

Supporting Information for Pandemic fatigue impedes mitigation of COVID-19 in Hong Kong

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Materials and Methods

Survey data

In each weekly survey from 5 May 2020 to 15 February 2021, we contacted either 500 or 1000 local residents through random digit dialing of landlines and mobile telephones, using age, gender, education, and employment information to weight the response frequencies to the adult population in Hong Kong (1). More than 31,000 local residents were interviewed through these 40 cross-sectional telephone surveys. We asked each participant about the perception of the risk of being infected and the compliance with physical distancing measures. Specifically, to assess the risk perception, we asked whether the participant was aware of being susceptible to the COVID-19 and worried about being infected. To assess the physical distancing behaviour, we asked whether the participant complied with the recommended distancing policies including the avoidance of going to crowded places (e.g., leisure venues and bars), staying at home as much as possible, avoidance of using public transportation, and avoidance of social gathering (e.g., dining together, weddings, funerals, religious services). Details about the surveyed questions can be found in ref. (2). The survey enables us to estimate (1) the percentage of participants perceived the risk of infection; and (2) the percentage of participants engaged in physical distancing policies.

Epidemic data

We collect the daily reported cases by reporting date in Hong Kong from COVID-19 Dashboard by the Center for Systems Science and Engineering at Johns Hopkins University (3) as the public reports, and the real-time effective reproductive number for local cases and the daily symptomatic cases by onset date in Hong Kong from the real-time dashboard in School of Public Health, The University of Hong Kong (4).

Mobility data To estimate the dynamic of people traveling in the COVID-19 pandemic, we obtained the daily mobility data from the Google community mobility reports in Hong Kong (5). Based on visitors' daily numbers to specific categories of location (e.g. grocery stores; parks; train stations), Google compares it to baseline period (the 5-week period from January 3 to February 6, 2020) before the pandemic outbreak and reports six mobility categories to indicate how the numbers of visitors in Hong Kong to places of (1) retail and recreation (restaurants, cafes, shopping centers, theme parks, museums, libraries, and movie theaters), (2) grocery and pharmacy stores (grocery markets, food warehouses, farmers markets, specialty food shops, drug stores, and pharmacies), (3) transit stations (public transport hubs such as subway, bus, and train stations), (4)

workplaces, (5) residential areas, and (6) parks (local parks, national parks, public beaches, marinas, dog parks, plazas, and public gardens) have changed (5).

Epidemic model

We simulate the transmission of COVID-19 using a compartmental model, in which the health status of each individual can be susceptible (S), exposed (E), asymptomatic (A), presymptomatic (P), symptomatic (Y), or recovery/death (R) at any time. After infection, an individual remains in an exposed state (E) for a non-infectious incubation period, which is on average $1/\sigma$ days. Then, the exposed individual (E) becomes asymptomatic (A) or pre-symptomatic (P) with probabilities of $1 - p_{sym}$ and p_{sym} , respectively. The asymptomatic case (A) has a reduced ability to infect others, and is recovered/died (R) after an asymptomatic infectious period, which is on average $1/\hat{\gamma}$ days. Pre-symptomatic cases also have a reduced ability to infect others. Pre-symptomatic case (P) becomes symptomatic at a rate ϵ , after which will recover/die at a rate γ . Recovered individuals are assumed to be immunized against re-infection throughout the duration of simulation (3 months).

The infectiousness of a case depends on the infection status (i.e., pre-symptomatic, asymptomatic or symptomatic). Compared to symptomatic cases, the infectiousness of asymptomatic and pre-symptomatic cases is reduced by a factor of $\hat{\omega}$ and ω , respectively. Let β be the transmission rate between each pair of susceptible and infectious individuals, which accounts for the influence of protective behaviours by formulating as $\beta = \alpha(d) \Phi(d) + \rho + \xi(d)$. Here $\Phi(d)$ is the daily percentage of people avoiding social gathering, $\alpha(d)$ the coefficient of $\Phi(d)$, and ρ the intercept at day d . $\xi(d)$ denotes the noise uniformly distributed between -0.1 and 0.1. To avoid overfitting due to the multicollinearity between surveyed indicators, we only incorporate the data for the avoidance of social gathering. We build compartments to model the transitions between the states: susceptible (S), exposed (E), pre-symptomatic infectious (P), symptomatic infectious (Y), asymptomatic infectious (A), recovered (R).

