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Where did it hit harder? The geography of excess mortality during the COVID-19 pandemic

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This paper analyses the uneven geography of the COVID-19 health impact in OECD and European countries. It first describes the increase in all-cause mortality – i.e. excess mortality – across subnational regions between January and December 2020. Subsequently, it investigates the regional factors associated with higher excess mortality, looking at demographic, socio-economic, institutional and environmental features of regions. Results show that excess mortality has a significant spatial dimension, with the hardest hit regions having excess mortality rates that were, on average, 17 percentage points higher than the least affected regions in the same country. During the first year of the pandemic, lower health system capacity, followed by population density, air pollution, share of elderly population and lower institutional quality were associated with higher excess mortality. While health system capacity and population density have been strongly associated to excess mortality throughout the COVID-19 crisis, trust in government and air pollution showed stronger correlations with excess mortality in the later phases of the pandemic. Finally, prolonged remote working, particularly after two-months, is also associated with lower excess mortality.

JEL codes: R10, I18, R58, J61
Keywords: regions, COVID-19, excess mortality, mobility

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1 Introduction

The COVID-19 crisis was declared a pandemic by the World Health Organisation on 11 March 2020. Since then, nearly four million deaths across the globe have been accredited to COVID-19 as of July 2021. One million of those deaths were reported in the OECD countries in this study during 2020 (Ritchie et al., 2021[2]), the period covered in this paper.[1] Official declarations of deaths from COVID-19 however vary across countries, reflecting not only differences in the success in containing the impact of the pandemic, but also differences in definitions used to accredit deaths to the COVID-19 disease and internal capacities or policies (including testing strategies) to identify it as a cause of death. Beyond the deaths directly attributable to the COVID-19 virus, the pandemic has potential knock-on effects for deaths due to other means. On the one hand, there might be additional deaths that would not have occurred outside the pandemic, e.g. because of the strain put on health care systems due to the surge in hospitalisations – in particular those requiring intensive care. On the other hand, behavioural changes and lockdown measures might have reduced deaths that would have occurred due to other sources, e.g. the 2020 "flu season" was less severe than in prior years and the number of road fatalities decreased compared to prior years.[2]

A better way to compare the human deaths associated with the COVID-19 pandemic across and within countries is to consider *excess mortality*, i.e. above average deaths. In OECD countries, compared to the average for 2018 and 2019, the total number of deaths was 14% higher in 2020, corresponding to over 1.5 million excess deaths.

Significant differences exist across countries as do differences within countries. Indeed, differences within countries are larger than those across countries. In Spain, Mexico and Colombia, for example, excess mortality in 2020 in the most affected region was 40, 60 and 90 percentage points higher respectively, than in the least affected one. This compares with the 47-percentage point gap observed between the most and least affected OECD country (Figure 1).

Building on data from official registers of deaths, this paper examines the patterns of excess mortality across regions in 33 OECD and three other European countries (Bulgaria, Malta and Romania) during 2020, and investigates the role that specific place-based factors may have played.

While a fast growing literature is already integrating the subnational lens to analyse the drivers of the spatially heterogeneous health impact of the COVID-19 pandemic, only limited research has looked at this issue from an international perspective. This paper contributes to filling this gap. To the authors' knowledge, there are no similar studies covering a large set of countries with a subnational focus and using consistent indicators and geographical definitions. The use of all-causes excess mortality provides important advantages in terms of international comparability, as this measure does not suffer from differences in COVID-19 testing policies nor differences in reporting of COVID-19 deaths.[3]

[1] The statistical overview does not include Costa Rica, Iceland, Ireland, Slovenia and Turkey due to lack of subnational data at the time of writing. Bulgaria, Malta and Romania are included. For the regression analysis Colombia, Israel, Lithuania and New Zealand are excluded due to lack of relevant covariates.

[2] https://www.webmd.com/cold-and-flu/news/20210225/what-happened-to-flu-season (accessed 7 July 2021) and https://ec.europa.eu/transport/modes/road/news/2021-04-20-road-safety-statistics-2020_en (accessed 7 July 2021).

[3] Advantages and limitations of using excess mortality statistics have been discussed by Morgan et al., (2020[47]).

The analysis takes a broad set of place-based characteristics into account to understand spatial patterns of excess mortality. Regional indicators in many domains – including socio-demographics, health system capacity, environmental quality, as well as institutional and geographical features – are used to analyse the spatial distribution of excess deaths. Most of these indicators come from the OECD Regional Statistics database (OECD, 2021[3]).

Results indicate that regions with stronger health system capacity – an index combining the availability of hospital beds and active physicians relative to population – experienced lower excess mortality since the first months of the pandemic. On average, an increase of one standard deviation in the health capacity index (e.g. around five more hospital beds per 1 000 people or two more doctors per 1 000 people) is associated to a decrease of 1.8-3.4 percentage points in excess mortality. This negative association has been strong and significant throughout 2020. In line with expectations and with results of other studies, excess mortality was higher – all else being equal – in denser and more polluted regions and those with older populations. In addition, trust in government was associated with a lower health impact, highlighting the role played by institutional quality, as found in the recent literature (Rodríguez-Pose and Burlina, 2021[4]). Finally, prolonged remote working is also associated with lower excess mortality, particularly after two-months of remote working. More precisely, reducing home-to-work mobility today by 25% with respect to pre-pandemic levels (January 2020) would lead to a decrease in excess mortality of 1-2.5 percentage points in two months.

The remainder of the paper is organised as follows: Section 2 presents the indicators used in the analysis and provides an assessment of the geographical patterns of excess mortality. Section 3 describes the data sources and empirical specifications. Section 4 discusses the results, and section 5 provides some concluding remarks.

2 Understanding the geography of excess mortality across regions

Excess mortality during the COVID-19 pandemic

The association of the increase in all-causes mortality – i.e. excess mortality – with COVID-19 requires caution. However, excess mortality provides a robust indicator of the human losses caused by the pandemic as it avoids problems of misreporting of COVID-19 deaths due to low levels of testing (OECD, 2020[1]), as well as differences in definitions and measurement capacities across and, sometimes, within countries.

Excess mortality can be broken down by different periods of 2020. This study distinguishes twelve sub-periods by considering January (when the first cases of COVID-19 appeared in most OECD countries), January-February, January-March, and so on until January-December (just before vaccination rollouts started in most countries). Excess mortality data are derived from official registers of deaths provided by national statistical offices or health ministries.[4]

The COVID-19 pandemic has hit certain parts of countries harder than others within the first twelve months of 2020. In 2020, subnational regions in 36 OECD and European countries registered on average 14% more deaths than the average number of deaths of the previous two years (2018-2019).[5] Increases in deaths were highly concentrated in specific regions. For example, New York (United States), Lombardy (Italy), Madrid (Spain), Mexico City (Mexico) and Amazonas (Colombia) experienced 30% to 90% more deaths in 2020 than in 2018-2019 – at least 20 percentage points higher than the average excess mortality in their respective country.

Considering a reduced sample of regions – consisting of 342 large regions (Territorial Level 2, TL2)[6] in 32 countries with a large set of covariates available to undertake a regression analysis (see list of countries in Annex C) – the maximum excess mortality for the period January-December 2020 reached 72%. Within

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[4] For more details on the data and metadata see *OECD Regions and Cities at a Glance 2020* (OECD, 2020[1]) and the related *Excess mortality* repository (https://github.com/oecd-cfe-eds/ccsa-excess-mortality) (OECD, 2021[7]).

