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Impact of Climate and Public Health Interventions on the COVID-19 Pandemic: Prospective Cohort Study

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Abstract

BACKGROUND:

It is unclear whether seasonal changes, school closures or other public health interventions will result in a slowdown of the current COVID-19 pandemic.

METHODS:

We performed a prospective cohort study of all 144 geopolitical areas worldwide (375,609 cases) with at least 10 COVID-19 cases and local transmission by March 20, 2020, excluding China, South Korea, Iran and Italy. Using weighted random-effects regression, we determined the association between epidemic growth (expressed as ratios of rate ratios (RRR) comparing cumulative counts of COVID-19 cases on March 27 with cumulative counts on March 20) and latitude, temperature, humidity, school closures, restrictions of mass gatherings, and measures of social distancing during an exposure period 14 days previously (March 7 to 13).

RESULTS:

In univariate analyses, there were little or no associations of epidemic growth with latitude and temperature, but weak negative associations with relative humidity (RRR per 10%, 0.91, 95%-CI 0.85 to 0.96) and absolute humidity (RRR per 5g/m^3, 0.92, 95%-CI 0.85 to 0.99). Strong associations were found for restrictions of mass gatherings (RRR, 0.65, 95%-CI 0.53 to 0.79), school closures (RRR, 0.63, 95%-CI 0.52 to 0.78), and measures of social distancing (RRR, 0.62, 95%-CI 0.45 to 0.85). In a multivariable model, there was a strong association with the number of implemented public health interventions (p for trend=0.001), whereas the association with absolute humidity was no longer significant.

INTERPRETATION:

Epidemic growth of COVID-19 was not associated with latitude and temperature, but may be associated weakly with relative or absolute humidity. Conversely, there were strong associations with public health interventions.

Introduction

Seasonality and climate-dependency of influenza are well established. Suggested mechanisms for the slowdown of influenza epidemics in summer months in temperate climates are related to higher temperature, higher humidity or higher solar radiation.[1] These three characteristics are all associated with geographic latitude, a measure that can be determined effortlessly and with precision. Another possible explanation for the slowdown of influenza epidemics during summer months is school closures for summer breaks.[2–4]

To slow the growth of the current Coronavirus Disease 2019 (COVID-19) pandemic, many countries are mandating school closures[5] and use other public health interventions, such as restrictions of mass gatherings, social distancing or closure of non-essential businesses. However, it is unclear whether these interventions, or seasonal changes mediated by climate[6] will impact the pandemic. We performed an analysis of the association of the current epidemic growth in geopolitical areas affected by COVID-19 to determine whether epidemic growth is associated with climate, school closures, or other public health interventions aimed at reducing contact rates in the population and thereby reducing transmission of SARS-CoV-2, the coronavirus driving the pandemic.[7–9]

Methods

Design

This was a prospective cohort study of geopolitical areas with documented COVID-19 outbreaks to determine the association of epidemic growth of COVID-19 during a pre-specified follow-up period (March 21 to March 27, 2020) with characteristics ascertained during an exposure period 14 days previously (March 7 to March 13, 2020). The time lag between exposure and follow-up was set to 14 days to reflect the assumed time between transmission of SARS-CoV-2[10] and reporting of confirmed COVID-19 cases (Figure 1).[11] Analyses were performed according to a pre-specified protocol. Results of a preliminary unpublished analysis, conducted according to protocol version 1.0, are summarized in protocol version 1.2 (available in Appendix). An explanation of protocol changes is provided in the supplementary methods in the Appendix.

Eligibility

We included all geopolitical areas (states in case of Australia and the United States, provinces in case of Canada, countries and overseas territories for the rest of the world) with at least 10 cases March 20, 2020 (reference) and documented local transmission according to the WHO's Situation Report 61.[12] China was excluded as its epidemic growth had decelerated and the outbreak appeared contained, suggesting it had progressed to the hyperendemicity phase of the epidemic curve. South Korea, Italy and Iran were excluded as their disease outbreak was fully established, being further ahead on the epidemic curve than the rest of the world, with the possibility to reach the hyperendemic state during the follow-up period.

Exposure

The exposure period was pre-specified to last from March 7 to March 13, 2020 (Figure 1). Geographic latitude was pre-specified as primary exposure variable, mean temperature, absolute humidity, school closures, restrictions of mass gatherings and measures of social distancing as secondary exposure variables. Latitude, mean temperature and mean relative humidity (to derive absolute humidity) were collected for the capital of each geopolitical area, data on school closures, restrictions of mass gatherings and measures of social distancing at the level of the geopolitical area. Absolute humidity describes the absolute water content in g/m^3, relative humidity describes absolute humidity relative to the maximum possible humidity in percent given the current temperature. We gave precedence to absolute humidity over relative humidity, as it was more strongly associated with influenza than relative humidity,[1] and showed less variation than relative humidity, but included relative humidity as a post-hoc exposure variable. Mean temperature and humidity were calculated for the entire exposure period, deriving arithmetic means across all available measurement timepoints (median 8 per day, interquartile range [IQR] 8 to 45).[13] For school closures, restrictions of mass gatherings, and measures of social distancing, we determined whether they were implemented by a pre-specified cutoff, mid workweek of the exposure period (Wednesday March 11, 2020).