Let $S(t)$, $E(t)$, $A(t)$, $P(t)$, $Y(t)$, and $R(t)$ denote the number of susceptible, exposed, asymptomatic, presymptomatic, symptomatic, and recovery/death individuals at time t , respectively. The total population size is $N = S + E + A + P + Y + R$. We use the following ordinary differential equations to simulate the transmission of COVID-19:

$$S(t + 1) = S(t) - \beta S(t) (\hat{\omega}A(t) + \omega P(t) + Y(t))/N$$

$$E(t + 1) = E(t) + \beta S(t) (\hat{\omega}A(t) + \omega P(t) + Y(t))/N - \sigma E(t)$$

$$P(t + 1) = P(t) + \sigma p_{sym} E(t) - \epsilon P(t)$$

$$A(t + 1) = A(t) + \sigma(1 - p_{sym})E(t) - \hat{\gamma}A(t)$$

$$Y(t + 1) = Y(t) + \epsilon P(t) - \gamma Y(t)$$

$$R(t + 1) = R(t) + \hat{\gamma}A(t) + \gamma Y(t)$$

We estimate the transmission rate β by fitting the daily reported local symptomatic cases (4) via the Ensemble Adjustment Kalman Filter (EAKF) algorithm (6) with 10,000 particles. To account for the reporting delay of local confirmed cases at day d , we assume the new infections $\beta S(t) (\hat{\omega}A(t) + \omega P(t))$ with the proportion p_{sym} following the normal distribution with mean $I^Y(d + 1/\sigma + 1/\epsilon)$ and standard deviation

$\sqrt{\frac{\sum_{i=1}^3 (I^Y(d + 1/\sigma + 1/\epsilon - i))^2}{10}}$. In our study, we aligned the reconstructed daily time series of exposed cases to the observed data by 5 days (as $1/\sigma + 1/\epsilon$) to track the new infections.

Many potential factors (e.g., climate effects) other than the influence of PHSMs and local policies on human behavior can also impact the reproduction of viruses within host and human behaviors. As such, the product of the coefficient $\alpha(d)$ and the surveyed data $\Phi(d)$ is used to capture the comprehensive impact of all potential factors on the COVID-19 transmission, with daily changes in $\alpha(d)$ inferred by the above mentioned EAKF algorithm. The transmission rate $\beta(d)$ is $\alpha(d) \Phi(d) + \rho$, where $\Phi(d)$ is the percentage of people avoiding gathering, estimated from Google mobility data; the coefficient of protective-behaviour forcing at day d , $\alpha(d)$, is calibrated to local cases reported at day d and assumed with the range between -1 and 0.1; and ρ is assumed to be 0.5.

For other settings, the daily number of reported symptomatic cases at day d by onset date, $I^Y(d)$, follow the report in ref. (4). The population size of Hong Kong, N , is 7.5 million (7). The transition rate out of exposed state, σ , is 1/3 (8). The recovery rate of symptomatic individuals, γ , is 1/4 (9, 10). The recovery rate of asymptomatic individuals, $\hat{\gamma}$, is 1/9 (11). The transition rate from the pre-symptomatic to symptomatic stage, ϵ , is 1/2 (8). The relative infectiousness of pre-symptomatic and asymptomatic cases, ω and $\hat{\omega}$, is 1.57 (9, 10) and 0.5 (12), respectively. The proportion of infections that are symptomatic, p_{sym} , is 75% (10, 13). The initial number of the local symptomatic cases reported is 6 for the third wave and 5 for the fourth wave as reported in Hong Kong.

To estimate the outbreak size averted in the fourth wave between 31 October in 2020 and 15 January in 2021, we introduce the epidemic model with values of $\alpha(d)$, calibrated by the EAKF algorithm informed by local cases. Accordingly, we estimate the median

symptomatic incidence across scenarios with increases in the percentage of people avoiding social gathering per day.