[5] Excess mortality estimates based on a relatively short reference period have drawbacks and advantages. On the one hand, using a two-year period (i.e. 2018-19) – compared to, for example, a four-year period (i.e. 2016-19) – is less effective to smooth out potential errors and or outliers (e.g. due to other crises or natural disasters) in death registers. On the other hand, a two-year period reduces the biases generated by demographic trends – particularly the long run increase in life expectancy in most regions. The latter bias would come from the well-documented megatrend of demographic change with heterogeneous effects within countries (OECD, 2019[49]; OECD, 2020[1]) rather than from unclear sources of errors and outliers, the two-year reference period is therefore chosen in this exercise.

[6] Subnational regions within the 38 OECD countries are classified into two territorial levels reflecting the administrative organisation of countries: large regions (territorial level 2 or TL2) and small regions (TL3).

this sample, 5% of regions experienced negative or no increase in excess mortality for the same period, while excess mortality above 20% and 30% occurred in 20% and 8% of regions, respectively (Figure 1).

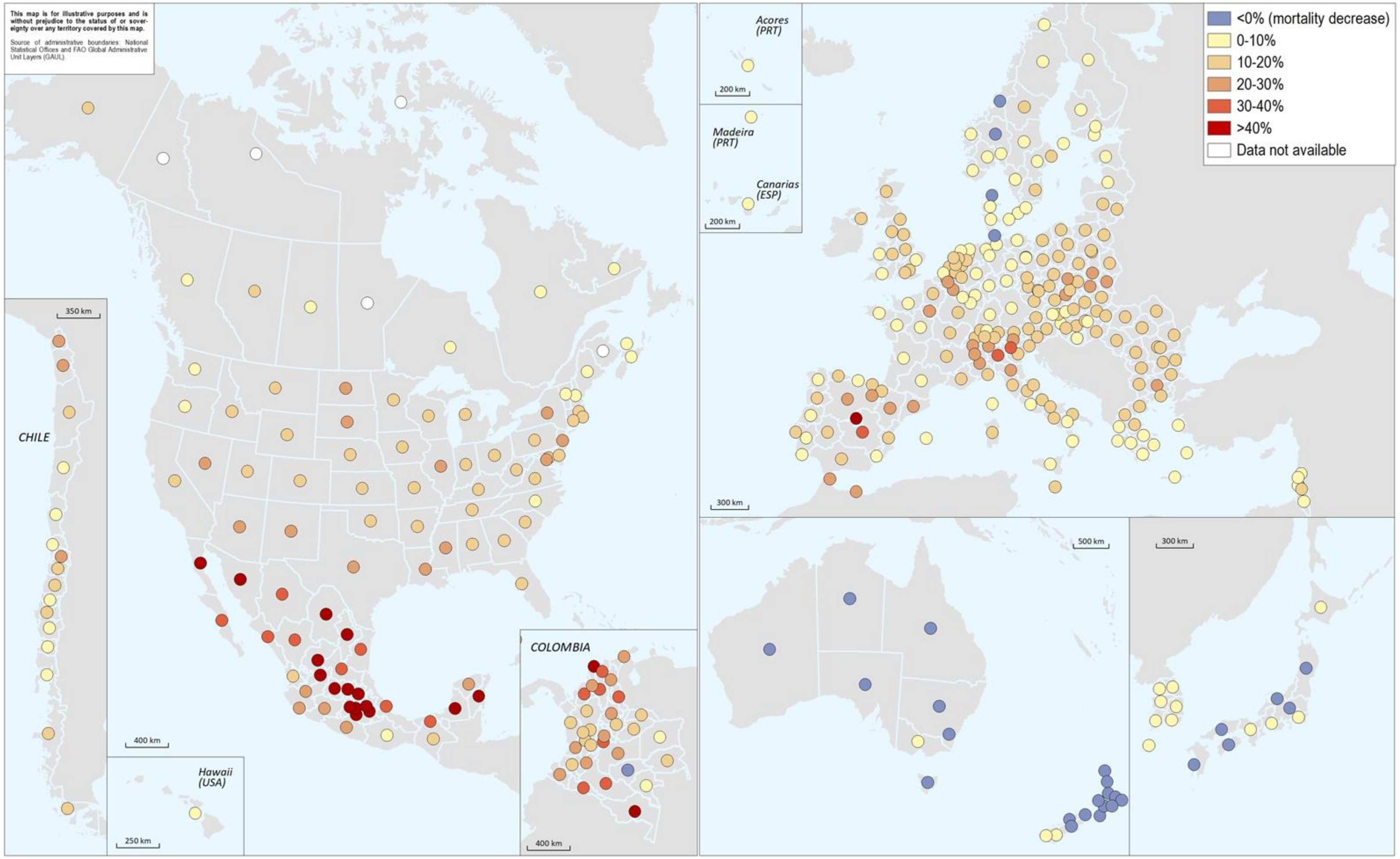
A first approach to understand the geographical patterns of the health impact of the pandemic is to examine excess mortality across types of regions, from metropolitan regions to low-density remote regions. To do so, we use an OECD classification of small regions (Territorial Level 3, TL3) based on the share of the regional population living within or near (up to one-hour drive) a metropolitan area[7] (Fadic et al., 2019[5]). According to this typology, small regions are classified into metropolitan regions (including large metropolitan areas), regions close to a metropolitan area, or regions far from a metropolitan area (which can be sub-divided into regions near a small-medium city, or remote regions).

In most OECD countries, metropolitan regions experienced higher excess mortality than remote regions in 2020. Across 23 countries with available data for TL3 regions, excess mortality was close to 18% in large metropolitan regions compared to 14% in remote regions, on average. This pattern is also observed within countries. In 16 out of 23 OECD countries, metropolitan regions recorded higher excess mortality than regions far from a metropolitan area. Nevertheless, this gap has not been homogeneous over time. While the gap reached its peak by the end of the first wave of the pandemic (June 2020), a process of regional convergence during the second half of 2020 – driven by growing excess mortality in remote regions – has been closing the gap. This process is in line with the way in which the virus spread across the world. While the virus first arrived to countries through their largest and highly connected metropolitan areas (mainly through international air travel, see Daon, Thompson and Obolski, (2020[6])), it then spread more widely within countries reaching practically all types of places.

[7] Metropolitan areas are captured through the existence of a Functional Urban Area of at least 250 000 inhabitants. See Dijkstra, Poelman and Veneri (2019[43]) for a detailed definition of Functional Urban Area.

Figure 1. Excess mortality in regions of OECD countries, January-December 2020

Percentage increase in 2020 deaths relative to the 2018-19 average, large regions (TL2)



Source: (OECD, 2021[7]).

Place characteristics and the health impact of the pandemic: A view from the literature

During the first year of the pandemic, many studies investigated potential risk factors for COVID-19 severity and death. One of the first risk factors to be identified was old age (WHO, 2020[8]). For people infected with SARS-CoV-2, the probability of death increases sharply with age, suggesting that places with larger shares of elderly population (e.g. aged 65 or above) are particularly vulnerable to the virus (Kashnitsky and Aburto, 2020[9]; Dowd et al., 2020[10]). In the OECD area, the share of elderly population is significantly different both across and within countries. For example, more than 25% of the population is 65 years or older in some regions in Italy, Spain and Portugal, compared to a national average of 21%, while in many regions of Mexico and Chile the share of elderly is 10% or less. Within countries, regions with higher shares of elderly people tend to be far away from metropolitan areas. In 2019, elderly dependency rates (i.e. the number of people aged 65 or over as a share of the working-age population – 15-64 year-olds) were around 35% in remote regions of OECD countries, 6 percentage points higher than in large metropolitan areas (OECD, 2020[1]).

