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Ecosystem, Health, Socio-economic and Mobility Factors for COVID-19 Mortality

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Author's contribution

The sole author designed, analysed, interpreted and prepared the manuscript.

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ABSTRACT

Epidemiological literature identifies a variety of factors that can affect the mortality of COVID-19. We use a sample of 42 countries and 46 States of the US, and analyse 19 factors that could affect mortality. The factors that were found significant were the following: Population in nursing homes; pollution; prevalence of lung cancers, hypertension and diabetes; median age of population and percentage of the population above 65 years old; air traffic; population concentration; mean temperature; and UV radiation. Regarding mobility policies, quarantines to passengers arriving and suspending the entry of air passengers were found to reduce mortality; community mobility reduction in public spaces was not found to reduce mortality and the influx of people in the healthcare system in the following weeks to the outbreak.

Keywords: COVID-19 mortality; ecosystem; health; socio-economic; mobility factors.

1. BACKGROUND

Mortality and the spread of COVID-19 is affecting various regions in different ways. As we shall discuss, there are several factors that from an epidemiological point of view can justify this. From the ecosystem conditions, for example, air and water pollution, UV exposure and

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temperature are expected to have effects in the immunological capacity of the host and also in the contagion capacity of the SARS-COV-2 (the virus that causes COVID-19). Comorbidity factors increase risks of mortality and therefore certain populations are considered at high risk (e.g those with respiratory problems, cancers, diabetes, hypertension). Additionally, socio-economic specific aspects of each place, like the quality of the health system, age structure of the population, urbanization of the country and density of the cities, the connectivity of the cities, are some of those often regarded as having impacts. Given the existence of news regarding the high percentage of deaths in nursing homes, the percentage of the population living in these places was also a variable considered.

Furthermore, policies also influence contagion and mortality rates. Almost all countries have implemented some sort of mobility restriction measures. Restricting public gatherings with different sizes and according to the type of meetings was one of the approaches and the most widely applied. Controlling incoming passengers with mandatory or selective quarantines or fully suspending incoming flights were other of the policies. Schools and non-essential businesses closures were also some of the measures implemented. Stay-at-home orders were also pursued by restricting the going of citizens to the streets according to specific reasons (essential tasks or to work in essential businesses). All the countries affected by COVID-19 and US States had some level of community mobility reduction measures.

The objective of this study is to help understanding how to deal with COVID-19 in the future as well as future outbreaks of virus-related diseases with similar characteristics. While in the beginning of the outbreak there was no data to understand the most relevant factors to increase or decrease the fatality and contagion capacity of COVID-19, as time passes, more information is available, helping to improve decision-making in the future.

2. METHODOLOGICAL ASPECTS

Through all the models tested we included five groups of indicators: ecosystem, health, socio-economic, mobility and other factors that may condition mortality in the period of analysis.

The model that we hypothesized was the following.

Mortality = $\alpha + b_{1,2,...}$*ecosystem + $c_{1,2,...}$*health + $d_{1,2,..}$socioeconomic + $e_{1,2,...}$*mobility + $f_{1,2,...}$ *otherfactors

2.1 Dependent Variable

We defined as the dependent variable the weekly mortality per million, between weeks 3 and 7 after the beginning of the social distancing measures (i.e. between March 30 and May 3). We defined this time period given the existing literature on incubation period and time between having symptoms and the occurrence of death, and that it should suffice to capture the impacts on mortality of the measures.

A study [1] estimates the median incubation period of COVID-19 to be 3 days (from 0 to 24 days), and other [2] 5.1 days. Regarding the time between having symptoms to death. An article about Italy found it to be 8 days [3]. Another estimates that it varies from 11.5 days on average (from 6 to 19 days) for persons above 70 years old to 20 days for those below that age. Both these indicators highly change according to the age group and whether there are comorbidity factors. Additionally, roughly 80% of deaths occur to people older than 70 years old, and 95% above 60 years old [4].

