How do pandemics end? Two decades of recurrent outbreak risk following the main waves

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Abstract

We analyse the dynamic evolution of disease outbreak risk after the main waves of the 1918-19 "Spanish flu" pandemic in the US and in major cities in the UK, and after the 1890-91 "Russian flu" pandemic in England and Wales. We compile municipal public health records and use national data to model the stochastic process of mortality rates after the main pandemic waves as a sequence of bounded Pareto distributions with an exponentially decaying tail parameter. In all cases, we find elevated mortality risk lasting nearly two decades. An application to COVID-19 under model uncertainty shows that in 80% of model-predicted time series, the annual probability of outbreaks exceeding 500 deaths per million is above 20% for a decade, remaining above 10% for two decades.

Introduction

Pandemics are large negative system-wide shocks, affecting humans via increases in health and income risk, as well as reductions in income and welfare.1-5 However, pandemics are not one-off events. They typically have several waves spanning more than one year. Moreover, following the main waves, recurrent outbreaks may occur due to re-introduction of the virus, new variants, waning immunity, human behaviour (e.g. vaccine refusal), or population turnover leading to reductions in population-level immunity.6-9 Researchers from a range of relevant disciplines have expressed concern about increased mortality and disease outbreak risk post-COVID-19 in academic outlets6,7,10 and in the media.11,12

The potential for elevated mortality, and sizeable disease outbreaks, after the main waves of the pandemic, combined with their importance for health and socioeconomic outcomes,12,13-15 imply that empirical evidence on medium-run mortality risk is required to aid the modelling of its health and economic implications. A characterisation of mortality risk dynamics is essential to understand the risk exposure that societies and economies face after exiting the main pandemic waves and the speed at which this risk fades in the decades that follow the pandemic. Evidence from pandemics from a period without the recent advances in medicine, public health and technology is particularly valuable in this respect. It is important because it can shed light on the underlying epidemiological risk after the main waves of the pandemic before the effect of modern means of intervention, and thus highlight the potential gains from such preventive and mitigating intervention.

Post-pandemic mortality rates

To analyse mortality risk in the period following the main waves of previous pandemics, we compiled data on mortality rates from influenza for eight large municipalities from across the UK, for England and Wales combined, and for the US (Figure 1). We collected city-level data on annual influenza mortality rates between 1895 and 1950 from public health records kept at the municipal level in the UK, namely the Medical Officer for Health (MOH) reports (see Supplementary Material A for more details).

Focusing first on the eight large British municipalities, the main insight from Figure 1 is that mortality rates are higher and more variable for a long period after the 1918-19 pandemic than prior to it. Although the most striking feature is the massive increase in mortality in 1918 and 1919 due to the main pandemic waves, we also observe spikes of high mortality in the series post-1920 that continue for an extended period. This feature implies increased disease outbreak risk. Although rates during these outbreak years are lower than those of 1918 and 1919, they are significantly higher than those before 1918 and those two decades later. Contemporary expert evaluations by the Medical Officer for London also identify 1922, 1924, 1927, 1929, 1933 and 1937 as years of elevated mortality from influenza (see Supplementary Material A).

We also examine post-pandemic disease outbreaks using national-level data. Figure 1 also shows the mortality rate from influenza for the US between 1900 and 1950. The same pattern as that observed for the UK municipalities emerges. Finally, using data on influenza mortality for England and Wales, we find a similar pattern of increased disease outbreaks following the aftermath of the 1890-91 “Russian Flu” pandemic. This pandemic began in the latter part of 1889 and claimed over 1 million lives worldwide, making it one of the most significant global pandemics of the time.19,20 Revisiting the first four rows of Figure 1, the spikes in mortality in the last decade of the 19th century and first decade of the 20th century are thus probably related to the increased risk following the 1890-91 pandemic.

Dynamics of mortality risk after the main pandemic waves

Here we conduct modelling analysis of the dynamic evolution of mortality risk after the main pandemic waves, particularly the level of disease outbreak risk and the speed at which it fades, conditional on the mortality effect of the main waves. We model the time series of mortality rates after the main waves of a pandemic as outcomes drawn from a sequence of bounded Pareto distributions such that mortality risk and the probability of large outbreaks declines over time relative to the impact of the initial waves. We choose the bounded Pareto distribution to model mortality risk in any given year because the size of epidemics and outbreaks has been shown to be highly over-dispersed, and is therefore well modelled by a fat-tailed distribution such as a bounded Pareto.21 We focus on the period following the main pandemic waves and assume that the inverse of the tail index of the bounded Pareto distributions decays exponentially after the main waves of the pandemic. The mortality effect of the main waves is reflected in the choice of the bounds of the Pareto distribution. Denote the mortality rate in year $t$ by $\mu_t$, for $t$, where the time period refers to for the eight cities in the UK and the US with reference to the 1918-19 pandemic, and to for England and Wales with reference to the 1890-91 pandemic. In each year, mortality rates are drawn from a bounded Pareto distribution...
where $\alpha_t > 0$ is the time varying Pareto tail index, and $d_l > 0$ and $d_u > d_l$ are, respectively, lower and upper bounds. Defining $\eta_t = \frac{1}{\alpha_t}$ we assume that

