age groups (last 80 and over) to estimate the ICU resource deficit. Specifically, the model is based on country-specific contact matrices (social interactions) between age groups.[66] The team modeled the propagation of COVID-19 from March 10 to April 14, across all metropolitan French Regions. At the national level, the total number of infected cases was expected to range from 22,872 in the best case (R0 = 1.5) to 161,832 in the worst considered case (R0 = 3). Regarding the total number of deaths, it was expected to vary from 1,021 to 11,032, respectively. Clearly the real data regarding mortality rate are higher. What is interesting, it is also that they estimated the timing according to which the capacity limit of French ICU would

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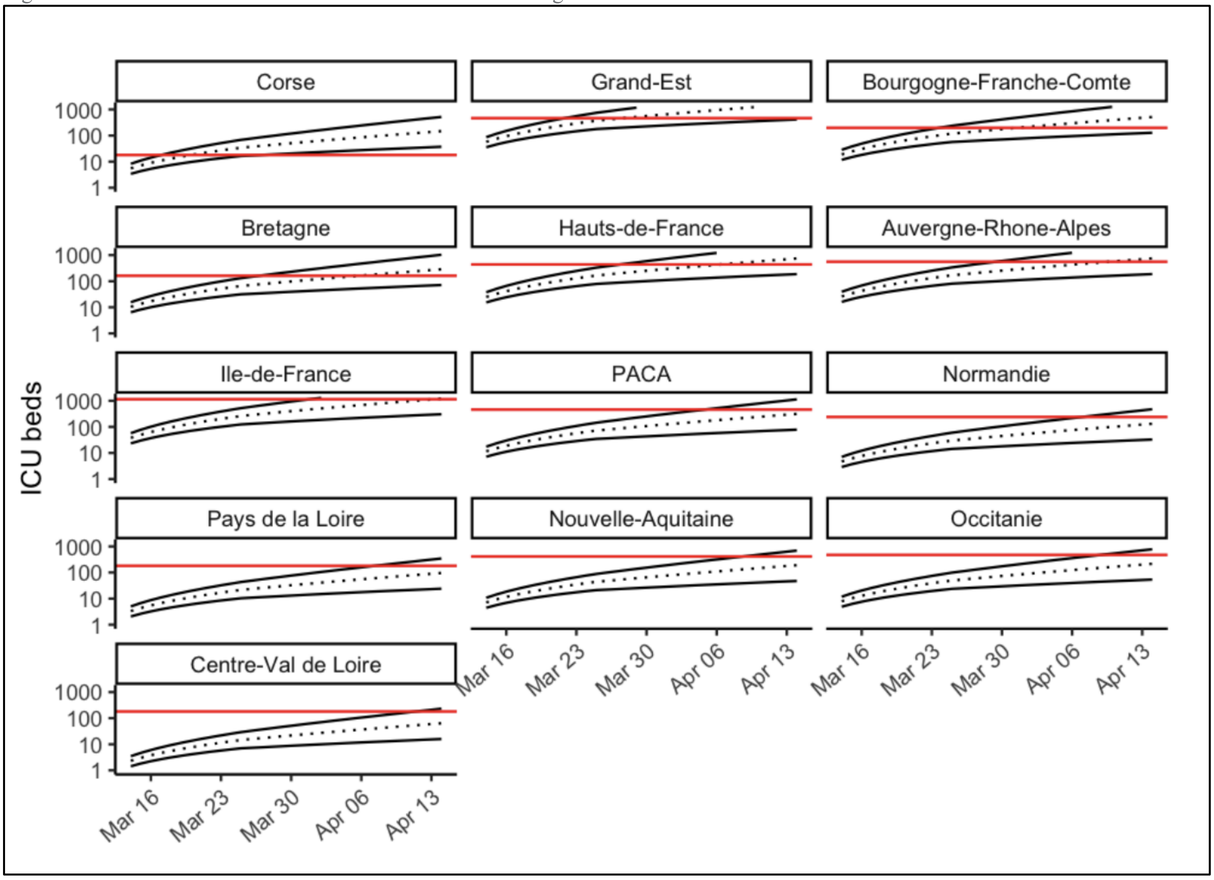
[64] https://www.medrxiv.org/content/10.1101/2020.03.21.20040022v1.full.pdf
[65] https://www.ea-reperes.com/wp-content/uploads/2020/03/PredictedFrenchHospitNeeds-EHESP-20200316.pdf
[66] The model builds on the study by Prem K, Cook AR, Jit M. Projecting social contact matrices in 152 countries using contact surveys and demographic data. PLOS Computational Biology 2017; 13: 1–21.

be overrun, building on data retrieved from the “Statistique Annuelle des Etablissements de Santé” (SAE).[67] The predicted ICU capacity limit, is depicted in figure Figure 30, where the dotted line stands for the scenario with R0 = 2.25, the black lines for the worst and best case scenarios (R0 = 3 and R0 = 1.5, respectively). Panels for each French Region are ordered by time of overrun (left to right and top to bottom).

Figure 30 - Predicted needs of ICU beds in the 13 French Regions



Source: https://www.ea-reperes.com/wp-content/uploads/2020/03/PredictedFrenchHospitNeeds-EHESP-20200316.pdf

Luckily, the French healthcare system was able to react and not be overwhelmed, most probably because the government reacted based on this model.

Another team of researchers that is advising the French government works at the **EPIcx-lab of INSERM** - (Institut national de la santé et de la recherche médicale) at the Pierre Louis Institute of Epidemiology and Public Health, Sorbonne Université. In one study they use a stochastic age-structured transmission model integrating data on age profile and social contacts in the Île-de-France region to assess the current epidemic situation, evaluate the expected impact of the lockdown implemented in France on March 17, and finally to estimate the effectiveness of exit strategies, building on hospital admission data of the region before lockdown.[68] Within this scope, they simulate different types and durations of social distancing interventions as well as a progressive lifting of the

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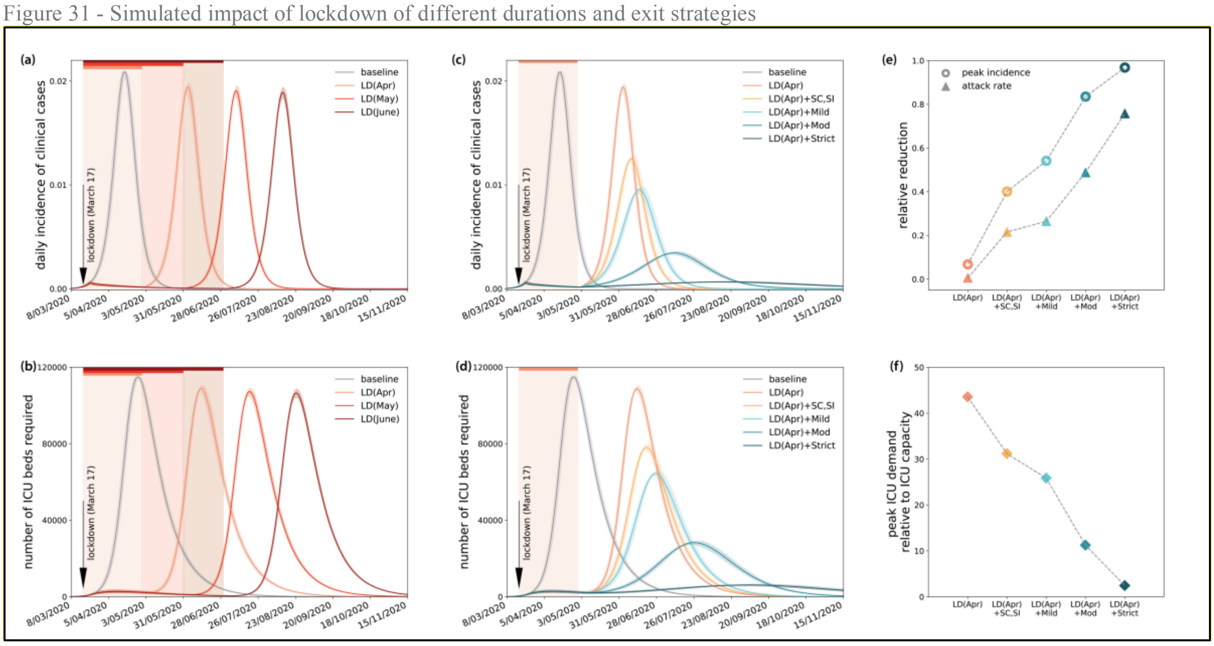
[67] DREES. Statistique annuelle des établissements de santé (SAE). https://www.sae-diffusion.sante.gouv. fr/sae-diffusion/accueil.htm.

