Associations between changes in population mobility in response to the COVID-19 pandemic and socioeconomic factors at the city level in China and country level worldwide: a retrospective, observational study

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Summary

Background Until broad vaccination coverage is reached and effective therapeutics are available, controlling population mobility (ie, changes in the spatial location of a population that affect the spread and distribution of pathogens) is one of the major interventions used to reduce transmission of SARS-CoV-2. However, population mobility differs across locations, which could reduce the effectiveness of pandemic control measures. Here we assess the extent to which socioeconomic factors are associated with reductions in population mobility during the COVID-19 pandemic, at both the city level in China and at the country level worldwide.

Methods In this retrospective, observational study, we obtained anonymised daily mobile phone location data for 358 Chinese cities from Baidu, and for 121 countries from Google COVID-19 Community Mobility Reports. We assessed the intra-city movement intensity, inflow intensity, and outflow intensity of each Chinese city between Jan 25 (when the national emergency response was implemented) and Feb 18, 2020 (when population mobility was lowest) and compared these data to the corresponding lunar calendar period from the previous year (Feb 5 to March 1, 2019). Chinese cities were classified into four socioeconomic index (SEI) groups (high SEI, high–middle SEI, middle SEI, and low SEI) and the association between socioeconomic factors and changes in population mobility were assessed using univariate and multivariable linear regression. At the country level, we compared six types of mobility (residential, transit stations, workplaces, retail and recreation, parks, and groceries and pharmacies) 35 days after the implementation of the national emergency response in each country and compared these to data from the same day of the week in the baseline period (Jan 3 to Feb 6, 2020). We assessed associations between changes in the six types of mobility and the country's sociodemographic index using univariate and multivariable linear regression.

Findings The reduction in intra-city movement intensity in China was stronger in cities with a higher SEI than in those with a lower SEI (r=–0·47, p<0·0001). However, reductions in inter-city movement flow (both inflow and outflow intensity) were not associated with SEI and were only associated with government control measures. In the country-level analysis, countries with higher sociodemographic and Universal Health Coverage indexes had greater reductions in population mobility (ie, in transit stations, workplaces, and retail and recreation) following national emergency declarations than those with lower sociodemographic and Universal Health Coverage indexes. A higher sociodemographic index showed a greater reduction in mobility in transit stations (r=–0·27, p=0·0028), workplaces (r=–0·34, p=0·0002), and areas retail and recreation (r=–0·30, p=0·0012) than those with a lower sociodemographic index.

Interpretation Although COVID-19 outbreaks are more frequently reported in larger cities, our analysis shows that future policies should prioritise the reduction of risks in areas with a low socioeconomic level—eg, by providing financial assistance and improving public health messaging. However, our study design only allows us to assess associations, and a long-term study is needed to decipher causality.

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Introduction

By May 2, 2021, more than 152 million confirmed cases of COVID-19 and more than 3 million deaths had been reported across 192 countries and regions.[1] So far, most countries have adopted a series of non-pharmaceutical interventions (NPIs) in an attempt to contain the spread of the virus, such as closing schools, prohibiting public and private gatherings, imposing travel restrictions,

Research in context

Evidence before this study

The extent to which socioeconomic factors are associated with changes in mobility and social mixing during a pandemic are currently unknown. The COVID-19 pandemic provides a valuable opportunity to investigate this issue to better inform policy. We searched Google Scholar, PubMed, and medRxiv for articles in English published up to Nov 20, 2020, relating to population mobility across sociodemographic contexts during the first wave of the COVID-19 pandemic using the search terms "COVID-19", "SARS-CoV-2", "coronavirus", "socioeconomic development", "mobility", "travel", and "social distancing", and "physical distancing". The search yielded 336 publications. Most of these publications investigated how population mobility related to the spread of SARS-CoV-2. Four studies reported a relationship between population mobility and socioeconomic factors. One of these studies considered only income in the USA and another was restricted to France. Two other studies described the effect of global inter-relationships and social connections from Facebook on population mobility. These studies showed that the heterogeneity in changes of population mobility were related to socioeconomic factors.

