


BMJ Open Impact of air temperature and containment measures on mitigating the intrahousehold transmission of SARS-CoV-2: a data-based modelling analysis

Di Liu,¹ Qidong Tai,² Yaping Wang,³ Miao Pu,³ Lei Zhang,² Bo Su ¹

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DL and QT contributed equally.

DL and QT are joint first authors.

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¹Central Laboratory, Tongji University School of Medicine, Shanghai, China

²Department of Thoracic Surgery, Tongji University School of Medicine, Shanghai, China

³Public Health and Preventive Medicine, Tongji University School of Medicine, Shanghai, China

Correspondence to

Professor Bo Su;
subo_group@hotmail.com

ABSTRACT

Objectives Air temperature has been considered a modifiable and contributable variable in COVID-19 transmission. Implementation of non-pharmaceutical interventions (NPIs) has also made an impact on COVID-19 transmission, changing the transmission pattern to intrahousehold transmission under stringent containment measures. Therefore, it is necessary to re-estimate the influence of air temperature on COVID-19 transmission while excluding the influence of NPIs.

Design, setting and participants This study is a data-based comprehensive modelling analysis. A stochastic epidemiological model, the ScEIQR model (contactable susceptible-exposed-infected-quarantined-removed), was established to evaluate the influence of air temperature and containment measures on the intrahousehold spread of COVID-19. Epidemic data on COVID-19, including daily confirmed cases, number of close contacts, etc, were collected from the National Health Commission of China.

Outcome measures The model was fitted using the Metropolis-Hastings algorithm with a cost function based on the least squares method. The LOESS (locally weighted scatterplot smoothing) regression function was used to assess the relationship between air temperature and rate of COVID-19 transmission within the ScEIQR model.

Results The ScEIQR model indicated that the optimal temperature for spread of COVID-19 peaked at 10°C (50°F), ranging from 5°C to 14°C (41°F–57.2°F). In the fitted model, the fitted intrahousehold transmission rate (β') of COVID-19 was 10.22 (IQR 8.47–12.35) across mainland China. The association between air temperature and β' of COVID-19 suggests that COVID-19 might be seasonal. Our model also validated the effectiveness of NPIs, demonstrating that diminishing contactable susceptibility (Sc) and avoiding delay in diagnosis and hospitalisation (η) were more effective than contact tracing (κ and ρ).

Conclusions We constructed a novel epidemic model to estimate the effect of air temperature on COVID-19 transmission beyond implementation of NPIs, which can inform public health strategy and predict the transmission of COVID-19.

INTRODUCTION

COVID-19 has been spreading for more than 2 years in many countries. Many factors

Strengths and limitations of this study

- We used a Metropolis-Hastings algorithm, the Markov chain Monte Carlo method, to establish a novel epidemiological ScEIQR (contactable susceptible-exposed-infected-quarantined-removed) model.
- Data on early spread and early social intervention for COVID-19 can fit well in the stochastic ScEIQR model.
- The study explored the influence of air temperature on the intrahousehold transmission of COVID-19.
- The limited latitude span in this study narrowed the range of air temperatures explored.

such as virus virulence, host defence potential and number of contacts *overall* could affect its transmission.¹ Since the influenza virus is affected by changes in temperature and relative humidity, air temperature might be an important factor that can influence the transmission of SARS-CoV-2, which caused the COVID-19 epidemic.² However, the effects of meteorological indicators on COVID-19 transmission are unclear. A few studies have reported that air temperature influences transmission of COVID-19. Bashir and colleagues found a significant association between temperature and the COVID-19 pandemic in the USA^{3 4} and Germany.⁵ However, some researchers have reported contradictory findings.^{6 7} Thus, the effect of air temperature on COVID-19 transmission remains controversial.

In the past 2 years, governments of many countries have implemented several non-pharmaceutical interventions (NPIs), including physical and social distancing, quarantine, and isolation, to mitigate the outbreak of COVID-19 at its early stage.⁸ In China, cases of COVID-19 declined within 2 months as a direct result of NPIs executed since 23 January 2020. Aside from increasing

physical and social distance, contact tracing and hospitalised isolation were also applied.⁹ These containment measures were effective in controlling the spread of COVID-19. However, what's the influence of air temperature on the COVID-19 incidence and transmission rate beyond the effects of NPIs?

We then used data from China as an appropriate example to evaluate the relationship between air temperature and the spread of COVID-19. First, social intervention in China was taken almost simultaneously and uniformly across provinces, differing only in intensity. Second, the latitude span of mainland China is large enough to reflect zones with a daily mean air temperature of -7°C to 20°C in winter. Third, we could acquire the daily number of cases in quarantine from the database of National Health Commission of The People's Republic of China. Thus, we constructed a new kind of SEIR (susceptible-exposed-infected-removed) model, called the ScEIQR model (contactable susceptible-exposed-infected-quarantined-removed), to depict a new pattern of spread of COVID-19, the intrahousehold transmission. The model can separate the influence of social intervention measures from confounding factors. Hence, with machine learning methods, we achieved the precise influence of air temperature on the spread of COVID-19. Moreover, this model validated the effectiveness of NPIs in controlling the transmission of COVID-19.

MATERIALS AND METHODS

Development of the dynamic, non-classic SEIR model for COVID-19

The ScEIQR model developed is an expanded SEIR epidemic model containing six compartments: Sc (contactable susceptible), E (exposed to SARS-CoV-2), Q (daily close contacts in quarantine), I (infectors outside the healthcare system), Rh (accumulative hospitalised infectors) and Rs (self-recovery individuals with asymptomatic infection or mild symptoms who have never been hospitalised and registered in the healthcare system) (figure 1). Sc represents the contactable susceptible subpopulation under the NPIs, such as lockdown, social distancing, cancelling gatherings and closing public places, which were set as random variables in the model. Q represents the close contacts of infectors found out by epidemiological survey, and notified to be in self-quarantine at home, in the hotel or indicated isolating room for 14-day medical observation. Rh represents confirmed and hospitalised infectors in isolation wards, reported daily by the public health agency. E, I and Rs compartments are outside of the healthcare system. Rh is the reported cumulative confirmed cases in the model. Several parameters linked the compartments, and the flow velocity of each compartment is illustrated in figure 1 (details are in the online supplemental methods).

