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

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Abstract
The health impact of the COVID-19 pandemic across OECD (Organisation for Economic Co-operation and Development) and European regions has been strikingly uneven. In 2020, excess mortality rates in the hardest-hit regions were, on average, 17 percentage points higher than those in the least affected regions of the same country. This paper shows that low health system capacity, followed by population density, air pollution, the share of elderly people, and low institutional quality were associated with higher excess mortality during the first year of the pandemic. Finally, reduced home-to-work mobility, following governments’ COVID-19 responses, was associated with lower excess mortality 2 months after implementation of the measures.

Keywords
COVID-19, excess mortality, mobility, regions

JEL Classification
R10, I18, R58, J61
1 | INTRODUCTION

The COVID-19 crisis hit the entire world with significant human losses. Compared with the average of 2018 and 2019, the total number of deaths in Organisation for Economic Co-operation and Development (OECD) countries increased by 14% in 2020, corresponding to 1.5 million more deaths over the year. One of the key features of the health impact of the COVID-19 pandemic is its geographical unevenness. Indeed, excess mortality—defined as the percent change in the number of total deaths compared with the average of the previous 2 years—reveals stark regional disparities. 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 that in the least affected one. Such differences were higher than the 47-percentage point gap observed between the most and least affected OECD countries.

This paper examines the patterns of excess mortality across regions in 33 OECD and other three European countries (Bulgaria, Malta, and Romania) during the first 12 months of the COVID-19 pandemic by building on data from official registers of deaths. The paper also sheds light on the place-based factors underlying such patterns.

While a fast-growing literature is already integrating the subnational lens to analyze 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 from different continents (including the Americas, Europe, and Asia-Pacific) 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.

The analysis takes into account a broad set of place-based characteristics to understand spatial patterns of excess mortality. First, it investigates the prepandemic regional factors (regional preparedness and vulnerabilities) associated with higher excess mortality. Then, using novel granular data, it explores the role of reducing home-to-work mobility to mitigate the impact of the pandemic. Prepandemic regional indicators—including sociodemographics, health system capacity, environmental quality, as well as institutional and geographical features—come from the OECD Regional Statistics database (OECD, 2021a), while the high-frequency (monthly) indicator on changes in home-to-work mobility comes from Google (2021).

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 during the first months of the pandemic. This negative association has been strong and significant from the first 4 months of the pandemic (January–April 2020) until the last available period considered (January–December 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, on average. In addition, trust in government was associated with lower health impact, highlighting the role played by institutional quality at the subnational level, as found in the recent literature (Rodríguez-Pose & Burlina, 2021). Finally, reductions in home-to-work mobility were significantly associated with lower excess mortality in the following months—coherent with the findings of Glaeser et al. (2020)—particularly after 2 months from the observed reduction. More precisely, reducing mobility today by 25% with respect to prepandemic levels (January 2020) would lead to a decrease in an excess mortality of 1–2.5 percentage points in 2 months.

The remainder of the paper is organized 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.

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1 The statistical overview does not include the OECD countries of 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 Advantages and limitations of using excess mortality statistics have been discussed by Morgan et al. (2020).
2 UNDERSTANDING THE GEOGRAPHY OF EXCESS MORTALITY ACROSS REGIONS

2.1 Excess mortality during the COVID-19 pandemic

The association of the increase in all-causes mortality—that is, 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 caused by low levels of testing, as well as differences in definitions and measurement capacities across and, sometimes, within countries (OECD, 2020d).

Excess mortality can be broken down into different periods of 2020. This study distinguishes 12 subperiods by considering January (when the first cases of COVID-19 appeared in OECD countries), January–February, January–March, and so on until January–December (just before vaccination rollouts started in most countries). While the period January–June 2020 can be considered as the first wave of the pandemic, the period comprising until December 2020 is unlikely to fully capture the second wave (as in many OECD countries the end of the second wave is extended until January or February 2021). Excess mortality data are derived from official registers of deaths provided by national statistical offices or health ministries.3

