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An investigation of the effects of lockdowns and COVID-19 vaccinations in Ireland

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Abstract. The COVID-19 pandemic resulted in many deaths and much upheaval worldwide. Public health responses to the pandemic differed greatly between countries. In 2023, as we emerge from the aftermath of the pandemic, it is now timely to assess the impact of specific public health response measures such as lockdowns and vaccinations. This assessment can help inform the development of evidence-based strategies for future public health responses in pandemic scenarios. We describe the implementation of a Bayesian Hierarchical Poisson Regression (BHPR) model to estimate the impact of pandemic response measures and vaccination on all-cause deaths, including COVID-19, in Ireland. We find that the implementation of lockdown measures and an appropriate vaccination timeline were effective in reducing the number of deaths in Ireland by, most likely, reducing the COVID-19 mortality rate. We believe our approach could be used to assess the impact of pandemic response measures and vaccination in other countries as well where similar data is available.

Keywords. COVID-19 pandemic, mortality rate, stringency index, vaccination rate, Bayesian spatiotemporal modelling

1 Introduction and motivation

The COVID-19 pandemic, which begun in early 2020 is one of the most globally impactful events in recent memory. No continent, country, or region remained untouched by the effects of the pandemic. At the end of December 2022, over $8,250$ people in Ireland had died from COVID-19 infection (Dong et al., 2020)[1]. At the time of writing, COVID-19 is still circulating and causing illness and fatalities in many countries. Mutations of this virus arise and continue lead to the emergence of new variants of concern (Dong et al., 2020). In the early days of the pandemic, without a vaccine or pharmaceutical treatment, efforts to contain the spread of COVID-19 focused on isolation measures for confirmed cases and self-quarantine for those who had been exposed. However, due to the high transmissibility of the virus, including spread from asymptomatic cases, these measures were not sufficient alone to fully contain the spread (Kissler et al., 2020b). Pandemic response measures, such as closing schools, public spaces, and non-essential businesses, were also implemented in an effort to reduce social interaction and opportunities for person-to-person transmission. The intended impact was to reduce the risk of overwhelming health systems and allowing more time for the development of effective treatments and vaccines (Kissler et al., 2020a, a; Li et al., 2020). As we know now a number of vaccines against Coronavirus were developed and subsequently deployed. The vaccination effort in Ireland started in December 2020 (Independent Ireland, 2020) with the overall goal of reducing the COVID-19 mortality rate in the country. Finding the answers to what approaches worked best during the pandemic is not easy. There is an ongoing debate among epidemiologists about the effectiveness of physical distancing measures and the efficacy of vaccines while many mathematical models have been created to predict impacts from the pandemic on health systems and national economies (Harjule et al., 2021). The implementation of pandemic response measures and the vaccination timeline have differed among countries. We believe that it is essential to assess the impact of both lockdowns and vaccination campaigns in order to inform the future development of evidence-based strategies for protecting people from a contagious virus such as COVID-19.

[1]https://covid19.who.int

1.1 Related Literature

There is significant existing literature in this domain of study. Many epidemiologists have attempted to understand the impact of pandemic responses on mortality rates. Studies have suggested that many lives have been saved as a result (Baud et al., 2020). Some studies, like the one conducted by Chaudhry et al. (2020), found no connection between the level of lockdown measures and COVID-19 death rates. In a separate study by Born et al. (2021), the authors used a synthetic control method to suggest that Sweden's decision not to implement widespread lockdown measures did not significantly contribute to its COVID-19 death cases. Other studies, such as Atkeson et al. (2020), Medica (2020), and De Larochelambert et al. (2020), also found no significant differences in mortality rates among different pandemic responses and population density. These findings challenge the widely held belief that pandemic responses are effective at controlling the spread of the virus. In contrast, other researchers, such as (Figueiredo et al., 2020; Lau et al., 2020), have found that pandemic measures are important and effective in reducing the likelihood of contagion and the spread of the COVID-19, based on the time-series analysis of confirmed cases in China. With the development of a mathematical model of COVID-19 transmission, Watson et al. (2022) found that vaccinations prevented an estimated 14.4 million COVID-19 deaths in 185 countries and territories between December 2020 and December 2021. Liang et al. (2021) conducted a regression analysis with a country-level random effect and found evidence supporting the importance of vaccination in preventing deaths among infected individuals. They also emphasized the significance of achieving consistent vaccine coverage to effectively translate the benefits of vaccines into desired public health outcomes. According to Jabłońska et al. (2021) who used a non-linear Poisson mixed regression model, COVID-19 vaccination coverage (the proportion of COVID-19 vaccinated inhabitants in an area) is effective at decreasing mortality in European countries and Israel. In addition to this, the study also found that reducing mobility within and between countries is effective at reducing COVID-19 mortality and suggests that there may be seasonal variations in COVID-19 incidence.

