Estimating the effect of physical distancing on the COVID-19 pandemic using an urban mobility index

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Abstract

Governments around the world are implementing population-wide physical distancing measures in an effort to control transmission of COVID-19, but metrics to evaluate their effectiveness are not readily available. We used a publicly available mobility index based on the relative frequency of trips planned in a popular transit application to evaluate the effect of physical distancing on infection growth rates and reproductive number in 34 states and countries. We found that a 10% decrease in relative mobility in the 2nd week of March was associated with a 11.8% relative decrease ($\exp(\beta) = 0.882$; 95% CI: 0.822, 0.946) in the average daily growth rate in the fourth week of March and a change in the instantaneous reproductive number of -0.054 (95% CI: 0.097, -0.011) in the same period. Our analysis demonstrates that decreases in urban mobility were predictive of declines in epidemic growth at national or sub-national scales. Mobility metrics offer an appealing method to calibrate population-level physical distancing policy and implementation.

Introduction

Policies limiting contact between individuals outside of households, via school closure, voluntary tele-commuting, and shelter-at-home orders, have been implemented in a growing number of regions to reduce the transmission of COVID-19. These physical distancing (previously termed social distancing) policies have helped control previous epidemics (1) and played a significant role in reducing COVID-19 transmission in China (2, 3). Many regions have since adopted physical distancing measures, incrementally increasing restrictions and enforcement over time. However, public health officials have not had access to measures indicating whether current interventions are sufficient for reducing transmission. A proximal indicator of future infection rates (at a known temporal lag) is urgently needed to guide the further implementation of physical distancing measures. In this analysis, we demonstrate that a mobility index based on regular users of a web-based transit application is able to capture the effect of physical distancing on the reproductive number and growth rate of COVID-19 in 34 states and countries spanning 4 continents.

Results

Mobility Index

We used a daily city-level mobility index to (a) measure adherence to large-scale movement restrictions, and (b) predict COVID-19 growth rate and instantaneous reproductive number at the national or sub-national level. The mobility index was provided by a public transit application (app) and uses the number of trips planned on the app to estimate the percentage of each city that is commuting relative to an internal reference from a recent usage period. The index is available from March 2nd to present and includes all 41 cities where the app operates. Importantly, outbreaks in major urban centers (like those in our dataset) represent a large proportion of total COVID-19 cases at national and sub-national (regional) levels (4). As a result, reduced mobility in these cities should have a significant impact on infection growth rates at larger geographies. Furthermore, changes in the city-level mobility index are related to physical distancing interventions, many of which were implemented at the national or sub-national level (5); thus, reduced mobility in major urban centers should serve as a reasonable proxy for larger-scale behavior change.

All cities experienced substantial reduction in mobility during March (Fig. 1). Cities within Europe, Australia, and the Americas showed strikingly similar patterns in mobility reduction that corresponded to the dates of national or sub-national physical distancing mandates, including restrictions on public gatherings or mandatory closures. Prior to the implementation of the first major physical distancing policy, the mobility index was declining by an average of 1.84% per day (95% CI: 1.53, 2.16); after implementation, the rate of decrease was 3.94% per day (slope change of 2.10%; 95% CI: 1.84, 2.36) (Fig. 1). Increasingly restrictive physical distancing policies were adopted in an incremental fashion following the index date and thus continued declines in mobility were expected through the remainder of the month. Messaging from public health authorities and news media likely contributed to changes in behavior prior to the index date.

COVID-19 Case Growth Rates

Most cities implemented their first major physical distancing policies throughout the second week of March (March 9th to March 15th). Assuming that, throughout March, the average time from initial infection to being reported as a case was approximately 10–20 days, we would expect changes in mobility in the second week of March to be reflected in case data from the fourth week of March.

The mean mobility index in the second week of March (March 9th to March 15th) was associated with the logarithm of the growth rate of cumulative cases in the fourth week of March (March 23rd to March 29th) (Fig. 2). A 10% lower mean mobility index in the second week was associated with a 11.8% lower mean daily growth rate in the fourth week ($\exp(\beta) = 0.882$; 95% CI: 0.822, 0.946). To ensure results were not unduly influenced by the early onset of the Italian epidemic (with concomitant lower mobility in early March), we removed these regions and found that the relationship remained ($\exp(\beta) = 0.870$; 95% CI: 0.787, 0.962). Our findings are also robust to estimation of median daily growth rate ($\exp(\beta) = 0.875$; 95% CI: 0.822, 0.932). When the model is adjusted for days since the 100th case (a measure of epidemic timing), the association is attenuated ($\exp(\beta) = 0.930$; 95% CI: 0.851, 1.015). However, these two variables are highly correlated, as physical distancing measures are rarely implemented prior to significant case growth (Spearman's $\rho = -0.66$). The mobility index in the first week of March (March 2nd to March 8th) showed a similar strength of association to outcomes in the fourth week, whereas the mobility index in the third week of March (March 16th to March 22nd) showed a much weaker association (Table 1).