The capacity of the health system is another crucial factor to consider. Failing to keep the number of COVID-19 cases needing medical attention below the capacity of the health system could result in many more fatalities due to COVID-19 as well as other diseases (McCabe et al., 2020[11]). In this sense, the availability of medical resources – measured in terms of hospital beds and physicians (doctors) per inhabitant – is crucial to prevent high excess deaths. For example, some regions in Mexico, Chile and the United Kingdom had around one physician per 1 000 people at the beginning of the pandemic, one third of the average observed in regions with the lowest physician rates in Austria, the Czech Republic and Germany. Such interregional inequality exists also within countries, notably in the United States and the Netherlands, as well as across types of regions. Prior to the pandemic, large metropolitan regions tended to be better equipped with hospital beds than remote regions, with an average of 9 beds per 1 000 inhabitants, compared to 5.5 in remote regions (OECD, 2020[1]).

Morbidity rates could also play a role in making some places more vulnerable to the pandemic. Within the first months of the COVID-19 crisis, the World Health Organization highlighted that people with pre-existing medical conditions – including high blood pressure, heart and lung diseases, cancer, diabetes and obesity – were among the most susceptible to developing severe forms of COVID-19 if infected with SARS-CoV-2 (WHO, 2020[8]). While related morbidity rates are not available for OECD regions, prevalence of obesity (where data are available) could serve as a proxy to capture some relevant pre-existing health conditions of the population. Recent literature shows that obesity is a risk factor for COVID-19 severity, not only by increasing the probability of other co-morbidities such as diabetes and high blood pressure, but also through a direct channel related to weakened respiratory capacity (Gao et al., 2020[12]; Bermont and Díaz Ramírez, 2021[13]). In some regions in Canada, Chile, Mexico and the United States, close to 40% or more of the population is obese – at least 8.5 percentage points higher than their national averages and twice the OECD average (OECD, 2020[1]).

In addition to age structure, health pre-conditions and the capacity of the health system, the level of environmental quality – as measured by air pollution levels – is another factor that can affect the vulnerability of regions to the pandemic. Recent studies have shown that higher exposure to fine particulate matter 2.5 (PM2.5) contributes to the airborne transmission of SARS-CoV-2 and to a higher risk of mortality due to COVID-19 (Comunian et al., 2020[14]; Cole, Ozgen and Strobl, 2020[15]; Coker et al., 2020[16]; Wu et al., 2020[17]). While differences in air pollution across OECD cities are larger across countries than within them, two thirds of cities in OECD countries still have exposure to PM2.5 above the 10 mg/m^3 (micrograms per cubic metre) limit recommended by the WHO (OECD, 2020[1]). In 30 countries, there is at least one city with air pollution levels above that threshold. In the sample of regions used for the analysis, exposure to PM2.5 varies from 4 mg/m^3 in the least affected region to 42 mg/m^3 in the most affected one (Table 1).

The role of air quality for the health impact of the COVID-19 pandemic might change depending on specific geographical characteristics, such as altitude and temperature. Recent studies support the idea that infection rates are lower and consequences less severe in regions with high altitudes and high temperatures for reasons related to the survival of the virus in such environments and the health conditions of people living in those areas (Millet et al., 2020[18]; Wang et al., 2021[19]). Nevertheless, other studies suggest that elevation could increase excess deaths by exacerbating the adverse effects of air pollution on health (Alvarez, Sosa-Echeverría and Alvarez Sanchez, 2012[20]; Bravo and Urone, 1981[21]).

The literature on the drivers of the health impact of the COVID-19 pandemic has also focused on the quality of institutions (Rodríguez-Pose and Burlina, 2021[4]). Trust in government can affect people's behaviours to comply with containment measures and medical advice, such as lockdowns, travel restrictions, wearing masks (Elgar, Stefaniak and Wohl, 2020[22]) that are key to slow the spread of COVID-19 and related deaths. Perception-based indicators such as the percentage of the regional population having confidence in the national government could serve as proxies for the quality of institutions and the capacity of regional decision makers to effectively coordinate with the national administration, which is crucial to elaborate effective policy responses (OECD, 2020[23]). Yet, regional differences in confidence in governments are stark across and within OECD countries, particularly in Latin American and Southern European countries. During the period 2014-18, the levels of confidence in national governments between the regions with highest and lowest confidence levels differed by 15 percentage points on average in OECD countries (OECD, 2020[1]).

Socio-economic characteristics such as educational attainment and material conditions (including household income, relative poverty and overcrowded housing) can be relevant factors for COVID-19 spread and related deaths (Brandily et al., 2021[24]). People with higher socio-economic status are more likely to be knowledgeable about COVID-19 (Zhong et al., 2020[25]), as well as to understand, trust and be able to follow experts' advice to cope with the pandemic. They might also be less prone to believe false information and to follow science denier leaders – which has been shown to influence individual risky behaviour (Ajzenman, Cavalcanti and Mata, 2020[26]). Finally, higher educational attainment tends to be associated with jobs that are more amenable to remote working (OECD, 2020[27]), a feature that allows workers to better comply with confinement measures. As in other parts of the world, in OECD countries adults with higher educational attainment tend to be concentrated in large metropolitan regions, including in capital regions (regions hosting the country's capital city). In the sample considered for this analysis, the share of the labour force with at least secondary education ranges from 33% to 98% in the regions with the highest and lowest educational attainment of the workforce, respectively (Table 1).

Other standard regional characteristics such as population size, GDP per capita and population density tend to be usual controls in the literature about the drivers of the pandemic's health impact. Some studies classify them as proxies of "regional agglomerations" and highlight that large, dynamic, and highly connected cities were among the first to register the arrival of the virus and to experience outbreaks (Coelho et al., 2020[28]; Rodríguez-Pose and Burlina, 2021[4]). While some research has shown evidence on the association between city size and COVID-19 spread (Stier, Berman and Bettencourt, 2020[29]), the role of density *per se* has been questioned (OECD, 2020[30]). Historically, higher exposure to diseases, including viruses, has been among the most important hazards of dense urban settlements (Duranton and Puga, 2020[31]; Glaeser, 2020[32]). In the case of COVID-19 – all else being equal – highly dense urban areas should, in theory, be at higher risk of spreading the virus due to the close proximity of residents and workers.

Table 1. Descriptive statistics

Indicator	Mean	Standard deviation	Minimum	Maximum	Sample
Dependent variable: Excess mortality (%)					
January 2020	-1.74	9.07	-21.01	100	407
January-February 2020	-0.31	9.24	-25	66.67	407
January-March 2020	0.46	8.37	-15.03	49.49	407
January-April 2020	3.66	11.45	-22.89	88.65	407
January-May 2020	5.37	12.84	-26	105.41	407
January-June 2020	5.96	13.21	-26.96	127.36	407
January-July 2020	6.72	14.37	-27.94	131.71	407
January-August 2020	8.43	14.74	-14.38	126.43	407
January-September 2020	9.93	13.6	-14.8	110.49	407
January-October 2020	9.94	13.25	-13.48	107.87	407
January-November 2020	11.78	12.79	-12.39	95.47	407
January-December 2020	14.37	12.81	-11.49	88.26	407
Regional characteristics and controls					
Percentage of elderly population (75+)	7.65	3.11	0.91	16.82	407
Percentage of youth population (0-14)	18.42	5.55	10.93	43.76	407
Population density (population-weighted grids, people per square km)	3462.35	3461.59	370	24294	407
Hospital beds per 1 000 people	4.15	3.1	0.3	22.2	390
Physicians per 1 000 people	3.08	1.39	0.4	8.4	388
Health system capacity (score 0-100)	25.61	12.67	0	63.94	388
Exposure to air pollution PM2.5 (micrograms per cubic metre)	13.25	6.51	4	41.93	405
Average disposable household income (USD 2015 PPP)	33240.29	19462.09	3514	100115	371
Percentage of adults with at least secondary education	74.41	17.88	32.7	97.5	374
GDP per capita (USD 2015 PPP)	36884.85	19143.03	4182	186726	398
Population (thousands of people)	3178.22	4496.64	29.79	39512.22	407
Percentage of people that trust in government	39.59	15.08	5.84	85.58	394
Prevalence of obesity (%)	23.89	9.93	7.6	48.9	266
Relative poverty rate (disposable income)	20.05	7.67	5.8	57.3	306
Rooms per inhabitant	1.76	0.55	0.69	3.07	372
Mean elevation (metres)	533.62	575.68	-3	3225	390
Average temperature (Celsius degrees)	13.16	5.8	-7.36	27.82	388
Change in mobility January-February 2020	-1.45	5.72	-16.4	17.9	346
Change in mobility January-March 2020	-16.15	9.91	-47.68	12.48	346
Change in mobility January-April 2020	-45.71	13.33	-75.52	-7.7	346
Change in mobility January-May 2020	-33.46	10.58	-64.73	-0.82	346
Change in mobility January-June 2020	-21.87	9.98	-58.21	4.68	346
Change in mobility January-July 2020	-23.14	9.91	-60.23	3.46	346
Change in mobility January-August 2020	-25.35	8.2	-58.96	11.25	346
Change in mobility January-September 2020	-18.98	9.37	-69.82	20.48	346
Change in mobility January-October 2020	-17.5	8.31	-66.92	12.8	346
Change in mobility January-November 2020	-22.1	9.1	-67.24	16.45	346
Change in mobility January-December 2020	-28.04	8.84	-71.37	0.86	346

