Quantifying the impacts of human mobility restriction on the spread of coronavirus disease 2019: an empirical analysis from 344 cities of China

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Abstract

Background: Since the outbreak of coronavirus disease 2019 (COVID-19), human mobility restriction measures have raised controversies, partly because of the inconsistent findings. An empirical study is promptly needed to reliably assess the causal effects of the mobility restriction. The purpose of this study was to quantify the causal effects of human mobility restriction on the spread of COVID-19.

Methods: Our study applied the difference-in-difference (DID) model to assess the declines of population mobility at the city level, and used the log–log regression model to examine the effects of population mobility declines on the disease spread measured by cumulative or new cases of COVID-19 over time after adjusting for confounders.

Results: The DID model showed that a continual expansion of the relative declines over time in 2020. After 4 weeks, population mobility declined by -54.81% (interquartile range, -65.50% to -43.56%). The accrued population mobility declines were associated with the significant reduction of cumulative COVID-19 cases throughout 6 weeks (ie, 1% decline of population mobility was associated with 0.72% [95% CI: 0.50%–0.93%] reduction of cumulative cases for 1 week, 1.42% 2 weeks, 1.69% 3 weeks, 1.72% 4 weeks, 1.64% 5 weeks, and 1.52% 6 weeks). The impact on the weekly new cases seemed greater in the first 4 weeks but faded thereafter. The effects on cumulative cases differed by cities of different population sizes, with greater effects seen in larger cities.

Conclusions: Persistent population mobility restrictions are well deserved. Implementation of mobility restrictions in major cities with large population sizes may be even more important.

Keywords: Coronavirus disease 2019; Mobility restriction; Disease spread; Causal effects

Introduction

Since the outbreak of coronavirus disease 2019 (COVID-19), non-pharmaceutical interventions (NPIs) have been used as a major strategy for mitigating the disease spread.[1,2] In response to the serious health crisis, China has taken unprecedented measures to contain COVID-19, including Wuhan lockdown and implementation of strict NPIs nationwide.[2] Those NPIs may generally be classified into two categories. One aimed at controlling sources of infection, including treatment and isolation of confirmed cases, quarantine of exposed persons, or screening of suspicious persons who traveled from Wuhan.[3] The other was the implementation of human mobility restriction, aiming to address asymptomatic transmission or transmission before symptom onset,[4,5] and the strategies included suspending intra-city public transport, prohibiting inter-city

travels, closing entertainment venues, or banning public gatherings.[2] Among the 342 Chinese cities, 39.7% suspended intra-city public transport and 64.3% closed entertainment venues.[3] The COVID-19 epidemic in China was under control for 3 months after the outbreak.[6,7]

COVID-19 continues to spread across the world.[8] In the context of resource-limited settings (eg, lack of virus detection kits), implementing a universal coverage to detect COVID-19 cases is unlikely. The necessary personal protective measures (eg, face masking) are still in short supply. As a result, human mobility restriction has been widely used to contain COVID-19 in most countries.[9-11] However, the effectiveness of this strategy is in doubt.[12] Emerging studies investigated its effects on containing COVID-19[3,11,13-15] including spatial–temporal relation between mobility restriction and disease transmission[13,14,16] and initial investigation about the impact of mobility restriction at the early stage. For instance, one study found that suspending intra-city public transport or closing entertainment venues was associated with the number of cases reported during the first week of outbreaks[3]; the other suggested that travel restriction was effective at the early stage of the outbreak, but may be less useful when the disease is widespread.[17] However, distinct knowledge gaps exist about the impacts of human mobility restriction on the disease spread. In particular, the real-world effects of mobility restriction policy remain less clear, as the policy implementation may differ across regions and over time. One plausible argument is that the effects of human mobility restriction may fade over time, and a decision on the level and length of mobility restriction represents a core question for policy makers, whereby disease control and economic growth have to be balanced. All these are linked to thorough assessments on the magnitude of the effects of human mobility restrictions by time and baseline risks. Thus, we conducted a study to bridge this important gap.

Methods

Ethical approval

This study was approved by the Ethics Review Board of West China Hospital, Sichuan University (No. 2020-99).

Design overview

Our study involved two logically linked analyses to quantify the causal effects of human mobility restriction on the spread of COVID-19. First, we applied the difference-in-difference (DID) model to assess the real-world effects of mobility restriction policies on mobility declines at the city level. The intra-city population mobility was measured as an index developed by Baidu, the largest nation-wide search engine provider in China. Given that Wuhan lockdown was implemented on January 23, we used that date as the starting point for implementing human mobility restrictions in China. Subsequently, we used the log–log regression model to examine the effects of mobility declines on the disease spread measured by cumulative or new cases of COVID-19, after adjusting for confounders; the analyses were at the city level given the availability of

data and policy implementation. We collected the number of laboratory-diagnosed cases from the National Health Commission of China,[7] Chinese Center for Disease Control and Prevention,[18] and Provincial Health Commission from January 11, 2020 to March 11, 2020, 7 weeks after Wuhan lockdown. We chose January 11, 2020, as the starting date because the complete genome sequencing of coronavirus was publicly available at that time.