According to the mentioned studies, between contracting the virus and this leading to death we should expect a median for the highest risk age group (above 70 years old) between 11 and 16 days, and between 23 and 25 days for the other age groups. If we consider a 2 weeks period to start to see a reduction of contacts, then we have four weeks (week 3 to week 7) where we can observe the impacts. The mortality by COVID-19 can be seen as a proxy to the number of hospitalizations, so if it reduces, it represents a diminishing of the influx of people in the healthcare facilities.

2.2 Independent Variables

For the different factors, we identified the following indicators to be investigated.

2.2.1 Ecosystem indicators

The selected indicators to be analysed were the following:

- Air pollution measured as the Particular Matters 2,5 [5,6] in the air. This indicator refers to atmospheric particulate matter

(PM) that has a diameter of less than 2.5 micrometers. Air pollution, especially nitrogen dioxide, is studied to cause lung damage and respiratory problems, and both of these are associated with COVID-19 [7]. In principle, the weaker the respiratory system, the deadlier can be this disease.
- Air and water pollution index for the largest city of the territory [8]. This adds water pollution as this may lead to immune suppression and the weaker the immunological system the higher the fatality rate associated with a virus [9]. This is why CDC [10] considers as a risk group people those that are immunocompromised, as well as the older population as the competency of the adaptive immune function decreases with age. Furthemore, this indicator has broader consideration of air pollution than just PM 2,5.
- UV radiation [11,12]. This factor is related to the improvements on the immunological system [13] as it induces Vitamin D synthesis. Additionally, solar exposure is found to reduce viruses transmission capacity [14]. The only indicator found for the whole sample refers to the yearly average, therefore it does not address seasonal specificities.
- Mean temperature in March in the most populated city (average between 1985 and 2015) [15]. A study [16] on the previous outbreak of a coronavirus member, SARS-COV, shows that it decreases its capacity of transmission at higher temperatures. Another paper [17] already on SARS-COV-2, shows that at temperature range between 5 to 11 Celsius Degrees combined with relative humidity between 44 and 84% lead to higher prevalence, whereas at higher temperatures it significantly reduces. Additionally, higher temperatures are also associated with higher UV radiation with the above mentioned impacts, so mean temperature shall capture both effects.
- Latitude of the capital city [18,19]. This is another indicator explored as it both relates to UV radiation and mean temperature, and the already mentioned paper [17] identifies that the 30-50° N corridor (which has the ideal weather patterns for the spread of the virus regarding temperature and humidity at this time of the year) also has a higher prevalence of COVID-19.

2.2.2 Health of population

Based on the CDC risk groups regarding health conditions, we considered the following indicators.

- Mortality of lung cancers per 100,000 inhabitants [20]. This indicator is representative of the respiratory problems that the population has, and lung cancers are considered one of the high risk groups for COVID-19 also in comparison with other cancer types [21].
- Prevalence of hypertension [21,22]. Having high blood pressure is associated with several health problems and with the intake of certain medications that may increase mortality.
- Prevalence of diabetes [23,24]. This is one of the often referred comorbidity factors for COVID-19 and CDC considers to be a high risk group.

2.2.3 Socio economic indicators

The following indicators were considered:

- Percentage of the population above 65 [25,26]. As discussed, this age group is often referred to as a risk group.
- Median age [27,28]. This indicator also reflects the age structure of society. Another indicator that tries to capture the age structure of society.
- Healthcare Index [29,30]. This serves to see if the quality of it improves the response and reduces fatalities. As the indicators are different for US States and countries, it is not the best representative to give the right comparison.
- Expenses with health care per capita [31,32]. For the same reason as the healthcare index.
- GDP per capita (Purchasing Power Parity) [33]. This serves to analyze if income affects the capacity to reduce mortality by providing better access to healthcare.
- Air traffic per capita [34,35]. This is calculated with the number of enplanements per capita per year, as the more air traffic the higher the global connection, therefore we should expect higher contagion chains.
- Population concentration is an indicator here created by multiplying the urbanization index [36,37] by the density of the most populated city [38,39] to have an indication of the typology of demographic distribution.

It should reveal if it increases the proximity/contacts between people, fostering the spread of the virus.

- Persons per 1000 inhabitants living in nursing homes [40,41]. As already discussed, this kind of facilities was found to have high mortality, as if the virus spreads there, it can quickly reach a large population within the risk groups.