[68] https://www.epicx-lab.com/uploads/9/6/9/4/9694133/inserm-covid-19_report_lockdown_idf-20200412.pdf

lockdown targeted on specific classes of individuals joint with large-scale testing. The authors also estimate the basic reproductive number at 3.0 prior to lockdown and assume that the population infected by April 5 to be in the range 1% to 6%. Further, they estimated that the average number of contacts is predicted to be reduced by 80% during lockdown, leading to the reduction of the reproductive number to 0.68. They show that the epidemic curve reaches ICU system capacity and slowly decreases during lockdown, and that lifting the lockdown with no exit strategy would cause a second wave. They also show that testing and social distancing strategies that gradually relax current constraints while keeping schools closed and seniors isolated will avoid a second wave and healthcare demand exceeding capacity. Figure 31 reports the simulated impact of lockdown of different durations and exit strategies: (a) Simulated daily incidence of clinical cases assuming lockdown till end of April, end of May, end of June; (b) Corresponding demand of ICU beds; (c) Simulated daily incidence of clinical cases assuming lockdown till end of April, followed by interventions of varying degree of intensity; (d) Corresponding demand of ICU beds. (e) Relative reduction of peak incidence and epidemic size after 1 year for each scenario; (f) Peak ICU demand relative to ICU capacity of the region.

Figure 31 - Simulated impact of lockdown of different durations and exit strategies



Source: https://www.epicx-lab.com/uploads/9/6/9/4/9694133/inserm-covid-19_report_lockdown_idf-20200412.pdf

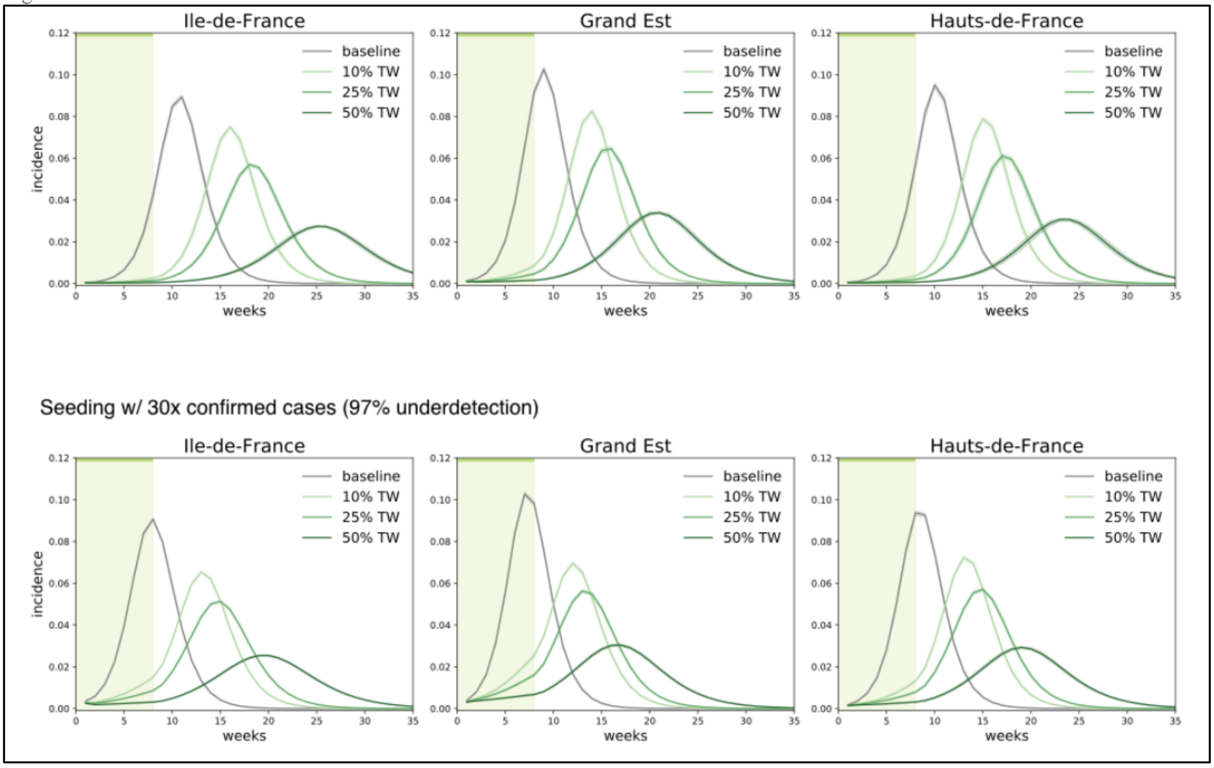
Another work from the institute aims to assess the expected impact of school closure and telework to mitigate COVID-19 epidemic in France[69]. The model builds on social contact data between children and adults for each region, and accounts for current uncertainties in the relative susceptibility and transmissibility of children. According to the model, mere school closure would have limited effects (i.e. <10% reduction with 8-week school closure for regions in the early phase of the epidemic), while coupled with teleworking for 25% adults there would be a delay of the peak by almost 2 months with an approximately 40% reduction of the case incidence at the peak. Therefore, explicit

[69] https://www.epicx-lab.com/uploads/9/6/9/4/9694133/inserm_covid-19-school-closure-french-regions_20200313.pdf

guidance on telework and interventions to facilitate its application to all professional categories who can adopt it should be urgently provided.

Figure 32 reports the incidence curves in case of no intervention (grey line) and the 8-week school closure scenario for Île-de-France (left), Grand Est (center), and Hauts-de-France (right), with 10%, 25%, and 50% of adult population teleworking. It has to be noticed that the shaded area indicates the 8-week period during which the school closure is implemented. The model is seeded with four times the number of confirmed cases (75% under-reporting at the top) and 30x the number of confirmed cases (97% under-reporting at the bottom).

Figure 32 - Incidence curves for the baseline scenarios and for several interventions



Source: https://www.epicx-lab.com/uploads/9/6/9/4/9694133/inserm_covid-19-school-closure-french-regions_20200313.pdf

1.3 In depth Analysis

All over the world predictive models are used as background and guide for policy making. However, as widely documented, there are several caveats to be taken into account when stemming from data and modelling assumption, particularly when the phenomena studied are still ongoing.[70] Considering the simplest SIR model, in principle the number of deaths from an infectious disease is given by the susceptible population times the infection rate times the fatality rate. Starting from the fatality rate, it is difficult to have an average single dimension as it depends on the age of individuals and the presence of comorbidities, and therefore it changes from cohort to cohort and from country to country. Furthermore, even in the same subset of individuals, there are many uncertainties. In fact, the fatality rate is the ratio of the number of people who have died from the disease and the number