The COVID-19 pandemic has hit certain parts of countries harder than others within the first 12 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 2 years (2018–2019).4 Increases in deaths were highly concentrated in specific regions, leading to stark regional differences in excess mortality. For example, New York (United States), Lombardy (Italy), Madrid (Spain), Mexico City (Mexico), and Amazonas (Colombia) experienced 30%–90% more deaths in 2020 than those in 2018–2019—at least 20 percentage points higher than the average excess mortality in their respective country (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 that, 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 1-h drive) a metropolitan area5 (Fadic et al., 2019). According to this classification, small regions are classified into metropolitan regions (including large metropolitan regions), regions close to a metropolitan area, or regions far from a metropolitan area (which can be subdivided 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 9.9% in remote regions in 2020.6

3For more details on the data and metadata see OECD Regions and Cities at a Glance 2020 (OECD, 2020d) and the related Excess mortality repository (https://github.com/oecd-cfe-eds/ccsa-excess-mortality) (OECD, 2021b).

4Excess mortality estimates based on a relatively short reference period have drawbacks and advantages. On the one hand, using a 2-year period (i.e., 2018–2019)—compared with, for example, a 4-year period (i.e., 2016–2019)—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 2-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, 2019b, 2020d) rather than from unclear sources of errors and outliers, the 2-year reference period is therefore chosen in this exercise.

5Subnational regions within the 38 OECD countries are classified into two territorial levels reflecting the administrative organization of countries: large regions (TL2) and small regions (TL3).

6Metropolitan areas are captured through the existence of a Functional Urban Area of at least 250,000 inhabitants. See Dijkstra et al. (2019) for a detailed definition of Functional Urban Area.
metropolitan regions compared with 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 (Glaeser & Cutler, 2021) (mainly through international air travel, see Daon et al., 2020), it then spread more widely within countries reaching practically all types of places.

2.2 | 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). 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 (Dowd et al., 2020; Kashnitsky & Aburto, 2020). 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 with a national average of around 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, 6.2 percentage points higher than in large metropolitan areas (OECD, 2020d).

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). 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. Yet, the preparedness to face the pandemic was heterogeneous across OECD regions. For example, some regions in Mexico, Chile, and the United Kingdom had around one physician per 1000 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, as well as across types of regions. Before the pandemic, large metropolitan regions tended to be better equipped with hospital beds than remote regions, with an average of 8.9 beds per 1000 inhabitants, compared with 5.6 in remote regions (OECD, 2020d).

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). While related morbidity rates are not available for OECD regions, the prevalence of obesity (where some 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 key risk factor for COVID-19 severity, not only by increasing the probability of other comorbidities, such as diabetes and high blood pressure, but also through a direct channel related to weakened respiratory capacity (Bermont & Díaz Ramírez, 2021; Gao et al., 2020). 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, 2020d).

In addition to age structure, health preconditions, 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 (Coker et al., 2020; Cole et al., 2020; Comunian et al., 2020; Wu et al., 2020). 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/m³ limit recommended by the WHO (OECD, 2020d). 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/m³ in the least affected region to 42 mg/m³ 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; Wang et al., 2021). Nevertheless, other studies suggest that elevation could increase excess deaths by exacerbating the adverse effects of air pollution on health (Alvarez et al., 2012; Bravo & Urone, 1981).

The literature on the drivers of the health impact of the COVID-19 pandemic has also focused on the quality of institutions (Rodríguez-Pose & Burlina, 2021). Trust in government can affect people's behaviors to comply with containment measures and medical advice (e.g., lockdowns, travel restrictions, and wearing masks; Elgar et al., 2020) that are key to slow the spread of COVID-19 and related deaths. Perception 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, 2020e). 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 2014–2018,
| 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/km²) | 3462.35 | 3461.59 | 370 | 24,294 | 407 |
| Hospital beds per 1000 people | 4.15 | 3.1 | 0.3 | 22.2 | 390 |
| Physicians per 1000 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 (mg/m³) | 13.25 | 6.51 | 4 | 41.93 | 405 |
| Average disposable household income (USD 2015 PPP) | 33,240.29 | 19,462.09 | 3514 | 100,115 | 371 |
| Percentage of labor force with at least secondary education | 74.41 | 17.88 | 32.7 | 97.5 | 374 |
| GDP per capita (USD 2015 PPP) | 36,884.85 | 19,143.03 | 4182 | 186,726 | 398 |
| Population (thousands of people) | 3178.22 | 4496.64 | 29.79 | 39,512.22 | 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 (m) | 533.62 | 575.68 | -3 | 3225 | 390 |
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, 2020d).