Added value of this study

We did a comprehensive analysis, involving multiple types of movement, and studied a range of socioeconomic factors at two scales (ie, at the city level in China and the country level worldwide). Our results show that the change in intra-city movement intensity in response to the COVID-19 pandemic was significantly associated with socioeconomic index (SEI). Between Jan 25 and Feb 18, 2020, intra-city movement intensity in areas with a higher SEI declined more than in areas with a lower SEI. However, the change in inter-city flows was not associated with SEI. Socioeconomic factors and changes in population mobility were associated at both city and country levels.

Implications of all the available evidence

Our study shows that changes in population mobility in response to the COVID-19 pandemic were strongly differentiated by socioeconomic factors. The success of efforts to reduce population mobility declined in areas with a lower socioeconomic level. Global prevention and control interventions should therefore be prioritised in such areas in preparation for future pandemic waves. However, our study design shows only an association between changes in mobility and socioeconomic factors; a long-term study will be needed to decipher causality.

implementing stay-at-home requirements, and closing workplaces.[2,3] Among these NPIs, movement restrictions have been shown to be one of the most robust across 130 countries and territories.[4]

Population movement is a key factor in the transmission of infectious diseases, and movement patterns have been carefully investigated in the study of several communicable diseases.[5,6] Since the year 2010, the widespread use of smartphones has made it possible to describe population mobility (ie, changes in the spatial location of a population that affect the spread and distribution of pathogens) patterns in an accurate and scalable way that was previously inconceivable.[6] During the early pandemic spread of COVID-19, reductions in population mobility, assessed using geo-located mobile phone data, were shown to substantially mitigate the spread of SARS-CoV-2.[7,8] Mobile phone data also showed that a mobility reduction of 20–60% in Chinese cities had a notable effect on controlling the spread of COVID-19.[9] The COVID-19 burden has also affected risk perception, which might have triggered increased population mobility responses.[10,11] Studies have shown that levels of population mobility in response to the COVID-19 pandemic were related to income and socioeconomic status in the USA[12,13] and France.[14] These three studies each focused on one country and all considered only a small number of factors. However, changes in population mobility were highly varied among regions, which motivated our more comprehensive analysis.

For **Google Mobility Reports** see https://www.google.com/covid19/mobility/

The ability of cities and countries with differing socioeconomic characteristics to cope with emergencies varies greatly. To identify factors related to the heterogeneity in changes in population mobility, we aimed to collect daily mobile phone location data from Baidu location-based services for all Chinese cities. From these data, we aimed to extract the intra-city movement intensity (ie, the proportion of people travelling within cities), inflow intensity (ie, the size of the inflow population), and outflow intensity (ie, the size of the outflow population) for each city. These three types of movement intensity reflect differences in population mobility in cities in response to the national emergency. To expand our analysis internationally, we also aimed to obtain mobility data for other countries from Google COVID-19 Community Mobility Reports. Identifying factors that contribute to the heterogeneity in changes in population mobility will help policy makers to improve NPI strategies based on specific city-level and country-level factors.

Methods

Study design

In this retrospective, observational study, we assessed changes in population mobility in response to the COVID-19 pandemic using mobile phone geolocation data and identified socioeconomic factors associated with these changes at the city level in China and at the country level worldwide.

For city-level analyses in China, we assessed three types of population mobility data (ie, intra-city movement intensity, inflow intensity, and outflow intensity) for 358 cities following the declaration of the national emergency response (Jan 25, 2020) and compared these to data from the corresponding period in 2019. Cities were divided into four socioeconomic index (SEI) groups based on 17 covariates related to COVID-19 (lockdown and cumulative number of COVID-19 cases), demographics (percentage of population with a post-secondary education level, urbanisation rate, population growth, population density, and population age group), the economy (gross regional product, gross regional product per capita, agricultural sector per capita, industrial sector per capita, and service sector per capita) and fiscal capacity (public budget revenue and expenditure, expenditure for science and technology, and expenditure for education; appendix p 16).

To identify factors associated with changes in population mobility on a country level, we assessed differences in population mobility between our baseline period and after the national emergency response was declared in each of 121 countries. Two socioeconomic indices were considered to examine the association with movement reduction: the sociodemographic index (SDI)[15] and Universal Health Coverage (UHC) index.[16]

Data collection

In China, population movements were anonymously collected at the city level with mobile phone data, through location-based services used by Baidu applications. We collected three types of population movement data (ie, intra-city movement intensity, inflow intensity, and outflow intensity) for each Chinese city (n=358, excluding Hong Kong, Macau, and Taiwan) from the Baidu migration flows database between Jan 1, 2019, and March 6, 2020.