70 https://fivethirtyeight.com/features/why-its-so-freaking-hard-to-make-a-good-covid-19-model/

of people infected with the disease. Now, it is first of all difficult to state how many people died from COVID-19, in particular in the presence of comorbidities. There are in fact differences in how countries record Covid-19 deaths.[71] Secondly, it is extremely impractical to determine the number of people that are infected at any given moment. This suggests that there are a lot of people walking around with COVID-19 who do not know it, and therefore the fatality rates are lower than what is currently argued in many countries. On the other hand, there are also several studies that suggest a higher mortality of the COVID-19 outbreak by looking at "excess mortality", i.e. the gap between the total number of people who died from any cause, and the historical average for the same place and time of year, as well as that many individuals were killed by conditions that might normally have been treated, had hospitals not been overwhelmed by a surge of patients needing intensive care.[72][73][74] Further, it is not easy to estimate to what extent fatality rate is influence by the hospital capacity, e.g. access to the best care (ICU). It is also difficult to have a precise estimation of the symptomaticity ratio, which calculates how many people are symptomatic versus asymptomatic. In fact, it is clear that in case the healthcare capacity of a country (or a region) is overwhelmed, the fatality rate goes up. The infection rate depends on the basic reproduction number (R0), which is the average number of new infections traced back to each infected person in a population where everyone is susceptible to the disease. This is influenced by the rate of contact, which is given by how many people an infected person interacts with in a given period of time and that depends on the circumstances, and by the rate of transmission per contact, which is basically how many of the people an infected person meets will become infected themselves. In turns, there are other variables that influence the infection rate: how long the virus can survive on a given surface, how far it can be flung through the air, the duration of infectiousness, and the extent to which asymptomatic individuals are infectious in comparison with symptomatic ones. And finally, all these dimensions are influenced by interventions such as social distancing and school closing, as well as of the modelling technique and the stage of the epidemics. Taking into account more concrete cases, different assumptions and modelling approaches can lead to different results and policy recommendations. In that regard, an interesting comparison[75] can be done between top down and bottom up approaches. The top down approach consists in fitting a curve to the data set and then to extrapolate the future data points. A bottom up approach consists in modelling a series of components mimicking the progress of the epidemics such as social distancing, allowing to separate the different mechanisms of the transmission process. The models by the Imperial College is based on the bottom up approach. In fact, they model the ways in which the virus can be transmitted, and then assess how social distance and transportation influence the process. On the other hand, the model by IHME fits curves representing deaths in various locations with a series of parameters, and then extrapolates the numbers of deaths and the need for hospitalization and equipment. This leads to uncertainty at the beginning of the outbreak in which less location-specific data is available. Another important issue

[71] https://www.bbc.com/news/52311014
[72] https://www.economist.com/graphic-detail/2020/04/16/tracking-covid-19-excess-deaths-across-countries?fsrc=scn/fb/te/bl/ed/covid19datatrackingcovid19excessdeathsacrosscountriesgraphicdetail&fbclid=IwAR2AqP18VghCYmX5PKH8ns0a-2yPXhzzNId01Ge7PWxg5HLjhaeD0yOPDng
[73] https://www.ispionline.it/it/pubblicazione/fase-2-morti-sommerse-eccesso-di-zelo-25878
[74] https://www.medrxiv.org/content/10.1101/2020.04.15.20067074v2
[75] https://nucleardiner.wordpress.com/2020/04/07/the-ihme-epidemiological-model/amp/?__twitter_impression=true

is that the IHME model assumes that the US has had a lockdown as strict as Wuhan, but this seems not to be the case. Further, only one location Wuhan has had a generalized epidemics, and therefore modelling the US fitting curve on such location is difficult, especially because the timing and extent of social distancing is difficult to mimic. When more US data will be available, the more will become more precise. Further, even though the model takes into account age structure, some other factors are not modelled, such as the prevalence of multi and co-morbidities, chronic lung disease, use of public transport, pollution and population density. On the top of that, the reduction in healthcare quality due to overload is not explicitly taken into account.

Another interesting comparison lies in recommendations stemming from the models. For instance, the first version (16 March) of the Imperial College model has grim predictions for what concerns the death toll in US and UK (respectively up to 500K and 2.2 million deaths) and the strain on ICU capacity, prompting the government to put in place mitigation measures. On the other hand, the Oxford model suggests that the new coronavirus may already have infected far more people in the UK than scientists had previously estimated (maybe half of the population), and that thereby the mortality rate from the virus is much lower than what is generally thought to be, as the vast majority of infected individuals develop mild symptoms or not at all.

However, both models are built on a series of extreme assumptions: for the Imperial College model the value of R0, the rate of death, the length of incubation, and the period in which infected and asymptomatics can be infectious. For the Oxford model the suggestion that the infection has reached the UK by December or January, and the figure that only one in 1,000 infections will need hospitalization is removed from reality. Clearly the two models provide different recommendations: the Oxford model recommends to put more effort in trying to achieve herd immunity, and concludes that the country had already acquired substantial herd immunity through the unrecognised spread of Covid-19 over more than two months, while the model by the Imperial College recommends to put more effort on containment measures. However, both models agree with the measures of social distancing put into place by the UK government, and the only point of argument concerns the timing of removing such restrictions. In that regard, the crucial info hidden from the modellers regards the number of people that have been infected without showing symptoms, and for which a reliable test would be a game changer for modellers as it might significantly alter the predicted path of the pandemics. A final consideration is linked to the availability of data and the data collection activity. In this regard, there is a huge difference across the countries. Very interestingly, the German central register for ICU beds is based on voluntary contributions from all hospitals seems to be a unique platform and maybe something to replicate in other countries[76]. In the following tables Table 2Table 3, and Table 4, an in depth classification of the models is provided.

[76] https://www.intensivregister.de/#/intensivregister

Table 2 – Model Description: Source, Country, Usage and Publication

Model	Source	Country	Is it published?	Are the results published?	Usage
IHME	https://www.medrxiv.org/content/10.1101/2020.03.27.20043752v1.full.pdf	US	Yes	Yes	Used in Policy Making
Los Alamos	https://covid-19.bsvgateway.org/#link%20to%20forecasting%20site	US	Yes	Yes	Used in Policy Making
COVID-19 Modelling	https://covid19.gleamproject.org/	US	Yes	Yes	Used in Policy Making
Epirisk	https://epirisk.net/	US	Yes	Yes	Used in Policy Making
Bakker et al.	http://curveflattening.media.mit.edu/Social_Distancing_New_York_City.pdf	US	Yes	Yes	Not clear
Columbia University	http://www.columbia.edu/~jls106/branas_etal_preprint.pdf	US	Yes	Yes	Used in Policy Making
Imperial College (1)	https://www.imperial.ac.uk/media/imperial-college/medicine/sph/ide/gida-fellowships/Imperial-College-COVID19-NPI-modelling-16-03-2020.pdf	UK	Yes	Yes	Used in Policy Making
Imperial College (2)	https://www.imperial.ac.uk/media/imperial-college/medicine/sph/ide/gida-fellowships/Imperial-College-COVID19-Global-Impact-26-03-2020v2.pdf	UK	Yes	Yes	Used in Policy Making
Imperial College (3)	https://spiral.imperial.ac.uk:8443/handle/10044/1/77731	UK	Yes	Yes	Used in Policy Making
UO	https://www.medrxiv.org/content/10.1101/2020.03.24.20042291v1	UK	Yes	Yes	Used in Policy Making
LSHTM	https://www.medrxiv.org/content/10.1101/2020.02.16.20023754v2.full.pdf	UK	Yes	Yes	Used in Policy Making
RKI (1)	https://www.rki.de/DE/Content/Infekt/EpidBull/Archiv/2020/Ausgaben/17_20_SARS-CoV2_vorab.pdf?__blob=publicationFile	DE	Yes	Yes	Used in Policy Making
RKI (2)	http://rocs.hu-berlin.de/corona/docs/analysis/importrisk/	DE	Yes	Yes	Used in Policy Making
COVID Mobility Project	http://rocs.hu-berlin.de/covid-19-mobility/mobility-monitor/	DE	Yes	Yes	Used in Policy Making
Hartl et al.	https://cepr.org/sites/default/files/news/CovidEcon1%20final.pdf	DE	Yes	Yes	Not clear
Italian STC	https://drive.google.com/file/d/1pe1gEp4-UAPxLW_vnqntAa4AT5D_nyR1/view	IT	No[77]	Yes	Used in Policy Making
COVID-19 working group et al.	https://www.medrxiv.org/content/10.1101/2020.04.08.20056861v1.full.pdf	IT	Yes	Yes	Not clear
Signorelli et al.	https://www.mattioli1885journals.com/index.php/actabiomedica/article/view/9511/8735	IT	Yes	Yes	Not clear
Grasselli et al.	https://jamanetwork.com/journals/jama/fullarticle/2763188	IT	Yes	Yes	Not clear
COVID-19 MMP	https://covid19mm.github.io/in-progress/2020/04/17/third-report.html	IT	Yes	Yes	Not clear
PREDICT COVID-19	https://www.predictcovid19.com/model.html	IT	No	Yes	Not clear
Martinez et al.	https://healthcare-in-europe.com/en/news/predicting-the-future-of-the-covid-19-pandemic-with-data.html	ES	No	Yes	Used in Policy Making
Uni Cat	https://biocomsc.upc.edu/en/covid-19/Methods.pdf/view	ES	Yes	Yes	Used in Policy Making
Inverence	https://covid19.inverence.com/	ES	No	Yes	Not clear
University of Zaragoza	https://www.medrxiv.org/content/10.1101/2020.03.21.20040022v1.full.pdf	ES	Yes	Yes	Not clear
Massonnaud et al.	https://www.ea-reperes.com/wp-content/uploads/2020/03/PredictedFrenchHospitNeeds-EHESP-20200316.pdf	FR	Yes	Yes	Used in Policy Making
EPIcx-lab of INSERM (1)	https://www.epicx-lab.com/uploads/9/6/9/4/9694133/inserm-covid-19_report_lockdown_idf-20200412.pdf	FR	Yes	Yes	Used in Policy Making
EPIcx-lab of INSERM (2)	https://www.epicx-lab.com/uploads/9/6/9/4/9694133/inserm_covid-19-school-closure-french-regions_20200313.pdf	FR	Yes	Yes	Used in Policy Making