Note: 407 large regions (TL2) from 33 OECD and 3 non-OECD EU countries (AUS, AUT, BEL, BGR, CAN, CHE, CHL, COL, CZE, DEU, DNK, ESP, EST, FIN, FRA, GBR, GRC, HUN, ISR, ITA, JPN, KOR, LTU, LUX, LVA, MEX, MLT, NLD, NOR, NZL, POL, PRT, ROU, SVK, SWE and USA). With the exception of the indicators of excess mortality and change in mobility (which cover all months of 2020), regional characteristics and controls refer to the latest pre-pandemic year with available data (i.e. 2019 or earlier).
Source: (OECD, 2021[3]; Gallup, 2020[33]; Jarvis et al., 2008[34]; Google, 2021[35]).

Beyond regional characteristics, local policy responses – notably effective confinement and social distancing measures – are also key. Since the beginning of the pandemic, countries, regions and cities worldwide have been applying different combinations of containment measures such as confinements, curfews and travel restrictions (Nouvellet et al., 2021[36]), as well as supporting work-from-home when possible for firms and workers. These measures tend to reduce social interactions (and thus the spread of the virus) and decrease people's mobility within and across regions, including daily home-to-work commuting. In this sense, the effectiveness of these measures (which depends on both government guidelines and people's compliance) can be proxied through the change in mobility between different periods (Pan et al., 2020[37]). In the OECD, regions have decreased their mobility, on average, since the beginning of the pandemic. The largest drop in mobility occurred in April 2020 – when home-to-work mobility decreased by almost 45% compared to January 2020. Nevertheless, changes in mobility have been heterogeneous across places even within the same period. For example, during January-September 2020 some regions reduced their mobility by twice the average of OECD regions, while other regions registered significant increases. In part, the differences reflect the fact that the prevalence of the virus varied within countries and so did confinement measures. Differences in mobility may also help explain the differentiated health impact of the pandemic across regions, as shown in the following sections.

3 Data sources and empirical specification

Excess mortality indicators at the regional level[8] were estimated using official deaths registers provided by national statistical offices or health ministries (OECD, 2020[1]; OECD, 2021[7]), while the main source of data for the regional characteristics – including risk factors for COVID-19 – is the OECD Regional Statistics database (OECD, 2021[3]).

The main explanatory variables included in the analysis are the share of elderly population (age structure), the physician and hospital bed rates (health system capacity), population density (proximity of people), exposure to air pollution (environmental risk factors), and trust in government (quality of institutions). Relevant controls are GDP per capita and, in some cases, the total resident population (in natural log). A set of additional controls were initially included in the analysis, but finally excluded due to high multi-collinearity with core explanatory variables or limited regional coverage (see Annex A for more details). These controls include the share of young population, average household income, percentage of labour force with at least secondary education, obesity rates, relative poverty rates, average rooms per inhabitant, average temperature, and average elevation. The indicators of trust in government, mean temperature and elevation, and change in mobility were estimated using different sources, namely Gallup World Poll (Gallup, 2020[33]), Google's Earth Engine Data Catalog (Jarvis et al., 2008[34]; NCEP, 2021[38]) and Google's COVID-19 Community Mobility Reports (Google, 2021[35]), respectively. All other indicators are sourced from the OECD Regional Statistics database (OECD, 2021[3]).

Estimating the associations between regional characteristics and higher excess mortality

The baseline model consists of a simple linear regression of excess mortality (dependent variable) against a core set of pre-pandemic regional characteristics (explanatory variables and controls). After examining the pairwise correlation between an exhaustive set of potential explanatory variables to avoid issues of multi-collinearity (see Annex A), the preferred set of regional characteristics is further limited and defined as in Equation 1. All regressions include country fixed-effects – to account for country time-invariant institutional and geographical characteristics – and correct for heteroscedasticity.

[8] Deaths in most countries are only reported by region of occurrence (with the exception of Germany that reported only by region of residence). The former definition is not robust to high interregional mobility, particularly for small regions (i.e. TL3 regions). For example, if – seeking for better medical care – many sick people travel from their region of residence to a region with higher health system capacity and die there, regional indicators on excess mortality would be biased. Nevertheless, considering the relative large area of TL2 regions (the main unit of analysis) – and thus that intra-country mobility is more likely to happen within these large regions – this should not highly affect the results.

$$ExcessMortality_{r,jan-m} = \alpha * ElderlySh_r + \beta * HealthCapacity_r + \gamma * PopDensity_r + \delta * AirPollution_r + \varphi * GDPpc_r + \theta * TrustGovernment_r + CountryFE + \varepsilon_{r,jan-m} \quad [1]$$

$ExcessMortality_{r,m}$ is the percentage increase in 2020 deaths relative to the 2018-19 average in region r and for the period between January 2020 and month m, 2020. While an arguably preferred period for excess mortality would be around January-June 2020, the analysis also looks into shorter (e.g. January-March 2020) and longer periods (e.g. January-December 2020) to capture cumulative effects. The period January-June 2020, also referred to as the pandemic's first wave, is likely preferred in the sense that it balances potential biases from measurement error in the dependent variable and from unobserved factors due to omitted variables. More specifically, the first 6 months of the pandemic give enough time for a meaningful quantification of excess mortality while it reduces the effect of differences in date of first COVID-19 case. In addition, compared to the largest period, a 6-month period is likely to be less sensitive (arguably more exogenous) to unobserved responses and behaviours arising over time (such as governments increasing medical capacity and resources).

$ElderlySh_r$ is the share of elderly population (aged 75 or above), while $HealthCapacity_r$ is a normalised index (from 0 to 100) that aggregates both the number of active physicians per 1 000 people and the number of hospital beds per 1 000 people (following the max-min normalisation method (OECD, 2019[39]))[9]. To minimise biases generated by administrative boundaries and consequent inaccuracy of measuring densities, $PopDensity_r$ provides the population-weighted average of the population in each of the one-km^2 cells within the region r. $AirPollution_r$ stands for the (population-weighted) exposure to fine particulate matter 2.5 (PM2.5, measured in micrograms per cubic metre or mg/m^3). $GDPpc_r$ is the GDP per capita in USD 2015 PPP, while $TrustGovernment_r$ refers to the percentage of regional population with confidence in the national government. The set of country fixed-effects is denoted as $CountryFE$, and the error term as ε_r.