Outcome

The analysis of confirmed cases[11] is complicated by potentially dramatic differences in detection and reporting of individuals infected with SARS-CoV-2,[14] which prevent a meaningful analysis of absolute event rates across different countries. Conversely, an analysis of epidemic growth,[15] which can be expressed in relative terms – a rate ratio comparing the current cumulative count of reported cases with the cumulative count of cases reported one week earlier – is likely to account for some of the variation in detection and reporting. This approach analyses the slope of the cumulative frequency rather than absolute rates, using each geopolitical area as its own comparison (Appendix, Figure S1). The follow-up period was pre-specified to last from March 21 to March 27, 2020 (Figure 1). The pre-specified outcome was epidemic growth defined as the rate ratio comparing the cumulative count of confirmed COVID-19 cases at the end of the follow-up period on March 27, 2020 with the cumulative count one week prior on March 20, 2020 (reference).

Additional covariates

Altitude, gross domestic product (GDP) per capita, health expenditure as percent of GDP, life expectancy, percentage of inhabitants aged 65 or over, the Infectious Disease Vulnerability Index,[16] urban population density, number of flight passengers per capita, closest distance to a country with already established epidemic (City of Wuhan, South Korea, Iran, Italy) were additional pre-specified covariates. Table S1 in the Appendix provides a justification for the choice of these covariates.

Data collection

Information on data sources is presented in Table S1 in the appendix. On March 28, 2020, we downloaded data covering the COVID-19 outbreak until March 27, 2020 from the online interactive dashboard hosted by the Center for Systems Science and Engineering at Johns Hopkins University, Baltimore.[11] The dashboard reports the cumulative number of cases daily at province level in China, at city or county level in Australia, Canada and USA, and at level of countries and overseas territories elsewhere.[11] The case data reported on the dashboard align with the daily WHO situation reports.[11,12] The data reported at city or county level for Australia, Canada and USA were aggregated to state or province level, overseas territories, such as Réunion or Guam were handled separately from their home country for the purpose of this study.

Temperature in °C and relative humidity were collected for the exposure period of March 7 to March 13, 2020 from a publicly accessible meteorological website,[13] with absolute humidity calculated from relative humidity and temperature for each measurement timepoint.[17] Data on school closures were obtained from UNESCO[18] and complemented with information on scheduled school holidays. Data on school holidays, restrictions of mass gatherings, and measures of social distancing were obtained by one out of 3 investigators (PJ, DG and a research assistant) from official school schedules, provisions and press releases of relevant administrative and governmental bodies, and newspaper articles, and checked by at least one other investigator (PJ or PB). Data on restrictions of mass gatherings and measures of social distancing were subsequently verified against timelines reported in the online encyclopaedia Wikipedia.[19] No documents were excluded based on language. Team members were able to read documents in English, German, Czech, Danish, Dutch, French, Greek, Italian, Portuguese, Slovak and Spanish directly. We used web-based translation services for remaining languages. Social distancing was defined as any measure that attempted to prevent small clusters of 10 individuals or less, such as strong recommendations or formal requirements of social distancing, closure of sit-in restaurants and bars, or closure of non-grocery stores.

The number of flight passengers per inhabitant was calculated from published passenger statistics of major airports.[20–22] Data on the highest urban density in major metropolitan areas of a geopolitical area was obtained from Demographia World Urban Areas[23] and complemented with data from the United States census.[24] Data on remaining covariates were obtained from the World Bank.[25] Latitude, altitude, temperature and humidity were collected for the capital of each geopolitical area, remaining covariates at the level of the geopolitical area. For Ecuador, we collected data for the de facto capital, Guayaquil.[25] The Infectious Disease Vulnerability Index[16] was only available at country level; therefore values of the home country were assigned to states, provinces and overseas territories. To make interpretation of the index more intuitive, we inverted it so that larger values indicate higher vulnerability to infectious diseases. All data were supplemented with publicly available information for overseas territories, states or provinces for the United States, Australia and Canada, and in case data was missing or implausible in the databases used, using the latest available information (Appendix, Table S1).

Statistical analysis

We used weighted random-effects regression[26] to determine the association between the log rate ratio of COVID-19 and exposure variables. Rate ratios were calculated as cumulative count of confirmed cases in a geopolitical area since the beginning of the epidemic as of March 27 divided by the cumulative count of confirmed cases since the beginning of the epidemic as of March 20 (Appendix, Figure S1). The observation time was identical across all areas. Since the populations in question were large, they could be considered equal at both time points and cancelled out in calculations of rate ratios. A rate ratio of 2 indicates that the number of cases in a geopolitical area doubled within one week. As the exposure period of March 7 to March 13 was near vernal equinox, no transformation was necessary to reflect the association of the log rate ratio of COVID-19 with the square of the latitude. Associations were expressed as ratios of rate ratios (RRR) per 400 degrees^2 increase in latitude, 5°C increase in temperature, 10% increase in relative humidity, 5g/m^3 increase in absolute humidity, and RRR comparing geopolitical areas with versus areas without implementation of school closures, restrictions of mass gatherings or measures of social distancing. The units of analysis were geopolitical areas; log rate ratios of COVID-19 (dependent variable) and exposure variables (independent variables) were defined at the level of geopolitical areas. An RRR below 1 indicates that an increase in one of the continuous exposure variables or the presence of a public health intervention is associated with a decrease in epidemic growth, with an RRR of 0.60 corresponding to a 40% relative reduction in epidemic growth.

