Excess Mortality (2020-2023) as Proxy of COVID-19 Deaths?

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SUMMARY

Importance: Concerns regarding excess mortality estimates and the subjective nature of diverse models utilized have emerged. We examined its theoretical underpinning by exploring two popular excess mortality models based on regression and time series analyses that highlight their weaknesses in forecasting excess deaths during COVID-19 emergency.
Observations: Excess mortality estimates are errors/residuals of prediction models increasingly used to determine the number of unreported deaths from COVID-19. That several prediction models are used to model baseline excess deaths underscores the lack of a definitive choice thereby signposting its subjective nature. A general lack of assessment of the assumptions governing such models was another drawback in relying on estimates of excess mortality derived from them.
Conclusions and Relevance: In assessing the impact of COVID-19 (or any public health emergency), reported death counts and other mortality statistics, when combined with relevant auxiliary information, can offer a better view of the pandemic impact rather than reliance on a subjective metric such as excess death which can be misleading. More importantly, mathematical modeling though useful in an unfolding pandemic, once data become available, this should supersede forecasted estimates in decision-making or impact assessment.

Keywords: Excess mortality; COVID-19; modeling.

INTRODUCTION

The outbreak of the corona virus (COVID-19) pandemic in 2020 resulted in an unprecedented global impact in public health policy formulation and implementation. The ramifications of the pandemic are still being felt across the globe even after World Health Organization (WHO) declared the pandemic over in May 2023 [1]. Excess mortality is a prominent and widely used metric in assessing the human toll of the COVID-19 pandemic. However, this measure has been the subject of extensive misinterpretation and it is even promoted over and above the reported death statistics from the pandemic itself.

Excess mortality is claimed to be a more objective and comparable measure of the mortality impact of COVID-19 across countries than the reported death counts [2,3]. It is generally believed that understanding excess mortality not only provides a more comprehensive view of the pandemic's impact, it can also help in the development and implementation of effective public health initiatives [3].

The emphasis placed on excess mortality extends beyond the public health community and appears to have informed views of politicians and media [4]. Surprisingly, there seem little to no critical appraisal of this projection-based approach [4]. In this contribution, we investigate the excess mortality statistic and examine whether its widespread use is justified theoretically. The excess mortality estimates based on linear regression [5] and time series analysis [6] are examined to highlight the serious limitations of the formulation that has been at the heart of public policy response to the COVID-19 pandemic globally.

Theoretical Basis

Excess mortality is a term used frequently in epidemiology and public health that refers to the number of deaths from all- causes during a crisis

DOI: 10.54103/2282-0930/27538
Accepted: 19th December 2024

above and beyond what we would have expected under normal conditions [3,7]. It is claimed in several studies that, excess mortality is a more comprehensive measure of the total impact of the pandemic on deaths than the confirmed COVID-19 death count alone. It was also claimed that it captures not only the confirmed deaths, but also COVID-19 deaths that were not correctly diagnosed and reported [3,7], in addition to deaths from other causes that could be attributable to the overall crisis conditions [7].

The use of excess mortality as a metric for gauging the impact of public health emergencies has been documented since 1665 [5]. Under-reporting of the number of deaths is a very critical factor and the possibility increases with countries at the lower rung of the economic spectrum (low and middle-income countries).

Excess Mortality Estimation based on Linear Regression

The excess mortality measure utilized in [5] uses a linear regression model to project all-cause mortality for 2020 and 2021 with historical data (2015-2019).

The specified regression model for all-cause mortality was given as [5]:

$$D_{t,Y}=\alpha_t+\beta\cdot Y+\varepsilon$$

where, $D_{t,Y}$ is the number of deaths observed on week (or month, or quarter) t in year Y, β is a linear slope across years, α_t is the time-varying intercept (fixed effects), and $\varepsilon \sim N(0,\sigma^2)$ is Gaussian noise.

We note that the residual or error variable , is assumed to be normally distributed with zero mean and constant variance σ^2. However, the assumption of a constant error variance (homoscedasticity) for time series count data is very tenuous, as such data are inherently heteroscedastic (time-varying error variance) [9]. It was indeed conceded in [5] that the residual may be temporally or spatially autocorrelated but no remedial measures were taken by the investigators to mitigate this serious drawback that limits the quality of estimates obtained .