Socioeconomic 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). People with higher socioeconomic status are more likely to be knowledgeable about COVID-19 (Zhong et al., 2020), 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 behavior (Ajzenman et al., 2021). Finally, higher educational attainment tends to be associated with jobs that are more amenable to remote working (OECD, 2020a), a feature that allows workers to better comply with confinement measures. As in other parts of the world, in OECD countries the 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 labor 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).

TABLE 1 (Continued)

| Indicator                                      | Mean | Standard deviation | Minimum | Maximum | Sample |
|------------------------------------------------|------|-------------------|---------|---------|--------|
| Average temperature (°C)                       | 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: In all, 407 large regions (TL2) from 33 OECD and three 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 the 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 prepandemic year with available data (i.e., 2019, or earlier).

Abbreviations: GDP, gross domestic product; OECD, Organization for Economic Cooperation and Development; PM, particulate matter; TL2, Territorial Level 2.

Source: Elaboration based on OECD (2021a), Gallup (2020), Jarvis et al. (2008), and Google (2021).
Historically, higher exposure to diseases, including viruses, has been among the most important hazards of dense urban settlements (Duranton & Puga, 2020; Glaeser, 2020). In the case of COVID-19—everything else being equal—highly dense urban areas should be at higher risk of spreading the virus due to the close proximity of residents and workers. In practice, high spread in denser areas is more likely to be observed at the beginning of the pandemic, before these places start developing and implementing mitigation measures (Gerritse, 2020).

Beyond regional characteristics, local policy responses—notably effective confinement and social distancing measures—are also key to cope with the health impact of COVID-19. 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 (Capello & Caragliu, 2021; Nouvellet et al., 2021), 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 approximated through the change in mobility between different periods (Glaeser et al., 2020; Pan et al., 2020). In the OECD, regions have decreased their mobility, on average, since the beginning of the pandemic. The largest drop in mobility was registered in April 2020—when home-to-work mobility decreased by almost 45% compared with 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 were estimated using official deaths registers provided by national statistical offices or health ministries (OECD, 2021b, 2020d), while the main source of data for the regional characteristics—including risk factors for COVID-19—is the OECD Regional Statistics database (OECD, 2021a).

The main explanatory variables included in the analysis are the share of elderly population (age structure), the physician and hospital beds 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 the GDP per capita and, in some cases, the total resident population (in natural log). A set of additional indicators to capture relevant regional characteristics was initially included in the analysis, but finally excluded due to high multicollinearity with core explanatory variables. Such indicators include the share of young population, the average household income, the percentage of labor force with at least secondary education, the obesity rates, the relative poverty rate, the average rooms per inhabitant, the average temperature, and the average elevation. The indicators of trust in government, mean temperature and elevation, and mobility were estimated using different sources, namely, Gallup World Poll (Gallup, 2020), Google’s Earth Engine Data Catalog (Jarvis et al., 2008; NCEP, 2021), and Google’s COVID-19 Community Mobility Reports (Google, 2021), respectively. All other indicators are sourced from the OECD Regional Statistics database (OECD, 2021a).

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7Deaths 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 relatively large area of TL2 regions (the main unit of analysis)—and thus that intracountry mobility is more likely to happen within these large regions—this should not highly affect the results.
3.1 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 regional characteristics (explanatory variables and controls). After examining the pairwise correlation between an exhaustive set of potential explanatory variables to avoid issues of multicollinearity (see Supporting Information Appendix 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.

\[ \text{ExcessMortality}_{r, \text{jan–m}} = \alpha \times \text{ElderlySh} + \beta \times \text{HealthCapacity} + \gamma \times \text{PopDensity} + \delta \times \text{AirPollution} + \varphi \times \text{GDPpc} + \theta \times \text{TrustGovernment} + \text{CountryFE} + \varepsilon_{r, \text{jan–m}}. \]  

(1)

\[ \text{ExcessMortality}_{r, \text{jan–m}} \] is the percentage increase in 2020 deaths relative to the 2018–2019 average in region \( r \) and for the period between January 2020 and month \( m \) of 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 the date of the first COVID-19 case. In addition, compared with the largest period, a 6-month period is likely to be less sensitive (arguably more exogenous) to unobserved responses and behaviors arising over time (such as governments increasing medical capacity and resources).