We determined associations of epidemic growth with exposure variables in univariate analyses, and in different multivariable models and analysis sets to determine robustness of associations as pre-specified in the protocol (see Appendix). Then, we developed two parsimonious multivariable models. For Model 1, we first prioritized covariates on theoretical grounds and then used unsupervised cluster analysis for variable selection (Appendix, Table S2);[27] for Model 2 we used stepwise backward selection of covariates based on the adjusted R^2 statistic. We pre-specified that Model 1 would take precedence over Model 2, as it would not be at risk of overfitting. Cluster analysis indicated clustering of the three public health interventions (Appendix, Figure S2). We therefore derived a post-hoc composite of exposure to any of the three interventions. In addition, we pre-specified to perform tests for trend according to the number of public health interventions implemented (0, 1, or 2 or more) under the assumption that the RRRs for the association of epidemic growth with school closures, restrictions of mass gatherings or measures of social distancing would have the same direction and a similar magnitude. We forced major geographical regions (Asia, Oceania, Europe, Africa, Americas) into both models to account for the geographic progression of the pandemic. Analyses were performed in Stata, Release 14 (StataCorp, College Station, TX) and R (R Foundation for Statistical Computing, Vienna, Austria).

Results

144 geopolitical areas with 375,609 cases were included in our analyses (Appendix, Figure S3 and Table S3). The median COVID-19 case rate per 1-million inhabitants for the 144 geopolitical areas was 87.6 (IQR 31.9 to 193.7), the median rate ratio representing epidemic growth was 3.56 (IQR 2.41 to 4.66, Table 1). Most geopolitical areas were in the northern hemisphere, near sea-level, with temperate climates. The median temperature was 12.8 °C (IQR 7.3 to 21.2), the median relative humidity was 69.0% (IQR 60.3 to 76.6), and absolute humidity was 7.1 g/m3 (IQR 5.1 to 10.8). Temperature was strongly associated with the square of the latitude, and to a lesser extent, so was absolute humidity; relative humidity was not associated (Appendix, Figures S4 to S6). Thirty-eight geopolitical areas had at least one public health intervention implemented by March 11, 2020, with 24 areas having 1 implemented (16.7%), and 14 areas having more than one intervention (9.7%); the remainder had no public health interventions in effect (73.6%). The implementation of public health interventions was correlated (Appendix, Figure S2). The median percentage of the population 65 years old or older was 14.0%, the median life expectancy at birth was 79 years, on average 9.2% of gross domestic products was spent on health (IQR 6.3% to 13.5%), and the median distance to the closest established epidemic was 4,300 km (IQR 1,300 to 8,000; Table 1).

In univariate analyses (Figure 2), there was no association between epidemic growth and latitude (ratio of rate ratios (RRR) per 400 degrees^2 increase, 0.99, 95%-CI 0.96 to 1.03, p=0.72) or mean temperature (RRR per 5°C increase, 0.97, 95%-CI 0.93 to 1.02). Conversely, there was a negative association with relative humidity (RRR per 10% increase, 0.91, 95%-CI 0.85 to 0.96) and with absolute humidity (RRR per 5g/m^3 increase, 0.92, 95%-CI 0.85 to 0.99). Figures S7 to S10 show bubble plots of the rate ratio of COVID-19 on a logarithmic scale against latitude, temperature, relative and absolute humidity.

The composite of any public health intervention (RRR, 0.62, 95%-CI 0.53 to 0.73), and its components, restrictions of mass gatherings (RRR, 0.65, 95%-CI 0.53 to 0.79), school closures (RRR, 0.63, 95%-CI 0.52 to 0.78) and measures of social distancing (RRR, 0.62, 95%-CI 0.45 to 0.85) all showed strong negative associations with epidemic growth during the follow-up period between March 21 and March 27 (Appendix, Figures S11 to S13). The negative association was more pronounced in geopolitical areas that had 2 or 3 public health interventions compared with regions that had one intervention implemented (p for trend<0.001; Figure 3). Epidemic growth varied by continent, health expenditure, Infectious Disease Vulnerability Index, and distance to closest established epidemic.

In pre-specified multivariable analyses and restricted analyses, associations with latitude and temperature remained non-significant (Appendix, Tables S4 and S5). The associations of epidemic growth with relative and absolute humidity attenuated and became mostly non-significant (Appendix, Tables S6 and S7). Negative associations with public health interventions remained robust (Appendix, Tables S8 to S12).

The main multivariable model (Figure 4) showed a weak, non-significant negative association of epidemic growth with absolute humidity (RRR per 5g/m^3, 0.92, 95%-CI 0.84 to 1.00, P=0.064), but a continued strong association with the number of public health interventions implemented (p-value for trend=0.001). A multivariable model based on stepwise backward selection (Appendix, Figure S14) showed a weak negative association with absolute humidity (RRR per 5g/m^3, 0.87, 95%-CI 0.77 to 0.99) and a strong negative association with the number of implemented public health interventions (p for trend=0.004), and additionally suggested a negative association of epidemic growth with increased life expectancy at birth, and residual variation by continent. Post-hoc analyses based on a different metric to estimate epidemic growth showed more pronounced reductions with public health interventions (Appendix, Tables S13 and S14).

