

Nowcasting COVID-19 transmission dynamics, severity, and effectiveness of control measures: abridged secondary publication

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KEY MESSAGES

1. Our model yielded unbiased estimates of the time-varying reproductive number of COVID-19 cases by accounting for differences in infectiousness between local and imported cases.
2. The case fatality risk of COVID-19 increased with age in 2020 in Hong Kong.
3. Incorporation of changes over time in the serial interval distribution enabled more accurate

estimation of the reproductive number.

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Introduction

During the initial period of the COVID-19 pandemic in Hong Kong, containment and suppression measures included intensive surveillance of infections among both incoming travellers and the local community. Once identified, patients were isolated until recovery and cessation of virus shedding. Their close contacts were traced (from 2 days prior to illness onset) and quarantined in designated facilities. Because not every infected person could be identified, containment was only effective when accompanied by social distancing measures and behavioural changes that reduced undetected community transmission.

To assess the effectiveness of suppression measures, we monitored the transmissibility of COVID-19 over time by estimating the effective reproductive number in real time. We also monitored the clinical severity profile by age and estimated the impact of various control measures on COVID-19 transmissibility. We aimed to provide evidence-based guidance on the most appropriate public health strategies for suppressing COVID-19 transmission.¹

Methods

COVID-19 data regarding infections, illnesses, and hospitalisations were compiled into a single database. Data sources included: (1) daily reports of laboratory-confirmed cases from the Centre for Health Protection; (2) detailed time-to-event interval data from a subset of cases; (3) detailed data on laboratory-confirmed and probable cases from the Hospital Authority, with regular updates; (4) a complete dataset from December 2020 regarding hospital admissions for pneumonia and other

respiratory causes, used as a reference to estimate the overall morbidity impact and epidemiology of COVID-19 in Hong Kong; and (5) snapshot data on community illness prevalence, obtained through telephone surveys and crowdsourced reporting platforms.

Advanced analytic techniques were used to estimate daily changes in the effective reproductive number (R_t), adjusting for delays between illness onset and reporting, via time series of confirmed cases, probable cases, pneumonia hospitalisations, and relevant data. Given the delay between onset and case notification, data were augmented for recent days using the estimated onset-to-notification distribution. We developed models to triangulate the various sources of information regarding infection incidence and transmissibility, including models assessing age-specific differences in transmissibility.

Severity was monitored via hospital fatality risk, symptomatic case fatality risk, and infection fatality risk, both overall and by age. Using very early data from cases in Wuhan, we estimated the hospital fatality risk to be 14%.² Care was taken to avoid estimating mortality risk among laboratory-confirmed cases in Mainland China because testing practices varied over time due to changes in clinical case definitions, laboratory procedures, and testing methods. Similarly, we avoided estimating fatality risk among laboratory-confirmed cases in Hong Kong. We aimed to characterise the clinical severity profile within a single Bayesian model for comprehensive assessment of age-specific severity.

The impact of school closures and other interventions on R_t was estimated by examining changes in that number over time. Using age-specific data on illnesses and hospitalisations, we constructed a detailed mathematical model to

simulate pandemic trajectories under alternative hypothetical scenarios. Model parameters were derived from available datasets and the literature. Comparisons of pandemic curves with and without various interventions, as well as comparisons across locations, provided estimates of the impact of those measures.

Results

Estimating reproductive number in real time throughout the pandemic

The framework developed by Cori et al³ was extended to estimate R_t for both imported and local cases by adjusting their differences in infectiousness. Surge in local case numbers corresponded to an estimated R_t of >1 during 14 to 26 March 2020, prior to tightening of public health measures. R_t then steadily declined after the implementation of special work arrangements for civil servants and additional social distancing measures (Fig 1). In contrast, during early March, R_t for imported cases fell <1 , despite daily numbers >10 , secondary to the enforcement of the 14-day quarantine for inbound travellers.

Estimating severity in real time throughout the pandemic

In Hong Kong, all confirmed COVID-19 cases were hospitalised during the study period. Using severity

profiles of 5088 laboratory-confirmed cases, we estimated the confirmed case fatality risk (cCFR). Cases were stratified by date of confirmation: 23 January to 30 September 2020 (waves 1-3) and after 30 September 2020 (after wave 3).