Measure of intra-city population mobility

Intra-city population mobility was measured by a mobility index expressed as an exponentially transformed ratio derived from the daily number of people with outdoor movements divided by the number of residents in a city, and was developed by Baidu, the largest nation-wide search engine provider in China.[19] We collected the population mobility index data from Baidu Huiyan system (https://qianxi.baidu.com/). These data were already used for measuring population mobility in previous studies.[17,20]

Effects of mobility restriction policies on population mobility

We used the DID model to examine the causal effects of mobility restriction policies on population mobility at the city level.

To compare the change of population mobility, we paired intra-city mobility index data between 2019 and 2020 by the lunar calendar to match the period of the Chinese New Year, during which the world's largest population movements occur. To further adjust for the weekend effect of population mobility, we finally matched January 12, 2019, to January 4, 2020, both on Saturdays, as the starting date. Through matching, we were able to fairly compare the population movements 24 days before the Chinese New Year and 36 days after that, between 2019 and 2020. The presence of a parallel trend between 2019 and 2020 confirmed that the assumption of common trends was met for using the DID model.

The population movement data were aggregated and anonymized at the county-level from China Unicom, one of the largest mobile operators in China. In the efforts to enhance the extrapolation of data, the operator helped us use a recognized machine learning algorithm, involving the users' age, gender, operator's coverage, and other parameters, to arrive at the whole network coverage with all users. The same data resource has been used in a previous study.[21]

The DID model could be described as follows.

$$
\begin{aligned}
Y_{it} = a &+ bTreat_{it} + cPost_{it} \\
&+ d(Treat_{it}*Post_{it}) + eWeekend_t \\
&+ \epsilon_{it}
\end{aligned} \tag{1}
$$

where i, and t, respectively, index the city and date, and Y_{it} is the dependent variable representing the population mobility in the i city at t date. $Treat_{it}$ is a dummy variable, setting 0 for the status of 2019, where no human mobility

restriction was implemented, as the control group; one for the status in 2020, where human mobility restriction had been implemented in response to the outbreak, as the intervention group. $Post_{it}$ is a dummy, taking 0 for the period before the lockdown of Wuhan (eg, before January 23, 2020 or before February 3, 2019) and one for the period after that. $Weekend_t$ is a dummy measuring whether the t date is a weekend. The coefficient d of the interaction term, multiplying $Treat_{it}$ by $Post_{it}$, is the effective value to be estimated, which is the absolute decline of population activity in i city at t date of 2020, compared with those in 2019. We further calculated a relative decline of population mobility in 2020 over dates, expressed as a proportion of the absolute decline divided by the baseline population mobility index (ie, that in 2019), and reported relative declines by week (ie, 1, 2, 3, until 6 weeks from January 23, 2020) and by population size across cities.[22] There were 42, 112, 92, 83 and 15 cities with <1 million, ≥1 and <3 million, ≥3 and <5 million, ≥5 and <10 million, and ≥10 million residents, respectively.

Impacts of human mobility declines on the spread of COVID-19

We used the log–log regression model to quantify the impacts of human mobility declines on the spread of COVID-19 over time by the logarithmic transformation of dependent variables and population mobility declines, controlling for the number of population movements from Wuhan, geo-distances from Wuhan, and population size at each city.

The log-log regression model could be described as follows.

$$\begin{aligned} Y_{i,t+1} = {} & a + bPopulation\ mobility_{i,t} \\ & + cNumber\ of\ population\ movements_i \\ & + dNumber\ of\ resident\ S_i \\ & + dDistance_i + \epsilon_i \end{aligned} \quad (2)$$

where i is the index of the city, t is the index week ($t = 1, 2, 3, 4, 5, 6$), and $Y_{i,t+1}$ is the dependent variable representing the number of diagnosed cases in i city at time $t + 1$. $Population\ mobility_i$ is on behalf of the relative declines of population mobility in i city during time t, $Number\ of\ population\ movements_i$ means the number of times of population movements from Wuhan to imported regions before January 23, 2020, in i city. $Number\ of\ residents_i$ is the number of residents in i city, and $Distance_i$ is the geo-distance from Wuhan to i city. The dependent variable of $Y_{i,t+1}$ and population mobility underwent logarithmic transformation. Given that the average incubation period of COVID-19 is about 7 days (range 1–14 days), we assumed that the putative effect would occur 1 week after mobility decline. The coefficient of b thus represents the elasticity (ie, $\%\Delta y/\%\Delta x$) of the number of COVID-19 cases to population mobility decline.

Using aggregated and anonymized national mobile data,[21] we calculated population movements from Wuhan to other cities from January 1, 2020 to January 22, 2020, to resemble the baseline risk (ie, number of cases imported from Wuhan) in Chinese cities before Wuhan lockdown on January 23, 2020. We counted the number of movements from Wuhan if a person traveled from Wuhan multiple times. Those travelers who stayed in Wuhan for <2 h were not counted.[21] We also included other important city characteristics, including population size (in 10,000 persons) and geo-distance from Wuhan (kilometers). Both were collected from Baidu Encyclopedia.