At the international level, we analysed mobility for 121 countries (ie, countries that had mobile data available and had implemented interventions for COVID-19; appendix pp 17–21) from Google Mobility Reports (based on geolocated mobile phone data) from Feb 15 to Oct 6, 2020. Six types of mobility are included in this database: residential, transit stations, workplaces, retail and recreation, parks, and groceries and pharmacies. The baseline period was defined as Jan 3 to Feb 6, 2020.

Population sizes and socioeconomic data for Chinese cities were obtained from the China City Statistical Yearbook. The SDI for each of the 121 countries was obtained from the Institute for Health Metrics and Evaluation.[17] SDI is defined as a composite average of the rankings of per capita income, average education level, and fertility rate, ranging from 0 to 1. Countries were classified into five categories: high SDI, high–middle SDI, middle SDI, low–middle SDI, and low SDI. The UHC index for each country was obtained from WHO.

We collected epidemiological data on COVID-19 from the official reports of the health commission of 358 Chinese city-level units (appendix p 22). Only laboratory-confirmed cases of COVID-19 were used. Data for the country-level analysis were obtained from the Oxford COVID-19 Coronavirus Government Response Tracker (OxCGRT).[18]

Data for the national emergency response (eg, dates when curfews were imposed, cities were locked down, and mass gatherings were prevented) in China were based on previous work by Huaiyu Tian and colleagues.[19] At the country level, information on government declarations was obtained from both official websites and OxCGRT (appendix pp 17–21).[18] Since OxCGRT only collects the date of a specific government response (such as closing schools or travel bans), we collected the date of the emergency response in each of the 121 countries from official national websites and news. If there was no specific government declaration, the earliest date of any intervention implemented (such as closing schools or workplaces, cancelling public events, restricting gatherings, closing public transport, implementing stay-at-home orders, or restrictions on domestic travel) was obtained from OxCGRT.

Statistical analysis

To assess population mobility at the city level in China following introduction of the national emergency response on Jan 25, 2020, we focused on mobility data between Jan 25 and Feb 18, 2020 (when mobility intensity was the lowest). We compared population mobility (intra-city movement intensity, inflow intensity, and outflow intensity) during this period to mobility data from Feb 5 to March 1, 2019 (the corresponding lunar calendar period from the previous year).

The SEI for each city was calculated by collecting 17 socioeconomic variables and conducting principal component analysis. We calculated the weighted average for each city of the first seven principal components and standardised this to a value between 0 and 1. We then divided cities into four categories: high SEI, high–middle SEI, middle SEI, and low SEI.

To identify socioeconomic factors associated with reductions in population mobility we did univariate and multivariable linear regression analyses (appendix p 3). We treated all variables that were significant in the univariate analysis as candidate variables for the multivariate analysis. To avoid the multicollinearity in the multiple linear regression, we used the following procedure: first, we calculated the variance inflation factor (VIF) for the variables in the candidate pool and only retained the variables with a VIF score of less than 5; second, for the retained variables, we calculated pair-wise correlations for these variables. If the correlation between two variables was larger than 0·5, we removed the variable that

For more on **WHO universal health coverage** see https://www.who.int/health-topics/universal-health-coverage

See **Online** for appendix

For **Baidu migration data** see http://qianxi.baidu.com

For more on **Google Mobility Reports** see https://www.google.com/covid19/mobility

For more on the **China City Statistical Yearbook** see http://olap.epsnet.com.cn

