Historical trends demonstrate a pattern of increasingly frequent and severe spillover events of high-consequence zoonotic viruses

Amanda Jean Meadows, Nicole Stephenson, Nita K. Madhav, Ben Oppenheim

ABSTRACT
The COVID-19 pandemic has focused attention on patterns of infectious disease spillover. Climate and land-use changes are predicted to increase the frequency of zoonotic spillover events, which have been the cause of most modern epidemics. Characterising historical trends in zoonotic spillover can provide insights into the expected frequency and severity of future epidemics, but historical epidemiological data remains largely fragmented and difficult to analyse. We utilised our extensive epidemiological database to analyse a specific subset of high-consequence zoonotic spillover events for trends in the annual frequency and severity of outbreaks. Our analysis, which excludes the ongoing SARS-CoV-2 pandemic, shows that the number of spillover events and reported deaths have been increasing by 4.98% (confidence interval [CI]95% [3.22%; 6.76%]) and 8.7% (CI 95% [4.06%; 13.62%]) annually, respectively. This trend can be altered by concerted global efforts to improve our capacity to prevent and contain outbreaks. Such efforts are needed to address this large and growing risk to global health.

INTRODUCTION
The impact of COVID-19 and other contemporary epidemics on human health and livelihoods has highlighted the need to better understand trends in infectious disease spillover. Zoonotic viral pathogens cause most modern epidemics, as they jump from wildlife or domesticated animals to humans through hunting, habitat encroachment, and intensive livestock farming among other activities. Climate change and other forms of anthropogenic environmental change are predicted to increase the frequency of zoonotic spillover events, while increasing human population density and connectivity facilitate the spread of the outbreaks that occur. Yet there is limited empirical data on the frequency of zoonotic spillover and its variability over time, which makes it challenging to determine its implications for global health.

WHAT IS ALREADY KNOWN ON THIS TOPIC
⇒ The devastating impact of contemporary zoonotic spillover-driven epidemics, such as COVID, on human health and livelihoods has highlighted the need to better understand trends in infectious disease spillover.
⇒ Although the frequency of spillover-driven epidemics is predicted to increase as a result of human-driven climate and environmental change, the magnitude of its implications for global health in the future is difficult to characterise given the limited empirical data on the frequency of zoonotic spillover, and its variability over time.

WHAT THIS STUDY ADDS
⇒ This study draws on an extensive epidemiological database to examine a specific subset of zoonotic spillover events for trends in the frequency and severity of outbreaks.
⇒ We find the number of outbreaks and deaths caused collectively by this subset of pathogens (SARS Coronavirus 1, Filoviruses, Machupo virus, and Nipah virus) have been increasing at an exponential rate from 1963 to 2019.
⇒ If the trend observed in this study continues, we would expect these pathogens to cause four times the number of outbreaks and 12 times the number of deaths in 2050, compared with 2020.

HOW THIS STUDY MIGHT AFFECT RESEARCH, PRACTICE OR POLICY
⇒ This study suggests the series of recent impactful spillover-driven epidemics are not random anomalies, but follow a multi-decade trend in which epidemics have become both larger and more frequent.
⇒ These findings provide additional evidence that concerted global efforts to improve our capacity to prevent and contain outbreaks are urgently needed to address this large and growing risk to global health.

This study suggests the series of recent impactful spillover-driven epidemics are not random anomalies, but follow a multi-decade trend in which epidemics have become both larger and more frequent. These findings provide additional evidence that concerted global efforts to improve our capacity to prevent and contain outbreaks are urgently needed to address this large and growing risk to global health.
The data required to characterise these trends remains fragmented, making analysis of long-term trends difficult (but see Marani et al, and Jones et al[7,8]). In this study, we leverage our extensive epidemiological database[9,10] to examine a specific subset of zoonotic spillover events for trends in the frequency and severity of outbreaks. This database covers epidemics reported by the WHO in the form of Disease Outbreak News reports (WHO DON), outbreaks occurring since 1963 that were caused by a viral pathogen that resulted in 50 or more deaths, and historically significant outbreaks such as the 1918 and 1957 influenza pandemics.

Emerging zoonotic viruses that subsequently spread from human to human are the focus of this analysis because they were the cause of most 20th century pandemics, and account for 60% of all emerging human diseases.[8] After applying specific exclusion criteria (table 1) intended to limit the impact of surveillance bias on possible increasing trends in outbreak frequency and severity, we specifically focus our analysis on Filoviruses (Ebolavirus, Marburg virus), SARS Coronavirus 1, Nipah virus, and Machupo virus. These pathogens are of high-consequence, defined here as the potential to pose a significant risk to public health, economic, or political stability.