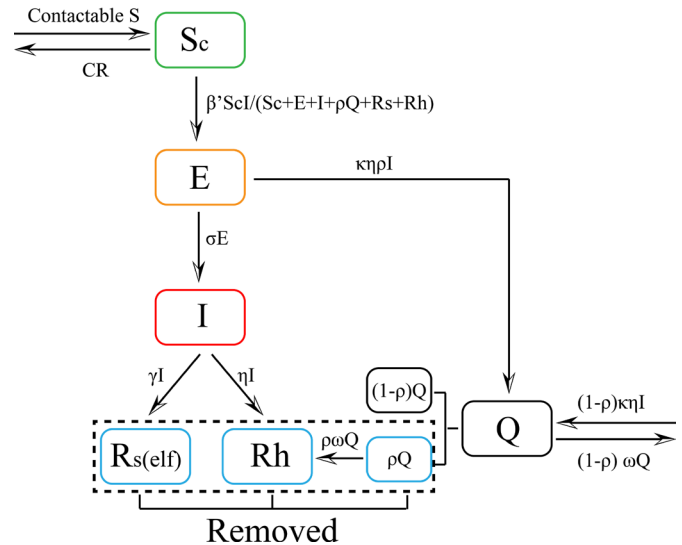


Figure 1 Flow diagram of the ScEIQR epidemiological model, with six compartments: contactable susceptible (Sc), exposed individuals (E), infected individuals who were outside public health measures (I), close contacts in quarantine (Q), self-recovery individuals (Rs) and cumulative hospitalised individuals (Rh). The flow velocities between the compartments are indicated. CR, contact rate; ScEIQR, contactable susceptible-exposed-infected-quarantined-removed model.

Parameters of the stochastic ScEIQR model

The definition and the initial range of parameters, β' , σ , γ , κ , ρ , ω , η and Sc, in the model are listed in table 1. β' is the rate of intrahousehold transmission dependent on the biological property of SARS-CoV-2. σ and γ are associated with the intrinsic incubation and communicable periods of COVID-19. κ , ρ and ω are associated with contact tracing and quarantine. η reflects the pace of confirmed diagnosis and hospitalised isolation among the infectors. Other indexes could be calculated from the solved model, such as contact rate (CR), quality of CCT (surveyQ), proportion of untraceable infectors (approximately equivalent to the asymptomatic) (utI%), and the incubation and communicable periods of SARS-CoV-2. Among these, CR reflects the proportion of Sc in the population under the integrated NPIs, while surveyQ represents the quality of contact tracing.

1. β' : rate of effective intrahousehold transmission for the contactable susceptible (Sc).
2. σ : rate of progression from being exposed to being infectious, which is the reciprocal of the incubation period (days) in the transmission chain.
3. γ : rate of removal for Rself, which is the reciprocal of the communicable period of propagating for a self-recovery infector in the transmission chain.
4. η : rate of removal for Rh, which is the reciprocal of the communicable period of propagating for a hospitalised infector in the transmission chain.
5. κ : average number of traceable close contacts for each confirmed case, which was investigated and notified to be in quarantine by the epidemiological survey group

Table 1 Definition and setting range of parameters in the ScEIQR model

Parameters	Definition	Method	Setting range
Sc	Contactable susceptible under the social NPIs.	MCMC	(1–0.01N)
β'	Transmission rate: the number of infected people by one infector.	MCMC	(1–19)
σ	Transition rate from exposure to being contagious.	MCMC	(0.27–0.5)
γ	Recovery rate of the asymptomatic infector.	MCMC	(0.04–0.3)
η	Hospitalisation rate and pace of symptomatic infectors.	MCMC	(0.001–0.999)
κ	Extent of epidemiological investigations.	MCMC	(0–350)
ρ	Positive rate of COVID-19 among quarantined people.	MCMC	(0–0.1)
ω	The transition rate of quarantined people developing to being contagious per day.	MCMC	(0.07–0.6)
CR	Proportion of contactable susceptible (Sc) under the interventive social prevention.	Sc/N	–
lpd	Time elapsed from exposure to SARS-CoV-2 to the first apparent symptoms.	$1/\sigma+1/\eta$	–
utl%	Proportion of untraceable infectors, approximately equates to the asymptomatic.	$\gamma/(\eta+\kappa\rho\eta+\gamma)$	–
SurveyQ	Quality of contact tracing.	$\kappa\rho$	–
Cpd	Time for untraceable infectors to becoming contagious among the susceptible.	$1/\gamma$	–

Cpd, communicable period; CR, contact rate; lpd, incubation period; MCMC, Markov chain Monte Carlo; N, total population of a province; NPIs, non-pharmaceutical interventions; ScEIQR, contactable susceptible-exposed-infected-quarantined-removed; utl%, proportion of asymptomatic infectors.

of each province. All close contacts found were assumed to be in 14-day quarantine.

- ρ : virus-positive rate among individuals in quarantine in each province.
- ω : The transition rate of quarantined people developing to being contagious per day.

Formulation and parameter setting of the ScEIQRsh model

The simultaneous differential equation system for the stochastic ScEIQR model is as follows:

- $dE/dt = \beta' ScI / (Sc + E + I + Rs + Rh + \rho Q) - \kappa \eta I - \sigma E$.
- $dI/dt = \sigma E - \eta I - \gamma I$.
- $dQ/dt = \kappa \eta I - \omega Q$.
- $dRh/dt = \eta I + \rho \omega Q$.
- $dRs/dt = \gamma I$.