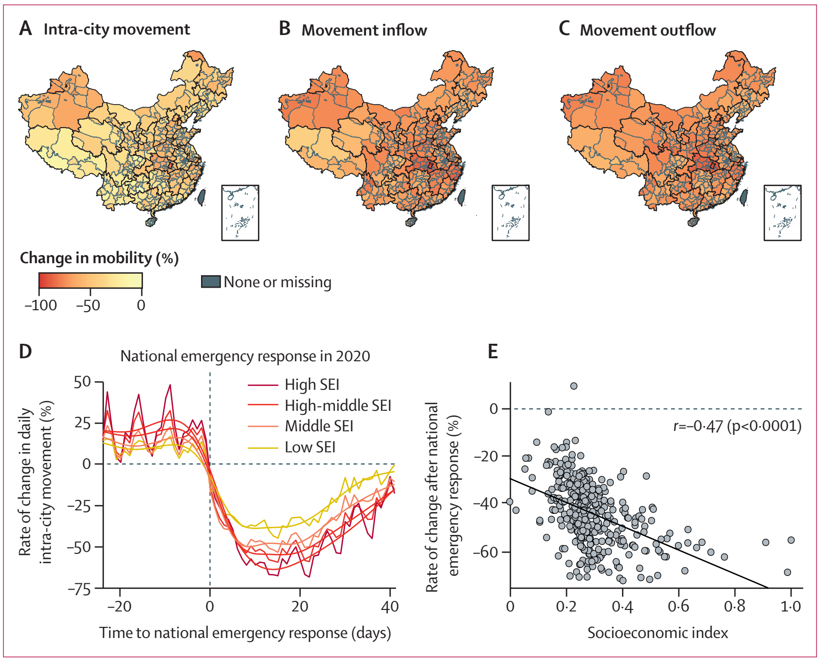


Figure 1: **Heterogeneity in population mobility changes in China following the COVID-19 national emergency response**

Maps show changes in intra-city movement intensity (A), movement inflow intensity (B), and movement outflow intensity (C) in the period following the COVID-19 national emergency response compared with the corresponding lunar calendar period from 2019. The black border indicates Hubei province and Wuhan city. (D) Change in daily intra-city movement between Jan 1 and March 6, 2020 (the first wave of COVID-19 in China outside Wuhan city). Thin lines are raw data and thick lines are smoothed values from a generalised additive model. A positive value indicates that the intra-city movement intensity is greater than values measured for 2019, whereas a negative value indicates that the intra-city movement intensity is less than the values measured for 2019. The association between socioeconomic index and changes in population mobility after national emergency response across cities of China (n=358; E). Each point represents a city.

correlated with Y (ie, the change in population mobility) with the smaller correlation score. After this procedure, we selected six variables for intra-city movement, four variables for inflow movement, and five variables for outflow movement. We also plotted the scatter plot between SEI and change in intra-city movement intensity across cities in China from Feb 19 to March 6, 2020 (appendix p 11). This analysis was done because during the period when control measures were relaxed the mobility reduction in cities with a high SEI was still large (figure 1D).

At the country level, we compared the change in mobility in each country 35 days after the national emergency response for each country to the median baseline value from the corresponding day of the week in the baseline period (Jan 3 to Feb 6, 2020). There were two reasons why the timeframe of 35 days was used; first, mobility reached its lowest value at an average of 26·8 (95% CI 24·8–28·8) days after the national emergency response in most countries and, second, the baseline length was 35 days. We did the univariate regression for the SDI, UHC, and the cumulative number of COVID-19 cases. Due to the high correlation between SDI and UHC, the SDI was included in the multivariable regression. The stay-at-home order was also incorporated into the multivarible regression.

Considering the biases in mobile data and the small number of NPIs implemented in the 121 countries analysed, additional analyses were done: first, we removed the African countries (91 countries in total) and did the univariate and multivariable regression using the remaining countries. Second, we used the COVID-19 Government Response Stringency Index (SI) instead of the stay-at-home order (appendix p 4). To further support the hypothesis that human mobility responses to COVID-19 are indeed differentiated by socioeconomic development, we did a similar analysis on mobility changes that occurred before the implementation of the first NPI at the country level. Specifically, we calculated the average mobility changes in the week before the introduction of the first NPI for each of the six types of movement. Countries with a time interval of less than a week between the date of the outbreak and the date of the first NPI were excluded from this analysis. Standard R packages (version 4.0.2) were used for all analyses. No custom code was developed.