**METHODS**

We drew on a historical database of over 3150 outbreaks and epidemics,[9] assembled according to the practices outlined in Badker et al[10] (also see online supplemental methods, which describe the data collection process) to analyse the temporal trend in the number of outbreaks and number of deaths caused by the selected emerging zoonotic viral pathogens which met the described criteria. We chose the number of deaths associated with an outbreak as a measure of outbreak severity because death data are typically more reliably reported than case count data, as asymptomatic or under-ascertained cases are not usually included in official case counts[11] and data on hospitalisations is often unavailable. The database has global coverage of infectious disease events from 1963 to the present; we focused on the time period from 1963 to 2019 for this analysis.

To model the temporal trend in the annual number of outbreaks and number of reported deaths, we fitted Poisson and negative binomial models and compared model fit using the Akaike information criterion (AIC). A negative binomial model was explored in addition to the Poisson because of the overdispersion in the data[12] owing to many years of zero outbreaks or deaths, coupled with fewer years of large mortality events during the study period. All data and code used to perform this analysis

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**Table 1**  Pathogen exclusion criteria

<table>
<thead>
<tr>
<th>Exclusion criterion</th>
<th>Rationale</th>
<th>Exclusion examples</th>
</tr>
</thead>
<tbody>
<tr>
<td>Has caused 100 or more annual cases for five consecutive years</td>
<td>Reporting effort for endemic pathogens varies substantially by country and throughout time, with endemic diseases in low-income countries often being significantly underreported.[25] Advances in public health capacity, surveillance technology, and surveillance effort over time could show an increase in outbreaks and deaths caused by these pathogens without a true increase in their occurrence.</td>
<td>MERS Coronavirus, Lassa virus, Monkeypox virus, Hantavirus</td>
</tr>
<tr>
<td>Fewer than 50 reported deaths</td>
<td>Pathogens that have caused minimal human mortality are generally not prioritised for diagnostic testing development and surveillance. These pathogens are more likely to go undetected; however, advances in healthcare and diagnostic technology are likely to increase the probability of detecting a spillover event over time. This criterion also excludes most non-vector-borne pathogens that have no documented human-to-human transmission, as the focus of this study is on pathogens that may cause significant epidemics.</td>
<td>Hendra virus, Lujo virus, Whitewater Arroyo virus</td>
</tr>
<tr>
<td>Vector-borne</td>
<td>The mechanism of spillover for vector-borne pathogens is different from non-vector-borne pathogens and may be influenced by different factors. Additionally, vector control/eradication programmes are likely to influence the frequency and severity of vector-borne pathogen spillover events.</td>
<td>Venezuelan equine encephalitis, Crimean-Congo haemorrhagic fever virus, Zika virus</td>
</tr>
<tr>
<td>Influenza</td>
<td>There are specifically targeted influenza surveillance programmes that have increased significantly over the time period being analysed[26] which could confound any temporal increase seen in spillover events or number of deaths.</td>
<td>2009 H1N1 pandemic</td>
</tr>
</tbody>
</table>
are available in our data and code repository (https://github.com/concentricbyginkgo/zoonotic_spillover_trend).

Surveillance bias poses a central challenge to assessing the rate of disease spillover from one period of time to another: an increasing trend may simply reflect stronger capacity to identify and report spillover events. There are no robust, direct measures of global reporting capacity and effort which can be taken into account, and only limited proxy measures (eg Jones et al.,8).

To address potential sources of bias, we applied exclusion criteria to identify pathogens and outbreak types which are less likely to be confounded by changes in reporting (table 1). We focused on viruses that spill over directly from the wildlife host to humans. Since endemic viruses or those that spill over frequently are not the focus of this study, we excluded any viruses which had caused 100 or more cases annually for five or more consecutive years. This criterion mainly led to the exclusion of endemic viruses that have been known long before this study period (eg, Hantaviruses and Lassa virus), but were endemic viruses or those that spill over frequently are not the focus of this study, we excluded any viruses which had caused 100 or more cases annually for five or more consecutive years. This criterion mainly led to the exclusion of endemic viruses that have been known long before this study period (eg, Hantaviruses and Lassa virus), but were not named and reported until the study period.13 14

Additionally, to limit the inclusion of rare and/or incidentally discovered non-pathogenic viruses, we included only viruses that have caused a total of 50 or more human deaths. This criterion screens out viruses that are likely to be detected now, but may have been missed in previous decades due to poorer diagnostic technology.