The adjusted cCFR was estimated by dividing the cumulative number of deaths by the sum of cumulative deaths and recoveries, whereas the overall cCFR was estimated by directly standardising the age-specific cCFR using the cumulative number of confirmed cases during waves 1-3. The all-ages adjusted cCFRs were 2.2% (95% confidence interval [CI]=1.8%-2.5%) during waves 1 to 3 and 1.4% (95% CI=1.1%-1.7%) after wave 3. The point estimates of the adjusted cCFR increased with age in both periods. Specifically, the adjusted cCFR rose from 0% in those aged <20 years to 12.2% in those aged ≥ 65 years during waves 1 to 3, and from 0% in those aged <20 years to 7.32% in those aged ≥ 65 years after wave 3 (Fig 2).

Temporal change in serial intervals during the pandemic

Contact tracing data were categorised into transmission pairs to explore temporal changes in serial intervals. Serial intervals were defined as the number of days between symptom onset in the infector and symptom onset in the infectee for each transmission pair. Transmission pairs were classified into pre-peak (9-22 January 2020), peak week

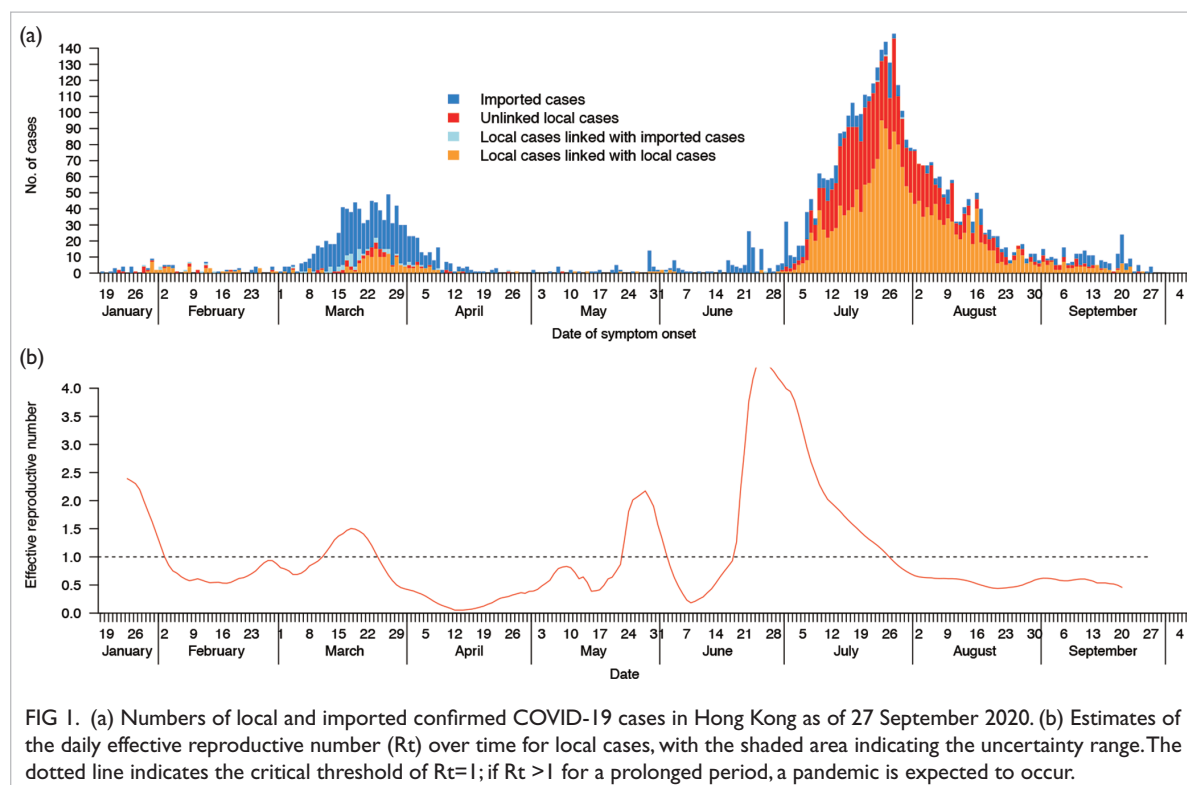


FIG 1. (a) Numbers of local and imported confirmed COVID-19 cases in Hong Kong as of 27 September 2020. (b) Estimates of the daily effective reproductive number (R_t) over time for local cases, with the shaded area indicating the uncertainty range. The dotted line indicates the critical threshold of $R_t=1$; if $R_t > 1$ for a prolonged period, a pandemic is expected to occur.