Interpretation

In this prospective cohort study of 144 geopolitical areas with 375,609 confirmed cases of COVID-19, epidemic growth of COVID-19 during the follow-up period from March 21 to March 27, 2020 was not associated with geographic latitude, nor with temperature during the exposure period 14 days prior when SARS-CoV-2 transmission was assumed to have occurred. We found associations with relative and absolute humidity, but these were attenuated in multivariable models. The associations of epidemic growth with both dimensions of humidity, despite their low mutual correlation,[28] were suggestive of a minor role of humidity in the epidemiology of COVID-19, but this remains hypothetical. On the other hand, it is of considerable importance that we found strong negative associations with three public health interventions commonly used to contain the COVID-19 pandemic: restrictions of mass gatherings, school closures and measures of social distancing. Even though we were unable to reliably quantify the independent contribution of the three interventions, our results are of immediate relevance as many countries currently consider the removal of some of the implemented public health interventions.

Our results are concordant with three studies from China,[29–31] which reported no evidence for an association of epidemic growth with temperature and relative humidity,[29] but strong decreases in epidemic growth associated with public health measures.[30,31] A recent rapid systematic review concluded that the evidence to support national closure of schools to combat COVID-19 is very weak and that data from influenza outbreaks suggest that school closures could have relatively small effects on SARS-CoV-2 due to its high transmissibility and apparent low clinical effect on school children.[32] Our results suggest that school closures are likely to have a larger effect than suggested in this review, but the clustering of school closures with other public health interventions means that we were unable to reliably estimate the independent effect of this intervention on the COVID-19 pandemic. The effect of restrictions of mass gathering, measures of social distancing and school closures on viral transmission is understudied.[32–34] However, mathematical models and limited observational evidence suggest that they can interrupt disease transmission. Our study provides important new evidence, using global data from the COVID-19 pandemic, that these interventions reduced epidemic growth to a relevant extent.

Limitations

Our study has a number of limitations. First, due to considerable differences in testing practices between different geopolitical areas, the actual rates of COVID-19 could not be reliably estimated. We assumed, however, that rate ratios as measures of epidemic growth could be reliably estimated as testing practices would affect both counts used to calculate the rate ratio in the same way during the ascertained one-week follow-up period. We were unable to identify reliable information on the number of SARS-CoV-2 tests per million inhabitants, and on different testing strategies, and could therefore not directly verify this assumption. GDP per capita, health expenditure as percent of GDP and Infectious Disease Vulnerability Index[16] may be associated to some extent with a healthcare system's capacity to test and could serve as imperfect surrogates. They were indeed both associated with epidemic growth in the univariate analysis, but the main multivariable model did not suggest an association with health expenditure. In addition, the random effects used in the regression model implicitly accounted for residual variation in characteristics of geopolitical areas that remained unexplained, including variation in testing strategies. Second, we assumed that SARS-CoV-2 testing strategies did not vary during the follow-up period. Testing capacity was limited globally in March 2020 and was unlikely to change rapidly during the follow-up period in most geopolitical areas. In addition, we believe that the time window of 1 week was short enough so that reported confirmed cases in each geopolitical area were likely to represent a constant percentage of the true actual cases. Third, only 38 geopolitical areas had implemented public health interventions by the cutoff date of March 11, 2020, and the implementation of interventions was clustered. We therefore refrained from exploring the individual contributions and potential interactions between these interventions in multivariable models and merely constructed a binary composite variable, and a variable representing the number of interventions implemented. This means that we were unable to reliably estimate the individual contributions of the three analyzed public health interventions. We therefore consider the magnitude of the association of epidemic growth with the composite of any public health intervention and the linear trend of the association with the number of public health interventions more reliable and relevant for decision making than the magnitude of associations of epidemic growth with the three public health interventions individually. Fourth, there was variation in measures of social distancing reported by different geopolitical areas, including recommendations or requirements of social distancing, closure of sit-in restaurants and bars, or closure of non-grocery stores, and the derived average association will not shed light on the specific components of social distancing. Fifth, we only analysed when restrictions of mass gathering were instituted, irrespective of the size of mass gatherings that were restricted. Sixth, we were unable to quantify compliance of the population with social distancing and restrictions of mass gatherings. Conversely, even though there may be local variations in strategies to implement school closures, we consider a high adherence to this intervention likely. Seventh, data on latitude, temperature and humidity were collected for the capital of each geopolitical area. The limited granularity of the available data may have resulted in non-differential misclassification of exposure, which in turn may have biased estimates of associations towards the null (see Tables S15 to S23 and Figure S15 for details on risks of bias for individual exposure variables).

Conclusion

Epidemic growth of COVID-19 was not associated with geographic latitude, nor with temperature during the exposure period, which suggests season will not influence the spread of COVID-19. The association between relative and absolute humidity and epidemic growth was suggestive but not consistent. Even if humidity proves important in the epidemiology of COVID-19 in the future, seasonal effects will likely be attenuated by the high levels of susceptibility associated with pandemic diseases.[35] In our study, only public health interventions were consistently associated with reduced epidemic growth, and the greater the number of co-occurring public health interventions, the larger the reduction in growth. Taken together, these findings suggest that seasonality is likely to play only a minor role in the epidemiology of COVID-19. Conversely, public health interventions (school closures, restricting mass gatherings, social distancing) appear to have a major impact. This impact needs to be weighed carefully against potential economic and psychosocial harms when deciding when and how to lift restrictions.

