The ongoing coronavirus disease 2019 (COVID-19) outbreak expanded rapidly throughout China. Major behavioral, clinical, and state interventions were undertaken to mitigate the epidemic and prevent the persistence of the virus in human populations in China and worldwide. It remains unclear how these unprecedented interventions, including travel restrictions, affected COVID-19 spread in China. We used real-time mobility data from Wuhan and detailed case data including travel history to elucidate the role of case importation in transmission in cities across China and to ascertain the impact of control measures. Early on, the spatial distribution of COVID-19 cases in China was explained well by human mobility data. After the implementation of control measures, this correlation dropped and growth rates became negative in most locations, although shifts in the demographics of reported cases were still indicative of local chains of transmission outside of Wuhan. This study shows that the drastic control measures implemented in China substantially mitigated the spread of COVID-19.

The outbreak of coronavirus disease 2019 (COVID-19) spread rapidly from its origin in Wuhan, Hubei Province, China (1). A range of interventions were implemented after the detection in late December 2019 of a cluster of pneumonia cases of unknown etiology and identification of the causative virus, severe acute respiratory syndrome–coronavirus 2 (SARS-CoV-2), in early January 2020 (2). Interventions include improved rates of diagnostic testing; clinical management; rapid isolation of suspected cases, confirmed cases, and contacts; and, most notably, restrictions on mobility (hereafter called cordon sanitaire) imposed on Wuhan city on 23 January 2020. Travel restrictions were subsequently imposed on 14 other cities across Hubei Province, and partial movement restrictions were enacted in many cities across China. Initial analysis suggests that the Wuhan cordon sanitaire resulted in an average 3-day delay of COVID-19 spread to other cities (3), but the full extent of the effect of the mobility restrictions and other types of interventions on transmission has not been examined quantitatively (4–6). Questions remain over how these interventions affected the spread of SARS-CoV-2 to locations outside of Wuhan. Here, we used real-time mobility data, crowdsourced line list data of cases with reported travel history, and timelines of reporting changes to identify early shifts in the epidemiological dynamics of the COVID-19 epidemic in China, from an epidemic driven by frequent importations to local transmission.

Human mobility predicts the spread and size of epidemics in China

As of 1 March 2020, 79,986 cases of COVID-19 were confirmed in China (Fig. 1A)(7). Reports of cases in China were mostly restricted to Hubei until 23 January 2020 (81% of all cases), after which most provinces reported rapid increases in cases (Fig. 1A). We built a line list dataset from reported cases in China with information on travel history and demographic characteristics (8). We note that the majority of early cases (before 23 January 2020; see the materials and methods) reported outside of Wuhan had known travel history to Wuhan (57%) and were distributed across China (Fig. 1B), highlighting the importance of Wuhan as a major source of early cases. However, initial testing was focused mainly on travelers from Wuhan, potentially biasing estimates of travel-related infections upward (see the materials and methods). Among cases known to have traveled from Wuhan before 23 January 2020, the time from symptom onset to confirmation was 6.5 days (SD = 4.2 days; fig. S2), providing opportunity for onward transmission at the destination. More active surveillance reduced this interval to 4.8 days (SD = 3.03 days; fig. S2) for those who traveled after 23 January 2020.

To identify accurately a time frame for evaluating early shifts in SARS-CoV-2 transmission in China, we first estimated from case data the average incubation period of COVID-19 infection [i.e., the duration between time of infection and symptom onset (9, 10)]. Because infection events are typically not observed directly, we estimated the incubation period from the span of exposure during which infection likely occurred. Using detailed information on 38 cases for whom both the dates of entry to and exit from Wuhan were known, we estimated the mean incubation period to be 5.1 days (SD = 3.0 days; fig. S1), similar to previous estimates from other data (11, 12). In subsequent analyses, we added an upper estimate of one incubation period (mean + 1 SD = 8 days) to the date of Wuhan shutdown to delineate the date before which cases recorded in other provinces might represent infections acquired in Hubei (i.e., 1 February 2020; Fig. 1A).