Here, we respectively investigated two dependent variables. In the first model, we assessed the effects of accrued mobility declines on cumulative cases, with the exposure of interest expressed as relative declines of population mobility during 1 week (ie, from January 23 to January 29), 2 weeks (ie, from January 23 to February 5), until 6 weeks (ie, from January 23 to March 4). In the second model, we investigated the impact of accrued mobility declines on newly diagnosed cases that occurred just one subsequent week. We additionally explored for potential heterogeneity of effects by population size, measured by the number of residents (<1 million, 1–5 million, and >5 million). We used STATA12.0 (StataCorp, College Station, TX, USA) for the statistical analysis.

Results

Declines of population mobility among cities in China

Using mobility index data from 344 cities outside Wuhan (four municipalities, 26 provincial capitals, and 314 cities), the average population mobility before January 23, 2020, was comparable to the matched dates in 2019 [Figure 1A]. Starting from January 23, 2020, the population mobility declined dramatically [Figure 1A]. The DID model suggested a continual increase in the relative declines over time in 2020. In the first week, the implementation of mobility restriction policies resulted in 31.35% decline (median [interquartile ranges]: −31.35% [−41.63% to −24.27%]). After 4 weeks, population mobility declined by 54.81% (−65.50% to −43.56%) [Table 1]. The relative declines differed by cities, with a larger number of residential populations associated with greater declines [Table 1].

Effects of human mobility declines on the spread of COVID-19

There were 335 cases diagnosed in cities outside Wuhan by January 23 at Wuhan lockdown. Four weeks later, the cumulative number of cases was stabilized, and then a small number of cases increased thereafter. By March 11, a total of 30,807 COVID-19 cases were diagnosed in cities outside Wuhan of the mainland of China [Figure 1B]. The new cases of COVID-19 were rapidly reduced over weeks [Figure 1C]. We also found the potential linear association between the relative declines of population mobility and the numbers of cumulative and new COVID-19 cases over time by population size of cities [Figure 2]. Supplementary Table 1, http://links.lww.com/CM9/A758 reports the median population size in cities (3,360,000 [1,837,700–5,320,400]), geo-distance from Wuhan (844.00 [561.50–1291.50] km), and the number of movements from Wuhan before Wuhan lockdown (2858 [661–9305] times).
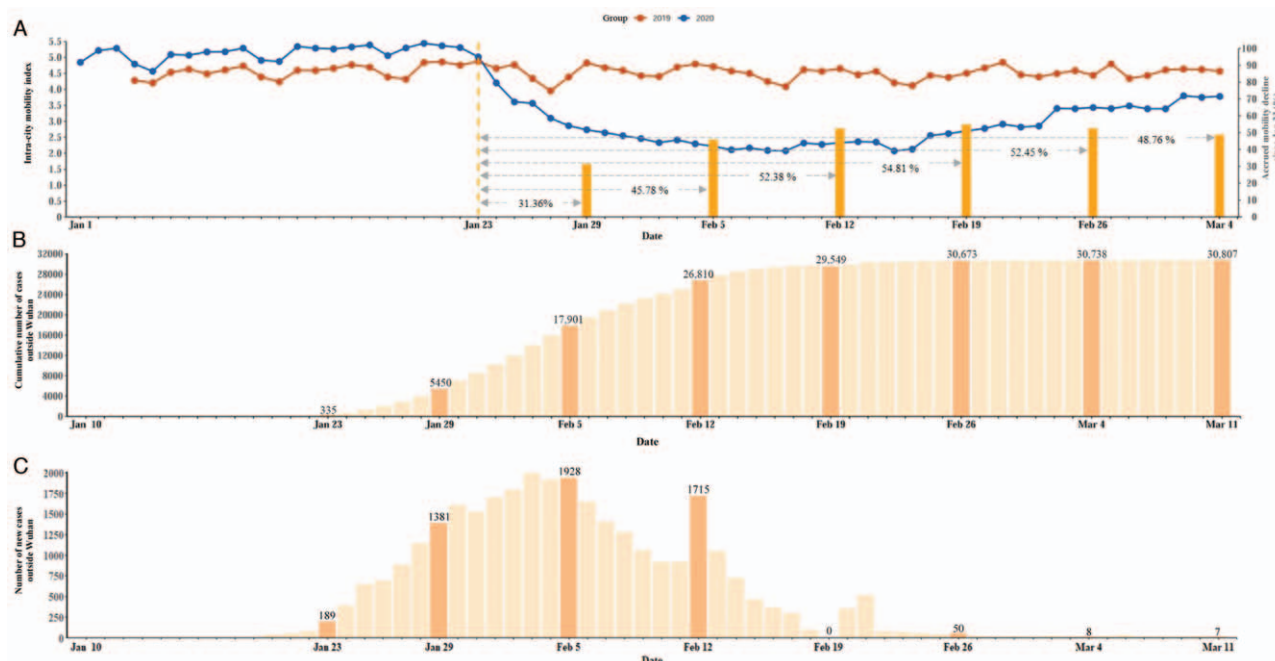
Figure 1: Human mobility declines and the spread of COVID-19 in China. (A) The left vertical axis represents the paralleled trend of average population mobility among cities outside Wuhan between 2019 and 2020 by matched dates, and the right vertical axis indicates the accrued mobility decline since January 23, 2020. Red dotted line represents the intra-city mobility index in 2019 over dates and the blue dotted line represents the paired intra-city mobility index in 2020 matched by lunar calendar; yellow dotted line represents the date of January 23, 2020. Yellow pillar represents the relative decline in population mobility between 2020 and 2019 over weeks, calculated by DID. Horizontal axis indicates the dates from January 1, 2020 to March 4, 2020. (B) The cumulative number of cases diagnosed in cities outside Wuhan over dates (from January 10, 2020 to March 11, 2020). (C) The number of new cases diagnosed in cities outside Wuhan over weeks (from January 10, 2020 to March 11, 2020). COVID-19: Coronavirus disease 2019; DID: Difference-in-difference.