[77] There is no specific and explicit information regarding which models are used by the Italian authorities to take their decisions. According to confidential sources, the Italian National Institute of Health and the Italian Scientific and Technical Committee, in agreement with the Italian Ministry of Health and Italian Civil Protection, are collaborating with Bruno Kessler Foundation in developing the models used by the Italian authorities in taking their policy decisions. The model will be available only when published.

Table 3 - Model Description: Typology, Topic, Predictions and Data

Model name	Type of model	Topic	Predictions	Data
IHME	Statistical model for the cumulative death rate developing a curve-fitting tool to fit a nonlinear mixed effects model to the available administrative cumulative death data. From the projected death rates, it is estimated the hospital service utilization using an individual-level microsimulation model. Deaths by age are simulate using the average age pattern from Italy, China, South Korea, and the US.	Epidemic and healthcare variables such as number of infected, deaths, hospital beds, ICU, and invasive ventilation needed	US: bed excess demand of 64,175 and 17,380 of ICU beds at the peak of COVID-19. Further, the peak ventilator use is predicted to be 19,481 in the second week of April, while the total estimated deaths were 81,114 over the next 4 months. Then, the estimates were amended downwards by predicting the death of 60.400 individuals by August, with a peak on the 12th of April. As for the UK, the model predicted 66,314 fatalities, more than Italy (a total of 23,000) and Spain (19,209)	Data Repository by Johns Hopkins CSSE
Los Alamos	The model consists of two processes. The first process is a statistical model of how the number of COVID-19 infections changes over time. The second process maps the number of infections to the reported data. It is a forecast model and does not produce projections, meaning it does not explicitly model the effects of interventions or other "what-if" scenarios.	Estimate at US state level the number of cases and deaths	For instance, for the state of New York the daily death where expected to peak at 3215 on the 19th of April	Data from the John Hopkins dashboard and the IHME website
Epirisk	Global Epidemic and Mobility Model (GLEAM), an individual-based, stochastic, and spatial epidemic model used to analyze the spatiotemporal spread and magnitude of the COVID-19 epidemic in the continental US.	EpiRisk is a computational platform designed to allow a quick estimate of the probability of exporting infected individuals from sites affected by a disease outbreak to other areas in the world through the airline transportation network and the daily commuting patterns. It also lets the user to explore the effects of potential restrictions applied to airline traffic and commuting flows.	There are many predictions related to exported cases (probability of exporting a given number of cases) and relative importation risk (probability that a single infected individual is traveling from the index areas to that specific destination).	The airline transportation data used in the platform are based on origin-destination traffic flows from the OAG database that are aggregated at specific time and spatial. Commuting flows are derived by the analysis and modeling of data for more than 5,000,000 commuting patterns among 78,000 administrative regions in five continents.
COVID-19 Modelling	Based on the GLEAM model.	Global Epidemic and Mobility Model (GLEAM), an individual-based, stochastic, and spatial epidemic model used to analyze the spatiotemporal spread and magnitude of the COVID-19 epidemic in the continental US. The model generates an ensemble of possible epidemic projections described by the number of newly generated	The model points to the days around April 8, 2020 as the peak time for deaths in the US. Based on the last projections, a total of 89795 COVID-19 deaths (range of 63719 to 127002) are currently projected through May 18, 2020.	Real-world data where the world is divided into subpopulations centered around major transportation hubs (usually airports). The airline transportation data encompass daily origin-destination traffic flows from the Official Aviation Guide (OAG) and International Air

		infections, times of disease arrival in different regions, and the number of traveling infection carriers.		Transport Association (IATA) databases, whereas ground mobility flows are derived from the analysis and modeling of data collected from the statistics offices of 30 countries on five continents.
Bakker et al.	Network analysis by mean of metrics such as mobility, which refers to how people move around a city (distance traveled, radius of gyration, number of people staying home, number of stays in public places, which we call visits); and contacts, which refers to how many people each person comes into contact with.	Use of mobility data from January 1st 2020 to March 25th 2020 to figure out how has social distancing policy changed mobility and social behavior, how social distancing behavior differs across the physical space of New York City, and how social distancing behavior differs across demographic groups	The researchers find that the instance travelled everyday dropped by 70 percent, the number of social contacts in places decreased by 93%, and that the number of people staying home the whole day has increased from 20% to 60%. Very interestingly, they found that the relative differences between different demographic groups for what concerns mobility and social contacts have been dramatically reduced. Finally, they found that supermarkets and grocery stores came to be the most common locations where social contact takes place.	Mobility data is provided by Cuebiq, a location intelligence and measurement company, and they consist in supplied anonymized records of GPS locations from users who opted-in to share their data anonymously across the U.S.
Columbia University	Metapopulation SEIR model1 to simulate the transmission of COVID-19 among 3,108 US counties. Two types of movement: daily work commuting and random movement. Information on county-to-county work commuting is publicly available from the US Census Bureau. Number of random visitors between two counties is assumed to be proportional to the average number of commuters between them. As population present in each county is different during daytime and nighttime, the transmission dynamics of COVID-19 is modelled separately for these two time periods as a discrete Markov process during both day and night times.	Estimate of the number of hospital critical care beds, including ICU beds and other hospital beds used for critical care purposes, that could be made available by hospitals in response to patient surges. Various scenarios are considered.	As many as 104,120 deaths could be averted through an aggressive critical care surge response, including roughly 55% through high clearance and preparation of ICU and non-ICU critical care beds and roughly 45% through extraordinary measures like using a single ventilator for multiple patients.	2020 Centers for Medicare & Medicaid Services (CMS), Health Care Information System (HCRIS) Data File, Sub-System Hospital Cost Report (CMS-2552-96 and CMS-2552-10), Section S-3, Part 1, Column 2; the 2018 American Hospital Association (AHA) Annual Survey; the 2020 US DHHS Health Resources and Services Administration, Area Health Resources Files (AHRF); and the 2017-2019 CMS Medicare Provider of Services file, Medicare Cost Report, Hospital Compare Files.
Imperial College (1)	Individual-based simulation model developed to support pandemic influenza planning to explore scenarios for COVID-19 in GB. The basic structure of the model remains as previously published. In brief, individuals reside in areas defined by high-resolution population density data. Contacts with other individuals in the population are made within the household, at school, in the workplace and in the wider community. Transmission events occur through contacts made between susceptible and infectious individuals in either the household, workplace, school or randomly in the community, with the latter depending on	Assess the potential role of a number of public health measures – so-called non-pharmaceutical interventions aimed at reducing contact rates in the population and thereby reducing transmission of the virus	In March 2016 update the model by the Imperial College reported up to 500K deaths in the UK and up to 2.2 million deaths in the US in case of no action by the government nor population. Further, the estimated figure that 15% of hospital cases would need to be treated in an ICU was then updated to 30%, arguing that the British ICU capacity (4K beds) would be overwhelmed.	Data on distribution size of households and age are taken from the census, while a synthetic population of schools distributed proportional to local population density is derived from data on average class sizes and staff-student ratios.