To understand whether the volume of travel within China could predict the epidemic outside of Wuhan, we analyzed real-time human mobility data from Baidu Inc., together with epidemiological data from each province (see the materials and methods). We investigated spatiotemporal disease spread to elucidate the relative contribution of Wuhan to transmission elsewhere and to evaluate how the cordon sanitaire may have affected it.

Among cases reported outside of Hubei province in our dataset, we observed 515 cases with known travel history to Wuhan and a symptom onset date before 31 January 2020, compared with only 39 cases after 31 January 2020, illustrating the effect of travel restrictions (Figs. 1B and 2A and fig. S3). We confirmed the expected decrease of importation with real-time human mobility data from Baidu Inc. Movements of individuals out of Wuhan increased in the days before the Lunar New Year and the establishment of the cordon sanitaire, before rapidly decreasing to almost no movement (Fig. 2A and B). The travel ban appears to have prevented travel into and out of Wuhan around the time of the Lunar New Year celebration (Fig. 2A) and likely reduced further dissemination of SARS-CoV-2 from Wuhan.

To test the contribution of the epidemic in Wuhan to seeding epidemics elsewhere in China, we built a naïve COVID-19 “generalized” linear model (GLM (13)) of daily case counts (see the materials and methods). We estimated the epidemic doubling time outside of Hubei to be 4.0 days (range across provinces, 3.6 to 5.0 days) and estimated the epidemic doubling time within Hubei to be 7.2 days, consistent with previous reports (5, 12, 14, 15). Our model predicted daily case counts across all provinces with relatively high accuracy (as measured with a pseudo-$R^2$ from a negative binomial GLM).
**Fig. 1. Number of cases and key dates during the epidemic.** (A) Epidemic curve of the COVID-19 outbreak in provinces in China. Bars indicate key dates: implementation of the cordon sanitaire of Wuhan (gray) and the end of the first incubation period after the travel restrictions (red). The black line represents the closure of the Wuhan seafood market on 1 January 2020. The width of each horizontal tube represents the number of reported cases in that province. (B) Map of COVID-19 confirmed cases (n = 554) that had reported travel history from Wuhan before travel restrictions were implemented on 23 January 2020. Colors of the lines indicate date of travel relative to the date of travel restrictions.

**Fig. 2. Human mobility, spread, and synchrony of the COVID-19 outbreak in China.** (A) Human mobility data extracted in real time from Baidu Inc. Travel restrictions from Wuhan and large-scale control measures started on 23 January 2020. Gray and red lines represent fluxes of human movements for 2019 and 2020, respectively. (B) Relative movements from Wuhan to other provinces in China. (C) Timeline of the correlation between daily incidence in Wuhan and incidence in all other provinces, weighted by human mobility.
control measures were implemented (Fig. 3C)
time before travel restrictions and substantial
rates between 9 January and 22 January 2020
outside of Hubei experienced faster growth
rials and methods). We found that all provinces
epidemic in all other provinces (see the mate-
aimed at halting local transmission increased
from Wuhan, other local mitigation strategies
have reduced the flow of case importations
suggests that whereas travel restrictions may
bility, such as local public health response. This
explained by factors unrelated to human mo-
among locations in daily case counts was better
mean + one SD incubation period after the
in importance later.

We found that the magnitude of the early epi-
demic (total number of cases until 10 February
outside of Wuhan was very well predicted by
the volume of human movement out of
Wuhan alone ($R^2 = 0.89$) from a log-linear re-
gression using cumulative cases; fig. S8). There-
fore, cases exported from Wuhan before the
cordon sanitaire appear to have contributed to
initiating local chains of transmission, both in
neighboring provinces (e.g., Henan) and in more
distant provinces (e.g., Guangdong and Zhejiang)
(Figs. 1A and 2B). Further, the frequency of in-
troductions from Wuhan were also predictive of
the size of the early epidemic in other provinces
(controlling for population size) and thus the
probability of large outbreaks (fig. S8).