In equation (1), unlike the classic SIR (susceptible, infected, and recovered) model, one of the most basic compartmental model in epidemiology, or SEIR model, the denominator of flow-in velocity is $(Sc + E + I + Rs + Rh + \rho Q)$ instead of N or any other constant. The denominator refers to all transmissible individuals in the system. The classic SIR or SEIR model assumes that the infectors mix with different susceptible individuals every day, while the ScEIQR model assumes that the infectors mix with fixed contactable susceptible individuals every day.

- Parameter setting: β' , σ , γ and η were set as random variables with Gaussian distribution; κ , ω and ρ were set as random variables with uniform distribution.
- Parameter range setting: β' (1–19), σ (0.27–0.5), γ (0.04–0.3), η (0.001–0.999), κ (0–350), ω (0.07–0.6) and ρ (0–0.1).

Sc was set as a random variable with Gaussian distribution, with a setting range of 0–0.002N, where N denotes the total population of the province. Other initial compartment values were estimated as the following: initial $R_h = H_0$, initial $R_s = 0$, initial $Q = Q_0$, initial $I = H_0 * (1 - \eta) / \eta$ and initial $E = \text{initial } I / \sigma$. H_0 and Q_0 denote the cumulative hospitalised cases and close contacts in quarantine at day 0 (23 February 2020) reported by the public health administration of the province. If H_0 or Q_0 is missing in some provinces, H_0 or Q_0 will be given an assumed number.

Epidemic data acquisition

The intrahousehold transmission of COVID-19¹⁰ was observed from the beginning of COVID-19 in mainland China.¹¹ Each provincial health commission would report the daily number of close contacts in quarantine along with the number of daily confirmed cases of COVID-19. These complete data from mainland China were appropriate for fitting in the ScEIQR model and for investigating the intrahousehold transmission of COVID-19. We collected data on daily accumulative confirmed COVID-19 cases from January to March 2020 from the provincial health commission in mainland China. The daily number of close contacts in quarantine and the daily number of those relieved of quarantine were also collected from the provincial government's website in China. The Xizang and Qinghai provinces were excluded because these provinces only had 1 and 18 confirmed cases, respectively. According to the COVID-19 guidelines of China, diagnosed cases of COVID-19 were hospitalised in isolation

wards; thus, the reported confirmed cases were hospitalised infectors in China. Details on the criteria for quarantine of confirmed cases and close contacts are provided in the online supplemental methods.

Simulation and model fitting

We fitted both the reported accumulative confirmed cases and the daily close contacts in each province with Rh and Q compartments in the ScEIQR model using the Markov chain Monte Carlo (MCMC) method with cost function based on the least squares method. Briefly, the model parameters and Sc were random samplings with a Metropolis-Hastings algorithm, the MCMC method. The proposal distribution for accept-reject is a Bernoulli distribution, which is from the comparison of the cost function of curve fitting in iteration (better or not). The simulated curves of both Rh and Q were simultaneously fitted with raw data (real-world data) using the least squares method and the cost function was the sum of squares for error/sum of squares for total (SSE/SST). The optimised parameters were documented with 100 000 iterations of 0.1 step size from 0 to 60 days with burn-in of 50 000 iterations for 29 provinces of mainland China. The expected values and SD for each parameter were then confirmed.

Air temperature in the provinces of China during the spread of COVID-19

The minimum, mean and maximum air temperatures in each province were collected from the National Meteorological Administration from 15 January 2020 to 15 February 2020 (1 week before and 3 weeks after day 0, which was on 23 January 2020). The LOESS (locally weighted scatterplot smoothing) regression depicted the relationship between air temperature in 29 provinces and the rate of COVID-19 transmission in the ScEIQR model.

Patient and public involvement

No patients were involved.

Statistical analysis

The 29 provinces enrolled were separated into seven geographical regions: North, Northeast, East, Central, Northwest, South and Southwest. The curves of Rh and Q were simultaneously fitted with raw data using the least squares method with a tolerance of 1.05. SSE/SST was the cost function. The data process was performed in R (V.3.6.1) and the 'deSolve' R package was used to solve the differential equations. The R source code can be found on GitHub. The parameters were denoted by mean±SD for each province and the median (IQR: 25%–75%) was used to describe the provinces.

RESULTS

Influence of air temperature on the transmissibility of COVID-19

The rate of intrahousehold transmission (β') was first calculated and subsequently the non-linear association

between β' and air temperature was depicted by LOESS fitting.

Calculation of intrahousehold transmission rate (β')

First, we fit COVID-19 transmission with the integrated social NPIs using the ScEIQR model, which could be well fitted with the reported number of daily accumulative confirmed cases and close contacts in quarantine in 29 provinces of mainland China (figure 2, online supplemental figure S1). The predicted daily Rh and Q compartments coincided with the provincial reported numbers. The fitting curves, yielded a median intrahousehold transmission rate (β') for 29 provinces were 10.22 (IQR 8.47–12.35), implying that 10.22 persons would be infected by one infector when the susceptible individuals are mostly acquaintances and the Sc is extrapolated to the infinite (figure 3A,B, table 2, online supplemental table S1).

Range of air temperature for spread of COVID-19

The mean air temperature for every province in China spanned from -15°C (5°F) to 20.25°C (68.45°F) between January and February 2020 (figure 3C). The relationship between air temperature and β' was evaluated. As the daily air temperature increased from 0°C (32°F), the value of β' raised gradually until the air temperature reached 7°C (44.6°F) for a minimum daily temperature or 15°C (59°F) for a maximum daily temperature, respectively, and then declined sharply as the temperature continued to rise (figure 3). We observed that the transmission rate (β') was higher than 11 for the mean air temperature in the 5°C – 14°C (41°F – 57.2°F) range, which may be most suitable for spread of COVID-19.

Validation of NPIs on mitigating the spread of COVID-19

The COVID-19 pandemic hit many countries due to coronavirus mutations. Therefore, containment measures are still pivotal in controlling its spread.