In a second step, the analysis looks into the potential spatial autocorrelation of the residuals, as a latent source of estimation biases. To deal with this issue, we estimate a spatial autoregressive model that controls for spatially autoregressive errors (hereafter SAR-E model) using a weighting matrix W – which is the inverse-distance matrix for each pair of regions in the sample (see Equation 2).

$$ExcessMortality_{r,jan-m} = \alpha * ElderlySh_r + \beta * HealthCapacity_r + \gamma * PopDensity_r + \delta * AirPollution_r + \varphi * GDPpc_r + \theta * TrustGovernment_r + CountryFE + (1-\rho W)^{-1}\varepsilon_{r,jan-m} \quad [2]$$

One limitation of the baseline and SAR-E models is that they can only account for country-wide containment measures for a given period of time (through country-fixed effects). Nevertheless, there are cases where lockdown measures also varied across places within the same country. Observed monthly reductions in home-to-work mobility can capture differences in containment efforts at the regional level and over time. The following section provides a panel model specification that accounts for such differences, as observed from Google's COVID-19 Community Mobility Reports (Google, 2021[35]), using a balanced panel of regions for the months of 2020.

[9] The health capacity index uses equal weights to aggregate the number of active physicians per 1 000 people and the number of hospital beds per 1 000 people, as there is no prior information to suggest one element is more relevant than the other. Only for two regions where the indicator of hospital beds rate was missing, we set the normalised value of active physicians rate as the health capacity index. Excluding these two regions from the sample (available upon request) does not affect the results.

Assessing the role of mobility in reducing excess mortality

To explore the relationship between changes in excess mortality and efforts in reducing home-to-work mobility, we define panel models with regional fixed effects, where $\Delta ExcessMortality_{r,m}$ stands for the change in excess mortality (in percentage points) in region r and month m with respect to month $m-1$, more precisely $\Delta ExcessMortality_{r,m}$ can be expressed as $ExcessMortality_{r,m} - ExcessMortality_{r,m-1}$. $RelativeMobility_{r,m-l}$ measures the (percent change) home-to-work mobility in region r and month m with respect to the average mobility registered in January 2020 (benchmark mobility). To minimise issues of reverse causality between mobility change and excess mortality – and consistently with expected delayed effects of containment measures – the $RelativeMobility_{r,m-l}$ variable is also lagged one month or more (the specifications show time lags up to three months, i.e. $l \in \{0,1,2,3\}$) relative to the dependent variable (which can go from April to December 2020). Since this specification exploits the time dimension of the panel of regions, it controls for all time-invariant regional characteristics through a set of regional fixed-effect dummies ($RegionFE$). $MonthFE$ denotes either month fixed-effects or country-month fixed-effects (depending on the regression), while $\varepsilon_{r,m}$ stands for the error term – standard errors are clustered at the regional level (see Equation 3).

$$\Delta ExcessMortality_{r,m} = \tau * RelativeMobility_{r,m-l} + RegionFE + MonthFE + \varepsilon_{r,m} \qquad [3]$$

4 Results

Overall, the results show that lower health system capacity, higher population density, air pollution, share of elderly population and lower institutional quality are significantly associated with higher excess mortality at the regional level. A breakdown of excess mortality by sub-periods of the year 2020 reveals that health system capacity and population density have been strongly associated with excess mortality from the first months of the COVID-19 crisis until the end of 2020. On the other hand, higher shares of elderly population and lower shares of trust in government appeared to be significantly correlated with higher excess deaths only during the first wave of the pandemic (January-June 2020). Air pollution was also strongly associated with higher excess mortality, although mainly in later and longer periods including the second wave. A novel result from the analysis shows that lower home-to-work mobility was associated with lower excess mortality, notably with a delay of two months. This suggests that policies that support remote working can be effective to reduce the health impact of the pandemic.

The two sets of regression results presented in Table 2 and Table 3 focus on excess mortality for different periods ranging from January-March 2020 to January-December 2020. Both models include selected core place-based characteristics that minimise issues of multi-collinearity and maximise the geographical coverage (342 regions from 32 countries, see full list of countries in Annex C). These pre-pandemic regional characteristics relate to the preparedness or vulnerabilities of regions to cope with the COVID-19 pandemic. The first specification is a linear regression estimated using OLS (baseline model, Table 2). Given that the observations in this empirical framework are spatial units, often close to each other, we address possible issues caused by the lack of spatial independence in the residuals. More specifically, we provide a second specification – a spatial autoregressive model – which includes spatially lagged errors using a weighting matrix (SAR-E model) (Table 3). The main results yielded by these models also hold when testing a generalised additive specification (GAM model) (see Annex Table B.1). The latter specification controls for spatial heterogeneity using bivariate spline functions whose arguments are the geographical coordinates (Basile et al., 2014[40]).

The coefficients of both the baseline and the spatial specifications show that at the regional level the most significant and persistent association is between excess mortality and health system capacity. On average, an increase of one standard deviation in terms of this index is associated to a decrease between 1.8 and 3.4 percentage points of excess mortality, depending on the period. Changes in population density also appear to be significant and strong in magnitude. A one standard deviation increase in weighted population density is associated to an increase of 2.3-4.7 percentage points in excess mortality.

Higher levels of GDP per capita, another common feature of regions hosting economically dynamic and internationally connected metropolitan areas, was positively correlated with higher excess mortality – even in January-March 2020, the first period where excess mortality shifted from negative values to slightly positive values due to the COVID-19 pandemic, on average. While the association was particularly strong during the first wave of the pandemic, the magnitude of the coefficient shrank by the end of the year. This finding is in line with other studies documenting that the virus first spread throughout the world via large, dynamic and highly internationally connected metropolis (Daon, Thompson and Obolski, 2020[6]). Once the virus entered the metropolitan regions of most countries, it started spreading across other types of regions.

Results also reveal significant associations of both the share of elderly population and the level of trust in government with excess mortality. In terms of magnitudes, an increase of three percentage points (or one standard deviation) in the share of elderly population is associated to an increase of 2.6-3.3 points in excess mortality. At the same time, an increase of 15 percentage points (or one standard deviation) in the share of population having confidence in the government is associated to a decrease of 1.6-3 percentage points in excess mortality.

In line with recent literature, the findings also support the existence of a positive association between exposure to air pollution and higher excess mortality during the first year of the pandemic. The association appears robust to different specifications, notably starting in June, and meaningful in terms of magnitude. More precisely, an increase of one standard deviation in exposure to PM2.5 (i.e. around 6 mg/m^3) is associated with an increase in excess mortality of 1.3-2.6 percentage points. These coefficients are in line with other studies that register elasticities between 8% and 16% depending on the region (OECD, 2020[41]). For example, using negative binomial regressions on a sample of municipalities in Northern Italy, Coker et al., (2020[16]) found that an increase of one mg/m^3 in PM2.5 is associated to an increase of 9% in excess mortality. When applying negative binomial specifications to the sample of OECD regions (for comparison purposes)[10], we find an elasticity of around 11%.

From the time perspective, the results indicate that health system capacity and population density have been consistently associated with excess mortality since the fourth month of the pandemic (i.e. January-April 2020), while share of elderly, trust in institutions, and air pollution appear to be significant (at the 95%) only after the fourth or fifth month (i.e. May and June). This suggests that the role of a larger share of elderly population started to be associated with excess mortality only after the virus had spread more systematically within countries. While at the very beginning, population density and GDP per capita – notably through a faster spread of the virus in large, dynamic and highly internationally connected metropolitan regions – were likely the factors driving the health impact of the pandemic. In the first period, during the peak of the emergency, the capacity of health systems to cope with the outbreak was already playing a crucial role in preventing deaths. Finally, once the pandemic had spread across the world, other place-based factors – including environmental and institutional quality – might have started to shape the spatial patterns of excess mortality.