\( \text{ElderlySh} \) is the share of elderly population (aged 75 or above), while \( \text{HealthCapacity} \) is a normalized index (from 0 to 100) that aggregates both the number of active physicians per 1000 people and the number of hospital beds per 1000 people (following the max–min normalization method from OECD, 2019a). To minimize biases generated by administrative boundaries and consequent inaccuracy of measuring densities, the measure of \( \text{PopDensity} \) is the population-weighted average of the population in each of the 1-km\(^2\) cells within the region \( r \). \( \text{AirPollution} \) stands for the (population-weighted) exposure to fine particulate matter 2.5 (PM2.5, measured in mg/m\(^3\)). \( \text{GDPpc} \) is the GDP per capita in USD 2015 PPP, while \( \text{TrustGovernment} \) refers to the percentage of the regional population with confidence in the national government. The set of country fixed-effects is denoted as \( \text{CountryFE} \), and the error term as \( \varepsilon_{r, \text{jan–m}} \).

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).

\[ \text{ExcessMortality}_{r, \text{jan–m}} = \alpha \times \text{ElderlySh} + \beta \times \text{HealthCapacity} + \gamma \times \text{PopDensity} + \delta \times \text{AirPollution} + \varphi \times \text{GDPpc} + \theta \times \text{TrustGovernment} + \text{CountryFE} + (1 - pW)^{-1}\varepsilon_{r, \text{jan–m}}. \]  

(2)

8The health capacity index uses equal weights to aggregate the number of active physicians per 1000 people and the number of hospital beds per 1000 people, as there is no prior information to suggest one element is more relevant than the other is. Only for two regions where the indicator of hospital beds rate was missing, we set the normalized 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.
3.2 Assessing the role of mobility in reducing excess mortality

Finally, 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 $\Delta \text{ExcessMortality}_{r,m}$ stands for the change in excess mortality (in percentage points) in region $r$ and month $m$ with respect to the month $m - 1$. $\text{RelativeMobility}_{r,m-1}$ 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 minimize issues of reverse causality between mobility change and excess mortality—and consistently with expected delayed effects of containment measures—the $\text{RelativeMobility}_{r,m-1}$ variable is also lagged 2 months or more (the specifications show time lags up to 3 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 ($\text{RegionFE}$). $\text{MonthFE}$ denotes either month fixed-effects or country–month fixed-effects (depending on the regression), while $\epsilon_{r,m}$ stands for the error term—standard errors are clustered at the regional level (see Equation 3).

$$
\Delta \text{ExcessMortality}_{r,m} = \tau \cdot \text{RelativeMobility}_{r,m-1} + \text{RegionFE} + \text{MonthFE} + \epsilon_{r,m}.
$$

(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 subperiods 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 beginning of 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 2 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 Tables 2 and 3 focus on excess mortality for different periods going from January–March 2020 to January–December 2020. Both models include selected core regional characteristics that minimize issues of multicollinearity and maximize the geographical coverage (342 regions from 32 countries, see a full list of countries in Supporting Information Appendix C). These prepandemic regional characteristics relate to the preparedness and or vulnerabilities of regions to cope with the COVID-19 pandemic. The first specification is a linear regression estimated using ordinary least squares (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 generalized additive specification (GAM model) (see Supporting Information Appendix Table B.1). The latter specification controls for spatial heterogeneity using bivariate spline functions whose arguments are the geographical coordinates (see Basile et al., 2014; Veneri, 2018; Wood, 2003).