2.2.4 Mobility indicators

- Air traffic entrances suspended [42]. This is a dummy variable that is 1 when countries have imposed total entry restrictions for nationals and/or passengers coming from more than 90% of countries by March 23. It is not by March 16 because there is a delay recording these measures by the International Organization for Migration.
- Mandatory quarantine to arriving passengers [42]. This is also a dummy variable and indicates those countries that opted for this measure while allowing flights to take place.
- To assess community mobility reduction we analyzed various possible indicators. Our preferred one is the Google community mobility reports [43] which is organized in six groups: Retail and Recreation, Grossery and Pharmacies, Transit Stations, Workplaces, Parks and Residential. For our study, we considered mobility reduction in public spaces indoors, by making the average of the four first groups here mentioned, that are relatively stable overtime, compared to parks, for example, that is highly dependent on climate conditions. We selected four Mondays after the implementation of the mobility reduction measures (March 16, 23, 30 and April 6), and we made the average of mobility reduction. As these reports mention, this information is not fully accurate, given possible problems regarding location accuracy and categorization of places. Doing the average of reduction of mobility with 4 categories helped to overcome the categorization problem. Additionally, we consider it more informative than simply considering a dummy for the implementation of social distancing measures, such as closure of schools and non-essential businesses, since countries that did not proceed to these measures had also reductions in mobility as there were many other measures implemented (e.g. limiting gathering of big groups, promoting home-stay with fines) or people optionally do not move as much. Therefore we preferred the mobility indicators by Google.

2.2.5 Other factors

To try to avoid biases in the estimations we considered the following three indicators:

- Increase of deaths per million from the first week to the second after the implementation of the social distancing measures. This serves to take into consideration the dynamics previous to the established starting date (March 16).
- Deaths per million in week 1 after March 16. This helps to consider the prevalence of the virus in the beginning of the period here considered.
- Testing per million inhabitants by April 20 [44]. This helps to avoid biases in countries that tested more, where one should expect to have more deaths identified as caused by COVID-19 in proportion to the population.

2.3 Sample Size

Defining the sample is one of the most sensitive aspects of building a model as it can affect the outcomes of the results. For the US, we considered all the 50 states of the United States. Regarding the selection of countries, we considered 60 countries with the highest deaths per million inhabitants by April 1.

We excluded all the countries or States that proceed to social distancing measures such as schools and/or non-essential businesses closures before or after March 16 as it changes the perception of the community mobility indicator and, subsequently, the other factors. Therefore, from the US we excluded: Wyoming that closed schools by March 20 and California that additionally closed non-essential businesses on the same date; and Ohio and West Virginia, which did it by March 23. From the countries sample, the following were excluded: China and Hong Kong that did this kind of measures in February; Japan and South Korea that closed schools and San Marino that additionally closed non-essential businesses by March 2; Italy, Spain and Iran that closed both by March 7; the UK, Brazil and Panama that did the same by March 23 and Colombia by March 25; Hungary that closed non-essential businesses by March 28.

For unexisting data for community mobility, the following countries had to be removed: Albania, Algeria, Andorra, Iceland, Morocco and Russia.

We ended up with a sample of 88 territories, 46 states of the US, and 42 countries. For the second sample, for which there was comparable data on residents of nursing homes, apart from the 46 States, we found information for 25 countries, ending with a sample of 71 territories. They are all either members of OECD or European, so sharing common cultural and socioeconomic characteristics.

3. FINDINGS

We ran the models for the two samples in panel data, and ran an OLS model to look for significance and signal of the variables, and found that the following factors were significant (see details in Annex 1).

3.1 Ecosystem Significant Indicators

- Air and water pollution index was a consistent and significant indicator in both samples, increasing mortality.
- Air pollution index was found significant, increasing mortality.
- Mean temperature in March was also a very significant indicator in both samples supporting existing literature, that the higher temperature, the lower mortality,
- UV radiation was also found significant, but not as much as the mean temperature as it is the yearly average and is not adjusted to the month. In any case, mean temperature in March also contains information about the level of UV radiation.