The log–log regression models reported the effects of accrued mobility declines on cumulative cases [Figure 3]. At 1 week, a 1% decline of population mobility was associated with 0.72% (95% CI: 0.50%–0.93%) reduction in the number of cumulative cases, after adjusting for other confounders. The magnitude of effects continued to increase until 4 weeks (1.42%, 95% CI: 1.11%–1.74% for 2 weeks; 1.69%, 95% CI: 1.34%–2.03% for 3 weeks; 1.72%, 95% CI: 1.38%–2.05% for 4 weeks; 1.64%, 1.35%–1.94% for 5 weeks and 1.52%, 1.25%–1.78% for 6 weeks). However, the effects of mobility declines differed among cities of varying population sizes, with larger effects among larger cities, as opposed to smaller ones (<1 million) [Figure 4].

There were also statistically significant associations between accrued mobility declines and new cases that occurred in the subsequent week. At 2 weeks, a 1% decline in population mobility corresponded to 1.20% (95% CI: 0.86%–1.54%) reduction in new cases at the subsequent week (ie, third week). Even after 6 weeks, the effect was observed, although small [Figure 3]. No heterogeneity of effects was observed in this model by city-scale [Supplementary Table 2, http://links.lww.com/CM9/A758].

Discussion

Summary of our findings

Human mobility restriction has ever been used at the outbreak of fulminating infectious diseases, such as severe acute respiratory syndrome (SARS) in 2003[23,24] and influenza A in 2009,[25,26] but with a narrower scope or a

transitory period.[25,27,28] The outbreak of COVID-19 in China, which coincided with the world's largest population movements surrounding Chinese New Year (ie, Chun Yun), offered an unprecedented opportunity to investigate the real-world effects of population mobility restrictions.

By the counter-fact DID model, we found almost one-third of mobility declines occurred in the first week after the policy implementation; after 4 weeks, the population mobility was lowered by 54.8%. Policies' impacts on mobility decline varied by the population size of a city and the effects persisted over time. In our critical analyses that assessed the effects of mobility declines on the disease spread, we found that the accrued population declines were associated with the reduction of both cumulative COVID-19 cases and new cases across the 6 weeks after the policy implementation. More interestingly, we found that its impact on new cases seemed larger in the first 4 weeks and faded after 5 weeks.

So, what do these findings tell us? First, we believe that the implementation of population mobility restrictions is appropriate and strongly needed in balancing the serious pandemic and the fatal consequences it has caused *vs.* the economic loss and temporary loss of personal mobility. Up to March 2020, several documents have been issued from national governmental authorities. These policy documents covered nearly all social activities across cities and rural areas, including healthcare services, education, transportation, tourism, elderly care, child welfare service, employment, work at home, and community management. Accordingly, the continual policies implementation

Table 1: Relative declines in population mobility index between 2020 and 2019 (%).