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 with a decrease between 1.8 and 3.4
Table 2  Regression results: Baseline model

| Dependent variable: Excess mortality (%) | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|-----------------------------------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| 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/m³) | 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) |

(Continues)
| Dependent variable: Excess mortality (%) | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|----------------------------------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| January–March 2020                     | −0.0543 |      |     |     |     |     |     |     |     |     |
| January–April 2020                     | −0.0461 |      |     |     |     |     |     |     |     |     |
| January–May 2020                       | −0.152* |      |     |     |     |     |     |     |     |     |
| January–June 2020                      | −0.200** |     |     |     |     |     |     |     |     |     |
| January–July 2020                      | −0.184** |     |     |     |     |     |     |     |     |     |
| January–August 2020                    | −0.146* |     |     |     |     |     |     |     |     |     |
| January–September 2020                 | −0.125 |     |     |     |     |     |     |     |     |     |
| January–October 2020                   | −0.0899 |     |     |     |     |     |     |     |     |     |
| January–November 2020                  | −0.0579 |     |     |     |     |     |     |     |     |     |
| January–December 2020                  | −0.0350 |     |     |     |     |     |     |     |     |     |

| Trust in government (%)                | (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 |
| $R^2$                                  | 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. $R^2$                             | 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.
Abbreviations: FE, fixed-effects; GDP, gross domestic product; PM, particulate matter.

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$. 
percentage points of excess mortality, depending on the period. Population density also appears to be significantly and strongly associated with excess mortality. A one standard deviation increase in weighted population density is associated with an increase between 2.3 and 4.7 percentage points in excess mortality—with the strongest effects at the beginning of the pandemic. This result is in line with Gerritse (2020), who finds (for USA counties) that densely populated areas are more prone to faster viral spread at the start of outbreaks—before they develop stronger sheltering responses.

Higher levels of GDP per capita, another common feature of regions hosting economically dynamic and internationally connected metropolitan areas, were positively correlated with higher excess mortality—even from 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 viruses first spread throughout the world via large, dynamic, and highly internationally connected metropolis (Daon et al., 2020; Glaeser & Cutler, 2021). 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 with an increase of 2.6–3.3 points in excess mortality, while an increase of 15 percentage points (or one standard deviation) in the population that have confidence in the government is associated to a decrease from 1.6 to 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 6.5 mg/m³) is associated with an increase in excess mortality ranging from 1.3 to 2.6 percentage points. These coefficients are in line with other studies that register elasticities between 8% and 16% depending on the region (OECD, 2020c). For example, using negative binomial regressions on a sample of municipalities in Northern Italy, Coker et al. (2020) found that an increase of 1 mg/m³ in PM2.5 is associated with an increase of 9% in excess mortality. When applying negative binomial specifications to the sample of OECD regions (for comparison purposes),9 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 and internationally connected metropolitan regions—was linked more significantly to higher excess mortality. 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 (in coherence with the findings of Glaeser et al., 2020). Put differently, a decrease in home-to-work mobility is linked to lower excess mortality in the following months—particularly after 2 and

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9 Coker et al. (2020) 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 deaths” (which can take negative values) is more appropriate, and thus a negative binomial model is not suitable.
## Table 3: Regression results: Spatial model

| Dependent variable: Excess mortality (%) | (1)       | (2)       | (3)       | (4)       | (5)       | (6)       | (7)       | (8)       | (9)       | (10)      |
|-----------------------------------------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|
| January–March 2020                      | 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)   |
| Percentage of elderly population (75+)  | -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/m³)| 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)  |
| Dependent variable: Excess mortality (%) | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|-----------------------------------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| January–March 2020          | 0.0305 | 0.487 | 1.203*** | 1.775*** | 2.367*** | 2.329*** | 2.018*** | 1.896*** | 1.921*** | 2.403*** |
| January–April 2020           | (0.559) | (0.681) | (0.113) | (0.287) | (0.569) | (0.554) | (0.413) | (0.336) | (0.332) | (0.590) |
| January–May 2020             | 342 | 342 | 342 | 342 | 342 | 342 | 342 | 342 | 342 | 342 |
| SAR error correlation        | | | | | | | | | | |
| Observations                | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Pseudo $R^2$                | 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. 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.