After 1 February 2020 (corresponding to one
mean + one SD incubation period after the
cordón sanitario and other interventions were
implemented), the correlation of daily case
counts and human mobility from Wuhan decreased (Fig. 2C), indicating that variability
among locations in daily case counts was better
explained by factors unrelated to human mo-

We also estimated the growth rates of the
epidemic in all other provinces (see the mate-
rials and methods). We found that all provinces
outside of Hubei experienced faster growth
rates between 9 January and 22 January 2020
(Fig. 3, A and B, and fig. S4b), which was the
time before travel restrictions and substantial
control measures were implemented (Fig. 3C
and fig. S6); this was also apparent from the
case counts by province (fig. S6). In the same
period, variation in the growth rates is almost
entirely explained by human movements from
Wuhan (Fig. 3C and fig. S9), consistent with the
theory of infectious disease spread in highly
coupled metapopulations (16, 17). After the
implementation of drastic control measures across
the country, growth rates became negative (Fig.
3B), indicating that transmission was success-
fully mitigated. The correlation of growth rates
and human mobility from Wuhan became nega-
tive; that is, provinces with larger mobility
from Wuhan before the cordon sanitario (but
also larger number of cases overall) had more
rapidly declining growth rates of daily case
counts. This could be due partly to travel re-
strictions but also to the fact that control mea-
ures may have been more drastic in locations
with larger outbreaks driven by local trans-
mision (for more details, see “Current role of
imported cases in Chinese provinces” section).

The travel ban coincided with increased test-
ing capacity across provinces in China. There-
fore, an alternative hypothesis is that the
observed epidemiological patterns outside of
Wuhan were the result of increased testing
capacity. We tested this hypothesis by includ-
ing differences in testing capacity before and
after the rollout of large-scale testing in China
on 20 January 2020 [the date that COVID-19
became a class B notifiable disease (18, 19)]
and determined the impact of this binary
variable on the predictability of daily cases
(see the materials and methods). We plotted
the relative improvement in the prediction of
our model (on the basis of normalized re-
didual error) of (i) a model that includes daily
mobility from Wuhan and (ii) a model that
includes testing availability (for more details,
see the materials and methods). Overall, the
inclusion of mobility data from Wuhan pro-
duced an improvement in the model’s pre-
diction [delta-Bayesian information criterion
> 250 (20)] over a naïve model that consid-
ers only autochthonous transmission with a
doubling time of 2 to 8 days (Fig. 3B). Of the
27 provinces in China reporting cases through
6 February 2020, we found that the largest
improvements in prediction for 12 provinces
could be achieved using mobility only (fig. S5).

In 10 provinces, both testing and mobility im-
proved the model’s prediction, and in only one
province (Hunan) was testing the most import-
ant factor improving model prediction (fig. S5).
We conclude that laboratory testing during the
early phase of the epidemic was critical; how-
ever, mobility out of Wuhan remained the main
driver of spread before the cordon sanitario.
Large-scale molecular and serological data will
be important to investigate further the exact
magnitude of the impact of human mobility
compared with other factors.

Current role of imported cases in
Chinese provinces

Because case counts outside of Wuhan have
decreased (Fig. 3B), we can further investigate
the current contribution of imported cases to
local epidemics outside of Wuhan by investigat-
ing case characteristics. Age and sex distribu-
tions can reflect heterogeneities in the risk of
infection within affected populations. To inves-
tigate meaningful shifts in the epidemiology of
the COVID-19 outbreak through time, we ex-
amined age and sex data for cases from differ-
ent periods of the outbreak and from individuals
with and without travel from Wuhan. However,
details of travel history exist for only a fraction
of confirmed cases, and this information was
particularly scant for some provinces (e.g., Zhejiang
and Guangdong). Therefore, we grouped con-

confirmed cases into four categories: (i) early cases
(i.e., reported before 1 February 2020) with travel