	spatial distance between contacts.			
Imperial College (2)	Estimation of the final epidemic size from an age-structured Susceptible-Infected Recovered model incorporating both the demographic structure of the population and the rates of contact between different individuals across different age groups. The impact of the different scenarios on the dynamics of likely healthcare demand over time was assessed by using an age-structured stochastic Susceptible-Exposed-Infected-Recovered (SEIR) model parameterised to match best estimates of key parameters determining the dynamics of spread of COVID-19.	Combine data on age-specific contact patterns and COVID-19 severity to project the health impact of the pandemic in 202 countries in the view to compare predicted mortality impacts in the absence of interventions or spontaneous social distancing with what might be achieved with policies aimed at mitigating or suppressing transmission	Impact of an unmitigated scenario in the UK and the USA up to 490,000 deaths and 2,180,000 deaths respectively, and up to 7.0 billion infections and 40 million deaths globally this year	Population sizes and age distributions by country were taken from the 2020 World Population Prospects. Estimates of household size and the age of members of each household were extracted from The Demographic and Health Surveys (DHS) Program using the rDHS package. Patterns of contact across different populations and countries were drawn from several sources, including previously published estimates of mixing from a number of HICs and a recent systematic review of social contact surveys including MICs and LMICs.
Imperial College (3)	Use of a semi-mechanistic Bayesian hierarchical model to attempt to infer the impact of mitigation interventions across 11 European countries. The methods assume that changes in the reproductive number are an immediate response to these interventions being implemented rather than broader gradual changes in behaviour. The model estimates these changes by calculating backwards from the deaths observed over time to estimate transmission that occurred several weeks prior, allowing for the time lag between infection and death.	Attempt to infer the impact of policy interventions across 11 European countries.	They estimate that the intervention has averted 59,000 deaths up to 31 March across all 11 countries, that between 7 and 43 million individuals have been infected, and that the proportion of the population infected to date is the highest in Spain followed by Italy and lowest in Germany and Norway, reflecting the relative stages of the epidemics. Specifically, they estimated that in Italy and Spain, respectively 38,000 and 16,000 deaths have been avoided.	Real-time death data from the ECDC, as well as data on the nature and type of major non-pharmaceutical interventions, excerpted from the government webpages from each country as well as their official public health division/information webpages.
UO	The researchers calibrated a susceptible-infected-recovered (SIR) model to data on cumulative deaths from the UK and Italy, building on the assumption that such deaths are well reported events that occur only in a vulnerable fraction of the population. The authors also assume estimates of critical epidemiological parameters such as the basic reproduction number (R0), infectious period and time from infection to death, probability of death in the vulnerable fraction of the population. This with the aim to assess the sensitivity of the system to the actual fraction of the population vulnerable to severe disease and death.	Percentage of population exposed to the virus.	In summary, the model suggests that the new coronavirus may already have infected far more people in the UK than scientists had previously estimated (maybe half of the population), and that thereby the mortality rate from the virus is much lower than what is generally thought to be, as the vast majority of infected individuals develop mild symptoms or not at all. The model suggests that the infection has reached the UK by December or January, and that therefore people started to be infected in huge numbers before the first official case was reported.	For Italy, a time series was obtained from the Italian Department of Civil Protection GitHub repository. For UK, a time series was obtained from the John Hopkins University Centre for Systems Science and Engineering COVID-19 GitHub repository.
LSHTM	Generation of fine-scale age-specific population contact matrices by context (home,	Age specific social mixing patterns by encounter context (home, work, school	Estimation of high resolution age-specific social mixing matrices based	Population contact patterns for United Kingdom based self-

	work, school, other) and type (conversational or physical) of contact that took place.	or other, in respective rows) and type of contact (physical only shown with dashed lines or all contacts in solid line).	on data from over 40,000 participants, stratified by key characteristics such as contact type and setting. The matrices generated are highly relevant for informing prevention and control of new outbreaks, and evaluating strategies that reduce the amount of mixing in the population (such as school closures, social distancing, or working from home). In addition, they finally provide the possibility to use multiple sources of social mixing data to evaluate the uncertainty that stems from social mixing when designing public health interventions.	reported contact data from over 36,000 volunteers that participated in the massive citizen science project BBC Pandemic.
RKI (1)	The number of incident cases is estimated using the nowcasting approach and is presented as a moving 4-day average to compensate for random effects of individual days. With this approach, the point estimate of R for a given day is estimated as the quotient of the number of incident cases on this day divided by the number of incident cases four days earlier.	Estimation of the impact of mitigation measures on the reproduction number.	The policies carried out by the Federal Government, i.e. the cancellation of major events in different federal states (with more than 1,000 participants) on March 9 2020, the Federal-State Agreement on guidelines against the spread of the coronavirus on March 16 2020, and the nationwide extensive ban on contacts on March 23 2020, have had a great impact on the reproduction number.	Ministry of Health and data from the Intensive Care Register produced by the German Interdisciplinary Association for Intensive and Emergency Medicine (DIVI), the RKI and the German Hospital Federation (DKG)
RKI (2)	Stochastic network dynamic modelling of an import risk model and relative import risk analysis.	Relative import risk at the airport, country and continental levels, as predicted by the computational model and the worldwide air transportation network.	The implementation of mitigation measures altered the infection pattern and spread of the disease and helped to keep it under control.	The core of the data used come from the worldwide air transportation network (WAN). This network has 3893 nodes (airports) that are connected by 51476 directed links (flight routes). Each link is weighted by the traffic flux between nodes, i.e. the average number of passengers that travel each route per day.
COVID Mobility Project	Analysis of the deviation in mobility from a "normal" baseline by counting all movements and compare them to the number to bee expect in a usual, comparable timeframe.	General picture of mobility reduction in Germany due to Covid-19 mobility restrictions.	Initial drop in mobility: mobility fell to -39% below normal in mid-March 2020, after the majority of restrictions in Germany took effect. Slow recovery of mobility: in late March mobility slowly increased and finally plateaued at -27% in the second week of April. As restriction policies hardly changed during this time, this increase might be attributed mostly to a relaxing of self-imposed, individual mobility restrictions, paired with increased mobility due to warmer weather. Beginnings of an opening: starting April 20th, some mobility restriction policies have been lifted. We observe an immediate increase in mobility to -21% in the week starting April 20th.	Mobility flows of this kind are collected by many mobile phone providers. The team uses data from the German Telekom, which is distributed by the company Motionlogic, as well as data from Telefónica, which is analyzed and aggregated by the company Teralytics. This kind of data is commercially available and is used, for example, by public transportation companies, for predicting traffic or to improve road infrastructure.