1.2 Contribution of this work

We believe it is very important to thoroughly test the effectiveness of pandemic measures and vaccination rates on mortality. As described above in section 1.1 there have been several studies on this topic. However, to the best of our current knowledge, no research has specifically evaluated the impact of these measures and vaccination rates on mortality within Ireland. The aim of this research is to fill this knowledge gap for Ireland. In this work we investigate the effects of: lockdowns strictness, COVID-19 confirmed cases, and vaccination rate on overall mortality in Ireland. More precisely, we attempt to estimate the number of lives that lockdown and vaccination efforts have saved in Ireland since the start of the COVID-19 pandemic. The data used in our study are available publicly and the references to these datasets are provided below. As mentioned in the previous section, existing works have implemented different modelling frameworks including: Spatial Autoregressive (SAR), Geographically Weighted Regression (GWR), and Bayesian Spatially Varying Coefficient Model, to capture the spatial variation in the factors that impact mortality (Sun et al., 2021; Cupido et al., 2021; Konstantinoudis et al., 2022) from COVID-19. In our work, we present a Bayesian Hierarchical Poisson Regression (BHPR) model that allows us have both county-level effects (administrative regions within the country of Ireland) and also country-level effects to capture both spatial variations and estimate the overall effects at the country level. Ireland is divided into counties which have administrative and governance responsibilities for specific matters (taxation, housing management, road and environmental management, and so on). Very often in Ireland, public health services are organised around county-level approaches. Indeed, in some cases, public health services may combine several counties into one management region. There are 26 counties in the Republic of Ireland with 6 counties in Northern Ireland. This work applies only to the counties within the Republic of Ireland as there were different public health strategies pursued in the Republic and Northern Ireland during the time periods of this study. Additionally, health services in the 6 counties in Northern Ireland are managed by the government in Northern Ireland and the UK.

Our results show that there are variations among the counties of Ireland with respect to the effectiveness of lockdowns and vaccination. At the country level, we show that both of these factors resulted in an overall reduction in mortality from COVID-19. Furthermore, we attempted to calculate the number of deaths if there were no vaccination and lockdowns in order to estimate the number of lives saved by these actions. We estimated the number to be $16,876$ (CI: $13,799$ - $20,140$). The goodness of fit of our model is measured by $R^2 = 0.98$, which indicates an overall good performance.

In summary, this work provides some evidence indicating that the use of lockdowns and vaccination efforts in Ireland were effective in reducing mortality. Furthermore, we suggest the BHPR model is a suitable candidate for use in studying the effects of various factors on mortality for the following reasons:

- The BHPR model provides a flexible framework for modeling count data which is often encountered in mortality studies.
- The BHPR model can handle complex data structures including data with multiple levels, such as country and sub-country levels.
- The approach can take advantage of *information pooling*. This is an important feature of the hierarchical models. Information pooling refers to the sharing of information across different levels of the model and this information can improve parameter estimation and reduce uncertainty. In the context of this study, this means that information from different

counties or regions can be combined to obtain more accurate estimates.

- The Bayesian framework allows prior information to be incorporated into the model and this can improve parameter estimation and reduce uncertainty.
- The model framework provides a more natural way to quantify uncertainty in model estimates. Quantification of uncertainty is important for making informed decisions and drawing valid conclusions from the subsequent analysis.