Assessment of NPI measures by suppositional simulation

We assessed three independent parameters, CR, η and surveyQ, which were crucial to stopping the spread. Our model estimated a median Sc of 26.98 (IQR 13.97–54.57), with the highest value in the province of Hubei and lowest in Neimenggu (online supplemental table S1). The median CR for 29 provinces was $6.84\text{E-}07$ (IQR $3.77\text{E-}07$ – $1.44\text{E-}06$) (figure 4A). To illustrate the influence of NPI measures on COVID-19 transmission in the ScEIQR model, we arbitrarily adjusted CR, κ , ρ and η values with representative 30% or 50% upregulation/downregulation to simulate the suppositional spreading situation. If CR were 30% or 50% enlarged, the eventual accumulative hospitalised cases (Rh) would strongly increase and the infectors (I) would reduce and vice versa (figure 4B,C). The median velocity of hospitalised isolation of infectors (η) was 0.69 (IQR 0.47–0.87) for 29 provinces (figure 4D). η had an opposite influence on CR. If

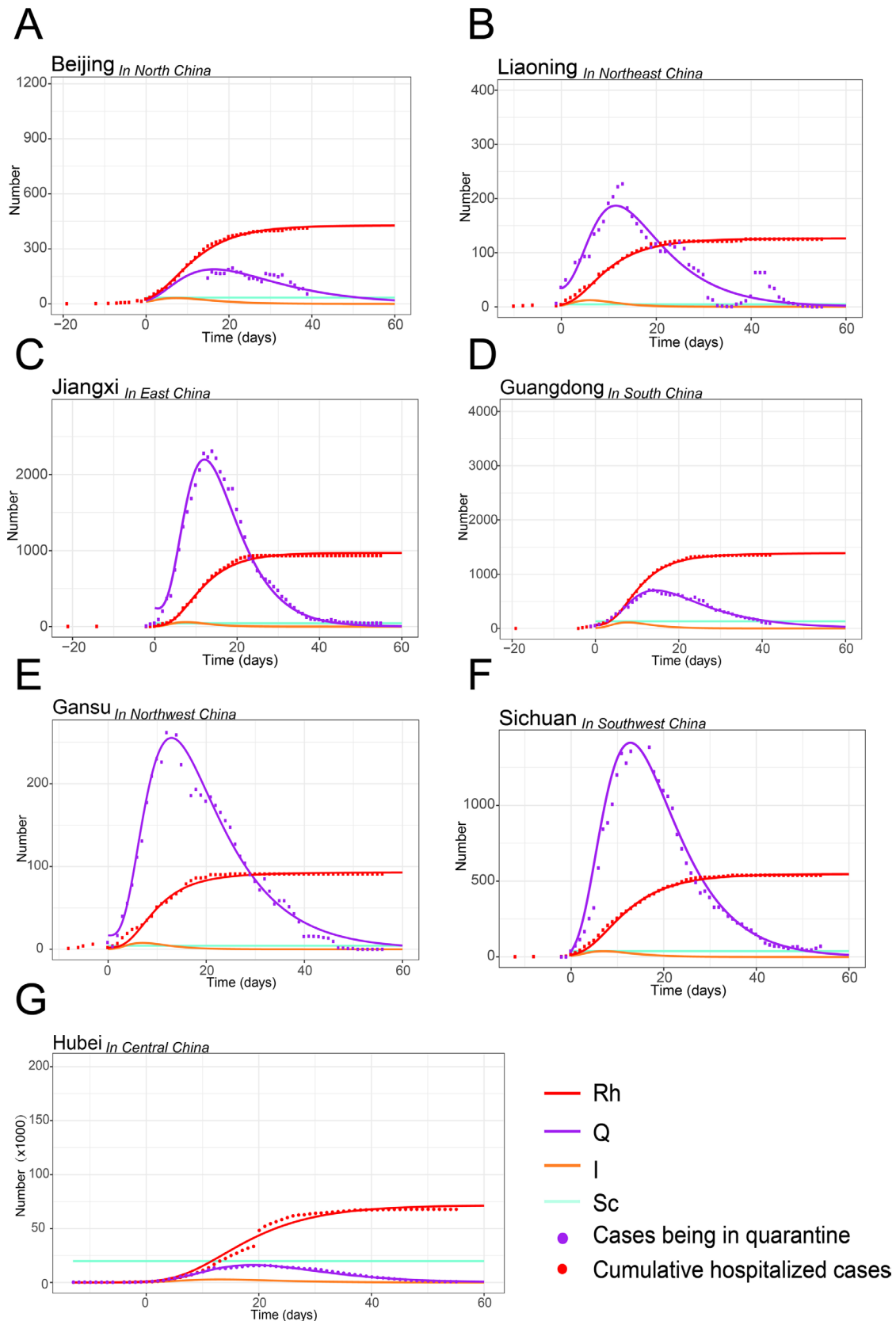


Figure 2 Fitting curves of confirmed cases and close contacts predicted by the ScEIQR model from day 0 to 23 January 23, 2020. Fitting curves of confirmed cases and close contacts in (A) Beijing, representing North China; (B) Liaoning, representing Northeast China; (C) Jiangxi, representing East China; (D) Guangdong, representing South China; (E) Gansu, representing Northwest China; (F) Sichuan, representing Southwest China; and (G) Hubei, representing Central China. I, infected individuals who were outside public health measures; Q, close contacts in quarantine; Rh, cumulative hospitalised individuals; Sc, contactable susceptible; ScEIQR, contactable susceptible-exposed-infected-quarantined-removed model.