COVID-19 Reproductive Number

The mobility index in the second week of March was associated with the estimated instantaneous reproductive number in the fourth week of March (Fig. 3). A 10% lower mean mobility index in the second week was associated with a decrease in the instantaneous reproductive number of 0.054 in the fourth week ($\beta = -0.054$; 95% CI: -0.097, -0.011). The point estimate remained similar if Italian regions were removed (-0.058; 95% CI: -0.120, 0.004). When the model is adjusted for days since the 100th case, the association is attenuated ($\beta = -0.031$; 95% CI: -0.085, 0.024).

Discussion

We found that a mobility index of public transit users in cities spanning 4 continents predicted growth in reported cases of COVID-19 two to three weeks later. Such an index could be used by public health and governments attempting to understand the impacts of physical distancing and mobility restriction measures during the COVID-19 pandemic.

While the metric we evaluated is predictive, its availability is limited to a handful of cities located mainly in Europe and North America. The index also reflects the movement of a limited portion of the population—transit users—and provides no insight into the number and distribution of close contacts that could lead to transmission. Although we have justified the use of a city-level mobility metric above, this inevitably introduces measurement error for an outcome aggregated at the national or sub-national level. Variation across countries and regions in the delay between symptom onset and public reporting of cases adds uncertainty regarding the correct lag between changes in mobility and the expected effects on growth rates. This should become less of an issue as more rapid and standardized testing is implemented across regions.

Our study had other limitations. Our analysis does not confirm a causal pathway through mobility, but rather a strong association that warrants further evaluation. For example, it is possible that those countries that most successfully enforce physical distancing are also more successful at implementing interventions such as contact tracing or widespread testing, which may also contribute to the observed association. We also did not account for imported cases in the calculation of the instantaneous reproductive number; however, locally acquired cases were certainly undercounted during this period, and likely to a greater degree than imported cases due to the increased attention on international travelers.

Additional measures of human mobility and physical distancing are urgently needed in order to better understand the impacts of these policies on transmission dynamics. Recently published publicly available mobility data may contain a greater variety of contact and mobility patterns, but are restricted in breadth and data access (https://www.google.com/covid19/mobility/). We call for all organizations with access to mobility data to publicly release them. These metrics need not be granular, as physical distancing measures can be implemented at a broad scale. Further evaluation of the utility of these metrics in guiding population interventions are needed, particularly for illuminating the steps necessary to keep the reproductive number of the disease below 1.

Though necessary, these strategies are already proving to have dire consequences on other aspects of health and well-being (6, 7). The value of mobility metrics is set to increase dramatically as countries consider a transition toward intermittent or cyclical physical distancing measures that aim to minimize these negative externalities (8). Finally, we hope our results will be helpful to reassure the public that, despite the immense economic, social and psychological costs, their continued cooperation will have powerful long-term benefits.

References

1. P. Caley, D. J. Philp, K. McCracken, Quantifying social distancing arising from pandemic influenza. *J. R. Soc. Interface*. **5**, 631–639 (2008).

2. M. U. G. Kraemer, C.-H. Yang, B. Gutierrez, C.-H. Wu, B. Klein, D. M. Pigott, O. C.-19 D. W. Group†, L. du Plessis, N. R. Faria, R. Li, W. P. Hanage, J. S. Brownstein, M. Layan, A. Vespignani, H. Tian, C. Dye, O. G. Pybus, S. V. Scarpino, The effect of human mobility and control measures on the COVID-19 epidemic in China. *Science* (2020).

3. R. Li, S. Pei, B. Chen, Y. Song, T. Zhang, W. Yang, J. Shaman, Substantial undocumented infection facilitates the rapid dissemination of novel coronavirus (SARS-CoV2). *Science*, eabb3221 (2020).