The remainder of the paper is structured as follows. In section 2 we describe the overall methodology including a discussion of the data requirements (section 2.1 and the modelling procedure used (section 2.2). Section 3 outlines some of the key results of this work. Section 4 is the penultimate section of the paper and provides some concluding remarks and ideas for future work. We close, in section 5, with a description of our data and software availability.

2 Our methodology and approach

In this section, we carefully describe the data used in our analysis (section 2.1) and then proceed to describe the modelling framework and procedure we followed to build the BHPR model (section 2.2).

2.1 Data Requirements

For this work, we aimed at investigating the impact of lockdown strictness and vaccination rate on mortality during the COVID-19 pandemic period (2020-2022). However, we have used data from during the period 2016 to 2022 in order to better estimate the non-pandemic related effects, such as weather temperature, and to also better understand the overall time trend. To examine the effect of these factors, we have used five data sources:

1. **Temperature:** As temperature is associated with mortality (Son et al., 2019), we retrieved data on the monthly average temperature in Ireland from 2016-2022 from the website of Met Éireann, Ireland's National Meteorological Service (The Irish Meteorological Service, 2022).
2. **All-causes mortality:** The data on all-cause deaths at a town level for each day was obtained from the `RIP.ie` website[2] which is widely considered one of the most reputable sources of bereavement information in Ireland (CSO, 2022a). The data includes the surname, date of death, and location for each bereavement notice. Having the date of the notice and the county name associated with each location we calculated the number of monthly deaths for each county in Ireland by taking the total number of the notices within each county on a monthly basis.
3. **COVID-19 vaccination rate:** Since January 2021, the Central Statistics Office of Ireland (CSO) (CSO, 2022b) has provided the monthly cumulative proportion of COVID-19 vaccinated inhabitants at the local electoral area (LEA) level. We calculated the monthly cumulative vaccination rate for each county by aggregating the LEAs (with each county) cumulative vaccination rates.
4. **Confirmed COVID-19 cases:** Daily data on new confirmed cases of COVID-19 at the county level in Ireland is available from Ireland's COVID-19 data hub (Ireland's COVID-19 Data Hub, 2022). We calculated the monthly total of confirmed cases for each county using this data source.
5. **Government Response Oxford Stringency Index:** The Oxford Stringency Index (SI) measures the strictness of physical distancing and lockdown-style policies that primarily restrict people's behaviour (Hale et al., 2021). The SI is calculated using various containment and closure policy indicators. As well as being an indicator for public information campaigns it is reported daily at the country level. It is a numerical scale ranging from 0 to 100, with 0 indicating the loosest restrictions and 100 indicating the strictest. In our study, the monthly SI values were calculated by taking the monthly averages of the index to match the temporal resolution of other variables used in this study.

[2] https://www.rip.ie

2.2 Modelling Procedure

In this section, we explain the modelling framework that we followed to build the BHPR model. We denote $y_{t,k}$ as the number of deaths at time t where $t = 1, 2, \ldots, 79$ (from January 2016 to August 2022) and county $k (k = 1, 2, ..., 26)$. We write the model hierarchically as follows:

$$y_{t,k} \sim Poisson(\lambda_{t,k}) \tag{1}$$

where $\lambda_{t,k}$ is the average mortality at month t and county k, and it is modelled as:

$$\begin{aligned} log(\lambda_{t,k}) = \alpha_k &+ \beta_k^{SI} \times SI_t + \beta_k^{temp} \times temperature_t \\ &+ \beta_k^{case} \times case_{t,k} \\ &+ \beta_k^{int} \times cases_{t,k} \times vaccination_{t,k} \\ &+ \beta_k^{trend} \times t \end{aligned} \tag{2}$$

where α_k is the county-level intercept, β_k^{SI} is the county-level effect of the stringency index, β_k^{temp} is the county-level effect of temperature, β_k^{case} is the county-level effect of confirmed cases, β_k^{int} is the county-level effect of the interaction between confirmed cases and vaccination rate, β_k^{trend} is the county-level effect of time. We add the country-level effects to the model as hierarchical priors on the county-level effects as follows in Equation 3. For brevity we denote β_k^i as the i^{th} effect in county k.