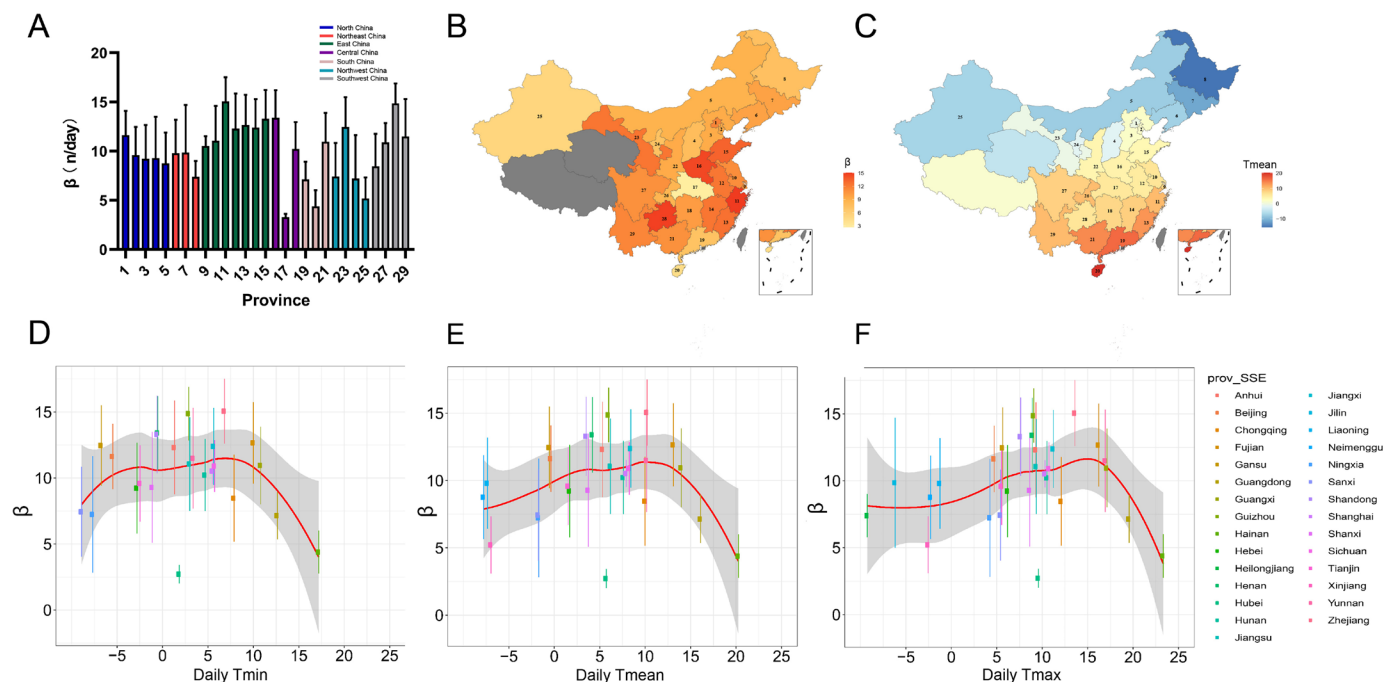


Figure 3

Figure 3 Association between air temperature and transmission rate (β') of COVID-19. (A) Transmission rates of COVID-19 among acquaintances in 29 provinces grouped by geographical region. (B) Mapping the transmission rate of COVID-19 in 29 provinces of mainland China. In A and B, the number represents the provinces in each geographical region: North, 1–5; Northeast, 6–8; East, 9–15; Central, 16–18; South, 19–21; Northwest, 22–25; and Southwest, 26–29. (C) Mapping the daily mean temperature from 15 January 2020 to 15 February 2020 in 29 provinces of mainland China. (D) Association between daily minimum temperature (Tmin) and transmission rate (β') of COVID-19 depicted by LOESS regression. (E) Association between daily mean temperature (Tmean) and transmission rate (β') of COVID-19 depicted by LOESS regression. (F) Association between daily maximum temperature (Tmax) and transmission rate (β') of COVID-19 depicted by LOESS regression. Dots of different colour represent temperature in different provinces. SSE, the sum of squares due to error.

Table 2 Median value of parameters and indexes in 29 provinces of mainland China using the ScEIQR model

Variables	Median	IQR (25%–75%)	Range
β'	10.22	8.47–12.35	3.29–15.06
σ	0.42	0.40–0.44	0.33–0.48
γ	0.15	0.10–0.22	0.05–0.26
η	0.69	0.47–0.87	0.16–0.97
κ	42.0	27.83–60.78	5.35–147.79
ρ (%)	0.9	0.4–1.6	0.03–5.10
ω	0.12	0.10–0.15	0.07–0.21
Sc	26.98	13.97–54.57	5.91–25525.54
CR	6.84E-07	3.77E-07–1.44E-06	1.64E-07–4.33E-04
lpd	4.17	3.60–4.71	3.27–9.62
utl%	14.88	8.17–25.37	3.92–34.36
SurveyQ	0.39	0.22–0.55	0.04–2.61
Cpd	6.77	4.53–10.36	3.91–19.90
$1/\sigma$	2.39	2.26–2.56	2.07–3.01

Cpd, communicable period; CR, contact rate; lpd, incubation period; Sc, contactable susceptibility; ScEIQR, contactable susceptible-exposed-infected-quarantined-removed; utl%, proportion of asymptomatic infectors.