Duration of policy implementation	Mean (standard deviation)	Median (percentile 25–75)
1 week (January 23, 2020–January 29, 2020)	−33.54 (13.88)	−31.35 (−41.63 to −24.27)
<1 million	−22.27 (13.70)	−20.57 (−28.39 to −12.18)
≥1 and <3 million	−31.03 (11.48)	−29.89 (−36.30 to −22.94)
≥3 and <5 million	−33.39 (10.71)	−32.37 (−39.62 to −22.50)
≥5 and <10 million	−39.27 (13.78)	−39.49 (−47.24 to −28.48)
≥10 million	−52.98 (15.30)	−48.89 (−61.46 to −42.60)
2 weeks (January 23, 2020–February 5, 2020)	−47.59 (14.75)	−45.78 (−56.10 to −37.19)
<1 million	−38.38 (15.32)	−36.93 (−49.03 to −25.44)
≥1 and <3 million	−44.98 (11.53)	−42.58 (−51.07 to −36.81)
≥3 and <5 million	−46.81 (11.85)	−45.56 (−54.59 to −38.08)
≥5 and <10 million	−52.81 (16.06)	−53.02 (−62.10 to −41.17)
≥10 million	−68.76 (14.36)	−65.20 (−80.15 to −60.10)
3 weeks (January 23, 2020–February 12, 2020)	−53.10 (15.28)	−52.38 (−62.51 to −42.10)
<1 million	−46.11 (16.75)	−46.25 (−57.10 to −35.03)
≥1 and <3 million	−50.52 (11.92)	−48.16 (−57.40 to −42.01)
≥3 and <5 million	−52.00 (12.85)	−51.37 (−60.40 to −41.99)
≥5 and <10 million	−57.58 (17.21)	−56.82 (−67.50 to −46.77)
≥10 million	−73.93 (13.16)	−71.72 (−82.98 to −66.02)
4 weeks (January 23, 2020–February 19, 2020)	−54.65 (15.60)	−54.81 (−65.50 to −43.56)
<1 million	−50.05 (18.45)	−51.24 (−62.01 to −38.43)
≥1 and <3 million	−52.07 (12.45)	−49.77 (−61.64 to −44.04)
≥3 and <5 million	−53.43 (13.62)	−52.94 (−73.03 to −42.99)
≥5 and <10 million	−58.14 (17.25)	−57.95 (−69.71 to −46.60)
≥10 million	−75.01 (12.18)	−73.87 (−82.78 to −66.97)
5 weeks (January 23, 2020–February 26, 2020)	−52.48 (16.20)	−52.45 (−64.70 to −40.72)
<1 million	−51.21 (20.10)	−51.19 (−67.38 to −36.28)
≥1 and <3 million	−49.80 (13.61)	−48.56 (−60.20 to −39.90)
≥3 and <5 million	−50.82 (14.51)	−50.35 (−58.05 to −40.03)
≥5 and <10 million	−54.89 (17.15)	−57.66 (−66.44 to −42.72)
≥10 million	−72.85 (11.57)	−73.52 (−81.29 to −63.88)
6 weeks (January 23, 2020–March 4, 2020)	−49.44 (16.67)	−48.76 (−61.18 to −36.91)
<1 million	−50.52 (21.38)	−49.54 (−68.51 to −32.81)
≥1 and <3 million	−46.81 (14.68)	−44.38 (−55.85 to −36.25)
≥3 and <5 million	−47.44 (15.03)	−46.82 (−55.23 to −36.37)
≥5 and <10 million	−51.11 (16.82)	−53.67 (−62.91 to −38.12)
≥10 million	−69.13 (10.91)	−70.05 (−79.26 to −59.61)

resulted in prompt mobility declines, and further led to effective and rapid reduction of new cases in subsequent weeks, which would, in turn, rapidly eliminate the impact of the pandemic. Second, we may also infer from our findings that the effects of the mobility restriction policies would be large in the first few weeks, but attenuate over time. After 5 weeks, their effects became smaller. This alerts that persistent mobility restrictions are highly deserved, but flexible mobility restriction policies may be warranted particularly after several weeks of rigorous mobility restriction. Third, our study suggested larger effects among bigger cities over time, which highlighted that the implementation of mobility restrictions in major metropolises is particularly important and meaningful. Fourth, the findings strongly advised that, in resource-limited settings where healthcare resources are not readily available, non-medical interventions may be optimal strategies in containing the disease transmission. We also believe that these strategies are not only effective in the early stage of the disease outbreak but also at the stage of widespread, because of its sheer mechanism to block

population contacts at emergencies. Thus, those nations amid the disease pandemic may still consider implementing these strategies.

Comparison with previous studies

As an initial mobility restriction intervention, Wuhan lockdown was extensively assessed.[3,29-32] Previous studies showed that the Wuhan lockdown delayed the arrival of COVID-19 in other Chinese cities by 2.9 days,[3] and lowered 64.8% of cases in 347 Chinese cities outside Hubei.[30] However, a large number of movements actually occurred before Wuhan lockdown, and such populations were likely infected or even asymptomatic patients that could lead to outbreak in cities outside Wuhan.[3]