4. E. Dong, H. Du, L. Gardner, An interactive web-based dashboard to track COVID-19 in real time. *The Lancet Infectious Diseases*, S1473309920301201 (2020).

5. S. Flaxman, S. Mishra, A. Gandy, H. J. T. Unwin, H. Coupland, T. A. Mellan, T. Berah, J. W. Eaton, P. N. P. Guzman, N. Schmit, L. Cilloni, K. E. C. Ainslie, I. Blake, A. Boonyasiri, O. Boyd, L. Cattarino, C. Ciavarella, L. Cooper, Z. Cucunubá, G. Cuomo-Dannenburg, A. Dighe, B. Djaafara, I. Dorigatti, S. van Elsland, R. FitzJohn, H. Fu, K. Gaythorpe, L. Geidelberg, N. Grassly, W. Hinsley, B. Jeffrey, D. Jorgensen, E. Knock, D. Laydon, G. Nedjati-Gilani, K. Parag, I. Siveroni, H. Thompson, R. Verity, E. Volz, P. G. Walker, H. Wang, Y. Wang, O. Watson, X. Xi, P. Winskill, C. Whittaker, C. A. Donnelly, S. Riley, L. C. Okell, M. A. C. Vollmer, N. M. Ferguson, S. Bhatt, Estimating the number of infections and the impact of non-pharmaceutical interventions on COVID-19 in 11 European countries (2020) (available at https://www.imperial.ac.uk/mrc-global-infectious-disease-analysis/covid-19/report-13-europe-npi-impact/).

6. G. Miller, Social distancing prevents infections, but it can have unintended consequences. *Science* (2020).

7. D. Gura, A record 6.6 million Americans filed for unemployment last week. *NBC News* (2020) (available at https://www.nbcnews.com/business/economy/record-6-6-million-americans-filed-unemployment-last-week-n1174776).

8. S. M. Kissler, C. Tedijanto, M. Lipsitch, Y. Grad, https://www.medrxiv.org/content/10.1101/2020.03.22.20041079v1 (2020).

9. R Core Team, *R: A Language and Environment for Statistical Computing* (R Foundation for Statistical Computing, Vienna, Austria, 2020; https://www.R-project.org/).

10. S. A. Lauer, K. H. Grantz, Q. Bi, F. K. Jones, Q. Zheng, H. R. Meredith, A. S. Azman, N. G. Reich, J. Lessler, The Incubation Period of Coronavirus Disease 2019 (COVID-19) From Publicly Reported Confirmed Cases: Estimation and Application. *Ann Intern Med* (2020).

11. G. Chowell, C. Viboud, L. Simonsen, S. M. Moghadas, Characterizing the reproduction number of epidemics with early subexponential growth dynamics. *Journal of The Royal Society Interface*. **13**, 20160659 (2016).

12. C. Fraser, Estimating Individual and Household Reproduction Numbers in an Emerging Epidemic. *PLOS ONE*. **2**, e758 (2007).

13. A. Cori, *EpiEstim: Estimate Time Varying Reproduction Numbers from Epidemic Curves* (2019; https://CRAN.R-project.org/package=EpiEstim).

14. A. Cori, N. M. Ferguson, C. Fraser, S. Cauchemez, A New Framework and Software to Estimate Time-Varying Reproduction Numbers During Epidemics. *Am J Epidemiol*. **178**, 1505–1512 (2013).

15. Z. Du, X. Xu, Y. Wu, L. Wang, B. J. Cowling, L. A. Meyers, Serial Interval of COVID-19 among Publicly Reported Confirmed Cases. *Emerg. Infect. Dis.* **26** (2020).

Tables

Table 1. Model coefficients for the association between a 10% decrease in the mobility index and the mean daily growth rate or instantaneous reproductive number in the fourth week of March assuming a lag of either 1, 2, or 3 weeks. Model coefficients are presented with and without adjustment for days since 100th case. Models include outcomes for 34 countries and states (33 in adjusted models).