Contributors:

Peter Jüni conceived and designed the study, collected, analysed and interpreted data, wrote the first draft of the article, and contributed to all revisions. Martina Rothenbühler and Bruno R. da Costa analysed and interpreted data, and contributed to all revisions. Pavlos Bobos contributed to designing the study, collected and interpreted data, and contributed to all revisions. Kevin E. Thorpe analysed and interpreted the data, and contributed to all revisions. David N. Fisman and Arthur S. Slutsky contributed to designing the study, interpreted data, and contributed to all revisions. Dionne Gesink contributed to designing the study, collected and interpreted data, wrote the first draft of the Article, and contributed to all revisions. All of the authors gave final approval of the version to be published and agreed to be accountable for all aspects of the work.

Competing interests:

All authors declare no competing interests.

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Figure Legends

Figure 1. Study design. Δ, difference between day 1 of exposure period and day 1 of follow-up period.

Figure 2. Caterpillar plot presenting results of univariate analyses. GDP, gross domestic product; RRR, ratio of rate ratios. Shown are RRRs with 95% confidence intervals and two-sided p-values. The p-value for number of public health interventions is a p-value for trend. Reference categories are no public health intervention for Number of public health interventions, and Asia for Major geographical regions. An RRR of 0.62, for example, indicates a 38% relative reduction in epidemic growth.

Figure 3. Bubble plot of epidemic growth against the number of public health interventions (0, 1, or 2 or more). Each bubble represents a geopolitical area, with the size of the bubble proportional to the weight of the geopolitical area in weighted random-effects regression with inverse-variance weights. Box and whisker plots, with the box representing median and interquartile range, whiskers the most extreme values within 1.5 times of the interquartile range beyond the 25th and 75th percentile. The p-value for trend us from univariate weighted random-effects regression (see Figure 2). A rate ratio of 2, for example, indicates that the cumulative case count in a geopolitical area doubled within one week, a rate ratio of 3 indicates that it tripled.

Figure 4. Caterpillar plot presenting results of the main parsimonious multivariable model. GDP, gross domestic product; RRR, ratio of rate ratios. Shown are RRRs with 95% confidence intervals and two-sided p-values. The variables presented are those included in the parsimonious model. The p-value for number of public health interventions is a p-value for trend. Reference categories are no public health intervention for Number of public health interventions, and Asia

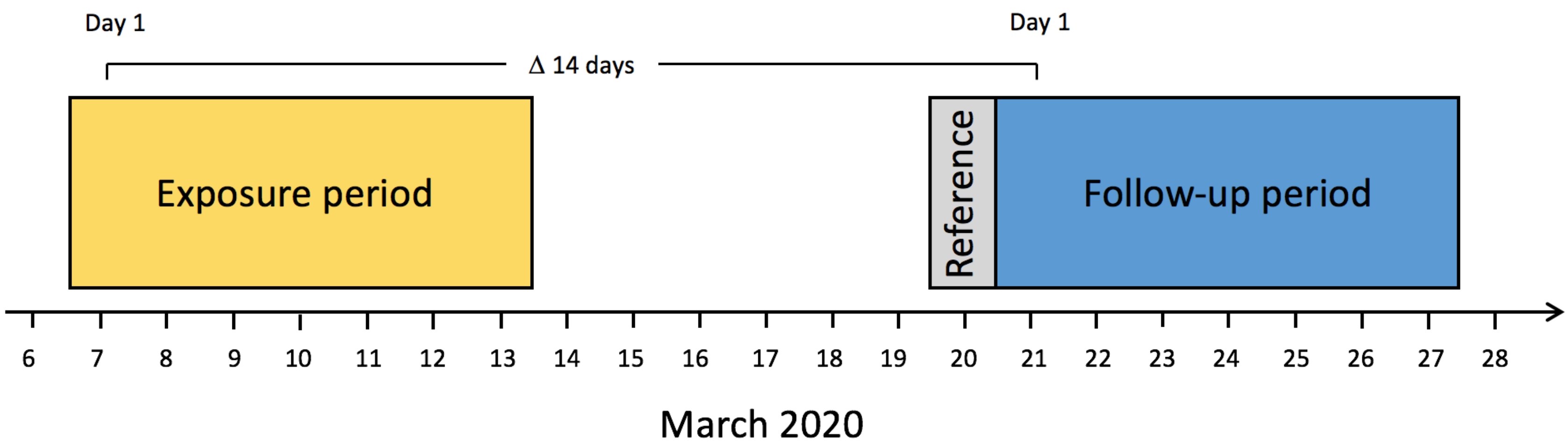
for Major geographical regions. An RRR of 0.70, for example, indicates a 30% relative reduction in epidemic growth.

Table 1. Characteristics of analysed geopolitical areas (n=144)

Variable	**Median/n**	**IQR/%**
Number of cases	558	221 to 1419
Case count (per 1 million inhabitants)	87.6	31.4 to 193.7
Rate ratio	3.56	2.41 to 4.66
Latitude (degrees)	38.4	21.8 to 44.6
Temperature (°C)	12.8	7.3 to 21.2
Relative humidity (%)	69.0	60.3 to 76.6
Absolute humidity (g/m^3)	7.1	5.2 to 10.8
Altitude (m)	82.5	16.0 to 274.0
Passenger flights (passengers/inhabitant/year)	2.3	1.0 to 4.7
Urban density (1000 inhabitants/km^2)	3.6	1.8 to 6.2
Population (million inhabitants)	7.1	3.1 to 20.6
Percentage of inhabitants aged 65 or above	14.0	8.3 to 17.2
Life expectancy at birth (years)	79	76 to 81
GDP (1000 USD/inhabitant)	40.1	8.4 to 56.3
Health expenditure as percentage of GDP	9.2	6.3 to 13.5
Infectious Disease Vulnerability Index	0.87	0.64 to 0.92
Any public health intervention	38	(26.4%)
Restrictions of mass gatherings	24	(16.7%)
Social distancing	10	(6.9%)
School closures	25	(17.4%)
Number of public health interventions		
0 interventions	106	(73.6%)
1 intervention	24	(16.7%)
2 or 3 interventions	14	(9.7%)
Global region		
Asia	30	(20.8%)
Oceania	6	(4.2%)
Europe	36	(25.0%)
Africa	10	(6.9%)
Americas	62	(43.1%)
Closest distance to established epidemic (1000 km)	4.3	1.3 to 8.0