3.2 Health Significant Indicators

- Lung cancers mortality was the most significant indicator of this category, increasing mortality.
- Prevalence of hypertension was also found significant.
- Prevalence of diabete was found significant in both samples.

3.3 Socio-economic Significant Variables

- Percentage above 65 years old was a consistent significant variable across the models and samples, increasing mortality the higher the percentage of people within that age group.
- Mean age of the population was also found significant with the same direction (the older the median age, the more mortality).
- Air traffic per capita was found to be a significant variable in the various models that we ran with a positive effect on mortality.
- Population concentration was found to be a significant variable.
- Residents of nursing homes as a percentage of the total population was found to increase mortality.

3.4 Mobility Significant Factors

- Suspension of incoming flights was found to be an indicator to reduce mortality in the samples.
- Mandatory quarantine was equally found significant also in the two samples, reducing mortality.
- Mobility reduction in public space was found significant in both samples, increasing mortality.

The variables not found significant were: Latitude, health care index, expenses with health care per capita, GDP per capita.

4. CONCLUSION

Generally speaking, epidemiological knowledge was supported in the models here presented, and some recommendations can be derived.

In the models conducted, it was shown that, as expected, the elders indeed are one of the highest risk groups. Yet, the number of elders residents in nursing homes per thousand inhabitants significantly increases the mortality, and appears to be a more significant factor than the percentage of the population above 65 years old. It would be interesting to have data regarding the size of the nursing house (average number of residents per nursing house) to understand if larger ones lead to higher spreading in this risk group and therefore to even higher mortality. One of the conclusions is that nursing homes should be highly controlled during outbreaks. Another conclusion is that concentrating the elderly population in nursing homes, especially if they have many residents, may foster the spread of viruses. Therefore, this should be taken into consideration when planning the support to the elders, promoting smaller nursing homes, to be more resilient in these situations, or to spread them in smaller units in case of outbreaks as such.

Secondly, the immunological condition of the host is also a relevant factor. UV radiations and mean temperature indicators allow us to consider that in warmer countries or during the warmer seasons the populations are less at risk. Exposure to solar radiation during the Winter is beneficial to strengthen the immunological system, and therefore, even the population that should be more protected (the risk groups), should keep having some time of direct sun per day. Also for patients being treated, some solar exposure per day can be considered. At last, colder countries should have more intensive care facilities in proportion to the total populations for when these outbreaks occur.

Thirdly, the higher the prevalence of certain health conditions (i.e. respiratory problems, diabetes and hypertension) advise us to give more attention to people with them. They should have preference for being tested and should be more closely accompanied in comparison to those without these diseases. Respiratory problems may be addressed by improving air quality, as air pollution is one of the relevant variables. Diabetes and hypertension are often affected by food habits, lack of exercise or having a stressful life. At a structural level, these topics also should be further emphasized as they also contribute to increase the mortality level during the outbreaks of this kind of virus. Countries with high prevalence of these risk groups should also be more concerned regarding the dimension of their intensive care facilities.

Contagion factors such as proportion of flights to the whole population and concentration of population increase mortality, meaning that they help to foster transmission channels. This means that rural places or less connected regions in general should be less concerned in comparison to more urbanized and connected areas. The latter should be better prepared to provide a better response from their health care system, again by having more intensive care facilities in proportion to the population to respond to these outbreaks.

Mobility policies on suspending flights or enforcing quarantines to the passengers was also found to have a similar effect of reducing mortality. Yet, mandatory quarantines are less restrictive and therefore have lower overall socio-economic impacts. Anyway, during the beginning of the outbreak, in case a country fears the collapse of its health system, any of these policies can be temporarily considered.

The only counterintuitive result was regarding the reduction of community mobility in public spaces, which apparently is not being able to reduce mortality in the period between 3 and 7 weeks after the implementation of such measures. Therefore, we shall also not expect that it is reducing the influx of people in the health care facilities in the following weeks to their implementation as mortality is a good proxy of the number of hospitalizations.