The excess mortality projection for New Zealand has been highlighted to be flawed because it ignored the changes in the population growth rate [4]. There was no discussion in the report [5] of why this model should accurately forecast expected deaths, with a claim that there is a '*yearly trend over recent years due to changing population structure or socio-economic factors*", which is rather vague [4]. The model lacks a population variable, so whatever the population growth rate was from 2015 to 2019 is implicitly projected forward at the same linear rate into the future [4]. This is poorly suited to capture migration-induced changes in population growth, which was the case with New Zealand during the early years of the pandemic with lockdowns and border closure [4].

Excess death estimates that do not incorporate statistical uncertainty cannot be used for inference. The excess mortality estimates presented in [5] importantly overlooks confidence intervals.

It has been suggested [4] that peer review in public health tends to be more collegial than adversarial, with less critical reviews which are faster and author teams larger (internalizing different views). Specifically, the claimed negative cumulative excess mortality in the case of New Zealand was just an artifact of an inappropriate way to predict expected deaths in a country with a fluctuating population growth rate [4] and this highlights a visible inadequacy of the excess death conceptualization.

There is an evident dissonance in the excess mortality arguments presented in [5]. For one, France and Belgium were mentioned to have accurate COVID-19 reporting and the excess mortality estimates for these countries were underestimated by the model. It was adduced that the likely reason for negative excess mortality was that the non-COVID mortality has decreased, mostly due to the influenza suppression, leading to the excess mortality underestimating the true number of COVID deaths [5]. A counter position to this argument is that if negative excess mortality translates to an underestimation of the true COVID-19 deaths, why does positive excess mortality not equally translate to an overestimation of the true COVID-19 deaths?

Evaluation of Excess Mortality Model based on Seasonal Time Series

The Seasonal Autoregressive Integrated Moving Average (SARIMA) model was used in [6] as the baseline model to predict expected deaths from all-causes mortality. The training data covered from January 2015 to February 2020, utilizing estimated monthly populations as covariates. Spearman correlation coefficients between all-cause excess mortality and reported COVID-19 deaths were computed for the different demographic groupings in the dataset. It was reported that, based on the analysis, COVID-19 comprised >99.992% of deaths. The 95% confidence intervals for all relative risks (RR) were determined via the geometric means of monthly RRs within specific periods (yearly, pre-pandemic, and pandemic).

Further, the index case of COVID-19 in the US was reported on February 2, 2020 while vaccination commenced on December 14, 2020. It is therefore unclear why data of deaths from February 2020 were not incorporated into the analysis as reported [6]. The report also lumped part of the post-vaccination era (December 2020 to February 2021) into the pre-vaccination period. The correct pre-vaccination period for the US was February 2020 to December 12, 2020.

Excess mortality as a measure for highlighting the impact of COVID-19 deaths can provide misleading results. For example, the total cumulative observed deaths in the US between 2020 and 2023 during the

ISSN 2282-0930 • Epidemiology Biostatistics and Public Health - 2024, Volume 19, Issue 2

COVID-19 global health crisis were under-estimated by 1,382,480 deaths based on the SARIMA model deployed by the investigators [6,8]. While this error in prediction seem large (Table 1), the report did not contain *goodness–of-fit* metrics to allow for assessment of the predictive capacity of the model used to forecast the all-cause deaths up to 2023 when the pandemic emergency was declared over.

Excess Mortality are Residuals **:** Residuals measure the departure of fitted values from observed values of the dependent variable [9]. They can be used to detect model *mis-specification, outliers, or observations* with poor fit; and to detect influential observations, or observations with a big impact on the fitted model [9]. For count data, the simple residual (excess mortality in this case) is heteroscedastic and asymmetric, even in large samples [9]. The residuals in count data modeling do not have zero mean, constant variance, and symmetric distribution, unlike what obtains using ordinary least squares regression [9].

Model adequacy procedures such as the examination of the residuals, goodness-of-fit, and tangential measures are important procedures in a model assessment and these were lacking in both models[5,6]. In establishing a strong relationship between excess mortality and COVID-19 deaths, the Spearman rank correlation coefficient was used with the assumption of non-normality in [6]. However, if the authors have assumed non-normality of the time series data of death counts, then the utilization of the SARIMA model is not justified.