GDP, gross domestic product; USD, United States Dollars; IQR, interquartile range.

Figure 1.


Day 1
Day 1
Δ 14 days
Exposure period
Reference
Follow-up period
6
7
8
9
10
11
12
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14
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16
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28
March 2020

Figure 2.

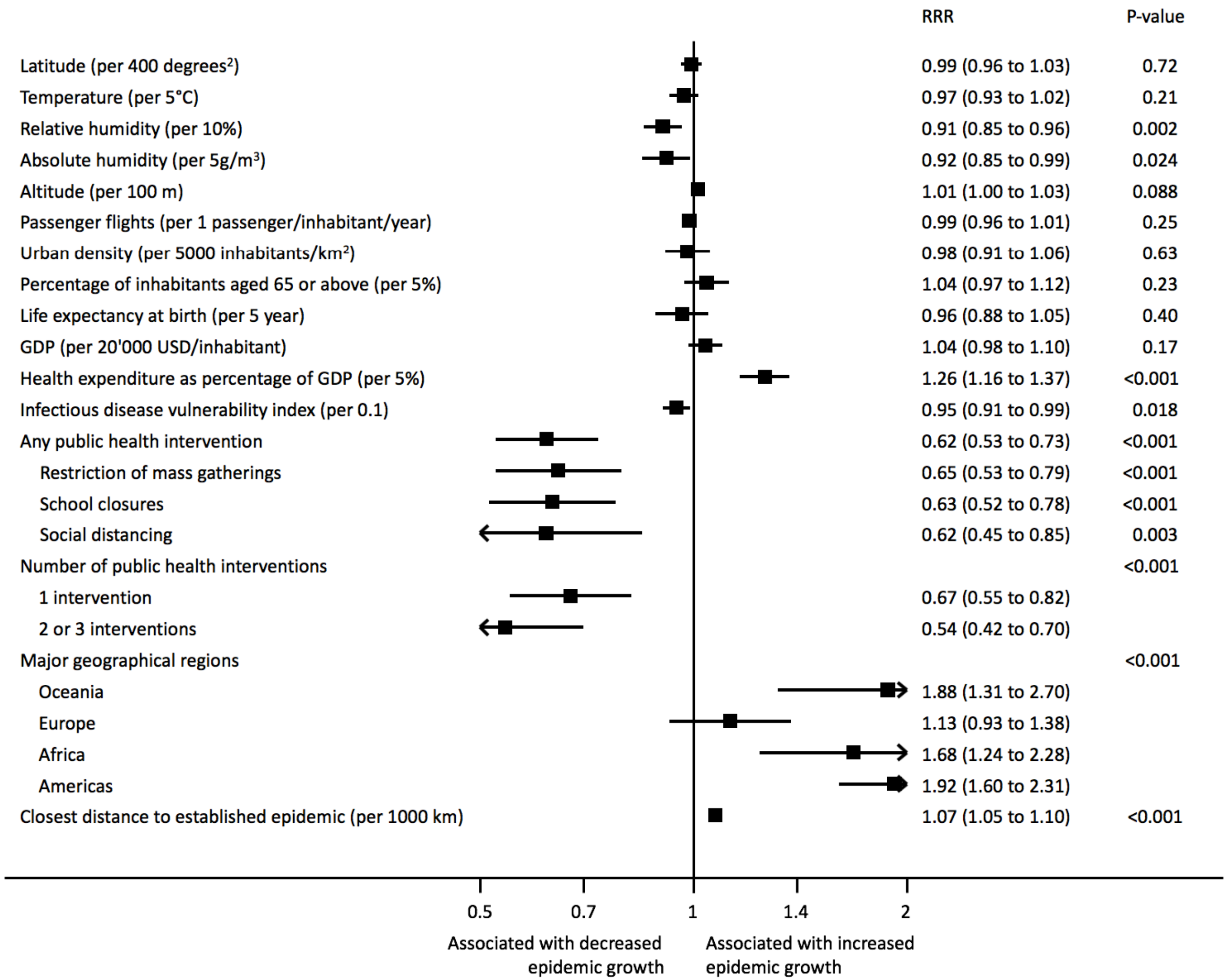

RRR
P-value
Latitude (per 400 degrees²) 0.99 (0.96 to 1.03) 0.72
Temperature (per 5°C) 0.97 (0.93 to 1.02) 0.21
Relative humidity (per 10%) 0.91 (0.85 to 0.96) 0.002
Absolute humidity (per 5g/m³) 0.92 (0.85 to 0.99) 0.024
Altitude (per 100 m) 1.01 (1.00 to 1.03) 0.088
Passenger flights (per 1 passenger/inhabitant/year) 0.99 (0.96 to 1.01) 0.25
Urban density (per 5000 inhabitants/km²) 0.98 (0.91 to 1.06) 0.63
Percentage of inhabitants aged 65 or above (per 5%) 1.04 (0.97 to 1.12) 0.23
Life expectancy at birth (per 5 year) 0.96 (0.88 to 1.05) 0.40
GDP (per 20'000 USD/inhabitant) 1.04 (0.98 to 1.10) 0.17
Health expenditure as percentage of GDP (per 5%) 1.26 (1.16 to 1.37) <0.001
Infectious disease vulnerability index (per 0.1) 0.95 (0.91 to 0.99) 0.018
Any public health intervention 0.62 (0.53 to 0.73) <0.001
Restriction of mass gatherings 0.65 (0.53 to 0.79) <0.001
School closures 0.63 (0.52 to 0.78) <0.001
Social distancing 0.62 (0.45 to 0.85) 0.003
Number of public health interventions <0.001
1 intervention 0.67 (0.55 to 0.82)
2 or 3 interventions 0.54 (0.42 to 0.70)
Major geographical regions <0.001
Oceania 1.88 (1.31 to 2.70)
Europe 1.13 (0.93 to 1.38)
Africa 1.68 (1.24 to 2.28)
Americas 1.92 (1.60 to 2.31)
Closest distance to established epidemic (per 1000 km) 1.07 (1.05 to 1.10) <0.001
0.5
0.7
1
1.4
2
Associated with decreased epidemic growth
Associated with increased epidemic growth

Figure 3.