Influenza and vector-borne pathogens were also excluded, due to significant differences in disease emergence and reporting patterns which include large, specifically targeted surveillance programmes that have increased significantly over the time period being analysed.

The viruses that were included in this analysis were epidemic Filoviruses (Ebola, Marburg), SARS Coronavirus 1, Nipah virus, and Machupo virus. We considered all known zoonotic viruses within the 25 high-priority viral families as designated by the Global Virome Project.15 If the virus was not represented in our epidemiological database,9 we performed an additional literature search for epidemiologically linked cases or as defined in the original source.

For the viruses that met our inclusion criteria, we identified a total of 75 spillover events occurring in 24 countries from 1963 to 2019, causing a total of 17232 deaths from 1963 to 2019 (table 2; figure 1). Events were defined as epidemiologically linked cases or as defined in the original source.

We used the negative binomial model to fit the historical trend in reported outbreaks and reported deaths. Although AIC showed a similar fit of the negative binomial and Poisson models to the number of reported outbreaks, it supported the use of the negative binomial over the Poisson for reported deaths (table 3). For consistency, we chose to use the negative binomial model for both outcomes despite the similar fit of the negative binomial and Poisson models for the number of reported spillover events. The model results show a significant annual increase in the number of reported outbreaks and reported deaths caused by the selected viral zoonotic pathogens (table 3).

The fitted negative binomial models estimate that the number of reported outbreaks has been increasing by 4.98% (CI95%[3.22%; 6.76%]) annually, while the number of reported deaths has been increasing by 8.7% (CI95%[4.06%; 13.62%]) annually (figure 2). If these annual rates of increase continue, we would expect the analysed pathogens to cause four times the number of spillover events and 12 times the number of deaths in 2050 than in 2020.

The outlier point present in figure 2 corresponds to the West Africa Ebola outbreak, which is a high

### Table 2 Number of outbreaks and deaths caused by the selected viruses from 1963 to 2019.

<table>
<thead>
<tr>
<th>Virus group</th>
<th>Viruses</th>
<th>Outbreaks</th>
<th>Deaths</th>
<th>Main continent(s) impacted</th>
</tr>
</thead>
<tbody>
<tr>
<td>Filoviruses</td>
<td>Marburg virus,</td>
<td>40</td>
<td>15771</td>
<td>Africa</td>
</tr>
<tr>
<td></td>
<td>Ebolaviruses</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Epidemic coronaviruses</td>
<td>SARS Coronavirus 1</td>
<td>2</td>
<td>922</td>
<td>Asia</td>
</tr>
<tr>
<td></td>
<td>(SARS-CoV-1)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Other</td>
<td>Machupo virus,</td>
<td>33</td>
<td>529</td>
<td>South America (Machupo virus),</td>
</tr>
<tr>
<td></td>
<td>Nipah virus</td>
<td></td>
<td></td>
<td>Asia (Nipah virus)</td>
</tr>
</tbody>
</table>
leverage point in the time series. Exclusion of this event still results in a significant, although smaller, increasing trend in annual deaths (5.13% annual increase; p=0.009).

**DISCUSSION**

We found the number of outbreaks and deaths caused by SARS Coronavirus 1, Filoviruses, Machupo virus, and Nipah virus have been increasing at an exponential rate from 1963 to 2019. This finding supports other studies that have found significant increases in the frequency of emerging infectious disease outbreaks, and further suggests that outbreaks are becoming more severe. If the trend we observe in this study continues, we would expect to see these pathogens cause four times the number of spillover events and 12 times the number of deaths in 2050, compared with 2020. We believe this is a conservative estimate for two main reasons: 1) we applied strict inclusion criteria for pathogens in this analysis, resulting in a trend that is less likely to be an artefact of advances in surveillance and detection capacity over the study period; and 2) we omitted the ongoing COVID-19 pandemic, which is several orders of magnitude larger than other events, from the trend analysis (see online supplemental data).