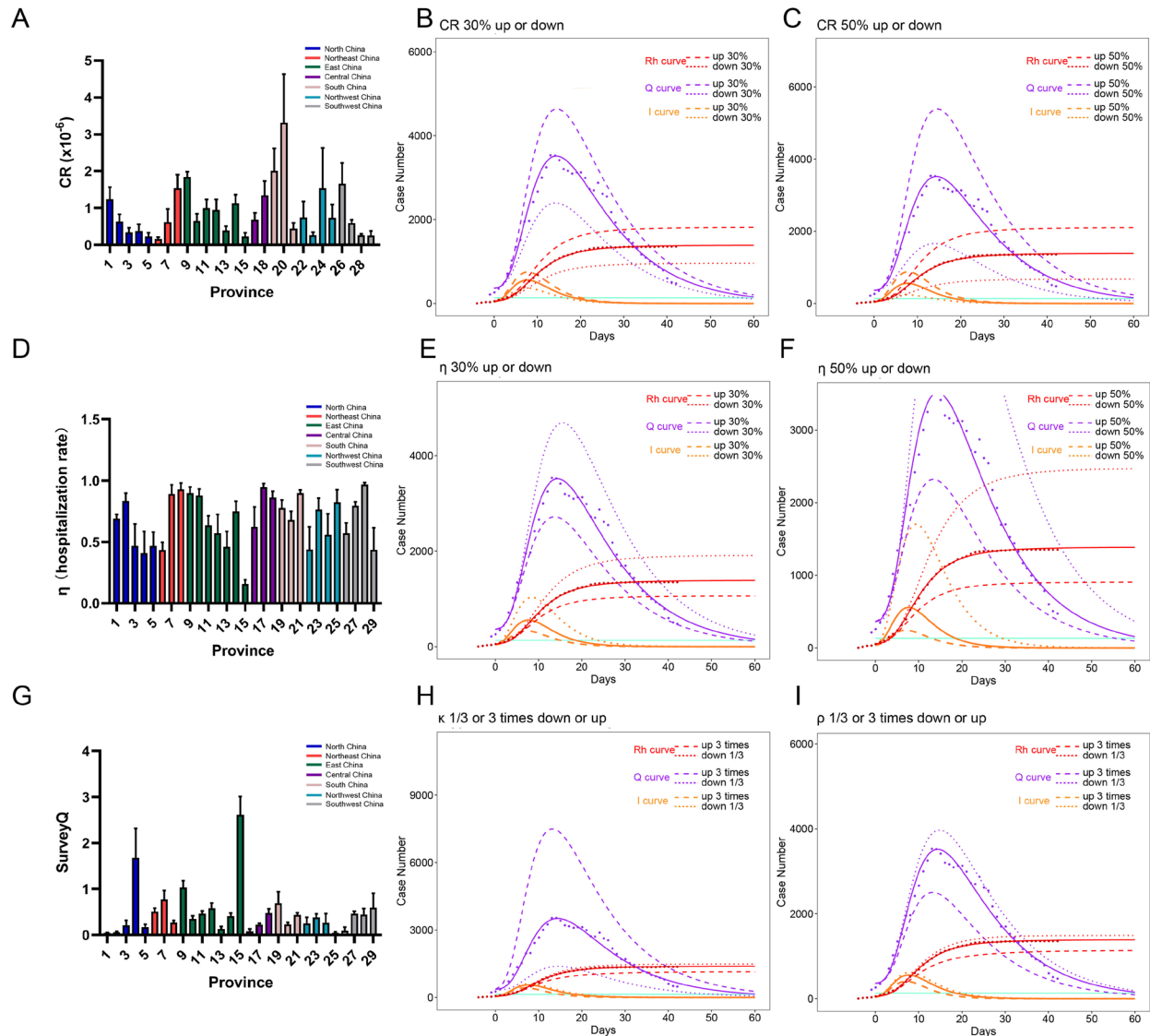


Figure 4 Evaluation of the effectiveness of three NPI measures and the suppositional simulation. (A) The model was used to calculate CR for 28 provinces. In B, C, E, F, H and I, the solid curves are the fitted curves in our modelling analysis. The dashed lines represent the suppositional simulation curves after adjusting the value of three NPI measures. The small dashed line shows the upregulation of the values of the NPI measures, while the big dashed line shows the downregulation of the values of the NPI measures. The red curves represent the Rh compartment; the purple curve represents the Q compartment; and the orange curve represents the I compartment. (B) Change in Rh, Q and I compartments after adjusting the CR 30% up or down. (C) Change in Rh, Q and I compartments after adjusting the CR 50% up or down. (D) Hospitalisation rate and pace, η , in the 29 provinces. (E) Change in Rh, Q and I compartments after adjusting η 30% up or down. (F) Change in Rh, Q and I compartments after adjusting η 50% up or down. (G) Quality of contact tracing, surveyQ, was depicted among 29 provinces. (H) Simulation of Rh, Q and I compartments after adjustment for κ for one-third down or three times up. (I) Simulation of Rh, Q and I compartments after adjustment of ρ 1/3 down or 3 times up. CR, contact rate.

η increased by 30% or 50%, the eventual Rh would be strongly reduced and vice versa (figure 4E,F).

The value of surveyQ, the product of κ times ρ , was 0.39 (IQR 0.22–0.55), which indicated that on average 0.39 of positive cases were in close contact with confirmed infectious individuals according to CCT (figure 4G). κ and ρ can be used to assess the effectiveness of CCT. The median κ in 29 provinces was 42.0 (IQR 27.83–60.78), suggesting that, on average, 42 close contacts of an infector had been traced by CCT (online supplemental figure S2A). The COVID-19 positivity rate (ρ) among close contacts

was 0.98% (IQR 0.47%–1.60%), ranging from 0.03% to 5.10% (online supplemental figure S2B), which was quite close to the WHO-China joint report of 0.9%–5% in China.¹¹ With higher κ or ρ , the eventual accumulative number of confirmed COVID-19 would diminish and the Rh would reach a plateau (figure 4H,I, online supplemental figure S2C,D,E,F). For the same adjusted extent, the effectiveness of CR and avoiding delay in diagnosis and hospitalisation in preventing spread was stronger than that of CCT parameters κ and ρ . The incubation and communicable periods of COVID-19 were calculated