Finally, the results of the panel model reveal a positive and significant association between lagged mobility and excess mortality. Put differently, a decrease in home-to-work mobility is linked to lower excess mortality in the following months – particularly after two and three months (delayed effects). Reducing mobility today by 25% with respect to pre-pandemic levels would lead to a decrease in excess mortality of 1-2.5 percentage points in two months. These results are robust to including either time or time-country fixed-effects (Table 4), and stable when controlling for spatially lagged error terms (see spatial panel model in Annex Table B.2). Unsurprisingly, contemporaneous mobility is negatively correlated to excess mortality due to an issue of reverse causality. When the virus is hitting harder (e.g. increased rates of cases and deaths), governments tend to implement stronger containment measures that reduce mobility in the same period. Nevertheless, the benefits of reducing mobility today are only expected to pay off (in terms of excess mortality) several weeks after implementation in large part reflecting the needed time to bring the basic reproduction number of SARS-CoV-2[11] to a level lower than one, as well as the lag between time of

[10] Coker et al., (2020[16]) use a negative binomial specification as their dependent variable is the number of excess deaths (count) at the municipal level. In this paper, which uses larger geographical units (TL2 regions), the dependent variable % increase in excess deaths is more appropriate, and thus a negative binomial model is not needed.

[11] The basic reproduction number (R_0) of SARS-CoV-2 is the expected number of new SARS-CoV-2 cases directly generated by one case of SARS-CoV-2 in a population where all individuals are susceptible to infection. In the absence of interventions, a virus with an R_0 greater than one would keep increasing the number of cases in the population. On the contrary, if R_0 is lower than one the contagion is expected to stop spreading. Different studies have estimated an

infection, hospitalisation (if any) and time of death. In addition, our preferred panel specifications – those controlling for time and country-month fixed-effects (which to a certain extent should capture country-specific containment restrictions over time) (Table 4, columns 4-12) – suggest that earlier reductions in home-to-work mobility are more effective at preventing increases in excess mortality.

R_0 for SARS-CoV-2 around 3, particularly at early stages of the pandemic when interventions and knowledge about the virus were limited (D'Arienzo and Coniglio, 2020[48]).

Table 2. Regression results: Baseline model

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent variable: ***Excess mortality (%)***	January-March 2020	January-April 2020	January-May 2020	January-June 2020	January-July 2020	January-August 2020	January-September 2020	January-October 2020	January-November 2020	January-December 2020
Percentage of elderly population (75+)	0.0888	0.813*	1.088**	0.944**	0.654*	0.421	0.317	0.254	0.280	0.443
	(0.244)	(0.491)	(0.458)	(0.420)	(0.369)	(0.330)	(0.305)	(0.282)	(0.286)	(0.313)
Health system capacity (score 0-100)	-0.0814	-0.233**	-0.251***	-0.269***	-0.274***	-0.252***	-0.224***	-0.179***	-0.155***	-0.162***
	(0.0529)	(0.0912)	(0.0898)	(0.0835)	(0.0773)	(0.0687)	(0.0609)	(0.0526)	(0.0511)	(0.0535)
Population density (population-weighted)	0.000135	0.00122**	0.00161***	0.00158***	0.00117**	0.00102**	0.000991**	0.000956***	0.000958***	0.00110***
	(0.000253)	(0.000563)	(0.000540)	(0.000533)	(0.000491)	(0.000431)	(0.000383)	(0.000338)	(0.000315)	(0.000359)
Exposure to air pollution PM2.5 (mg per m^3)	0.204	0.254	0.268	0.375**	0.430**	0.374**	0.266	0.274*	0.290**	0.305**
	(0.198)	(0.214)	(0.196)	(0.178)	(0.186)	(0.178)	(0.162)	(0.140)	(0.135)	(0.134)
GDP per capita (2015 USD PPP)	0.000109***	0.000253***	0.000248***	0.000220***	0.000224***	0.000195***	0.000165***	0.000128***	0.000104***	8.79e-05***
	(3.81e-05)	(6.20e-05)	(5.05e-05)	(4.24e-05)	(5.31e-05)	(5.13e-05)	(4.36e-05)	(3.52e-05)	(3.31e-05)	(3.19e-05)
Trust in government (%)	-0.0543	-0.0461	-0.152*	-0.200**	-0.184**	-0.146*	-0.125	-0.0899	-0.0579	-0.0350
	(0.0463)	(0.0680)	(0.0804)	(0.0800)	(0.0851)	(0.0845)	(0.0778)	(0.0723)	(0.0689)	(0.0722)
Observations	342	342	342	342	342	342	342	342	342	342
R-squared	0.438	0.466	0.510	0.512	0.605	0.684	0.700	0.755	0.756	0.739
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.370	0.401	0.450	0.453	0.557	0.646	0.663	0.725	0.726	0.707

Note: Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Table 3. Regression results: Spatial model

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent variable: ***Excess mortality (%)***	January-March 2020	January-April 2020	January-May 2020	January-June 2020	January-July 2020	January-August 2020	January-September 2020	January-October 2020	January-November 2020	January-December 2020
Percentage of elderly population (75+)	0.0886	0.804*	0.957**	0.880**	0.659*	0.443	0.332	0.254	0.272	0.442
	(0.257)	(0.418)	(0.411)	(0.392)	(0.383)	(0.356)	(0.326)	(0.291)	(0.282)	(0.293)
Health system capacity (score 0-100)	-0.0834	-0.230***	-0.227***	-0.249***	-0.255***	-0.233***	-0.208***	-0.165***	-0.143**	-0.148**
	(0.0530)	(0.0857)	(0.0829)	(0.0784)	(0.0763)	(0.0710)	(0.0653)	(0.0584)	(0.0565)	(0.0585)
Population density (population-weighted)	0.000139	0.00122***	0.00156***	0.00151***	0.00110***	0.000949***	0.000922***	0.000892***	0.000905***	0.00101***
	(0.000193)	(0.000313)	(0.000304)	(0.000290)	(0.000283)	(0.000263)	(0.000241)	(0.000216)	(0.000209)	(0.000217)
Exposure to air pollution PM2.5 (mg per m^3)	0.207**	0.248	0.202	0.327**	0.386**	0.332**	0.226*	0.233**	0.251**	0.264**
	(0.101)	(0.165)	(0.165)	(0.158)	(0.156)	(0.145)	(0.132)	(0.118)	(0.114)	(0.119)
GDP per capita (2015 USD PPP)	0.000109***	0.000249***	0.000212***	0.000193***	0.000204***	0.000180***	0.000153***	0.000120***	9.73e-05***	8.38e-05**
	(2.85e-05)	(4.67e-05)	(4.70e-05)	(4.46e-05)	(4.35e-05)	(4.05e-05)	(3.72e-05)	(3.32e-05)	(3.21e-05)	(3.33e-05)
Trust in government (%)	-0.0542	-0.0452	-0.127**	-0.159***	-0.142**	-0.111**	-0.0968*	-0.0662	-0.0398	-0.0135
	(0.0399)	(0.0651)	(0.0641)	(0.0615)	(0.0603)	(0.0560)	(0.0513)	(0.0457)	(0.0443)	(0.0461)
SAR error correlation	0.0305	0.487	1.203***	1.775***	2.367***	2.329***	2.018***	1.896***	1.921***	2.403***
	(0.559)	(0.681)	(0.113)	(0.287)	(0.569)	(0.554)	(0.413)	(0.336)	(0.332)	(0.590)
Observations	342	342	342	342	342	342	342	342	342	342
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R-squared	0.438	0.466	0.468	0.503	0.600	0.681	0.697	0.752	0.752	0.734

Note: Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1. All regressions control for spatially lagged error terms using the weighting matrix W, which is the inverse-distance matrix for each pair of regions in the sample.