Abbreviations: FE, fixed-effects; GDP, gross domestic product; PM, particulate matter; SAR, spatially autoregressive.

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$. 
|                  | (1)     | (2)     | (3)     | (4)     | (5)     | (6)     | (7)     | (8)     | (9)     | (10)    | (11)    | (12)    |
|------------------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|
| Change in excess mortality | -0.147*** | -0.156*** | -0.111*** | -0.103*** | -0.148*** | -0.181*** | -0.139*** | -0.122*** | -0.173*** | -0.232*** | -0.192*** | -0.117*** |
|                  | (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     | 3078    | 3078    | 3078    | 3078    | 3078    | 3078    | 3078    | 3078    | 3078    | 3078    | 3078    | 3078    |
| R²               | 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      | No      | Yes     | Yes     | Yes     | No      | No      | No      | No      |
| Country–month FE | No      | No      | No      | No      | No      | Yes     | Yes     | Yes     | No      | No      | Yes     | Yes     |
| Adj. R²          | 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. FE, fixed-effects. *p < 0.1; **p < 0.05; ***p < 0.01.
Reducing mobility today by 25% with respect to prepandemic levels would lead to a decrease in excess mortality between 1 and 2.5 percentage points in 2 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 Supporting Information Appendix 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 to a level lower than one,\(^{10}\) as well as the lag between time of infection, hospitalization (if any), and time of death. In addition, our preferred panel specifications—the ones controlling for time and country-time fixed-effects (Table 2, columns 4–12)—suggest that earlier reductions in home-to-work mobility are more effective at preventing increases in excess mortality.

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 minimize issues of misreporting or differences in testing policy, 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 prepandemic characteristics are effective to account for spatial differences in excess mortality across the large sample of regions considered. Indeed, in the wake of COVID-19, regions were not equally prepared and some were particularly vulnerable. Health system capacity was among the strongest and most robust predictors, but other features, such as population density, exposure to air pollution, and trust in institutions also play a role. In addition, prepandemic health capacity and population density are persistent factors affecting excess mortality since the beginning of the crisis—although the magnitude of their effects weakens over the year (as countries and regions develop and implement other mitigation strategies).

Understanding the main determinants of the geography of excess mortality is crucial to build effective policy responses and recovery packages. Results reported in this paper suggest that strong health systems, environmental and institutional quality have helped to mitigate the health impact of the pandemic. Recovery packages should consider these factors to build long-term resilience in the face of likely future pandemics. The findings also provide 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 lower trust in institutions, and where policies aimed at reducing mobility are more difficult to implement.

Finally, this study also contributes to the policy debate on the effectiveness of strong and timely physical distancing measures, reflected in reductions in home-to-work mobility, which is central to justify them (i.e., build political and social support) and to manage trade-offs between the health and the economic impacts of such measures.

\(^{10}\) 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 \(R_0\) for SARS-CoV-2 around three, particularly at early stages of the pandemic when interventions and knowledge about the virus were limited (D’Arienzo & Coniglio, 2020).
ACKNOWLEDGMENTS
The Authors are grateful to Maria Paula Caldas, Eric Gonnard and Claire Hoffmann, who provided substantial statistical support. The paper also benefited from comments by Nadim Ahmad, Rudiger Ahrend, Carlo Menon, Fabrice Murtin, Jolien Noels, Cem Ozguzel, Mark Pearson and Alison Weingarden. Finally, the authors would like to thank Prof. Edward Coulson and the two anonymous reviewers for their insightful and helpful suggestions that contributed to improve the paper. The opinions expressed and arguments employed are those of the authors and should not be reported as representing the official views of the OECD or of its member countries.

DATA AVAILABILITY STATEMENT
The data that support the findings of this study are available from the corresponding author upon reasonable request.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Díaz Ramírez, M., Veneri, P., & Lembcke, A. C. (2022). Where did it hit harder? Understanding the geography of excess mortality during the COVID-19 pandemic. Journal of Regional Science, 62, 889–908. https://doi.org/10.1111/jors.12595