Hartl et al.	Search for a trend break in cumulated confirmed Covid-19 cases as reported by the Johns Hopkins University (2020). The trend break has been estimated though maximum likelihood methods.	The impact of the German public shutdown on the spread of COVID-19.	Their finding is that confirmed Covid-19 cases in Germany grew at a daily rate of 26.7% until 19 March. From March 20 onwards, the growth rate drops by half to 13.8%, which is in line with the lagged impact of the policies implemented by the German administration on 13 March and implies a doubling of confirmed cases every 5.35 days. Before 20 March, cases doubled every 2.93 days. In their update of the model they test the impact of the 22 March policies. From 30 March on, the estimated average growth rate is 5.8%, so that the cases double every 12.20 days, therefore the containment policies are being effective.	Data from Johns Hopkins University (2020), which links data from the Robert Koch Institute, the World Health Organization, and the European Centre for Disease Prevention and Control.
Italian STC	?	Assessment of the risks of epidemic spread for COVID-19 disease associated with various scenarios for the release of the lockdown introduced on 11 March on national territory.	Restarting all the sectors without teleworking and with schools open, the country would need 151 thousand intensive care units already in June and a number of hospitalizations, by the end of the year, equal to 430,866	?
COVID-19 working group et al.	In depth review of the first month of the Italian outbreak through descriptive and analytic epidemiology and an estimation of the R0 and Rt taking into account the diversity of transmission across the country.	It is provided a descriptive epidemiological summary on the first 62,843 COVID-19 cases in Italy as well as estimates of the basic and net reproductive numbers by region.	The COVID-19 infection in Italy emerged with a clustering onset similar to the one described in Wuhan, China and likewise showed worse outcomes in older males with comorbidities. Initial R0 at 2·96 in Lombardia, explains the high case-load and rapid geographical spread observed. Overall Rt in Italian regions is currently decreasing albeit with large diversities across the country, supporting the importance of combined non-pharmacological control measures.	The team analysed data from the national case-based integrated surveillance system of all RT-PCR confirmed COVID-19 infections as of March 24th 2020, collected from all Italian regions and autonomous provinces.
Signorelli et al.	Statistical estimate of period-prevalence of the disease.	Impact of mitigation measures.	The team concludes that suspending flights from China and airports' checkpoints with thermos-scan did not have a significant effect in containing the epidemic, the implementation of a "red zone" in Lombardy effectively contained the spread of the infection within that area, even though it did not have the same effect in the neighboring provinces (Bergamo, Brescia, and Piacenza); the failure to establish a second "red zone" near Bergamo in the Municipalities of Alzano and Nembro despite the proposal of local authorities (on March 3rd), led to a dramatic out-break with about 10,000 cases in Bergamo with over	Data from Italian Civil Protection and from Local Authorities

			1,000 death toll and similar figures in the neighbouring areas (Brescia and Piacenza); and finally that General mitigation measures seem to be effective to flatten the epidemic curve of new notified infections	
Grasselli et al.	Based on data to March 7, when 556 COVID-19–positive ICU patients had been admitted to hospitals over the previous 15 days, linear and exponential models were created to estimate further ICU demand.	Estimation of ICU capacity and admissions.	The article shows that despite prompt response of the local and regional ICU network, health authorities, and the government to try to contain the initial cluster, the surge in patients requiring ICU admission has been overwhelming. Therefore, other health care systems should prepare for a massive increase in ICU demand during an uncontained outbreak of COVID-19. This experience would suggest that only an ICU network can provide the initial immediate surge response to allow every patient in need to be cared for.	Patients in 15 first-responder hub hospitals, chosen because they either had expertise in infectious disease or were part of the Venous-Venous ECMO Respiratory Failure Network (RESPIRA).
COVID-19 MMP	The researchers built a proximity network among users based on the locations they visited and the hour of the day when these visits occurred. In this way, they assess the effect of intervention on the average contact rate, or the number of unique contacts made by a person on a typical day.	Investigate the number of unique contacts made by a person on a typical day, and evaluate the effect of interventions on the social mixing of our users' sample by defining a proxy of the potential encounters each user could have in one hour. In order to do that, the researchers build a proximity network among users based on the locations they visited and the hour of the day when these visits occurred.	The results of the exercise show that on April 12, Easter Day, the average degree of all users was 86% lower than the pre-outbreak averages in the North, 83% in the Center and 82% in the South and the Islands. In conclusion, in the past 4 weeks, the adherence to the mobility restrictions imposed since March 12 has remained high and constant all over the country.	Mobility data is provided by Cuebiq, a location intelligence, and measurement platform.
PREDICT COVID-19	?	Predictive model on the development of positive and death cases due to COVID-19. The study assumes that the first 17 days of infection are those that determine the slope of the curve, the duration of the epidemic depends on when the daily peak is reached which depends in turn on the containment strategies, and the curve can be divided into two different sections, before and after daily peak.	The model shows that although the peak is close, in some regions the positive cases are underestimated, and also that containment strategies are working.	Data from Italian Civil Protection and from Local Authorities
Martinez et al.	Verhulst model, a population growth scale that looks at the initial population to identify velocity and propagation constant. This approach enables to calculate the level of uncertainty in the short run, by adjusting epidemics history and identifying parameters.	Prediction tool that is helping Spanish emergency departments know how many patients with Covid-19 will need to be admitted in intensive care units (ICU) and prepare adequately.	The total number could oscillate between 90,000 and 160,000, depending on the data received every day.	Data at regional level from Asturias, Cantabria and Castile Leon, together with data from the Spanish ministry of health since March 18th, and the estimations issued by Johns Hopkins University.
Uni Cat	Empirical model, verified with the evolution of	The model estimates the number of	The model predicted 203795 cases for Spain	The data sources of the model are

	the number of confirmed cases in previous countries where the epidemic is close to conclude, including all provinces of China. The model and predictions are based on two parameters that are daily fitted to available data: the velocity at which spreading specific rate slows down; the higher the value, the better the control; the final number of expected cumulated cases, which cannot be evaluated at the initial stages because growth is still exponential.	cases, and permits the evaluation of the quality of control measures made in each state and a short-term prediction of tendencies.	on April 19 2020.	World Health Organization (WHO) surveillance reports the European Centre for Disease Prevention and Control (ECDC) and the Spanish Ministry of Health.
Inverence	Based on data released by Spain's Ministry of Health (Ministerio de Sanidad), predictive models have been developed based on Bayesian time series analysis.	The modelling strategy considered the number of daily ICU admissions in every region and linking it, via a transfer function, to the number of deaths, assuming that the number of ICU admissions is a good indicator of the number of infected individuals in critical condition. Later on, the research team has developed models for the number of infected cases, based on a dynamical transmission rate model, which allows to understand in a straightforward way the effect of public authorities' actions, which are aimed precisely at reducing this transmission rate.	The number of deaths per million people shows the pandemic's different spreading velocities in different countries. Spain appears as the country with the largest epidemic spreading velocity among the set of countries considered.	Data released by Spain's Ministry of Health.
University of Zaragoza	The research team adapted a Microscopic Markov Chain Approach (MMCA) metapopulation mobility model to capture the spread of COVID-19 that stratifies the population by ages, and accounts for the different incidences of the disease at each stratum.	The model is used to predict the incidence of the epidemics in a spatial population through time, permitting investigation of control measures.	We have applied the results to the validation and projection of the propagation of COVID–19 in Spain. Our results reveal that, at the current stage of the epidemics, the application of stricter containment measures of social distance are urgent to avoid the collapse of the health system. Moreover, we are close to a scenario in which the complete lockdown appears as the only possible measure to avoid the former situation. Other scenarios can be prescribed and analyzed after lockdown, as for example pulsating open-closing strategies or targeted herd immunity.	Estimates of the epidemiological parameters and the mobility and demographic census data of the national institute of statistics (INE).
Massonnaud et al.	Deterministic SEIR model for hospital areas with predictions at one month and 17 five-year age groups (last 80 and over) to estimate the ICU resource deficit. Specifically, the model is based on country-specific contact matrices (social interactions) between age groups.	Estimation of the daily number of COVID-19 cases, hospitalizations and deaths, the needs in ICU beds per Region and the reaching date of ICU capacity limits.	At the national level, the total number of infected cases was expected to range from 22,872 in the best case (R0 = 1.5) to 161,832 in the worst considered case (R0 = 3). Regarding the total number of deaths, it was expected to vary from 1,021 to 11,032, respectively. Clearly the real data regarding mortality rate are higher. What is interesting,	Population structure was inferred for each catchment area from 2016 and 2017 census data provided by the French National Institute of Statistics and Economic Studies (Insee). Catchment areas were then aggregated by metropolitan