Table 4. Regression results: Panel model

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Change in excess mortality	Change in excess mortality	Change in excess mortality	Change in excess mortality	Change in excess mortality	Change in excess mortality	Change in excess mortality	Change in excess mortality	Change in excess mortality	Change in excess mortality	Change in excess mortality	Change in excess mortality
Relative mobility (%)	-0.147***	-0.156***	-0.111***	-0.103***	-0.148***	-0.181***	-0.139***	-0.122***	-0.173***	-0.232***	-0.192***	-0.177***
	(0.0128)	(0.0141)	(0.0133)	(0.0127)	(0.0183)	(0.0211)	(0.0188)	(0.0179)	(0.0447)	(0.0544)	(0.0500)	(0.0468)
Relative mobility (%) (1-month lag)		0.0494***	0.0202**	0.0338***		0.0707***	0.00951	0.0284		0.130***	0.0532	0.0599
		(0.0113)	(0.00969)	(0.0120)		(0.0199)	(0.0183)	(0.0185)		(0.0420)	(0.0376)	(0.0380)
Relative mobility (%) (2-month lag)			0.0573***	0.0430***			0.104***	0.0537***			0.115***	0.0754*
			(0.0103)	(0.00973)			(0.0156)	(0.0164)			(0.0425)	(0.0392)
Relative mobility (%) (3-month lag)				0.0242***				0.0918***				0.0670**
				(0.00836)				(0.0147)				(0.0289)
Observations	3,078	3,078	3,078	3,078	3,078	3,078	3,078	3,078	3,078	3,078	3,078	3,078
R-squared	0.118	0.133	0.149	0.153	0.144	0.153	0.170	0.183	0.568	0.572	0.576	0.577
Number of id	342	342	342	342	342	342	342	342	342	342	342	342
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	No	No	No	No	Yes	Yes	Yes	Yes	No	No	No	No
Country-Month FE	No	No	No	No	No	No	No	No	Yes	Yes	Yes	Yes
Adj. R-squared	0.118	0.132	0.148	0.151	0.142	0.150	0.167	0.180	0.528	0.533	0.537	0.538

Note: Changes in excess mortality are measured in percentage points. Standard errors clustered at the regional level. ***p<0.01, **p<0.05, *p<0.1.

5 Conclusions

This paper provides evidence on the regional characteristics that might be driving the highly unequal impact of COVID-19 across space within OECD countries. To minimise issues of misreporting or differences in testing policy and cause of death across and indeed within countries the analysis builds on internationally comparable measures of excess mortality for different periods of 2020 as a headline measure of health impact of the pandemic.

The results show that several place-based characteristics are associated with spatial differences in excess mortality across the large sample of regions considered. Health system capacity is among the strongest and most robust predictors, but other features, such as reductions in home-to-work mobility, exposure to air pollution and trust in institutions also play a role. In addition, health capacity and population density are persistent factors that have been affecting excess mortality since the beginning of the crisis, while other regional characteristics appear to be significantly associated with excess mortality only at later stages of the pandemic.

Understanding the main determinants of the geography of excess mortality is crucial to build effective policy responses. Results reported in this paper suggest that strong health systems and physical distancing measures, including through teleworking efforts, have helped to mitigate the health impact of the pandemic. The analysis also provides insights on the relevance of a place-based management of the pandemic – including for the rollout of the current COVID-19 vaccination campaigns – which should consider the higher vulnerability of areas with relatively lower health resources, higher air pollution and population density, and where policies aimed at reducing mobility are more difficult to implement.

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Annex A. Assessing multi-collinearity between regional variables

A first naïve specification would regress excess mortality against all identified explanatory variables available, as in Equation A.1. However, such specification risks to present strong multi-collinearity issues which could undermine the reliability of the affected coefficients.

$$\begin{aligned} ExcessMortality_{r,m} &= \alpha * AgeStructure_r + \beta * HealthSystemCapacity_r + \gamma * PopDensity_r \\ &+ \delta * AirPollution_r + \omega * SocioEconomic_r + \rho * GDPpc_r + \vartheta * LnPop_r \\ &+ \theta * TrustGovernment_r + \varphi * Geographic_r + CountryFE + \varepsilon_r \end{aligned} \quad [A.1]$$

$AgeStructure_r$ includes the two variables share of elderly population (aged 75 or above) and share of youth population (aged 0-14), while $HealthSystemCapacity_r$ includes both the number of hospital beds per 1 000 inhabitants and the number of active physicians per 1 000 people. $SocioEconomic_r$ includes the percentage of workforce (aged 15-64) with at least secondary education (levels 3 to 8 of the International Standard Classification of Education 2011) and average household income (in 2015 USD PPP). $LnPop_r$ stands for the natural log of population, and $Geographic_r$ for both the mean average elevation and the average yearly temperature. $PopDensity_r$, $AirPollution_r$ and $GDPpc_r$ are defined as in Section 3.[12]

To explore potential issues of multi-collinearity, we first look at the pairwise correlations for the large set of regional characteristics (Table A.1). At first glance, the correlation matrix suggests strong linear relations between the share of elderly and both the share of youth and the rate of hospital beds. In addition, regarding health system capacity, the hospital bed rate is also significantly correlated with the active physicians rate. To deal with the latter, we create a normalised index for health capacity (from 0 to 100), which aggregates both hospital beds and physicians rates. In terms of economic variables, the set of socio economic characteristics (including household income and educational attainment) appears to be highly collinear with the GDP per capita. Finally, average temperature is highly correlated with both educational attainment and GDP per capita.

The results of the variance inflation factors (VIF) for the different regional characteristics confirm the presence of multi-collinearity, notably driven by the variables share of youth, average household income, share of the labour force with at least secondary education, average temperature and, to a lower extent, mean elevation (Table A.2, columns 1 and 2). When excluding these variables, a new VIF analysis applied to the preferred specification (column 3) suggests that multi-collinearity is no longer an issue in our model.

[12] Previous specifications also included the relative poverty rate (percentage of population with an income below 60% of the national income), the average rooms per inhabitant, and the percentage of obese population. These variables are already excluded from the analysis, as they were costly in terms of the sample size (while they were also highly correlated with GDP per capita and educational attainment of the labour force). Population was also excluded from the final specifications based on the interpretability of its coefficient (since the model already controls for the effect of agglomerations, through population density, GDP per capita and country-fixed effects) and the VIF analysis. However, including population (in natural log) does not affect the main results presented in this paper (available upon request).

Table A.1. Pearson correlations between regional characteristics

	Percentage of elderly population (75+)	Percentage of youth population (0-14)	Hospital beds per 1 000 people	Physicians per 1 000 people	Population density (population-weighted grids)	Air pollution PM2.5 (mg per m^3)	Average disposable household income	% of labour force with at least secondary education	GDP per capita	Ln of population	Trust in government (%)	Mean elevation (metres)
Percentage of elderly population (75+)	1											
Percentage of youth population (0-14)	-0.839*	1										
Hospital beds per 1 000 people	0.509*	-0.574*	1									
Physicians per 1 000 people	0.520*	-0.585*	0.248*	1								
Population density (population-weighted grids)	-0.283*	0.254*	-0.0631	-0.0496	1							
Air pollution PM2.5 (mg per m^3)	-0.259*	0.213*	0.155*	-0.217*	0.462*	1						
Average disposable household income	0.101	-0.218*	0.0158	0.163*	-0.333*	-0.572*	1					
Percentage of labour force with at least secondary education	0.108	-0.376*	0.164*	0.250*	-0.384*	-0.339*	0.607*	1				
GDP per capita	0.0888	-0.231*	0.0983	0.310*	-0.0867	-0.453*	0.776*	0.541*	1			
Ln of population	-0.0255	0.0884	0.127*	-0.191*	0.270*	0.0386	0.155*	0.0147	0.127*	1		
Trust in government (%)	0.0536	-0.146*	0.176*	0.124*	-0.201*	-0.162*	0.241*	0.250*	0.350*	-0.0762	1	
Mean elevation (metres)	-0.300*	0.402*	-0.274*	-0.228*	0.262*	0.146*	-0.0811	-0.299*	-0.125*	-0.120*	-0.208*	1
Average temperature (Celsius degrees)	-0.276*	0.438*	-0.234*	-0.164*	0.300*	0.195*	-0.338*	-0.592*	-0.356*	0.205*	-0.248*	-0.00716
Observations	297											

Note: *$p < 0.05$. Observations: 315.