$$\beta_k^i \sim Normal(\mu^i, \sigma^i) \tag{3}$$

where μ^i represents the country-level effect of the effect i with σ^i representing the country-level standard deviation of the effect i. Below we show the non-informative hyperpriors used:

$$\begin{aligned} \mu^i &\sim Normal(0, 10) \\ \sigma^i &\sim StudentT(0, 1, 1) \end{aligned} \tag{4}$$

During the early stages of the pandemic, due to lack of widespread testing, there is great uncertainty about the true number of cases. Different sources have reported different figures from 7 to 12 times the reported cases (Rahmandad et al., 2021; MIT Sloan, 2020; National Public Radio, 2021). Taking a sensible and pragmatic approach to this issue, we do not consider the number of cases during the first seven months of 2020 as fixed. Instead, to account for the uncertainty, we assume that they are subject to a distribution that can be inferred along with the other parameters of the model as outlined here in Equation 5:

$$cases_{t,k} \sim Poisson(10 \times x_{t,k}) \tag{5}$$

In Equation 5, $cases_{t,k}$ is the inferred number and $x_{t,k}$ is the reported number of cases at time t (only the first seven months of the year 2020) and county k. The model is implemented in R (Team et al., 2013) using the JAGS software (Plummer et al., 2003) and is run for $7,000$ iterations. The first 500 iterations are discarded as burn-in. The model is run for 4 chains and the convergence of the chains is checked using the R-hat diagnostic (Brooks and Gelman, 1998; Gelman and Rubin, 1992), that were all close to the target value of 1, indicating good convergence.

3 Experimental Results

Overall, given the difficulty of the problem, we are very pleased with the outcomes of our experimental results. In this section, we now describe the three most important results of our work. Figure 1 compares the predicted outcomes from the implemented model to the actual number of cases of deaths. The vertical lines indicate the 95% posterior predictive credible intervals. The goodness of fit is measured using the $R^2 = 0.98$ criterion. Figure 1 demonstrates clearly that the model can successfully retrieve the actual number of deaths in Ireland over the time period of study.

In order to estimate the number of lives saved by lockdowns and vaccinations we needed to generate counterfactual scenarios (Chernozhukov et al., 2013; Born et al., 2021). This involves modifying a factual prior event and then assessing the consequences of the modification. We performed this by setting the Stringency Index (SI) and the vaccination rate to zero and then generating predictions for the number of deaths within this scenario. After this, we compared the counterfactual number of deaths with the actual number of deaths to estimate the number of lives saved with the availability of vaccination. Following this procedure, we estimated the number of lives saved by lockdowns and vaccinations in Ireland to be $16,876$ with a 95% credible interval of $[13,799 - 20,140]$. We illustrate the results in figure 2 by comparing the counterfactual number of deaths generated by our model with the actual number of deaths at the country level. The red line depicts the expected number of deaths under the counterfactual scenario whereas the blue line represents the actual number of deaths. The shaded area in red illustrates the difference between the values. This gap begins to widen after the first quarter of 2021. We believe that this is likely due to the successful rollout of vaccines in Ireland which began around this time. As shown in the figure 2, this gap reached its peak between September 2021 and May 2022 when around 2.5 times more deaths were observed under the counterfactual scenario. This peak gap can be explained by widespread vaccination among people in Ireland despite the absence of restrictive social distancing measures compared to those in place during 2020.