Using crowdsourced case data, we found that cases with travel history (categories I and III) had similar median ages and sex ratios in both the early and later phases of the outbreak (age 41 versus 42 years; 50% interquartile interval: 32.75 versus 30.75 and 54.25 versus 53.5 years, respectively; $P$ value > 0.1, 1.47 versus 1.45 males per female, respectively; Fig. 4D and fig. S7). Early cases with no information on travel history (category II) had a median age and sex ratio similar to those with known travel history (age 42 years; 50% interquartile interval: 30.5 to 49.5, $P$ value > 0.1; 1.80 males per female; Fig. 4D). However, the sex ratio of later cases without reported travel history (category IV) shifted to ~1:1 (57 male versus 62 female; $X^2$ test, $P$ value < 0.01), as expected under a null hypothesis of equal transmission risk [Fig. 4, A, B, and D; see also (21, 22) and the materials and methods], and the median age in this group increased to 46 (50% interquartile interval: 34.25 to 58, $t$ test: $P$ value < 0.01; Fig. 4, A to C, and fig. S7). We hypothesize that many of the cases with no known travel history in the early phase were indeed travelers who contributed to disseminating SARS-CoV-2 outside of Wuhan. The shift toward more equal sex ratios and older ages in nontravelers after 31 January 2020 confirms the finding that epidemics outside of Wuhan were then driven by local transmission dynamics. The case definition changed to include cases without travel history to Wuhan after 23 January 2020 (see the materials and methods).

**Discussion**

Containment of respiratory infections is particularly difficult if they are characterized by relatively mild symptoms or transmission before the onset of symptoms (23, 24). Intensive control measures, including travel restrictions, have been implemented to limit the spread of COVID-19 in China. Here, we show that travel restrictions are particularly useful in the early stage of an outbreak when it is confined to a certain area that acts as a major source. However, travel restrictions may be less effective once the outbreak is more widespread. The combination of interventions implemented in China was clearly successful in mitigating spread and reducing local transmission of COVID-19, although in this work it was not possible to definitively determine the impact of each intervention. Much further work is required to determine how to balance optimally the expected positive effect on public health with the negative impact on freedom of movement, the economy, and society at large.

**REFERENCES AND NOTES**


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Competing interests: S.V.S. is on the advisory board for BioFire Diagnostics Trend Surveillance, which includes paid consulting. A.V. reports past grants and personal fees from Metabiota Inc. outside of the submitted work. The remaining authors declare no competing interests.

Data and materials availability: Code and data are available on the following GitHub repository: https://github.com/Emergent-Epidemics/covid19_cordon and permanently on Zenodo (25).

SUPPLEMENTARY MATERIALS

science.sciencemag.org/content/368/6490/493/suppl/DC1
Materials and Methods
Supplementary Text
Figs. S1 to S9
Tables S1 and S2
List of Members of the Open COVID-19 Data Working Group
References (26–39)

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10.1126/science.abb4218
The effect of human mobility and control measures on the COVID-19 epidemic in China


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Tracing infection from mobility data
What sort of measures are required to contain the spread of severe acute respiratory syndrome–coronavirus 2 (SARS-CoV-2), which causes coronavirus disease 2019 (COVID-19)? The rich data from the Open COVID-19 Data Working Group include the dates when people first reported symptoms, not just a positive test date. Using these data and real-time travel data from the internet services company Baidu, Kraemer et al. found that mobility statistics offered a precise record of the spread of SARS-CoV-2 among the cities of China at the start of 2020. The frequency of introductions from Wuhan were predictive of the size of the epidemic sparked in other provinces. However, once the virus had escaped Wuhan, strict local control measures such as social isolation and hygiene, rather than long-distance travel restrictions, played the largest part in controlling SARS-CoV-2 spread.

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