This suggests that the social distancing benefits by reducing overall contacts between people, may have been counterbalanced by contradictory effects, and it would be interesting to research possibilities of opposite effects that neutralize the positive ones. Therefore, some research questions could be investigated about other impacts of limiting the contact between people in the public spaces. According to the regional director of WHO for Europe, Hans Kluge [45], strong mobility restriction measures reduced the personnel in nursing residencies (with high-risk groups for COVID-19 such as advanced age population and those with underlying mental and physical illnesses) and there was also not enough testing and lack of equipment for the professionals being provided. Other possible reasons that could be investigated is if mobility restriction policies are prolonging/augmenting Winter effects, namely by increasing the duration and frequency of contacts between the persons inside the household and this may increase the opportunities for the virus to spread as also it favours the atmospheric conditions for the virus with less solar exposure. Additionally, this lower exposition to UV radiation leads to lower immunology of the host. It may also happen, that when the first cases are diagnosed in a country, the actual spread of the virus is much higher than initially thought, so a large number of people already may have it and by being closed at home, will promote the right conditions to spread to the other household members.

CONSENT

It is not applicable.

ETHICAL APPROVAL

It is not applicable.

COMPETING INTERESTS

Author has declared that no competing interests exist.

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ANNEX 1 - MODELS

Table 1. Model 1: 42 countries and 46 states of the US. Pooled OLS, with 430 observations

Included 88 cross sections units.
Dependent variable: Weekly per Million Deaths from Week 3 to Week 7 (Logarithmized)
Size of time series: minimal 2, maximum 5.

Independent variables	Coefficient	Std. error	T-Ratio	P-Value
constant	−4,99310	1,02311	−4,880	1,51e-06 ***
Mean temperature March	−0,0831833	0,00780173	−10,66	1,26e-023 ***
Pollution Index	0,00818569	0,00335615	2,439	0,0151 **
Lung Cancers	0,0192201	0,00483612	3,974	8,32e-05 ***
Diabetes Prevalence	0,0621958	0,0230655	2,696	0,0073 ***
Population above 65	0,0493493	0,0155563	3,172	0,0016 ***
Air traffic per capita	0,0521578	0,0150898	3,456	0,0006 ***
l_Pop concentration	0,335210	0,0769962	4,354	1,69e-05 ***
Suspending flights	−0,558220	0,152445	−3,662	0,0003 ***
Mandatory quarantine	−0,352715	0,117596	−2,999	0,0029 ***
Mobility Reduction	0,0196045	0,00421791	4,648	4,51e-06 ***
Deaths per million week 1	0,0753570	0,0266265	2,830	0,0049 ***
Increase deaths Week 1-2	0,0702064	0,00904567	7,761	6,58e-014 ***
Testing per Million	1,53278e-05	4,68478e-06	3,272	0,0012 ***

R-squared	0,687632	Adjusted R-squared	0,677871
F(13, 416)	70,44336	P-value (F)	2,13e-96
Log. Likelihood	−556,4758	Akaike Criterion	1140,952
Schwarz Criterion	1197,845	Hannan-Quinn Criterion	1163,417
rho	0,853452	Durbin-Watson	0,326035

Table 2. Model 2: With countries and US States with data regarding residents in nursing homes per million inhabitants. Pooled OLS, with 352 observations

Dependent variable: Weekly per Million Deaths from Week 3 to Week 7 (Logarithmized)

Included 71 cross sections units.
Dependent variable: Weekly per Million Deaths from Week 3 to Week 7 (Logarithmized)
Size of time series: minimal 3, maximum 5.

Independent variables	Coefficient	Std. error	T-Ratio	P-Value
constant	−10,0423	1,13831	−8,822	6,17e-017 ***
Mean temperature March	−0,0748227	0,00949051	−7,884	4,45e-014 ***
Pollution Index	0,00797400	0,00347199	2,297	0,0223 **
Lung Cancers	0,0135588	0,00541577	2,504	0,0128 **
Diabetes Prevalence	0,157804	0,0361092	4,370	1,66e-05 ***
Residents nursing homes	0,0983574	0,0202588	4,855	1,85e-06 ***
Population above 65	0,0477439	0,0218322	2,187	0,0294 **
l_Pop concentration	0,634595	0,0796495	7,967	2,53e-014 ***
Air traffic per capita	0,0703820	0,0154608	4,552	7,42e-06 ***
Suspending flights	−0,320958	0,192571	−1,667	0,0965 *
Mandatory quarantine	−0,242450	0,110151	−2,201	0,0284 **
Mobility Reduction	0,0176462	0,00463640	3,806	0,0002 ***
Deaths per million week 1	0,0489738	0,0240525	2,036	0,0425 **
Increase deaths Week 1-2	0,0545456	0,00824939	6,612	1,49e-010 ***
Testing per Million	2,18979e-05	5,95845e-06	3,675	0,0003 ***