$$\eta_t = \eta_0 e^{-\lambda t},$$

where $\lambda > 0$ determines the rate at which the inverse tail index decays over time, while $\eta_0$ sets the initial level of the probabilities by providing the initial value. Conditional on the time process in (2), and thus conditional on the sequence $(\alpha_t)_{t=0}^{\infty}$, $d_t$, is independently distributed over time following (1). We fit the model to the data after the main pandemic waves, taking as given the main pandemic event and its experience. Compared with the main pandemic event, recurrent outbreaks imply lower mortality, so that we set the upper bound of mortality rates to the mortality rate of 1918 in each city. Similarly, the lower bound of mortality is determined by the lowest mortality experienced in the longer-run in each city, i.e. background influenza mortality. As explained in Methods, our main results are robust to modelling $d_l$ and $d_u$ as the theoretical upper and lower bounds of mortality rates, but by exploiting information pertinent to the pandemic in parameterising $d_l$ and $d_u$, the model provides more accurate mortality risk predictions. Moreover, by letting these bounds differ between cities, we allow for differences in the mortality of the main pandemic waves, as well as in latent socioeconomic and public health conditions, to influence risk dynamics. Therefore, the modelling allows for heterogeneity in risk dynamics between geographical units and periods. In turn, this permits applications to predict medium-run mortality risk after the main waves of other pandemics, by conditioning on an upper and lower bound that are relevant for the pandemic and disease in question. Models were fitted to the data using maximum likelihood (see Supplementary Material B).

Figure 2 shows the time series of data points overlaid on model simulations, confirming that most observations are contained within the interquartile range of simulated outcomes. Observed outcomes outside these bounds are indeed those of the rarer events: the very large outbreak of 1929, and outbreaks in the later decades that are thus less affected by the modelled pandemic. Model predictions for the US, and England and Wales following the 1890-91 pandemic are also consistent with this pattern (Supplementary Material C, Figure S10).

Fitting the models to the data, we obtain the time series of distributions of mortality rates between 1920 and 1950. From these, we can calculate the probability of specific mortality rates in a given year. In particular, we can compute the time series of disease outbreak risk by defining a disease outbreak as mortality above a threshold. For the 1918-19 pandemic, we define two disease outbreak thresholds at 500 or at 1000 deaths per million. The first is about one-third the rate of the main waves (1918 and 1919) and significantly higher than any mortality rate between 1900 and 1918 (i.e. after the 1890-91 pandemic effects had died out). A death rate of 500 per million corresponds to that observed during the main waves of the 1890-91 pandemic and its recurrent outbreaks. This threshold identifies as outbreaks in the data post-1920, the same years as those described as being of exceptionally high mortality in the MOH reports for London. The 1000 threshold corresponds to recurrent disease outbreaks approaching the levels experienced in some cities during the main pandemic waves and approximately that of the severe 1929 outbreak. More generally, the 1000 threshold identifies particularly severe disease outbreaks that were possible given the dynamic process for mortality risk, even if unrealised ex post. Similar patterns are observed for the 1890-91 pandemic in England and Wales, which had lower mortality (Supplementary Material C, Figure S11).

We plot the post-1918-19 disease outbreak probabilities in Figure 3. Two main qualitative results stand out. First, the probability of a disease outbreak remains high for about two decades after the main pandemic waves. Disease outbreak risk does not decline exponentially, but instead there is a very low rate of decline for a prolonged period. During the transition to background influenza mortality, outbreaks with severe mortality can occur with relatively high probability. Second, the pattern of the time evolution of risk is similar across all cities and for the US. This pattern holds despite considerable differences between the geographical units that we study in the severity of the impact of the pandemic during the main waves (Figure 1) and in differences in background influenza mortality. Comparing the results for the two different thresholds, the dynamic pattern for all geographical units and the two pandemics in our data remains, despite the naturally higher outbreak probabilities for the lower threshold.

**Discussion: Lessons From The Past For The Present**

The similarity of the pattern of disease outbreak dynamics across geographic units with different socioeconomic characteristics and two historical pandemics highlights the generality of our finding that mortality risk remains elevated for a prolonged period after the main pandemic waves and motivates using the statistical model to predict mortality after the main waves of pandemics in the 21st century. The world in the 21st century is, if anything, more connected and densely populated than the world of more than one hundred years ago. Therefore, it is likely that without systematic intervention and the benefit of medical and scientific progress, pandemics in the modern world also have the potential to lead to a period of high and persistent mortality and disease outbreak risk.