Several studies investigated the effects of other measures,[3,11,13-15,33-35] among which simulations were extensively used to quantify the effects of physical distancing, early case detection or isolation, or combination of multiple
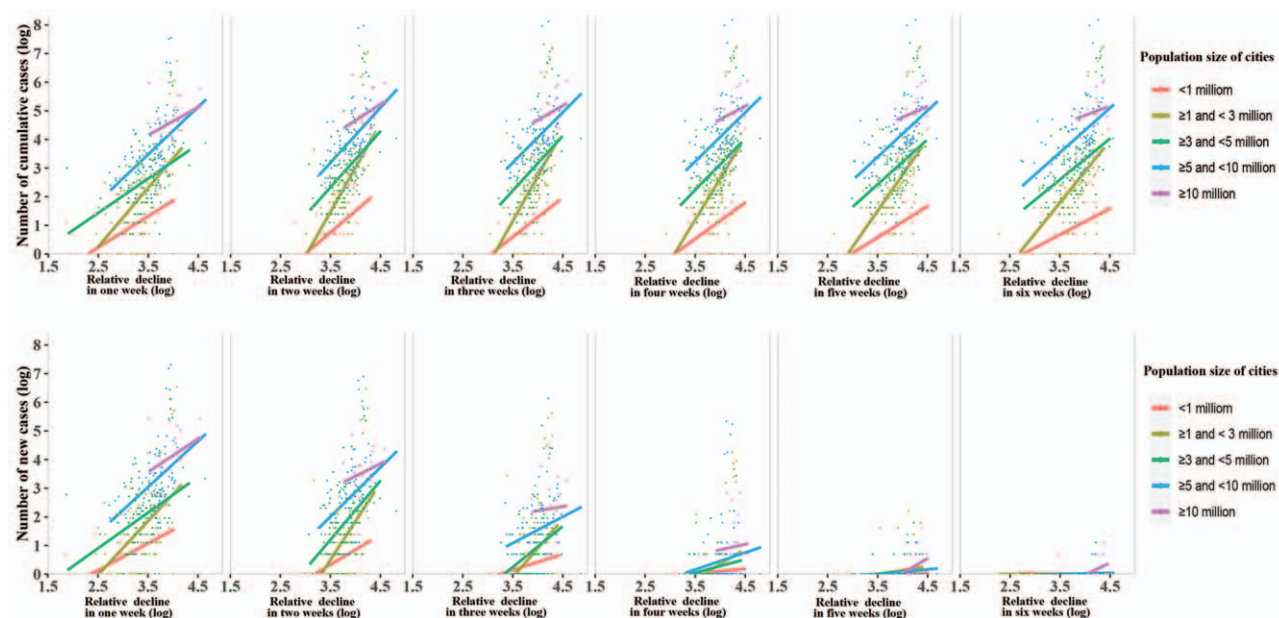
Figure 2: Linear associations between the relative declines of population mobility (logarithmic transformation) and numbers of cumulative and new COVID-19 cases (logarithmic transformation) over weeks by population size of cities. COVID-19: Coronavirus disease 2019.
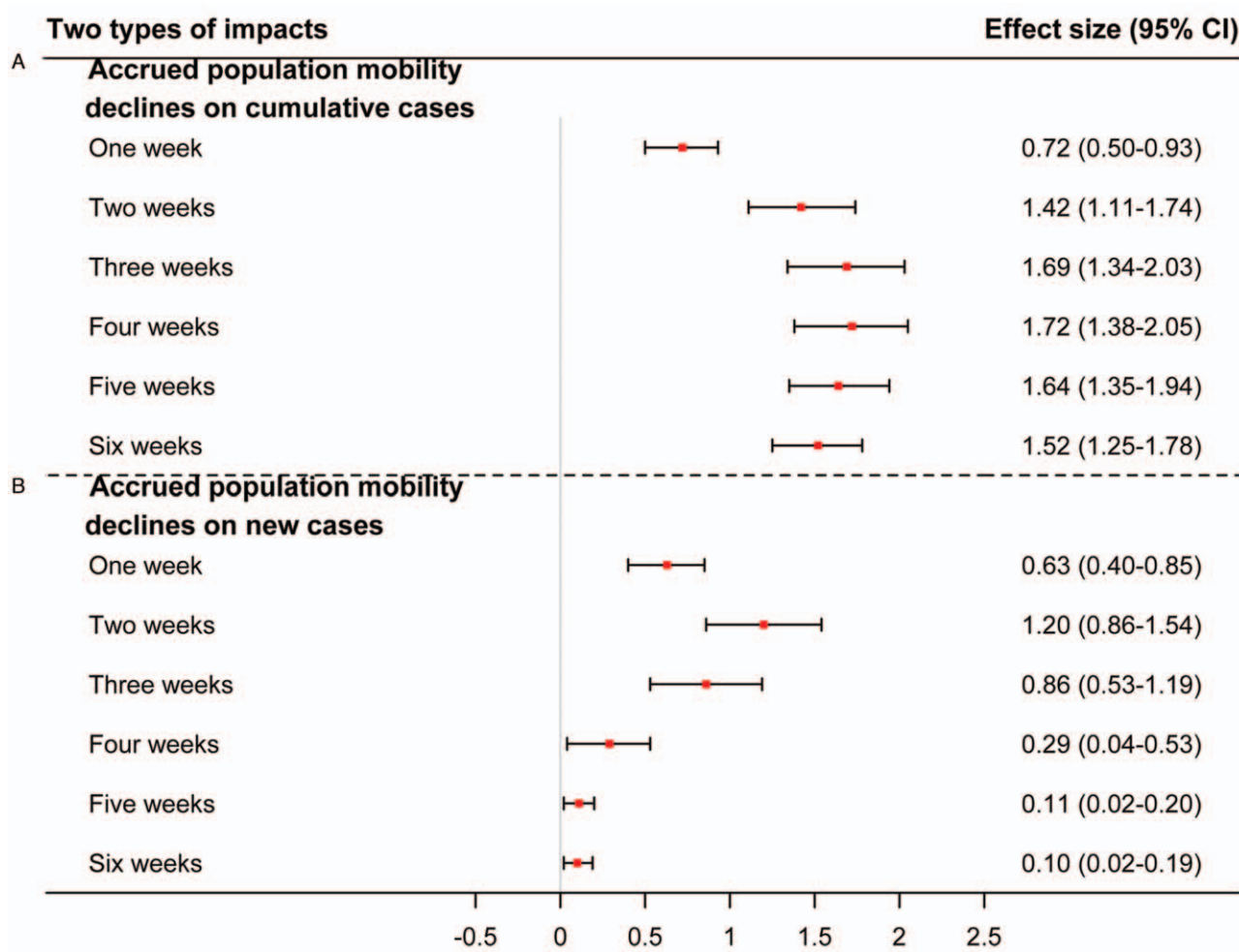
Two types of impacts	Effect size (95% CI)
A Accrued population mobility declines on cumulative cases	
One week	0.72 (0.50-0.93)
Two weeks	1.42 (1.11-1.74)
Three weeks	1.69 (1.34-2.03)
Four weeks	1.72 (1.38-2.05)
Five weeks	1.64 (1.35-1.94)
Six weeks	1.52 (1.25-1.78)
B Accrued population mobility declines on new cases	
One week	0.63 (0.40-0.85)
Two weeks	1.20 (0.86-1.54)
Three weeks	0.86 (0.53-1.19)
Four weeks	0.29 (0.04-0.53)
Five weeks	0.11 (0.02-0.20)
Six weeks	0.10 (0.02-0.19)