Our evaluation of the historical evidence suggests that the series of recent epidemics sparked by zoonotic spillover are not an aberration or random cluster, but follow a multi-decade trend in which spillover-driven epidemics have become both larger and more frequent. The continuation of this trend would represent a potentially large increase in global infectious disease risk and burden in terms of loss to human health and livelihoods. However, actions can be taken to disrupt this trend, including by rallying global efforts to improve capacity to prevent and contain outbreaks. Recent proposals have ranged widely, from establishing systems for disaster risk financing to fund response measures, creating an intergovernmental panel on pandemic risk to quantify, track, and assess risk over time; addressing the drivers of pandemic risk, including deforestation and climate change; and advancing the technology and infrastructure needed to detect and respond to public health threats; including surveillance programmes at key sentinel nodes, using a mixture of active and passive surveillance modalities and tools.

Some of these proposals, particularly in the area of advancing infrastructure and technology, have been successfully implemented in response to COVID-19. For example, rapid development of messenger RNA vaccines, implementation of focused surveillance at key travel hubs and congregate settings such as schools and universities using passive wastewater testing and active testing, and genomic surveillance to detect emerging variants have all demonstrated immense value in improving resiliency to public health threats. The ultimate package of measures to support global prevention, preparedness, and resilience is not yet clear. What is clear, however, from the historical trends, is that urgent action is needed to address a large and growing risk to global health.

### Table 3

<table>
<thead>
<tr>
<th>Outcome</th>
<th>Model form</th>
<th>Estimate</th>
<th>SE</th>
<th>P</th>
<th>AIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Reported outbreaks</td>
<td>Poisson</td>
<td>0.0479</td>
<td>0.0083</td>
<td>&lt;0.001</td>
<td>153.35</td>
</tr>
<tr>
<td></td>
<td>Negative binomial</td>
<td>0.0486</td>
<td>0.0086</td>
<td>&lt;0.001</td>
<td>155.17</td>
</tr>
<tr>
<td>Reported deaths</td>
<td>Poisson</td>
<td>0.110</td>
<td>0.0009</td>
<td>&lt;0.001</td>
<td>62.430.1</td>
</tr>
<tr>
<td></td>
<td>Negative binomial</td>
<td>0.0838</td>
<td>0.0224</td>
<td>&lt;0.001</td>
<td>457.1</td>
</tr>
</tbody>
</table>

AIC, Akaike information criterion; P, P-value; SE, standard error.
Figure 2  The annual number of reported outbreaks (A) and deaths (B) caused by Filoviruses, SARS Coronavirus 1, Machupo virus, and Nipah virus from 1960-2019 (points). The grey line shows the fitted temporal trend; the navy blue dashed lines show ±95% CI. Note the break in the y-axis in panel B which was added to increase visibility of the trend.

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Acknowledgements  We wish to thank Ben Ash, Rinette Badker, Anne Bucher, Liz Cey, Amanda Grassman, Dean Jamison, Cathine Lam, Melissa Leah, Christopher Ngion, Chris Pardee, Andrew P Rothsstein, John-Ann Rottingen, Patrick Savage, Thamar Shannugaramnam, Birgitte Sime, Vikram Sridharan, Lawrence Summers, Swati Sureka. Preliminary results and figures from this analysis were included in the G20 High-Level Independent Panel Report on Financing the Global Commons for Pandemic Preparedness and Response (see: https://pandemic-financing.org).

Contributors  NKM, BO, and NS conceptualised the study. AJM performed all analyses and led manuscript writing. All authors contributed to the study design, writing, and reviewing the manuscript. All authors reviewed and approved the final manuscript.

Funding  The authors have not declared a specific grant for this research from any funding agency in the public, commercial or not-for-profit sectors.

Map disclaimer  The inclusion of any map (including the depiction of any boundaries therein), or of any geographic or locational reference, does not imply the expression of any opinion whatsoever on the part of BMJ concerning the legal status of any country, territory, jurisdiction or area or of its authorities. Any such expression remains solely that of the relevant source and is not endorsed by BMJ. Maps are provided without any warranty of any kind, either express or implied.

Competing interests  None declared.

Patient and public involvement  Patients and/or the public were not involved in the design, conduct, or reporting, or dissemination plans of this research.

Patient consent for publication  Not applicable.

Ethics approval  Not applicable.

Provenance and peer review  Not commissioned; externally peer reviewed.

Data availability statement  Data are available in a public, open access repository. All data and code used to perform this analysis are available in our data and code repository (https://github.com/concentricbyginkgo/zoonotic_spillover_trend).

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