	Mean daily growth rate (%) (exp(β))		**Instantaneous reproductive number** (β)	
Mobility index	**Unadjusted (95% CI)**	**Adjusted (95% CI)**	**Unadjusted (95% CI)**	**Adjusted (95% CI)**
1-week lag	0.934 (0.841, 1.037)	1.024 (0.925, 1.135)	-0.050 (-0.109, 0.010)	-0.015 (-0.078, 0.048)
2-week lag	0.882 (0.822, 0.946)	0.930 (0.851, 1.015)	-0.054 (-0.097, -0.011)	-0.031 (-0.085, 0.024)
3-week lag	0.859 (0.792, 0.932)	0.907 (0.818, 1.005)	-0.069 (-0.119, -0.019)	-0.041 (-0.105, 0.023)

Figures

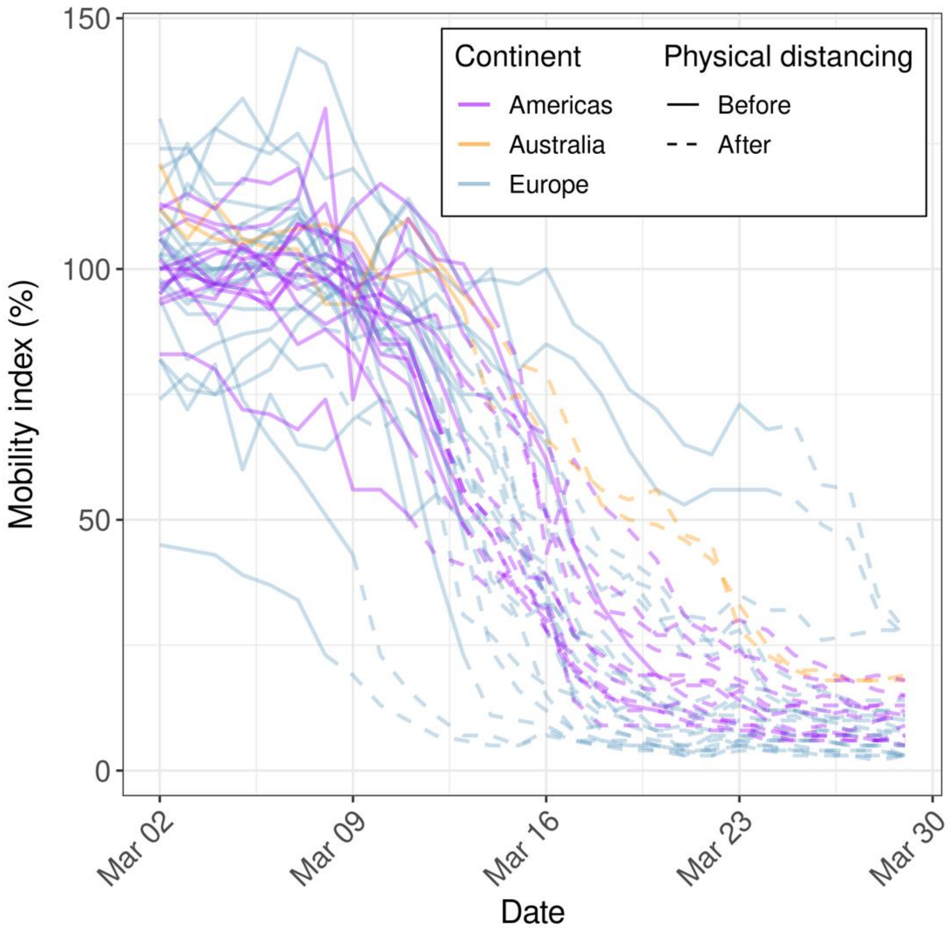

Fig. 1. Mobility index in 37 cities (excluding Asia) over a 4-week period in March 2020, before and after the first major state- or country-level physical distancing intervention was announced.