A model should be judged based on its performance in comparison with the observed data. The linear regression model itself [5] uses estimates of the population sizes (from the United Nations World Population Prospects [10] which distorts the true situation, as alluded to by [4]. Population growth, especially during the pandemic period is not expected to be a linear trend, but this was the basis of the formulation. The analysis as reported incorrectly used point estimates as the basis for establishing excess deaths, without providing any computed confidence intervals for the estimates.

Excess mortality as defined in the literature is in reality, the error of prediction. A POSER IS: *what will excess mortality be called if there was no pandemic or what would the excess deaths be attributable to?* Recent studies in the US [11,12] have clearly shown that COVID-19 and its related deaths were not the leading causes of death in the United States all through the pandemic period. The excess death formulation is highly correlated with reported COVID-19 deaths as highlighted in [5] (Figure 4) and [6] (Figure 2), respectively. Therefore its trajectory is actually based on the reported COVID-19 mortality that is *a priori* termed to be poorly collected.

Excess Mortality Assessment In Europe

One large-scale data-driven assessment of the impact of COVID-19 in Europe was presented by [13]. This spatio-temporal analysis of excess mortality correctly leveraged on quasi-Poisson regression models using the pre-pandemic data as baseline. The study in [13] incorporated population dynamics and control for potential cofounders in the method. While the modeling approach in [13] ticks several boxes, as this critical review points out, the field often takes model assumptions at face value without stringent residual diagnostics, thorough sensitivity analysis, and rigorous verification of the underpinning distributional assumptions.

A rich mix of socioeconomic indicators based on World Bank 2020 estimates (and in some instances 2018 and 2019 estimates) were integrated into the modeling framework by [13] to reflect possible country-level disparities in excess deaths. It is noted that the investigators [13] validated the baseline data with other data sources and this was consistent with other sources. Population data were obtained from the United Nations' regularly-updated database although as earlier pointed out in [4], this may distort the reality especially during the early stages of the pandemic. It is also worth stating that these population numbers are based on modeling and are not the observed population numbers for the countries surveyed. Sensitivity analysis was, however, carried out by the investigators in [13] to establish consistency of the model estimates in 2018-2019 (a year before the pandemic began).

Table 1: Predicted and Reported COVID-19 Death Statistics of SARIMA model*

S/N	<25 years (%)	25-64 years (%)	≥ 65 years (%)	TOTAL
Expected/Predicted Mortality/ Deaths (SARIMA model)	190,950 (2.06%)	2,174,407 (23.58%)	6,815,746 (74.46%)	9,261,003
Observed Mortality/Deaths	208,556 (1.96%)	2,610,917 (24.53%)	7,823,960 (73.51%)	10,643,433
Observed-Expected Ratio (Disparity)	1.09	1.20	1.13	1.15

**Constructed with data in [6]*

Summary and Synthesis

These observations make a case for using multiple metrics (such as cause-specific mortality, hospitalization rates, and long-term COVID-19 sequelae) in assessing the pandemic mortality impact. Such triangulation of findings from various indicators can lead researchers beyond a one-dimensional and potentially misleading proxy such as excess mortality. In particular, systematic integration of confidence intervals, scenario analyses, and comparison to alternative modeling approaches with well-established assumptions would enhance the robustness and interpretability of results.

The current availability of comprehensive death registries, COVID-19-specific mortality data, and cause-of-death statistics should take precedence over purely model-based excess mortality estimates. Observed data should guide adjustments or recalibrations of models to deliver the best results rather than an over-reliance on forecasts. Future analyses should routinely involve goodness-of-fit, heteroscedasticity, and temporal dependence and more flexible model structures.

CONCLUSION

Emerging data when a new pandemic breaks should be the basis for decision making rather than a recourse to predictive models whose utility are high only when new data are yet to be available. Such predictive models may be inappropriate in capturing the uncertainties and dynamics of an evolving pandemic as COVID-19 clearly show when it was predicted as catastrophic in Sub–Saharan Africa despite early pre-vaccine data showing otherwise. Additionally, a lack of establishing distributional assumptions underpinning any model casts aspersions on the quality of inference that could be extracted from such analysis.