Figure 3: Effects of accrued mobility declines on cumulative cases. Effect size represents the elasticity (ie, $\%\Delta y/\%\Delta x$) of the number of COVID-19 cases to population mobility decline. CI: Confidence interval; COVID-19: Coronavirus disease 2019.
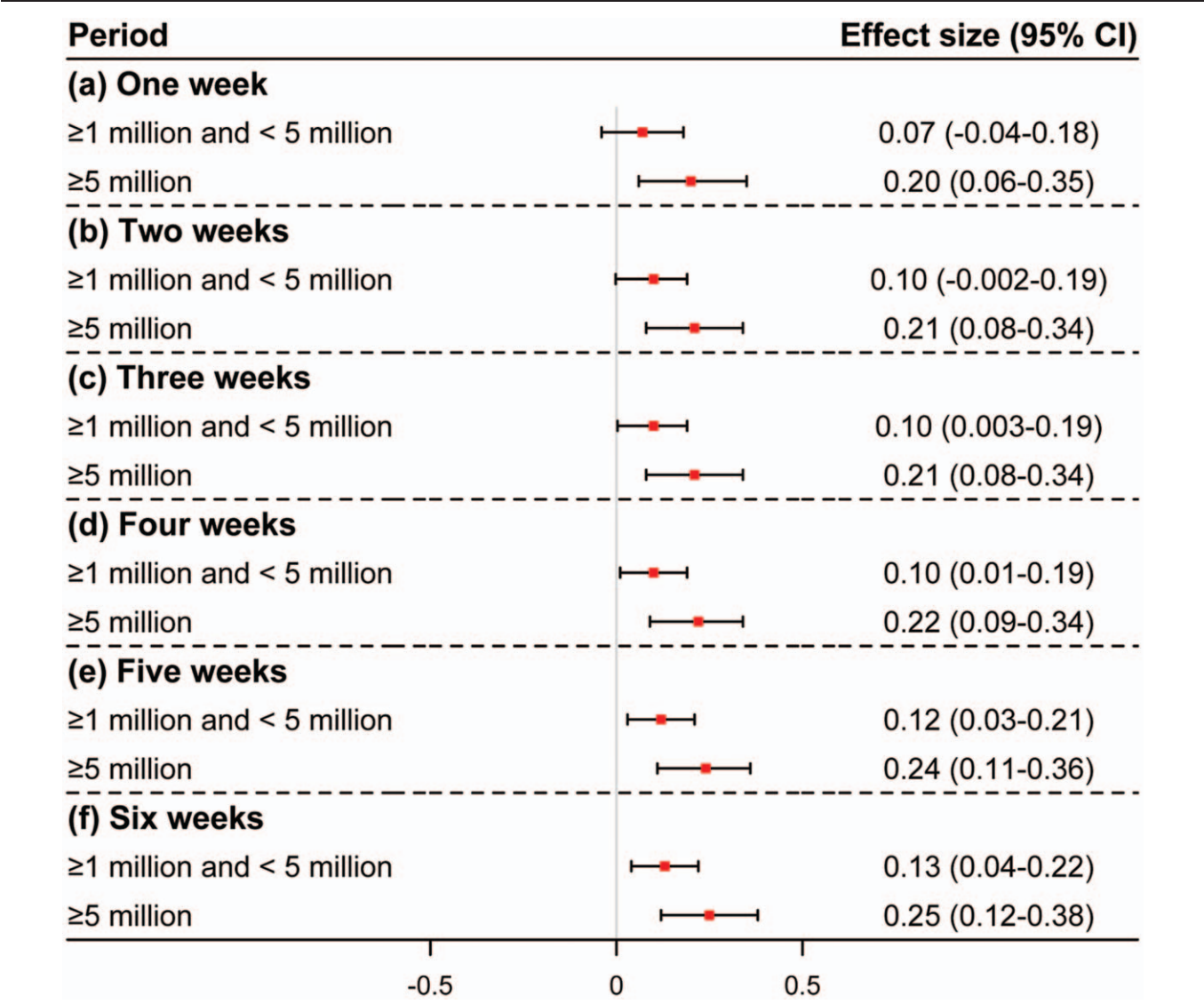
Period	Effect size (95% CI)
(a) One week	
≥1 million and < 5 million	0.07 (-0.04-0.18)
≥5 million	0.20 (0.06-0.35)
(b) Two weeks	
≥1 million and < 5 million	0.10 (-0.002-0.19)
≥5 million	0.21 (0.08-0.34)
(c) Three weeks	
≥1 million and < 5 million	0.10 (0.003-0.19)
≥5 million	0.21 (0.08-0.34)
(d) Four weeks	
≥1 million and < 5 million	0.10 (0.01-0.19)
≥5 million	0.22 (0.09-0.34)
(e) Five weeks	
≥1 million and < 5 million	0.12 (0.03-0.21)
≥5 million	0.24 (0.11-0.36)
(f) Six weeks	
≥1 million and < 5 million	0.13 (0.04-0.22)
≥5 million	0.25 (0.12-0.38)