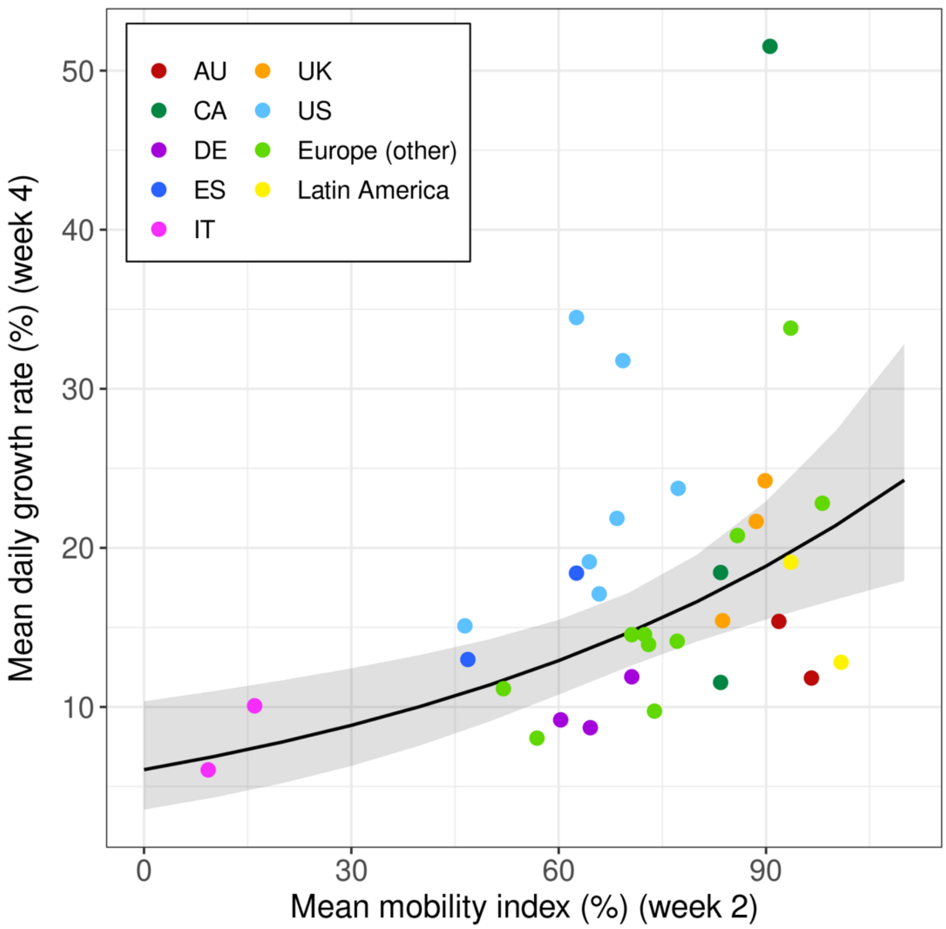

Fig. 2. The association between the mean mobility index in the 2nd week of March 2020 and the mean daily growth rate in the 4th week of March 2020 in 34 states and countries (excluding Asia). The 95% confidence interval of the predicted association is shown in gray.