			it is also that they estimated the timing according to which the capacity limit of French ICU would be overrun.	Regions [13 French administrative areas with an averaged population of 4.75 millions ranging from 300,000 (Corse) to 12.55 millions (Ile-de-France)]. Data on ICU beds capacity per French Region were retrieved from the "Statistique Annuelle des Etablissements de Santé" (SAE)
EPIcx-lab of INSERM (1)	Stochastic age-structured transmission model integrating data on age profile and social contacts in the Île-de-France region to assess the current epidemic situation, and estimate the effectiveness of possible exit strategies. The model is calibrated on hospital admission data of the region before lockdown and validated on syndromic and virological surveillance data.	In one study they use a stochastic age-structured transmission model integrating data on age profile and social contacts in the Île-de-France region to assess the current epidemic situation, evaluate the expected impact of the lockdown implemented in France on March 17, and finally to estimate the effectiveness of exit strategies, building on hospital admission data of the region before lockdown.	They estimated that the average number of contacts is predicted to be reduced by 80% during lockdown, leading to the reduction of the reproductive number to 0.68. They show that the epidemic curve reaches ICU system capacity and slowly decreases during lockdown, and that lifting the lockdown with no exit strategy would cause a second wave. They also show that testing and social distancing strategies that gradually relax current constraints while keeping schools closed and seniors isolated will avoid a second wave and healthcare demand exceeding capacity.	The model is calibrated on hospital data specifying the number of COVID-19 positive hospital admissions in Île-de-France prior to lockdown. Data for that period was consolidated up to April 3, to account for delays in reporting. The simulated incidence of clinical cases (mild and severe symptoms) is compared to the regional incidence of COVID-19 cases estimated by the syndromic and virological surveillance system for the weeks 12 (March 16 to 22, 2020) and 13 (March 23 to 29).
EPIcx-lab of INSERM (2)	Stochastic age-structured data-driven epidemic model based on demographic and social contact data between children and adults for each region, and is parameterized to COVID-19 epidemic, accounting for current uncertainties in the relative susceptibility and transmissibility of children.	Assess the expected impact of school closure and telework to mitigate COVID-19 epidemic in France by mean of a stochastic age-structured epidemic model integrating data on age profile and social contacts of individuals.	According to the model, mere school closure would have limited effects (i.e. <10% reduction with 8-week school closure for regions in the early phase of the epidemic), while coupled with teleworking for 25% adults there would be a delay of the peak by almost 2 months with an approximately 40% reduction of the case incidence at the peak. Therefore, explicit guidance on telework and interventions to facilitate its application to all professional categories who can adopt it should be urgently provided.	Demographic and age profiles of the regions of Île-de-France, Hauts-de-France, Grand Est

Table 4 – Estimates and Assessments of the Model Studied

Model name	**Estimating epidemic variables**[78]	**Estimating healthcare variables**[79]	**Assessing mitigation actions**[80]	**Assessing Epidemic spread/mobility of population**[81]
IHME	X	X		
Los Alamos	X			
Epirisk				X
COVID-19 Modelling				X
Bakker et al.			X	X
Columbia University		X		X
Imperial College (1)	X	X	X	
Imperial College (2)	X	X	X	
Imperial College (3)	X		X	
UO		X		
LSHTM			X	X
RKI (1)	X		X	
RKI (2)			X	X
COVID Mobility Project			X	X
Hartl et al.	X		X	
Italian STC	X	X	X	
COVID-19 working group et al.	X			
Signorelli et al.	X		X	
Grasselli et al.		X		
COVID-19 MMP			X	X
PREDICT COVID-19	X			
Martinez et al.		X		
Uni Cat	X		X	
Inverence	X	X	X	
University of Zaragoza	X	X		X

[78] E.g.: number of infected and deceased individuals
[79] E.g.: number of ICU available
[80] E.g.: limits to circulation
[81] E.g.: spread of epidemic across countries and regions, extent of population mobility in the country

Massonnaud et al.	**X**	**X**		
EPIcx-lab of INSERM (1)	**X**	**X**	**X**	
EPIcx-lab of INSERM (2)		**X**	**X**	

1.4 Policy Take-Outs

The exercise carried out allows to draw a set of assumptions on governance of modelling:

1 **Ensure transparency in the modelling assumptions**. Using models based on assumptions in absence of hard data can lead to over interpretation and exaggeration in the magnitude of the outbreak. As an example, the aforementioned model elaborated by UO in its most extreme scenario suggests that 68% of the UK population had been exposed to the virus. Likewise, the aforementioned model from the Imperial College, based on the code developed 13 years ago for describing an influenza pandemic, assumed that the demand for intensive care units would be the same for both infections, thereby leading to the belief that herd immunity could be reached at a small cost. However, data from both Italy and China show that COVID-19 leads to a much higher percentage of admissions to ICU (5-10%). Therefore, assumptions must be transparent and clear to the reader and the policy maker in order to be aware of the caveats.

2 **Collect data from different sources in a standardized fashion.** Some experts argued that the initial spread of the virus might have been due to the incapability to recognize anomalous infections in some hospitals at the beginning of the epidemics. Further, other experts argue that the inconsistency in mortality rates between Italy and other countries and within Italian regions may be driven by different data collection approaches, while some others argue that mortality rates are underestimated.[82] Overall a system for standardized data collection across regions and at macro and micro level is needed in order to ensure comparability among statistics and modeling results and therefore boost increase situational awareness. A survey of the data sources available to download is presented in the annex.

3 **Perform validation and sensitivity analysis exercises.** As we have seen, the results of many modeling exercises have been deeply influenced by the modeling and estimation techniques used. In this respect, a core activity ensuring the robustness of the modelling exercises performed consists in applied different modelling and estimation techniques to the same set of data, as well as changing the values of the input and internal parameters of a model to determine the effect upon the model output. Related to this issue is the necessity to validate the models by employing them on comparable but different data sources to see how the model results change, and to keep them open in order to scrutiny and criticisms by other researchers. Last but not least, also keeping data open allows to carry out different modelling and estimation techniques by different researchers.

4 **Generate collaborative model simulations and scenarios.** Clearly the collaboration of several individuals in the simulation and scenario generation allows for policies and impact thereof to be better understood by non-specialists and even by citizens, ensuring a higher acceptance and take up. On the other hand, modelling co-creation has also other advantages: no person typically

[82] Specifically, Buonanno et al. 2020, combining official statistics, retrospective data and original data stemming inter al. by obituaries and death notices, suggest that the reported mortality rate attributable to COVID19 accounts only for 26.6% of the observed excess mortality rate between March 202 and March 2019.

understands all requirements and understanding tends to be distributed across a number of individuals; a group is better capable of pointing out shortcomings than an individual; individuals who participate during analysis and design are more likely to cooperate during implementation. In the case at hand, the joint elaboration of simulations and scenarios by policy makers and scientists helps in producing models that are refined to tackle the containment policies adopted.