Finally, we considered the estimation of the number of deaths prevented in all of the counties of Ireland. As reported above, we consider the 26 counties in the Republic of Ireland. Figure 3 illustrates the estimated number of deaths prevented in the counties of Ireland by lockdowns and vaccinations using three county-based maps. In figure 3 the maps from left to right indicate the 2.5%, 50% and 97.5% estimation percentiles respectively. Within the space available in this paper, there are a few interesting observations to note. The county of Galway, a mixture of rural and urban populations and represented by dark green in all maps had the highest number of lives saved. Galway is in the west of Ireland, on the Atlantic coast. Two other Atlantic coastal counties (Kerry in the south-west and Donegal in the north-west) follow as having the 2^{nd} and 3^{rd} highest number of lives saved. The lowest number of lives saved is shown in white for Limerick and Offaly counties according to the middle panel. This is an interesting result as Limerick (in the south-west) has a significant urban population while Offaly, in the Irish midlands, has a significant rural population overall. Of course, these county-level results and our interpretations can be improved with additional socio-demographic and public health policy considerations which are, at this time, beyond the scope of this work.

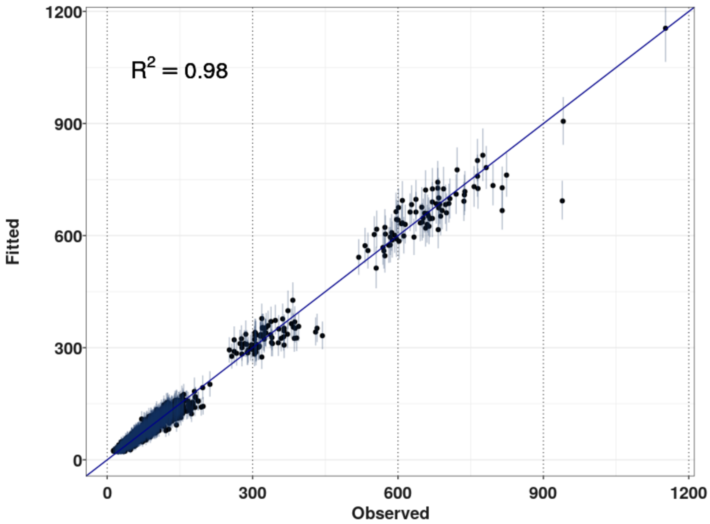

Figure 1. Comparison of predicted values from the model to actual death count in counties of Ireland from 2016 to 2022. The 95% uncertainty intervals are depicted by vertical bars.

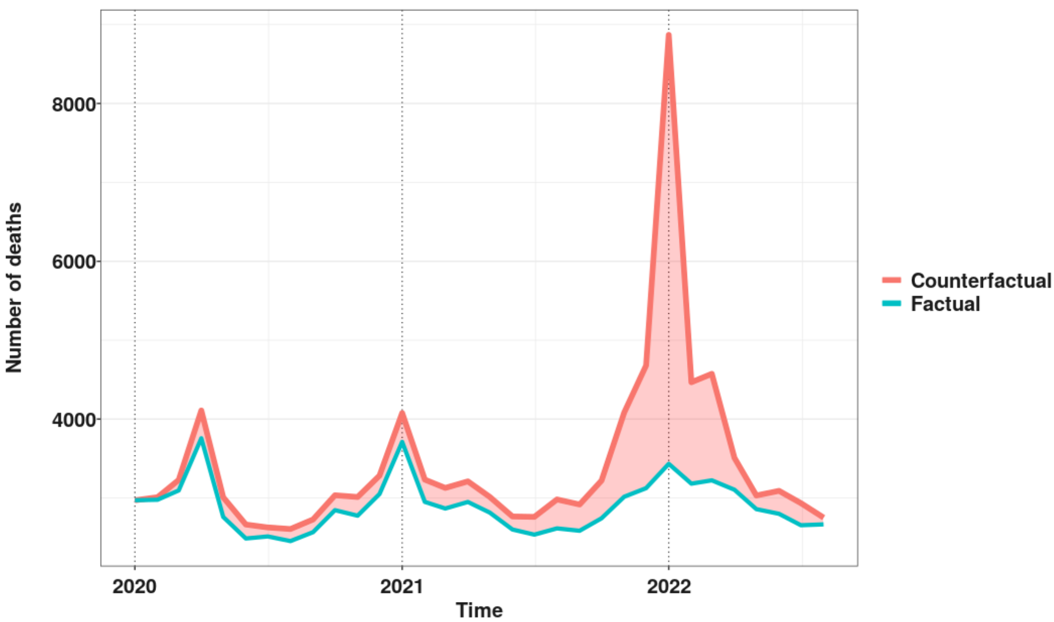

Figure 2. Comparison of the counterfactual number of deaths (red) against the observed number of deaths (blue) during 2020 to 2022 in Ireland.