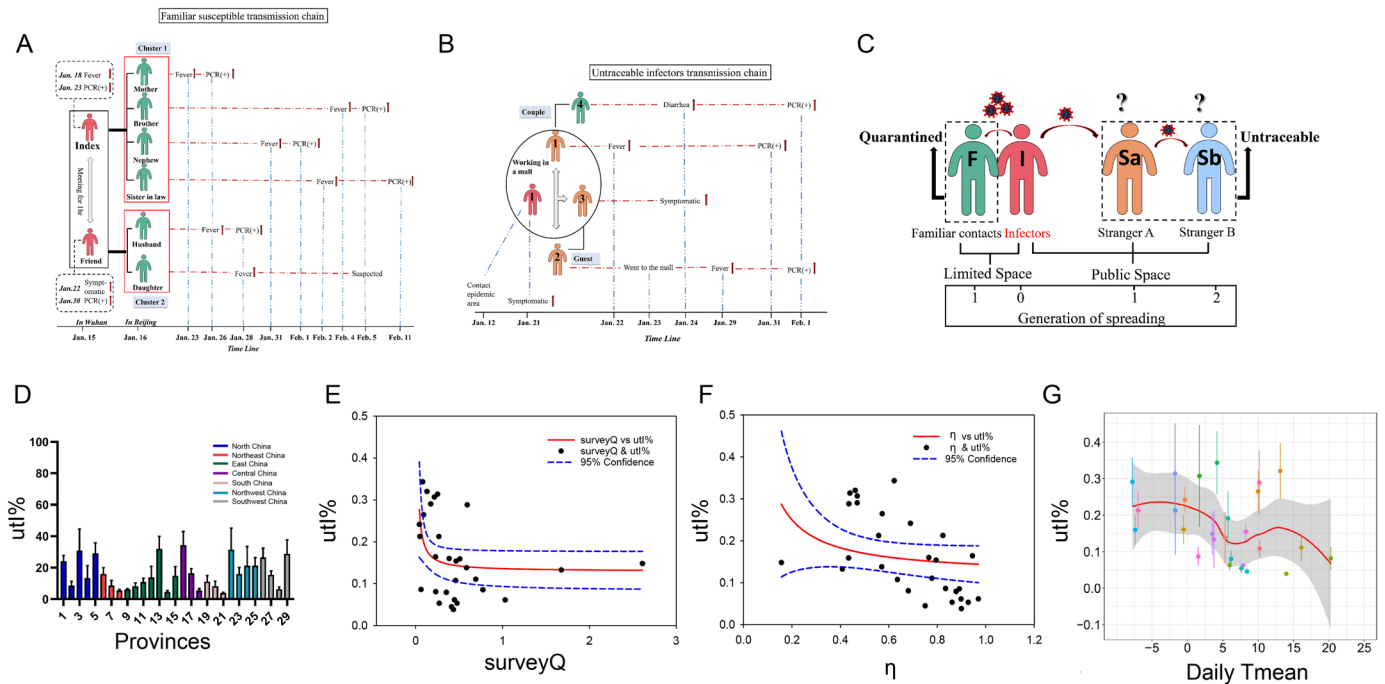


Figure 5

Figure 5 Transmission patterns of COVID-19 under social NPIs and the association of untraceable infectors with surveyQ, η and air temperature. (A) A representative example of intrafamily and interfamilial transmissions of COVID-19 in Beijing. (B) A representative example of COVID-19 transmission among strangers in a large mall. (C) Stranger–stranger transmission is the blind zone of contact tracing. (D) Median proportion of asymptomatic infectors among 29 provinces. (E) Non-linear association between the ratio of untraceable infectors and surveyQ. Higher surveyQ could reduce the ratio of untraceable infectors. However, as surveyQ increases, the proportion of untraceable infectors remains constant. (F) Non-linear association between the ratio of untraceable infectors and η . Higher η could reduce the ratio of untraceable infectors either. (G) Relationship between the ratio of untraceable infectors and daily mean temperature (Tmean). NPIs, non-pharmaceutical interventions; utI%, proportion of asymptomatic infectors.

using the ScEIQR model and the results were consistent with other studies (table 2, online supplemental figure S3), suggesting that this novel model is reasonable.

Blind zone of contact tracing and asymptomatic infectors in NPIs

With the integrated social NPIs, COVID-19 transmission occurred between undetected infectors and acquaintances and a few strangers with whom the infectors had contact with for daily necessities. In a typical intrahousehold transmission, the index case infected directly four family members and one friend and indirectly the friend's family within half a month¹² (figure 5A). CCT can easily find the close contacts of acquaintances but would be inefficient in identifying transmission among strangers in public spaces. For example, a salesman infected two unacquainted sales associates in other sales areas sequentially without gathering in a large mall, and one of the infected sales associates transmitted the infection to a customer without direct contact after lingering for 30 min (figure 5B). This transmission chain among strangers could not be easily identified by contact tracing and was only revealed after all participants' symptoms appeared (figure 5C).

Another blind spot of contact tracing is the asymptomatic infection. The ScEIQR model showed that the

proportion of infectors who are asymptomatic and with mild symptoms without hospitalisation (the proportion of untraceable infectors, utI%) was 14.88% (IQR 8.17%–25.37%), ranging from 3.92% to 34.36% across 29 provinces, which implied that 14.88% of patients with COVID-19, on average, could not be identified with social NPIs and the average proportion of asymptomatic patients with COVID-19 was 14.88% (IQR 8.17%–25.37%) (figure 5D). The higher surveyQ of CCT can only reduce but not eliminate utI% (figure 5E), but high η could decline utI% (figure 5F). Hence, contact tracing is insufficient in finding all the infectors, especially in stranger–stranger transmission and asymptomatic infection. Air temperature also influences the ratio of asymptomatic infectors. When the mean air temperature was subzero, the utI% was high (figure 5G).

DISCUSSION

It is important to understand the effects of the meteorological conditions on the spread of COVID-19 to predict its prevalence, especially with intrahousehold transmission. In our study, we found that the transmission rate (β') increased as air temperature rose from -5°C