Predictive models serve as a guide and their projections can be helpful when an epidemic is unfolding. However, where data become available, the observed results must take greater precedence over forecasted values, as the issue of under-reporting (in the case of COVID-19 deaths) may be less debilitating than basing policy response on a *one-cap-fits-all* predictive model, which in itself suffers several deficiencies. In assessing the impact of COVID-19 (or any public health emergency), other metrics in addition to the death counts should be utilized. These statistics, when combined with relevant auxiliary information, offer a better view of the pandemic impact rather than reliance on a subjective and potentially misleading metric such as the *excess death*.

AUTHORS CONTRIBUTION

EOO and NAI are joint first authors.

ACKNOWLEDGEMENT

This work was self–funded; and we have no conflict of interest to declare.

DEDICATION

This work is dedicated to the memory of Dr. Patrick I Okoro (1940-2024).

REFERENCES

1. World Health Organization (2023) "Statement on the fifteenth meeting of the IHR (2005) Emergency Committee on the COVID-19 PANDEMIC " AVAILABLE AT: https://www.who.int/news/item/05-05-2023-statement
2. Leon DA, Shkolnikov VM, Smeeth L, Magnus P, Pecholdova M, and Jarvis CI (2020). Covid-19: a need for real-time monitoring of weekly excess deaths. *The Lancet*, 395, e81
3. Excess mortality during the Coronavirus pandemic (COVID-19). World Health Organization (WHO, 2023). Methods for estimating the excess mortality associated with the COVID-19 pandemic. Published August 4, 2023. Accessible online via https://www.who.int/publications/m/item/methods-for-estimating-the-excess-mortality-associated-with-the-covid-19-pandemic
4. Gibson J (2024), Cumulative excess deaths in New Zealand in the COVID-19 era: biases from ignoring changes in population growth rates , New Zealand Economic Papers ,58:1,95-106, DOI :10.1080/00779954-2024.2314770
5. Karlinsky A and Kobak D (2021). Tracking excess mortality across countries during the COVID-19 pandemic with the World Mortality Dataset. *Elife,* 10: e69336
6. Faust JS, Renton B, Bongiovanni T, et al. (2024) Racial and ethnic disparities in age-specific all-cause mortality during the COVID-19 pandemic. *JAMA Network Open.* 2024; *7*(10):e2438918. doi:10.1001/jamanetworkopen.2024.38918
7. Mathieu E, Ritchie H, Rodes-Guirao L, Appel C, Giattino C, Hasell J, Macdonald B, Dattani S, Beltekian D, Ortiz-Ospina E, and Roser M (2020). Coronavirus Pandemic (COVID-19). Published online at ourWorldinData.org. Retrieved from: https://ourworldindata.org/coronavirus
8. Okoro EO and Ikoba NA (2024) "Error in data interpretation in the Table of Article " Leading Causes of Death in the US, 2019-2023" Correction on:

ISSN 2282-0930 • Epidemiology Biostatistics and Public Health - 2024, Volume 19, Issue 2

Ahmad et al JAMA 2024, 332 (12),957-958 submitted on October 22, 2024, Posted online October 29, 2024. Accessed via https://www.jamanetwork.com/journals/jamaarticle-abstract/282207
9. Cameron AC, Trivedi PK (1998). Regression Analysis for Count Data. Cambridge University Press, Cambridge, United Kingdom.
10. United Nations, Department of Economic and Social Affairs, Population Division (2022). World Population Prospects 2022, Online Edition.
11. Ahmad FB, Cisewski JA, Anderson RN (2024), Leading Causes of Death in the US, 2019-2023, JAMA 332 (12): 957-958.doi.10.1001/jama.2024.15563
12. Curtin SC, Tejada-Vera B, Bastian BA (2024). Deaths: Leading causes for 2021. *National Vital Statistics Reports;* vol 73 no 4. Hyattsville, MD: National Center for Health Statistics. DOI: https://dx.doi.org/10.15620/cdc/147882.
13. Pizzato M, Gerli AG, La Vecchia C, Alicandro G (2024). Impact of COVID-19 on total excess mortality and geographic disparities in Europe, 2020-2023: a spatio-temporal analysis. *The Lancet Regional Health - Europe,*44: 100996; DOI: https://doi.org/10.1016/j.lanepe.2024.100996