4 Conclusions and Discussion

In this study, we have developed a Bayesian hierarchical Poisson regression model to estimate the number of lives saved by lockdowns and vaccinations in Ireland during the years 2020 to 2022. Overall our model, as described in section 2, was able to successfully retrieve the actual number of deaths in Ireland during the period of study. Using the model we estimated that on average $16,876$ (95% CI: $13,799 - 20,140$) lives were saved by lockdowns and vaccinations in Ireland. We also showed (for example in figure 2) that the number of saved lives peaked between September 2021 and May 2022 where an estimated 2.5 times more deaths were prevented as a result of widespread vaccination among the population in Ireland. This happened despite the absence of restrictive physical distancing measures compared to 2020. For county-specific analysis, we showed in figure 3 that Galway county had the most significant number of saved lives with Kerry and Donegal following closely behind.

We believe the BHPR approach we used in this study has the potential to be used in similar problem settings where data is nested in multiple levels and there is uncertainty about some of the observed values in the predictors.

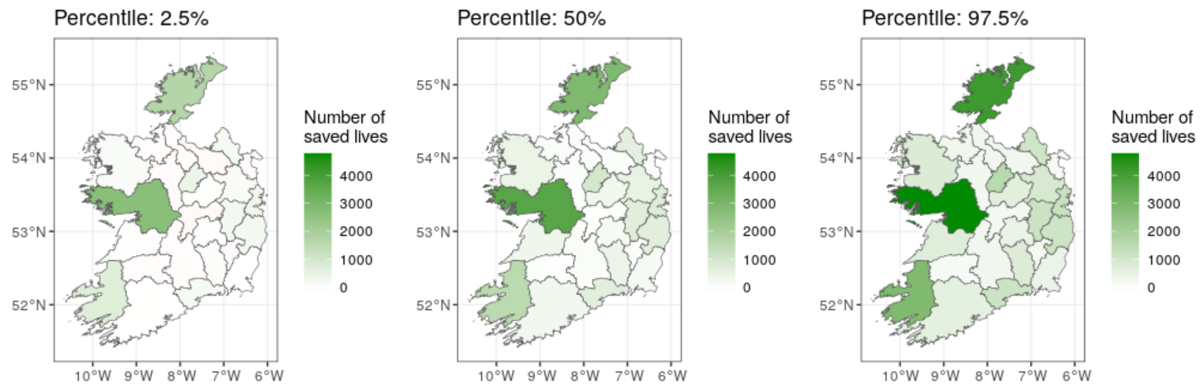

Figure 3. The number of lives saved because of lockdowns and vaccination in each county is depicted. From left to right, the maps are associated with 2.5%, 50% and 97.5% cumulative probability for the estimated numbers, respectively. The numbers in the 2.5% and the 97.5% maps indicate the 95% credible interval for saved lives in each county.

For example, we showed how to account for the uncertainty in the number of confirmed cases by putting a prior distribution on the suspicious values using the Bayesian framework. In this work, we did not focus on the variations of the effects in different counties and the reasons behind them. Many factors such as population density, demographics and socioeconomic variables could possibly explain the variations. Indeed, during summer 2020 one county (Kildare) experienced a county-level lockdown while its neighbouring counties (Laois, Offaly and Dublin) were not subject to such a lockdown[3]. Situations like this mean that further considerations are required for the future work which can interpret our results in a broader context.

5 Data and Software Availability

We provide both raw and the final version of the dataset we used for our study, and to ensure reproducibility and transparency to our model and results, the code for running the analysis is available online at https://github.com/nilips70/Covid-Project.git.