We use the historical mortality risk estimates to simulate mortality dynamics after the main waves of COVID-19, allowing for model uncertainty. Figure 4 shows model predictions regarding the probabilities of disease outbreaks (mortality rates exceeding 500 and 1000 per million) from a counterfactual analysis of disease outbreak risk after the main waves of COVID-19. We set the upper bound on future mortality to be determined by mortality in the UK in 2020 and the lower bound to reflect mortality in the non-pandemic state in the coming decades, which we approximate by background influenza mortality pre-2020. The results demonstrate elevated disease outbreak risk for two decades.

To obtain the model predictions in Fig. 4, we allow for model uncertainty. In particular, we allow for uncertainty about which sequence of distributions in $(PD)_t$ generates the data; this uncertainty is different from the epidemiological uncertainty regarding mortality rates that is generated by a given sequence of distributions. To account for uncertainty regarding the dynamic path of disease outbreak risk (given the bounds for the Pareto distributions), we
use the range of values of $\eta_0$ and $\Lambda$ across the different geographical units to approximate the joint distribution of possible parameter values. Then, we calculate the disease outbreak probabilities for one million draws and plot in Fig. 4 relevant percentiles of the distribution of disease outbreak probabilities over possible data generating processes. In 90% of model-predicted dynamic paths, the probability of outbreaks exceeding 500 deaths per million, which is 20 times higher than that of seasonal influenza, is above 20% for a decade and remains above 10% for two decades. Regarding outbreaks that come closer to the size of the main wave mortality, we find that in 80% of model-predicted dynamic paths, the probability of outbreaks exceeding 1000 deaths per million is above 10% for a decade.

Our findings can inform research to understand the implications of pandemics for a range of health and socioeconomic outcomes by quantifying post-pandemic mortality risk and its persistence over time. Disease outbreak risk generates health and economic uncertainty which has significant and unequal consequences for socioeconomic outcomes across the population. Given that disease outbreaks imply a deterioration in health outcomes that is not symmetric across the population\textsuperscript{1,2,13,14}, a period of increased disease outbreak risk implies the possibility of repeated negative shocks to health and health inequality. Moreover, outbreak risk generates social, political and economic uncertainty, stemming from possible impacts of the disease itself and of containment measures on economic activity. Increased aggregate-level uncertainty impacts economic decision-making, income inequality and economic fluctuations, either directly or via increased idiosyncratic risk\textsuperscript{22–26}.

Medicine, public health, technology, and better-informed and prepared policy intervention offer the opportunity in the modern world to confront post-pandemic recurrent outbreak risk better than a century ago. In this sense, our findings regarding the potential severity of disease outbreak risk for many years after a pandemic highlights the value of scientific and medical developments to mitigate these, and more generally of prevention and policy preparedness to mitigate disease outbreaks even after exiting the main pandemic waves.

Declarations

Conflicts of interest

The authors declare no conflicts of interest.

Data availability

The municipal level dataset generated during the current study are available on GitHub at https://github.com/maxschr90/Schroeder-et-al.-2021–How-long-do-pandemics-last. Data for the US and for England and Wales are available from original publications, as described and referenced in the caption of Figure 1.

Code availability

Code is freely available on GitHub at https://github.com/maxschr90/Schroeder-et-al.-2021–How-long-do-pandemics-last.

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**Figures**
Mortality rate in deaths per million population. The upper y-axis tick indicates the maximum mortality rate for each data series. Data for UK cities are taken from Medical Officer for Health reports. Data for US is taken from Lindner and Grove (1943)10 and Grove and Hetzel (1968).11 Data for England & Wales are taken from Langford (2002).12 Table S2. Information on population sizes and densities is provided in Table S2.

Figure 1
Annual mortality rate from influenza

Simulated median (solid black line), interquartile range (dark shading) and 80% prediction interval (light shading) are based on 1m random draws. Simulated outcomes are based on the model fitted using the average mortality rates across cities. Data are overplotted in red. Data for UK cities are taken from Medical Officer for Health reports.

Figure 2
Model predicted influenza mortality rates following the 1918-19 pandemic
Figure 3

Outbreak risk following the 1918-19 pandemic

Simulated median (solid black line), interquartile range (dark shading) and 80% prediction interval (light shading) are based on 1m random draws. Outbreak probabilities computed from model parameterisations that are drawn from a distribution of $\eta_0$ and $\lambda$ implied by the models fitted to historical data ($d_c = 1858, d = 24$).

Figure 4

Predicted outbreak risk following the 2020-21 pandemic

Supplementary Files

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- SupplementaryMaterial.docx