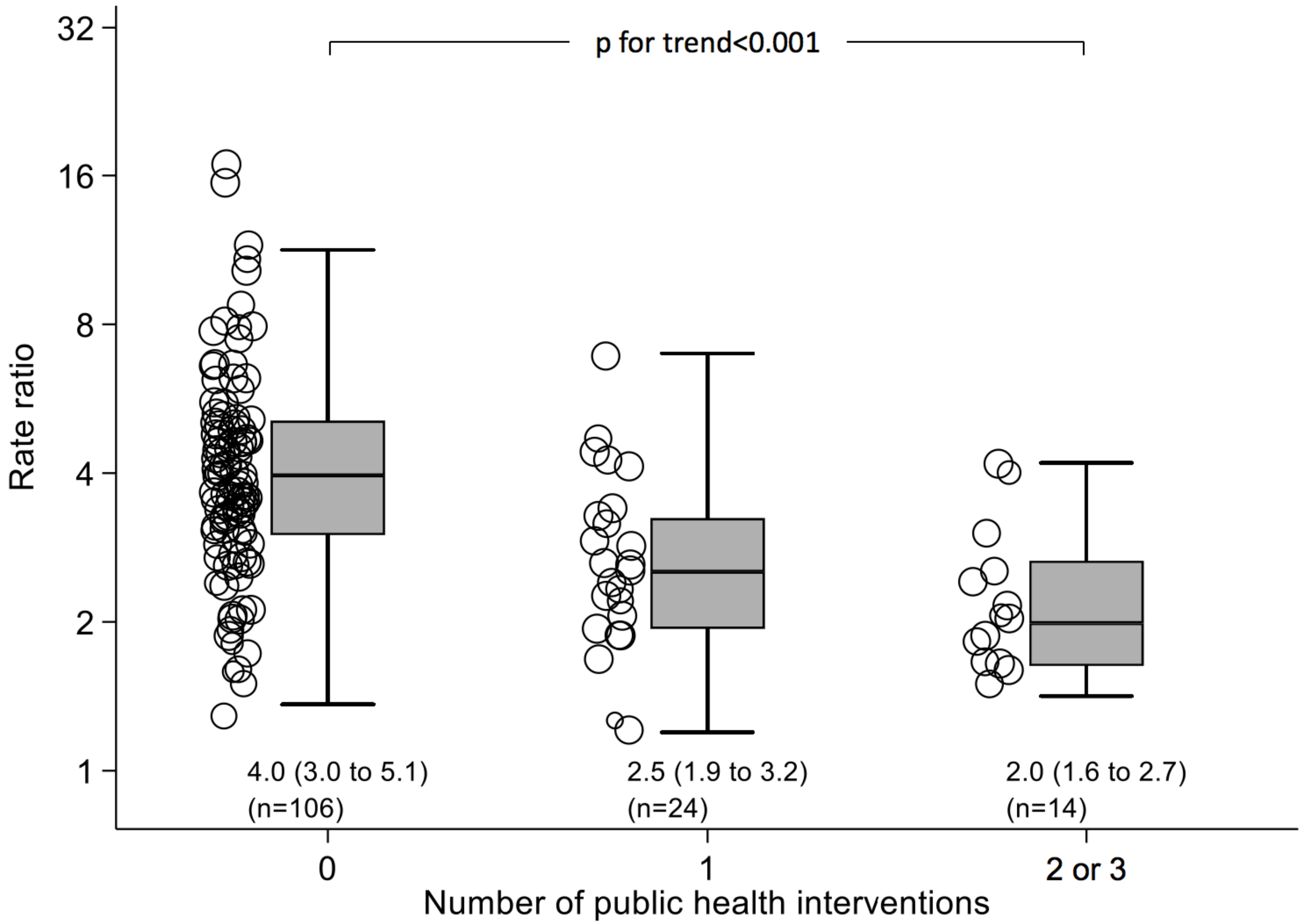
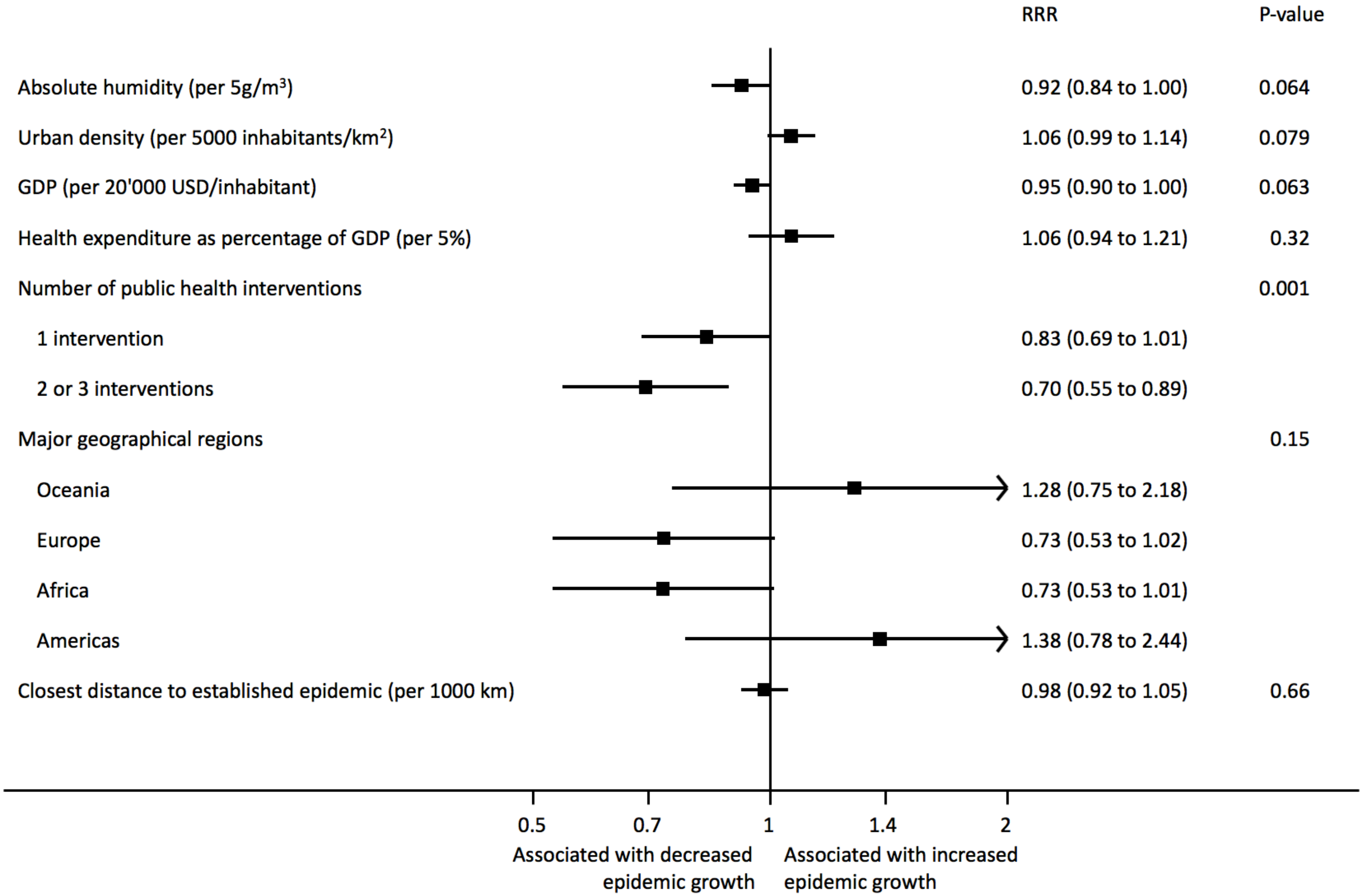

p for trend<0.001
32
16
8
4
2
1
Rate ratio
4.0 (3.0 to 5.1)
(n=106)
2.5 (1.9 to 3.2)
(n=24)
2.0 (1.6 to 2.7)
(n=14)
0
1
2 or 3
Number of public health interventions

Figure 4.


RRR
P-value
Absolute humidity (per 5g/m³)
0.92 (0.84 to 1.00)
0.064
Urban density (per 5000 inhabitants/km²)
1.06 (0.99 to 1.14)
0.079
GDP (per 20'000 USD/inhabitant)
0.95 (0.90 to 1.00)
0.063
Health expenditure as percentage of GDP (per 5%)
1.06 (0.94 to 1.21)
0.32
Number of public health interventions
0.001
1 intervention
0.83 (0.69 to 1.01)
2 or 3 interventions
0.70 (0.55 to 0.89)
Major geographical regions
0.15
Oceania
1.28 (0.75 to 2.18)
Europe
0.73 (0.53 to 1.02)
Africa
0.73 (0.53 to 1.01)
Americas
1.38 (0.78 to 2.44)
Closest distance to established epidemic (per 1000 km)
0.98 (0.92 to 1.05)
0.66
0.5
0.7
1
1.4
2
Associated with decreased epidemic growth
Associated with increased epidemic growth