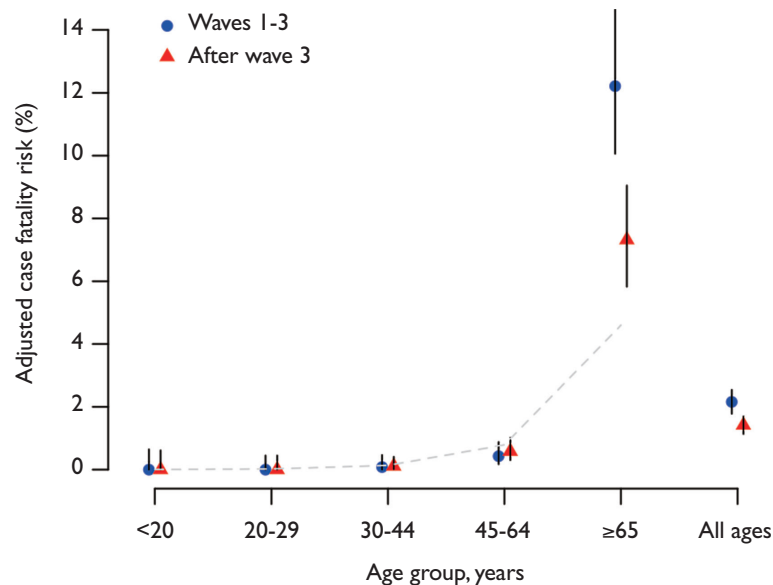


FIG 2. Confirmed case fatality risk of COVID-19 in Hong Kong, stratified by age group and pandemic wave.

(23-29 January 2020), and post-peak (30 January to 13 February 2020) periods, based on the symptom onset dates of infectors. After normal distributions were fitted to the empirical serial interval data, serial interval decreased from an average of 7.8 (95% CI=7.0-8.6) days during the pre-peak period to 2.6 (95% CI=1.9-3.2) days during the post-peak period. Stratification by isolation delay showed a similar trend such that average serial intervals were shortened by at least threefold. Additionally, estimated R_t obtained using a constant serial interval distribution versus a time-varying effective serial interval distribution was compared. The differences in estimated R_t were more pronounced during the pre- and post-peak periods but were relatively minor during the peak week when R_t was approximately 1.

There were positive associations between isolation delay and effective serial intervals. In a linear multivariable regression model, isolation delay alone explained up to 51.5% of variability in daily empirical serial intervals, indicating a primary predictor. Inclusion of either non-pharmaceutical intervention strategies or the accumulation of population immunity explained an additional 15.6% to 20.3% of variability.

Discussion

The extended framework for separately estimating R_t for local and imported cases was compared based on assumptions of (1) equal infectiousness of local and imported cases, and (2) all cases being local, which resulted in underestimation and overestimation

of local transmission, respectively. To account for presymptomatic transmission, a deconvolution approach was used instead of serial intervals to reduce bias arising from misspecification of the infectiousness profile. A bootstrap method was used to adjust for uncertainties in the analysis.

The cCFR increased with age across all waves, and the cCFR generally lowered after the third wave, likely due to improved detection of mild cases and better clinical management of patients. These findings were consistent with studies conducted in other countries.⁴ Similarly, a systematic review of the 2009 influenza A (H1N1) pandemic showed that mortality risk among symptomatic cases increased monotonically with age.⁵

A notable observation was a minimum threefold reduction in serial intervals over the 36-day period from 9 January to 13 February 2020. Non-pharmaceutical interventions designed to reduce isolation delays was the primary factor in shortening serial intervals over time. Specifically, serial intervals were shortened by >3 days among transmission pairs in which infectors were isolated promptly after symptom onset, compared with those isolated later. Our findings aligned with results of a study that showed a 60% reduction in COVID-19 transmissibility when case isolation and contact quarantine occurred within 1 day of symptom onset.

Conclusions

In Hong Kong, suppression of COVID-19 transmission during three pandemic waves was

achieved through a combination of public health measures, including travel restrictions, early and near-complete case identification, rapid interruption of transmission chains through contact tracing and quarantine, social distancing measures, and widespread use of face masks by the population. Maintenance of these interventions and population behaviours, along with strategies to address public fatigue, may help prevent future pandemic waves.

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Disclosure

The results of this research have been previously published in:

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