Figure 4: Heterogeneous effects of accrued mobility declines on cumulative cases by population size. Population size was divided into three categories (ie, the number of residents <1 million, ≥1 and <5 million, and ≥5 million; the first category was deemed as reference). Effect size represents the elasticity (ie, %Δy/%Δx) of the number of COVID-19 cases to population mobility decline. CI: Confidence interval; COVID-19: Coronavirus disease 2019.

measures.[33-35] These studies provided important insights about the impacts of mobility restriction measures, but had limitations given the use of modeling, whereby assumptions are often employed.

Up to now, empirical studies still fall short.[36] One early study assessed the impacts of human mobility restriction on COVID-19 cases at the first week, and the other suggested that travel restriction was more useful in the early outbreak, but attenuated if the outbreak was expanded. However, the extent to which the mobility restriction policy led to mobility decline and whether human mobility restriction causally controlled the spread of COVID-19 were not yet established. An earlier study, using mobility data from four metropolitan areas in the United States, mainly examined the temporal correlation between the timing of public policy measures and cumulative cases of COVID-19,[16] but indicated a lack of causality because of the nature of descriptive analyses.[16]

Strengths and limitations

Our study has several strengths. First, we have used rigorous methods to assess the causal effects of human mobility restriction on the spread of COVID-19. We have also profiled the declines of population mobility by using the DID model, which avoided the reverse causality and confounding by the usual fluctuation of population mobility over time. Second, we included important confounders in the models with precise measurements, such as the number of times of population movements from Wuhan to imported regions, number of residents and geo-distance from Wuhan (kilometers). As a result, good model fitting is achieved ($R^2 > 70\%$). Third, we have used thorough and real-time population mobility data to assess the impacts of NPIs during the outbreak of infectious diseases. Real-time mobility data, such as airline flights data[37,38] and aggregated human mobility data,[22,39] when combining with routine epidemiological surveillance, could play a crucial role during the disease pandemic.

Our study also had limitations. First, the measurement of population mobility may not be optimal because not everyone uses Baidu App in their smartphones and some subgroup populations (eg, children or elderly) were not covered. Nevertheless, it covers about 55% of smartphone users in China,[20] and was well used previously. Thus, we believe that it may be nationally representative to some extent. Second, in our analyses, we assumed that the mobility restriction would be effective 1 week after the implementation of mobility restriction given the reported incubation period between 1 and 14 days.[6] This assumption may affect the resulting estimates and slight changes may occur. Third, although we have satisfied the parallel trend assumption before using DID model, the substantial difference of lockdown strategies and resumption plans might occur among Chinese cities after Wuhan lockdown. The effect examined by DID model could be affected by these factors to some extent.

In conclusion, in response to the COVID-19 epidemic, China has implemented a comprehensive set of mobility restriction policies, which resulted in >50% population mobility declines just in a few weeks; the effect was more pronounced in large cities and remained consistent over time. The resulting population mobility declines had a direct impact on the reduction of cumulative and new COVID-19 cases; this effect particularly had a larger effect in the first few weeks and attenuated thereafter, and was also more pronounced in larger cities. Our study confirmed that strict implementation of comprehensive population mobility restriction policies was highly warranted, particularly in large cities.

Funding

Conflicts of interest

None.

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