5 **Develop easy to use visualizations.** As we have seen there are several data aggregators that visualize the data coming from the field every day and that improve the situational awareness of the policy makers. Further, an interesting feature of many models that have been developed and used by policy makers to tackle the COVID-19 pandemic is the use of visualization tools depicted the results of the underlying simulation models. In this regard, policy makers should be able to independently visualize results of analysis, make sense of data and interact with them. This will help policy makers and citizens to understand the impact of containment policies: interactive visualization is instrumental in making evaluation of policy impact more effective. A survey of the visualizations provided by the aggregators is available in the appendix.

6 **Consider carefully the sources of uncertainty in the model.** As the other simulation models, also the ones used to tackle the COVID-19 pandemics suffer from several sources of uncertainty. Such uncertainty could be merely statistically related (e.g. confidence intervals), related to parameters in the model that are difficult to estimate (e.g. the rate of transmission), concerning the data used (e.g. data on fatality rate might be not precisely measured), or of a more conceptual level (e.g. assuming a representative agent).

7 **Tailor the model to specific questions you are trying to address.** Specific modelling strategies (and level of complexity) should be used to address specific research questions. The simplest structure of predictive simulation is given by the aforementioned SIR models, which use few data inputs and can be useful to assess the epidemic outbreak in the short term. Such models cannot be used to depict uncertainty, complexity and behavioural change. Another class of models is given by forecasting models, which use existing data to project conclusions over the medium term. Finally, strategic models that encompass multiple scenarios assessing the impact of different interventions are able to capture some uncertainty underlying the epidemic outbreak and the behaviour of the population and are the foundation for policy making activity.

8 **Use models properly**. Models are not a commodity that provide a number which the policy makers use to take decisions. There needs to be a full understanding of the subtleties involved, the levels of uncertainty, the risk factors. In other words, you need in-house data and model literacy embedded in the policy making process, in house. You can’t outsource that. Indeed, a recent report for the US highlighted the limitations of a process that involved experts on an ad hoc, on demand basis, leaving much arbitrariness to the process: “Expert surge capacity exists in academia but leveraging those resources during times of crisis relies primarily on personal relationships rather than a formal mechanism.” On a similar token, in the UK, a recent article pointed out that experts involved in the SAGE were too "narrowly drawn as scientists from a few institutions". By the same token, there was insufficient in house capacity to manage this input: In the US, “there is currently limited formal capacity within the federal government”, while in the UK, “the criticism levelled at the prime minister

may be that, rather than ignoring the advice of his scientific advisers, he failed to question their assumptions”.

1.5 APPENDIX – Aggregators and Data Sources

Table 5 – List of main Aggregators and Data Sources

AGGREGATOR	DATA SOURCES	DATA FOR DOWNLOAD	SCOPE
Columbia University	• The 2020 Centers for Medicare & Medicaid Services (CMS), Health Care Information System (HCRIS) Data File, Sub-System Hospital Cost Report (CMS-2552-96 and CMS-2552-10), Section S-3, Part 1, Column 2 • The 2018 American Hospital Association (AHA) Annual Survey • The 2020 US DHHS Health Resources and Services Administration, Area Health Resources Files (AHRF) • The 2017-2019 CMS Medicare Provider of Services file, Medicare Cost Report, Hospital Compare Files	Yes at this link	Global

European Center for Disease Prevention and Control (ECDC)	Key sources:
	• Regular updates from EU/EEA countries through the Early Warning and Response System (EWRS), The European Surveillance System (TESSy), the World Health Organization (WHO) and email exchanges with other international stakeholders
	• Screening of sources from 196 countries:
	  ○ Websites of ministries of health
	  ○ Websites of public health institutes
	  ○ Websites from other national authorities (e.g. ministries of social services and governments)
	  ○ Websites on health statistics and official response team
	  ○ WHO websites and WHO situation reports
	  ○ Official dashboards and interactive maps from national and international institutions
	• Screening of social media accounts maintained by national authorities
		Yes,at this link	European/Global

European Data Portal	• ECDC for data on the epidemics • EUROSTAT Geographics for data on administrative units	Yes at this link	European/Global
Johns Hopkins University's Center for Systems Science and Engineering (CSSE)	• World Health Organization (WHO) • DXY.cn. Pneumonia. 2020. • BNO News • National Health Commission of the People's Republic of China (NHC) • China Centers for Disease Control and Prevention (CCDC) • Hong Kong Department of Health • Macau Government • Taiwan Centers for Disease Control and Prevention • U.S. Centers for Disease Control and Prevention (CDC) • Government of Canada • Australia Government Department of Health • European Centre for Disease Prevention and Control (ECDC) • Ministry of Health Singapore (MOH) • Italian Ministry of Health and Civil Protection	Yes at this link	Global

	• 1Point3Arces • Worldometers		
Our World in Data (Global Change Data Lab, and University of Oxford)	• European Center for Disease Prevention and Control (ECDC).	Yes at this link	Global
World Health Organization (WHO)	• World Health Organisation based on Government agencies and health ministries and other IHR States Parties under the International Health Regulations • For EU/EEA countries and UK the European Center for Disease Prevention and Control (ECDC)	No	Global
Worldometers	• Crowdsourcing: individuals can provide data about cases • Government agencies from all over the world, such as U.S. Centers for Disease Control and Prevention (CDC) • World Health Organization (WHO)	No	Global
SAS Coronavirus Report	• World Health Organization (WHO) • Government agencies from all over the world, such as U.S. Centers for Disease Control and Prevention (CDC) • European Center for Disease Prevention and Control (ECDC) • National Health Council	Yes at this link	Global
Official COVID19 Dashboard public information	• Austrian district administrative authorities and provincial health directorates, the health ministry, as well as the Agency for Health and Food Safety (AGES)	Yes at this link	National Level (Austria)
COVID - 19: Overview of the current situation in the Czech Republic	• National Health Information System, Regional Hygiene Stations, Ministry of Health of the Czech Republic	Yes at this link	National Level (Czech Republic)
Danish Health Authority COVID-19 statistics and charts	• Sundhedsstyrelsen (National board of Health)	No	National Level (Denmark)
Koroonakaart	• Health and Welfare Information Systems Center (TEHIK)	Yes at this link	National Level (Estonia)
Robert Koch-Institut: COVID-19-Dashboard	• Data collected are transmitted to the Robert Koch Institute (RKI) by the responsible health authority at county level in accordance with the Infection Protection Act • There is also a centralized intensive care register	Yes at this link	National Level (Germany)
Italian Department for Civil Protection	• Italian Ministry of Health collects data from all the hospitals	Yes at this link	National Level (Italy)
Population and business statistics related to COVID-19	• Lithuanian Ministry of Health (SAM) • National Center for Public Health (NVSC) • Government of the Republic of Lithuania (LRV) • Information published by municipalities	No	National Level (Lithuania)
COVID-19 Dashboard - Malta	• Ministry for Health	Yes at this link	National Level (Malta)
Development of COVID-19 in the Netherlands	• Ministry of Health, Welfare and Sport	Yes at this link	National Level (Netherlands)
Slovenian COVID-19 Data Tracker	• Daily reports and monitor the announcements of all hospitals for COVID-19 (UKC Ljubljana, UKC Maribor, UK Golnik, SB Celje)	Yes at this link	National Level (Slovenia)
Coronavirus (COVID-19) in the UK	• Lab-confirmed case counts for England and subnational areas are provided by Public Health England • All data on deaths and data for the rest of the UK are provided by the Department of Health and Social Care based on data from NHS England and the devolved administrations	Yes at this link	National Level (United Kingdom)

The COVID Tracking Project	• State/district/territory public health authorities—or, occasionally • Trusted news reporting, official press conferences • Tweets or Facebook updates from state public health authorities or governors.	Yes at this link	National Level (United States)