Temperature data in its raw form is obtained from the Met Éireann website[4]. The Government's Response Oxford Stringency Index is extracted from Our World in Data website[5]. The all-cause mortality data is gathered through web scraping from the RIP.ie website[6]. The COVID-19 vaccination rate data [7], confirmed COVID-19 cases[8], and population figures per county[9] are all sourced from the CSO website. Details on how to process the data is provided within the repository.

[3] https://tinyurl.com/ye22m39w
[4] https://www.met.ie/climate/available-data/monthly-data
[5] https://ourworldindata.org/coronavirus/country/ireland
[6] https://rip.ie/
[7] https://data.cso.ie/table/CDC47
[8] https://data.cso.ie/table/CRW02
[9] https://data.cso.ie/table/FP001

References

Atkeson, A., Kopecky, K., and Zha, T.: Four stylized facts about COVID-19, Tech. rep., National Bureau of Economic Research, 2020.

Baud, D., Qi, X., Nielsen-Saines, K., Musso, D., Pomar, L., and Favre, G.: Real estimates of mortality following COVID-19 infection, The Lancet infectious diseases, 20, 773, 2020.

Born, B., Dietrich, A. M., and Müller, G. J.: The lockdown effect: A counterfactual for Sweden, Plos one, 16, e0249 732, 2021.

Brooks, S. and Gelman, A.: General methods for monitoring convergence of iterative simulations, Journal of computational and graphical statistics, 7, 434–455, 1998.

Chaudhry, R., Dranitsaris, G., Mubashir, T., Bartoszko, J., and Riazi, S.: A country level analysis measuring the impact of government actions, country preparedness and socioeconomic factors on COVID-19 mortality and related health outcomes, EClinicalMedicine, 25, 100 464, 2020.

Chernozhukov, V., Fernández-Val, I., and Melly, B.: Inference on counterfactual distributions, Econometrica, 81, 2205–2268, 2013.

CSO: Measuring Mortality Using Public Data Sources 2019-2021 (October 2019 - December 2021), https://www.cso.ie/en/releasesandpublications/fb/b-mpds/measuringmortalityusingpublicdatasources2019-2021october2019-december2021/, 2022a.

CSO: COVID-19 Vaccination Rates, https://data.cso.ie/table/CDC47, 2022b.

Cupido, K., Fotheringham, A. S., and Jevtic, P.: Local modelling of US mortality rates: A multiscale geographically weighted regression approach, Population, Space and Place, 27, e2379, 2021.

De Larochelambert, Q., Marc, A., Antero, J., Le Bourg, E., and Toussaint, J.-F.: Covid-19 mortality: a matter of vulnerability among nations facing limited margins of adaptation, Frontiers in public health, p. 782, 2020.

Dong, E., Du, H., and Gardner, L.: An interactive web-based dashboard to track COVID-19 in real time, The Lancet infectious diseases, 20, 533–534, 2020.

Figueiredo, A. M., Codina, A. D., Figueiredo, D., Saez, M., and León, A. C.: Impact of lockdown on COVID-19 incidence and mortality in China: an interrupted time series study, Bull World Health Organ, 6, 2020.

Gelman, A. and Rubin, D.: Inference from iterative simulation using multiple sequences, Statistical science, 7, 457–472, 1992.

Hale, T., Angrist, N., Goldszmidt, R., Kira, B., Petherick, A., Phillips, T., Webster, S., Cameron-Blake, E., Hallas, L., Majumdar, S., et al.: A global panel database of pandemic policies (Oxford COVID-19 Government Response Tracker), Nature human behaviour, 5, 529–538, 2021.

Harjule, P., Tiwari, V., and Kumar, A.: Mathematical models to predict COVID-19 outbreak: An interim review, Journal of Interdisciplinary Mathematics, 24, 259–284, 2021.