Linear regression

Informed by the real-time reproduction number estimations in Hong Kong (4), we estimate the mean reproduction number for each week (averaged over 7 days in each week) from 5 May 2020 to 15 February 2021, and study the degree of determination (adjusted R^2) between the weekly reproduction number and one type of those proportions of protective behaviours.

Structural equation modeling

We used the structural equation modeling (14) to unravel the dependencies of these factors (**Fig. 1**), including risk perception, self-reported protective behaviours, transmission, and public reports, each with at least one measured variable. We estimate the t-statistic and p values, which denote the strong causal assumptions of these factors.

Estimation of percentage of people avoiding gathering

We compared the self-reported behavioural changes in our survey data with changes in population movements. Considering the large user base of Google's products and the real-time data of Google's Community Mobility Reports (5), we performed a stepwise regression analysis to examine the correlation between each surveyed indicator of protective behaviours and Google's daily mobility movement trends. We found that Google's mobility indexes were highly correlated with our surveyed self-reported protective behaviours. Therefore, with the aid of Google's mobility data, our weekly surveys of population behavioural changes can be interpolated into the daily resolution.

We thus estimate the daily percentage of the people avoiding gathering, $\Phi(d)$, from Google mobility data. Specifically, we study the relationship between the surveyed protective behaviours and six mobility movement trends of Google on average per week by a stepwise regression analysis to add or remove predictors with the criterion of p-value for F test. Informed by the stepwise regression, we further project $\Phi(d)$ using the daily mobility movement trends.

SI References

1. B. J. Cowling, *et al.*, Impact assessment of non-pharmaceutical interventions against coronavirus disease 2019 and influenza in Hong Kong: an observational study. *The Lancet Public Health* **5**, e279–e288 (2020).
2. Q. Liao, *et al.*, Community psychological and behavioural responses to coronavirus disease 2019 over one year of the pandemic in 2020 in Hong Kong. *Sci. Rep.* **11**, 22480 (2021).
3. E. Dong, H. Du, L. Gardner, An interactive web-based dashboard to track COVID-19 in real time. *Lancet Infect. Dis.* **20**, 533–534 (2020).
4. School of Public Health, The University of Hong Kong, Real-time dashboard. *School of Public Health, The University of Hong Kong* (March 11, 2021).
5. Google, COVID-19 Community Mobility Reports (March 15, 2021).
6. J. L. Anderson, An Ensemble Adjustment Kalman Filter for Data Assimilation. *Mon. Weather Rev.* **129**, 2884–2903 (2001).
7. Census and Statistics Department, Hong Kong Special Administrative Region, Press Release (18 Feb 2021) :Year-end population for 2020 (2021) (March 15, 2021).
8. J. A. Backer, D. Klinkenberg, J. Wallinga, Incubation period of 2019 novel coronavirus (2019-nCoV) infections among travellers from Wuhan, China, 20-28 January 2020. *Euro Surveill.* **25**, 2000062 (2020).
9. X. He, *et al.*, Temporal dynamics in viral shedding and transmissibility of COVID-19. *Nat. Med.* **26**, 672–675 (2020).
10. A. Aleta, *et al.*, Modelling the impact of testing, contact tracing and household quarantine on second waves of COVID-19. *Nat Hum Behav* **4**, 964–971 (2020).
11. Z. Du, *et al.*, Comparative cost-effectiveness of SARS-CoV-2 testing strategies in the USA: a modelling study. *Lancet Public Health* **6**, e184–e191 (2021).
12. D. McEvoy, *et al.*, Relative infectiousness of asymptomatic SARS-CoV-2 infected persons compared with symptomatic individuals: a rapid scoping review. *BMJ Open* **11**, e042354 (2021).
13. H. Nishiura, *et al.*, Estimation of the asymptomatic ratio of novel coronavirus infections (COVID-19). *Int. J. Infect. Dis.* **94**, 154–155 (2020).
14. C. M. Ringle, S. Wende, and Becker, J.-M.(2015). SMARTPLS 3. Boenningstedt: SmartPLS GmbH.