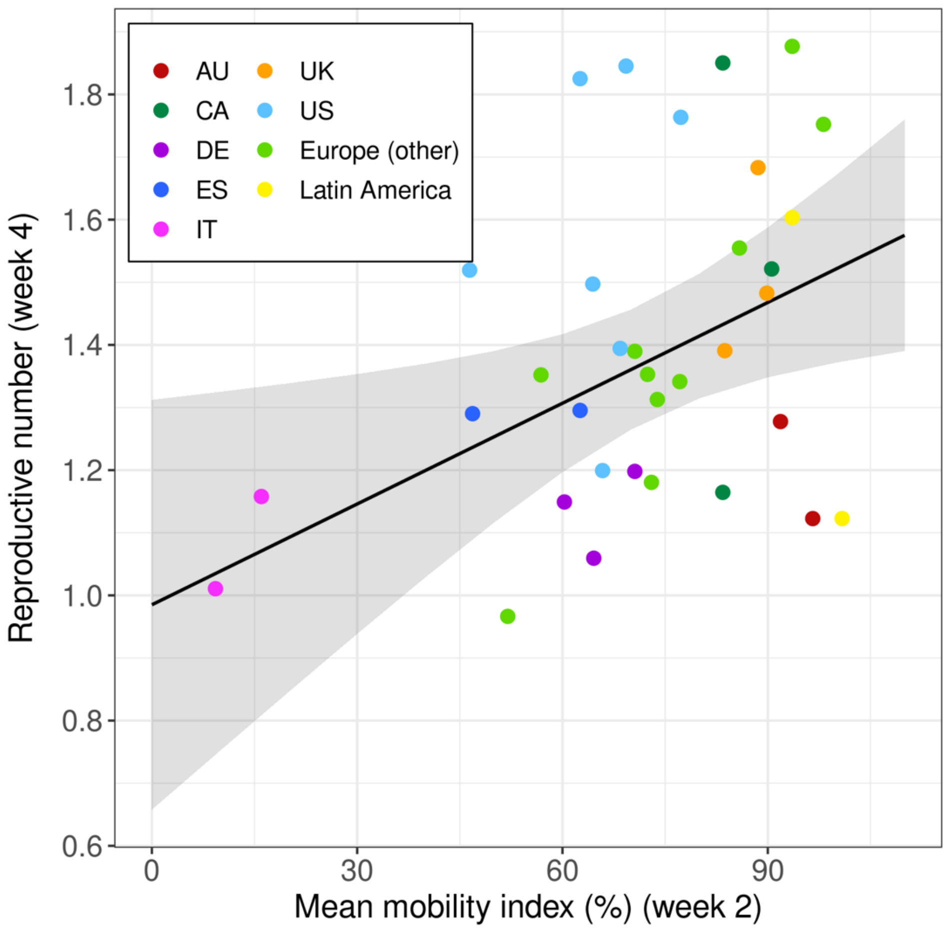

Fig. 3. The association between the mean mobility index in the 2nd week of March 2020 and the estimated instantaneous reproductive number in the 4th week of March 2020 in 34 states and countries (excluding Asia). The 95% confidence interval of the predicted association is shown in gray.

Supplementary Material

Materials and Methods

Mobility Index

The Citymapper Mobility Index (CMI; https://citymapper.com/cmi) includes data on 41 cities from 23 countries. CMI measures the relative frequency of trips planned within 41 cities across the Americas, Europe, Australia and Asia, compared to an internal reference at the beginning of 2020. We excluded the four Asian cities from all analyses since, at the time of writing, it was unclear if their reference periods included January 2020, at which time many cities in Asia were likely to have already experienced changes in mobility patterns. The CMI is available from March 2^{nd} to present.

All statistical analyses were performed in R (version 3.6.3) (9). To validate our use of CMI as a measurement for adherence to physical distancing measures, we used a linear mixed effect model with a random intercept for city. We defined a continuous covariate for days since March 2^{nd} (time) and a binary term denoting the first announcement of major national or sub-national physical distancing interventions, namely gathering restrictions and/or mandatory closures (1 = date follows announcement of physical distancing measure) (Table S1). Unlike a declaration of emergency, these measures have clear and consistent implications across regions. We included terms for time and the interaction between time and the binary variable for physical distancing to estimate the change in slope for the daily decline in CMI resulting from the announcement of physical distancing measures.

In subsequent analyses, population weighted CMI (based on metro area population) was calculated when mobility data was available for two or more cities in a given region (e.g., California) or country (e.g., Russia) but more granular case data were not available.

COVID-19 Case Growth Rates

We obtained national and sub-national (where available) cumulative case time series for countries represented in the Citymapper data (Table S2). In all, we obtained 34 regional- and national-level cumulative case time series. We calculated daily growth rates for each region (presented as a percentage) by dividing the number of new cases reported in a given day by the cumulative number of cases as of the previous day.

We used a mixed effects model with a random intercept for country (to account for clustering of sub-national units within a country) to estimate the association between mean CMI and the logarithm of the mean daily growth rate in prior weeks. Based on the known lag between infection and symptom onset of 5 days (10), plus an estimated lag between symptom onset and public reporting of 5 to 15 days, we use 2-week lag as our primary analysis and use 1- and 3-week lags as sensitivity analyses. To adjust for epidemic timing (e.g., sub-exponential growth that could occur due to the host contact network, behavioral changes and inhomogeneous mixing (11)), we ran an additional model including days since the 100^{th} case as a continuous covariate (excluding the Principality of Monaco, which had fewer than 50 cases by the end of week 4). However, we note that epidemic timing is strongly correlated with mean CMI in week 2. For example, Italy, which had an earlier epidemic than other European countries, had a substantially lower CMI in early March than other European countries in the dataset.

COVID-19 Reproductive Number

The instantaneous reproductive number is a quantity signifying the average number of secondary infections a person infected at time *t* would be expected to generate given that conditions remain unchanged (12). We estimated the instantaneous reproductive number in week 4 using the *EpiEstim* package (version 2.2-1) in R (13) and daily incidence from March 8 to March 30. We employed the parametric serial interval method (14) using parameters from Du et al. (15) (mean = 3.96 days, SD = 4.75 days). As data on case origins were not available in most sources, we did not adjust for imported cases in our calculations.

We used a linear mixed effects model with a random intercept for country to estimate the association between mean CMI in week 2 and the estimated instantaneous reproductive number in week 4. To adjust for epidemic timing, we ran an additional model including days since the 100th case as a continuous covariate (excluding the Principality of Monaco, which had fewer than 50 cases at the end of week 4).

Ethics

We used exclusively publicly available data for this study and thus did not require research ethics approval.