R-squared	0,672697	Adjusted R-Squared	0,659100
F(14, 337)	49,47338	P-value (F)	6,30e-73
Log. Likelihood	−396,8328	Akaike criterion	823,6655
Schwarz criterion	881,6200	Hannan-Quinn criterion	846,7286
rho	0,736693	Durbin-Watson	0,432736

ANNEX 2 - DATA REGARDING SAMPLES

Table 3. States of the US - main variables

US States	Deaths per million May 3	Mobility reduction	Mean temperature march average 1985-2015	Air and water pollution index	Lung cancer per 100,000	% Population above 65	Air traffic per capita	Testing per million by April 20
New York	989	43.19	6	54	40.28	16.40	6.03	32629
New Jersey	886	40.5	6	68	40.05	16.10	5.07	20045
Connecticut	700	32.56	4	30	42.13	17.20	0.84	17391
Massassuchets	580	39.38	4	27	44.49	16.50	5.57	23478
Louisiana	428	24.81	18	25	55.54	15.40	2.83	30870
Michigan	406	32.13	3	52	55.14	17.20	0.32	11323
Rhode Island	305	33.75	4	24	52.48	17.20	3.81	35238
Illinois	218	38.38	4	41	50.04	15.60	5.50	12333
Maryland	197	31.13	7	22	42.92	15.40	1.67	11900
Pennsylvania	191	35.06	6	43	53.98	18.20	2.42	12656
Delaware	182	27.81	7	75	56.22	18.70	0.05	16958
Indiana	169	20.63	6	45	56.57	15.80	1.42	9642
Colorado	146	30.63	5	41	25.84	14.20	5.21	7989
Georgia	111	27.63	12	44	41.38	19.40	10.09	7953
Washington	109	33.94	9	29	38.53	15.20	6.71	18158
Mississippi	101	15.88	14	9	60.10	15.90	0.37	17133
Nevada	87	32	16	50	43.60	15.70	7.67	10767
Vermont	83	34.38	2	30	57.14	18.10	0.94	20867
Virginia	78	28.63	8	40	43.66	15.40	2.82	6671
Minnesota	75	31.75	0	27	41.36	15.90	7.05	8357
New Mexico	72	18.94	10	26	32.06	17.50	1.20	17703
Florida	64	31.25	23	41	53.08	20.50	5.59	12385
New Hampshire	63	26.94	1	14	50.99	18.10	1.20	10375
Oklahoma	61	19.5	11	11	56.59	15.70	0.56	9128
Alabama	59	19.56	13	28	60.12	16.90	0.48	9367
Wisconsin	58	26.13	2	32	47.62	17.00	1.21	8673
Missouri	58	22.56	8	33	60.46	16.90	1.97	9180

US States	Deaths per million May 3	Mobility reduction	Mean temperature march average 1985-2015	Air and water pollution index	Lung cancer per 100,000	% Population above 65	Air traffic per capita	Testing per million by April 20
Iowa	58	16.5	4	12	51.13	17.10	0.79	8177
Kentucky	57	20.81	9	44	70.65	16.40	0.96	7287
South Carolina	53	18.69	15	27	52.43	17.70	0.78	7867
Arizona	50	23.03	19	57	38.46	17.50	6.42	7583
Kansas	49	20	8	15	47.66	15.90	3.79	6448
Maine	44	28	1	18	70.31	20.60	1.43	11538
Nebraska	41	16.36	5	17	42.45	15.70	1.20	8167
North Carolina	40	24.38	11	27	50.36	16.30	2.76	7562
Idaho	36	17.75	7	30	33.82	15.90	2.30	9775
North Dakota	33	20.75	-2	16	40.79	15.30	1.45	19342
Texas	31	27.06	18	56	32.56	12.60	0.14	6786
Tennessee	31	20.31	10	38	58.78	16.40	1.47	14794
Oregon	26	29	9	30	44.21	17.60	2.86	9524
Arkansas	25	15.88	12	10	65.17	17.00	0.70	8833
South dakota	25	14.88	1	8	50.00	16.60	0.95	14643
Montana	15	21.25	4	31	43.54	18.70	2.06	10300
Hawai	12	34.5	24	8.3	13.91	10.00	24.50	18
Alaska	12	25.81	-3	10	27.63	11.80	6.02	13680