Table A.2. Variance Inflation Factor of regional characteristics

	(1)	(2)	(3)
Percentage of elderly population (75+)	15.05	8.15	7.39
Percentage of youth population (0-14)	20.34		
Health system capacity (score 0-100)	6.26	5.77	5.32
Population density (weighted)	3.62	3.19	2.53
Air pollution PM2.5	5.38	4.62	4.71
Average disposable household income	25.12		
Labour force with at least secondary education	21.86		
GDP per capita	6.01	3.65	3.46
Ln of population	2.56	2.23	
Trust in government	4.4	4.08	4.4
Mean elevation	2.32	2.2	
Average temperature	3.91	3.63	
Number of country FE with VIF above 10	2	1	0

Note: All regressions include country fixed effects.

Annex B. Robustness checks

To test the robustness of the baseline and SAR-E model results, we estimate a generalised additive model (GAM). More precisely, the GAM model adds a smooth function $s(lat, lon)_r$ as an explanatory variable (see Equation B.1)[13]. The arguments of this function are the latitude and longitude geographical coordinates of the region's centroid.

$$\begin{aligned} ExcessMortality_{r,jan-m} &= \alpha * ElderlySh_r + \beta * HealthCapacity_r + \gamma * PopDensity_r + \delta * AirPollution_r \\ &+ \varphi * GDPpc_r + \theta * TrustGovernment_r + CountryFE + s(lat, lon)_r + \varepsilon_{r,jan-m} \end{aligned} \quad [\text{B.1}]$$

The results of the GAM specification (Table B.1) confirm the robustness of the main OLS and SAR-E coefficients.[14] In particular, the coefficients for health capacity, population density, and trust in government appear to be highly stable across both specifications. In the GAM model, only the share of elderly population became non-significant, as the smooth function might be capturing the spatial heterogeneity of the link between excess mortality and the proportion of elderly people in each region. However, the coefficients related to air pollution gained statistical significance and magnitude, notably in the last and longer periods (average increase of 25% with respect to the OLS estimates).

Table B.1. Regression results: GAM model

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent variable: ***Excess mortality (%)***	January-March 2020	January-April 2020	January-May 2020	January-June 2020	January-July 2020	January-August 2020	January-September 2020	January-October 2020	January-November 2020	January-December 2020
Percentage of elderly population (75+)	-0.036	0.235	0.492	0.433	0.301	0.178	0.105	0.111	0.12	0.093
	(0.28)	(0.467)	(0.466)	(0.453)	(0.439)	(0.404)	(0.37)	(0.332)	(0.327)	(0.353)
Health system capacity (score 0-100)	-0.059	-0.218**	-0.246***	-0.240***	-0.227***	-0.198**	-0.177**	-0.150**	-0.128**	-0.138**
	(0.056)	(0.091)	(0.09)	(0.087)	(0.084)	(0.077)	(0.071)	(0.065)	(0.063)	(0.065)
Population density (population-weighted)	0.0001	0.001***	0.002***	0.002***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0002)
Exposure to air pollution PM2.5 (mg per m^3)	0.275**	0.293	0.289	0.427**	0.494***	0.444***	0.342**	0.338***	0.358***	0.217
	(0.11)	(0.182)	(0.181)	(0.176)	(0.17)	(0.156)	(0.143)	(0.129)	(0.127)	(0.14)

[13] The term $s(lat, lon)$ is a smooth spatial trend surface based on thin plate regression splines, which account for the interaction between latitude and longitude. See Wood (2003[44]) for more details. On the use of GAM for similar regional analyses see, for example, Basile et al., (2014[40]) and Veneri (2018[45]).

[14] When applying Moran's test (1950[46]) to the residuals of the baseline model, the null hypothesis of independent and identically distributed (i.d.d.) residuals is rejected (p-value<0.1). On the other hand, when performing the test on both the SAR-E and GAM model's residuals, the i.d.d. hypothesis is not rejected (p-value>0.1).

GDP per capita (2015 USD PPP)	0.0001***	0.0002***	0.0002***	0.0002***	0.0002***	0.0001***	0.0001***	0.0001***	0.0001**	0.0001
	(0.00003)	(0.0001)	(0.0001)	(0.00005)	(0.00005)	(0.00004)	(0.00004)	(0.00004)	(0.00004)	(0.00004)
Trust in government (%)	-0.039	-0.015	-0.118*	-0.170**	-0.166**	-0.137**	-0.118**	-0.086*	-0.064	-0.067
	(0.043)	(0.071)	(0.071)	(0.069)	(0.066)	(0.061)	(0.056)	(0.051)	(0.05)	(0.052)
Observations	342	342	342	342	342	342	342	342	342	342
Adj. R-squared	0.397	0.44	0.496	0.505	0.624	0.705	0.711	0.747	0.748	0.752
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log-likelihood	- 1084.519	- 1249.877	- 1247.127	- 1234.318	-1219.37	-1190.65	-1163.045	- 1133.503	-1123.314	-1130.341

Note: ***p<0.01, **p<0.05, *p<0.1. All regressions include a smooth function, whose arguments are the latitude and longitude geographical coordinates.

To further examine the robustness of the panel model results (Table 4), we estimate a spatial autoregressive model for panel data (Kapoor, Kelejian and Prucha, 2007[42]). This model builds on the region fixed-effects panel specification presented by Equation 3 and adds the weighting matrix W (previously described in Section 3) to model the spatial dependence of the error terms. The results of the spatial panel model (Table B.2) suggest good stability for the effect of two- and three-month lagged mobility, particularly when including several lags in mobility.

Table B.2. Regression results: Spatial panel model

	(1)	(2)	(3)	(4)
	Change in excess mortality	Change in excess mortality	Change in excess mortality	Change in excess mortality
Relative mobility (%)	-0.110***	-0.126***	-0.0830***	-0.0756***
	(0.00999)	(0.00980)	(0.0112)	(0.0112)
Relative mobility (%) (1-month lag)		0.0482***	0.0213**	0.0402***
		(0.00920)	(0.00983)	(0.0109)
Relative mobility (%) (2-month lag)			0.0635***	0.0465***
			(0.00911)	(0.0100)
Relative mobility (%) (3-month lag)				0.0308***
				(0.00816)
SAR error correlation	2.127***	2.251***	2.348***	2.398***
	(0.0567)	(0.0635)	(0.0657)	(0.0681)
Observations	3,078	3,078	3,078	3,078
Number of groups	342	342	342	342
Region FE	Yes	Yes	Yes	Yes
Pseudo R-squared	0.0890	0.116	0.139	0.132

Note: Changes in excess mortality are measured in percentage points. ***p<0.01, **p<0.05, *p<0.1. All regressions control for spatially lagged error terms using the weighting matrix W, which is the inverse-distance matrix for each pair of regions in the sample.

Annex C. Sample for the regression analysis

Table C.1. Number of regions by country included in the regression analysis

Country (ISO code)	Number of large regions (TL2)
AUS	8
AUT	9
BEL	3
BGR	6
CAN	10
CHE	7
CHL	15
CZE	8
DEU	16
DNK	5
ESP	18
EST	1
FIN	4
FRA	13
GBR	12
GRC	13
HUN	8
ITA	21
JPN	10
KOR	7
LUX	1
LVA	1
MEX	32
MLT	1
NLD	12
NOR	7
POL	16
PRT	7
ROU	8
SVK	4
SWE	8
USA	51