(23°F), with the peak of β' occurring at the minimum, average and maximum temperatures of 7°C (44.6°F), 10°C (50°F) and 15°C (59°F), respectively, and then starting to decline at a higher temperature, across the 29 provinces in China. The finding is consistent with the curves reported by Wang *et al.*,¹³ who claimed that the peak of accumulative cases in 492 cities appeared at the minimum, average and maximum temperatures of 6.7°C (44.06°F), 8.72°C (47.7°F) and 12.42°C (54.36°F), respectively. Wang *et al.*¹³ and Sajadi *et al.*¹⁴ found that the regions along the 30°–50° N' latitude with an average temperature of 5°C–11°C (41°F–51.8°F) showed increased transmission of COVID-19. We also coincidentally discovered that the optimal mean temperature ranges for COVID-19 transmission is at 5°C–14°C (41°F–57.2°F). Lowen *et al.*² proved that the transmission of the influenza virus through droplets was greater and the peak duration of virus shedding lasted longer at 5°C (41°F) than at 20°C (68°F). Indeed, the transmission rate of COVID-19 at 5°C (7.39±1.62) was higher than the transmission rate at 20.25°C (4.39±1.63). Another similar infectious disease, SARS (severe acute respiratory syndrome), was found to have a higher transmission rate in temperatures below 24.6°C in Hong Kong.¹⁵ From the curves we have illustrated, we could suspect that the transmission rate would be further reduced, although not eliminated, at temperatures greater than 20.25°C (68.45°F). It can be expected that the spread of COVID-19 would be moderate in northern hemispheres in the summer and it is likely to become a seasonal infectious disease. The broader air temperature range for optimal COVID-19 transmission strongly suggests the current necessity and urgency of vaccines.

Besides air temperature, the most important measures to contain the COVID-19 epidemic are vaccines and NPIs. After the first-level public health emergency response on 23 January 2020, integrated NPIs were implemented in mainland China during the COVID-19 epidemic.⁹ The pattern of spread of COVID-19 changed to an intrahousehold transmission. A report of the 'WHO-China Joint Mission on COVID-19' verified that about 78%–85% of infections in the Guangdong and Sichuan provinces occurred within families.¹¹ In Beijing, 176 out of 262 confirmed cases were intrahousehold members.¹⁰ Using our ScEIQR epidemic model, we estimated for the first time the effectiveness of integrated NPIs in simulating the restricted spread of COVID-19 among acquaintances. The ScEIQR model can fit the realistic provincial epidemic and NPI data on COVID-19 in China without adjusting the parameters. Unlike the classic SEIR epidemic model, which assumes that infectors mix with all susceptible individuals daily, in the ScEIQR model the infectors mix with contactable susceptible individuals daily, which include family members, relatives, coworkers, friends and some other contactable strangers who provide daily necessities to the infectors. Because contact among acquaintances is more frequent than contact among the whole population,

the β' value tends to be larger in our model than in the classic SEIR model in other studies.¹⁶

In the NPI measures, CR and avoiding delay in diagnosis and hospitalisation are more effective in diminishing the eventual accumulative number of COVID-19 cases than the CCT parameters κ and ρ . In case of insufficient medical resources, better way to improve delay in diagnosis and hospitalisation could be to increase laboratory capacity for SARS-CoV-2 testing or to build makeshift hospitals to increase bed capacity.¹⁷ Contact tracing is also helpful in mitigating the spread of COVID-19, especially among close contacts (quarantine for targeted susceptible) than among the common susceptible individuals. The surveyQ ($\kappa\rho$) of CCT could be improved by adding more CCT staff, loosening the criteria for close contacts in CCT, broadening SARS-CoV-2 testing to close contacts or using digital tools. It is undeniable that the above methods require more human and financial resources and may not be suitable in every country.

Nevertheless, lockdown and stay-at-home orders profoundly affect the society and the economy. Contact tracing is a less severe option without unnecessary quarantines. In brief, decreasing the number of contactable susceptible (S_c or c) individuals and avoiding delay in diagnosis and hospitalisation are crucial factors in the control of COVID-19.

Additionally, asymptomatic but infectious individuals are the source of recurrence of COVID-19. We demonstrated that the median and highest proportions of asymptomatic infectious people were 14.88% and 34.36%, respectively, consistent with the reported 18% among 700 infectious individuals who never showed symptoms on the Diamond Princess in the study of Mizumoto *et al.*¹⁸ and with the 30.8% of asymptomatic cases among 565 Japanese citizens evacuated from Wuhan in the study of Nishiura *et al.*¹⁹ Low air temperature could also increase the proportion of asymptomatic infectors. Hence, in addition to monitoring air temperature, it is crucial to implement containment measures. The incubation period that emerged from the ScEIQR model aligns with the 3-day incubation reported in a study of 1099 laboratory-confirmed cases by Zhong *et al.*,²⁰ which indicates that the model accurately simulates real-world transmission.

Our study was based on a novel ScEIQR NPI model but only included epidemic data from mainland China for model validation because we could not access NPI data, for example, close contacts, in other countries. This model could be fitted even with limited NPI data, although the results might be less accurate. The limited latitude span in this study narrowed the range of air temperatures, especially higher temperatures; therefore, the association of air temperature with the rate of COVID-19 transmission was informative and suggestive.²¹



CONCLUSIONS

In conclusion, we provide a new tool for quantitatively assessing the influence of air temperature or the effectiveness of NPI strategy in the COVID-19 outbreak. We also speculated that the appropriate temperature for SARS-CoV-2 transmission is within 5°C–14°C (41°F–57.2°F) under implementation of NPIs. The stochastic ScEIQR model was constructed, which can fit well the early spread and early social intervention data of COVID-19. The effectiveness of NPIs in mitigating the transmission of COVID-19 was evaluated. Keeping a low number of contactable susceptible individuals and promoting prompt diagnosis and hospitalised isolation of COVID-19-positive individuals can mitigate early intrahousehold transmission of COVID-19, guiding the implementation of effective public health intervention strategies for COVID-19 prevention. This model can apply to other regions because the proportion of acquaintances and strangers can be auto-adjusted in the fitting process. It is also suitable for other infectious diseases.

Contributors BS and LZ conceived and designed the study. QT, MP and YW collected the epidemiological data in each province in mainland China. BS and DL analysed the data with the help of YW and MP. DL and QT drafted the manuscript. BS and LZ revised the manuscript critically. All authors reviewed and approved the final manuscript. LZ and BS are co-corresponding authors and guarantors. The corresponding authors attest that all listed authors meet the authorship criteria and that no others meeting the criteria have been omitted.

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ORCID iD

Bo Su <http://orcid.org/0000-0002-2823-2650>

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