Independent Ireland: first person to be vaccinated against Covid-19 in the Republic of Ireland, https://www.independent.ie/irish-news/health/there-is-hope-now-annie-lynch-79-first-person-to-receive-covid-19-vaccine-in-republic-of-ireland-39910282.html, 2020.

Ireland's COVID-19 Data Hub: COVID-19 County Statistics, https://covid-19.geohive.ie/maps/5117479f97724d4ead6171ec2b8b912d, 2022.

Jabłońska, K., Aballéa, S., and Toumi, M.: The real-life impact of vaccination on COVID-19 mortality in Europe and Israel, Public Health, 198, 230–237, 2021.

Kissler, S., Tedijanto, C., Lipsitch, M., and Grad, Y. H.: Social distancing strategies for curbing the COVID-19 epidemic, MedRxiv, 2020a.

Kissler, S. M., Tedijanto, C., Goldstein, E., Grad, Y. H., and Lipsitch, M.: Projecting the transmission dynamics of SARS-CoV-2 through the postpandemic period, Science, 368, 860–868, 2020b.

Konstantinoudis, G., Cameletti, M., Gómez-Rubio, V., Gómez, I. L., Pirani, M., Baio, G., Larrauri, A., Riou, J., Egger, M., Vineis, P., et al.: Regional excess mortality during the 2020 COVID-19 pandemic in five European countries, Nature communications, 13, 1–11, 2022.

Lau, H., Khosrawipour, V., Kocbach, P., Mikolajczyk, A., Schubert, J., Bania, J., and Khosrawipour, T.: The positive impact of lockdown in Wuhan on containing the COVID-19 outbreak in China, Journal of travel medicine, 2020.

Li, R., Rivers, C., Tan, Q., Murray, M. B., Toner, E., and Lipsitch, M.: The demand for inpatient and ICU beds for COVID-19 in the US: lessons from Chinese cities, MedRxiv, 2020.

Liang, L.-L., Kuo, H.-S., Ho, H. J., and Wu, C.-Y.: COVID-19 vaccinations are associated with reduced fatality rates: Evidence from cross-county quasi-experiments, Journal of Global Health, 11, 2021.

Medica, M.: COVID-19 mortality rates in the European Union, Switzerland, and the UK: effect of timeliness, lockdown rigidity, and population density, 2020.

MIT Sloan: COVID-19 cases are 12 times higher than reported, https://mitsloan.mit.edu/ideas-made-to-matter/covid-19-cases-are-12-times-higher-reported, 2020.

National Public Radio: Why The Pandemic Is 10 Times Worse Than You Think, https://www.npr.org/sections/health-shots/2021/02/06/964527835/why-the-pandemic-is-10-times-worse-than-you-think, 2021.

Plummer, M. et al.: JAGS: A program for analysis of Bayesian graphical models using Gibbs sampling, in: Proceedings of the 3rd international workshop on distributed statistical computing, vol. 124, pp. 1–10, Vienna, Austria., 2003.

Rahmandad, H., Lim, T. Y., and Sterman, J.: Behavioral dynamics of COVID-19: Estimating underreporting, multiple waves, and adherence fatigue across 92 nations, System Dynamics Review, 37, 5–31, 2021.

Son, J.-Y., Liu, J. C., and Bell, M. L.: Temperature-related mortality: a systematic review and investigation of effect modifiers, Environmental Research Letters, 14, 073 004, 2019.

Sun, Y., Hu, X., and Xie, J.: Spatial inequalities of COVID-19 mortality rate in relation to socioeconomic and environmental factors across England, Science of the total environment, 758, 143 595, 2021.

Team, R. C. et al.: R: A language and environment for statistical computing, 2013.

The Irish Meteorological Service: Mean temperature in degrees Celsius for DUBLIN AIRPORT, https://www.met.ie/climate/available-data/monthly-data, 2022.

Watson, O. J., Barnsley, G., Toor, J., Hogan, A. B., Winskill, P., and Ghani, A. C.: Global impact of the first year of COVID-19 vaccination: a mathematical modelling study, The Lancet Infectious Diseases, 22, 1293–1302, 2022.