Table 4. World - Main variables

Countries	Deaths per million May 3	Mobility reduction	Mean temperature March average 1985-2015	Pollution index most populated city	Lung cancer per 100,000	% Population above 65	Air traffic per capita	Testing per million by April 20
Belgium	684	50.56	7	63	32.14	19	0.99	13900
France	372	55.94	8	66	28.57	20	1.01	7100
Netherlands	294	38.06	6	32	32.79	19	2.06	10000
Switzerland	206	38.63	6	17	21	19	3.24	25900
Ireland	266	47.81	7	40	26.36	14	24.40	18300
Sweden	262	21.31	1	18	17.97	20	1.19	7380
Luxembourg	157	55.81	6	21	25.54	14	3.20	54000
Portugal	101	57.63	15	36	20.19	22	1.22	23100
Canada	98	39.75	0	38	30.94	17	2.20	14800
Ecuador	92	60.94	15	65	7.21	7	0.35	1800
Denmark	86	36.50	3	21	34.82	20	0.10	17300
Germany	83	31.81	5	41	26.45	21	1.40	20600
Austria	68	55.31	6	18	23.84	19	1.70	20300
Slovenia	46	56.88	7	24	30.87	20	0.54	20000
Finland	42	35.00	-1	13	19.01	22	1.82	12000
Peru	41	63.38	23	85	10.22	8	0.45	4480
Romania	41	48.06	6	75	30.56	18	0.19	5500
Estonia	41	38.13	-1	23	26.44	20	0.38	30500
Turkey	41	35.19	6	70	32.15	8	1.23	7990
Norway	40	35.81	2	26	25.21	17	2.40	26400
Serbia	28	43.75	9	63	38.6	18	0.34	4730
Republica Checa	23	42.88	4	36	26.04	19	0.47	16700
Poland	20	45.75	3.0	59.0	34.26	18.0	0.14	5600.0
Mexico	16	31.75	17	84	6.47	7	0.38	384
Lithuania	16	44.94	1	24	24.7	20	0.49	24500
Chile	14	40.00	19	71	13.1	12	0.83	6200
UAE	13	33.31	23	48	6.79	1	9.60	79000
Greece	13	50.94	13	58	27.48	22	1.17	5180
Saudi Arabia	5.5	43.44	22	67	5.53	3	1.04	5100

Countries	Deaths per million May 3	Mobility reduction	Mean temperature March average 1985-2015	Pollution index most populated city	Lung cancer per 100,000	% Population above 65	Air traffic per capita	Testing per million by April 20
Argentina	5.5	54.62	22	52	21.4	11	0.33	765
Bahrain	5.1	24.38	22	55	14.93	2	3.90	52000
Uruguay	5.0	38.81	18	49	27.6	15	0.62	3850
Slovakia	4.4	46.38	6	41	26.65	16	0.00	8500
New Zealand	4.1	37.88	19	29	22.37	16	3.33	18500
Australia	3.8	18.44	22	27	20.95	16	2.90	17100
Malaysia	3.4	49.69	29	68	19.29	7	1.61	3300
Indonesia	3.2	25.94	29	84	18.01	6	0.35	182
Singapore	3.0	13.81	29	33	23.46	11	6.02	16200
Oman	2.5	34.81	26	38	4.72	2	1.53	5100
South Africa	2.3	41.50	21	38	20.75	5	0.31	2049
Costa Rica	1.2	37.75	24	54	6.77	10	0.34	2100
Taiwan	0.3	5.69	19	50	36	15	2.69	2300

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