Role of the funding source

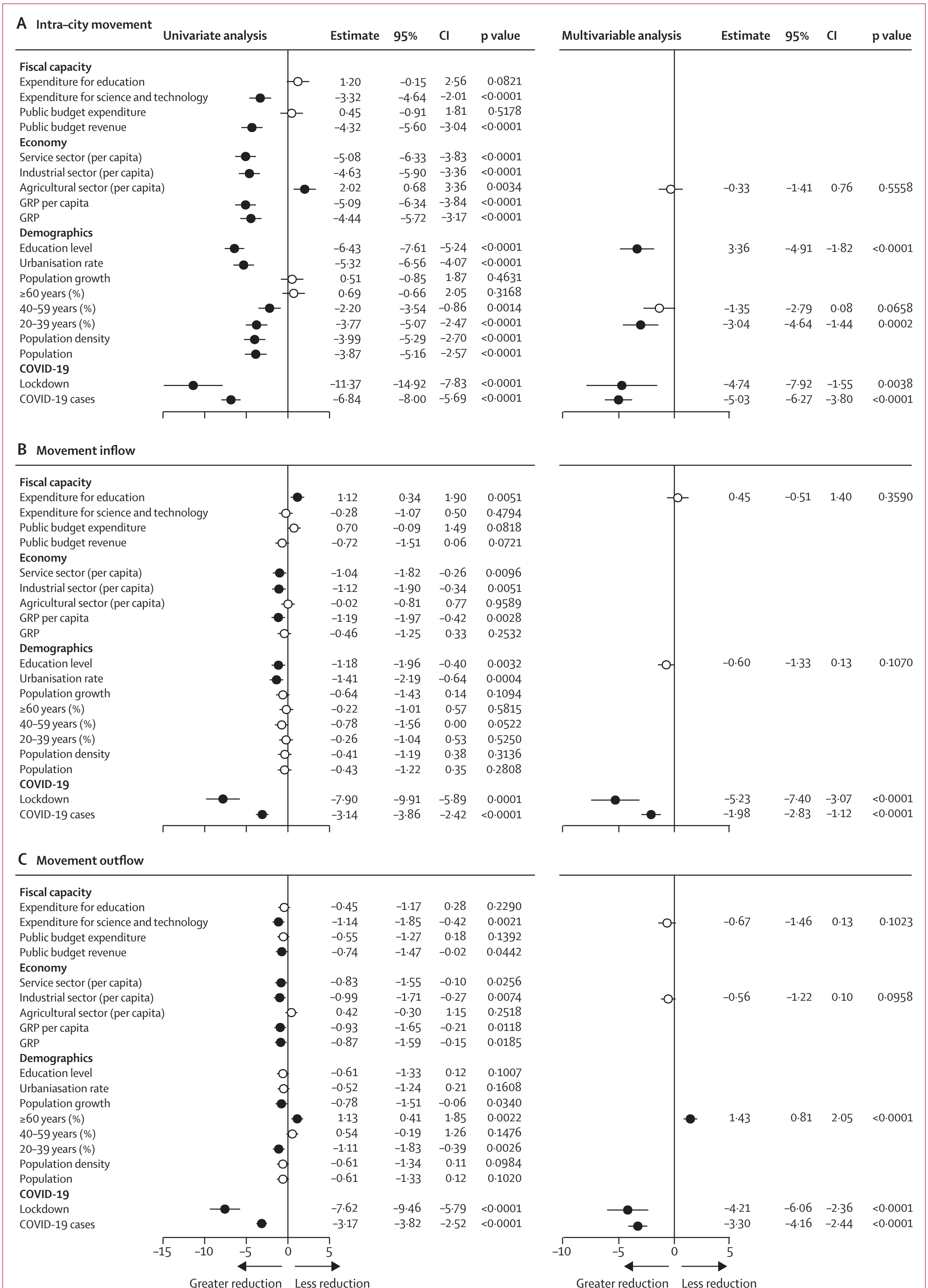
The funders had no role in study design, data collection, data analysis, data interpretation, or writing of the report.

Results

Changes in movement between 2019 and the period following introduction of the COVID-19 national emergency response in China display clear geographical differences between cities (figure 1). The average change in intra-city movement intensity ranged from –71·97% to –3·85% (figure 1A). The average change in movement inflow intensity ranged from –92·42% to –41·81% (figure 1B), and the average change in movement outflow intensity ranged from –91·62% to –52·87% (figure 1C). The changes in inflow and outflow intensities were very similar, with a correlation of 0·80 (ie, the greater the decrease in movement inflow intensity, the greater the decrease in movement outflow intensity; appendix p 5).

A weak spatial autocorrelation was detected (reduction in intra-city movement intensity [Moran's I=0·27, p<0·0001]; reduction in inflow intensity [0·12, p<0·0001]; and reduction in outflow intensity [0·12, p<0·0001]). The percentage changes in the three types of movement negatively correlated with the cumulative number of confirmed COVID-19 cases across the 358 cities (intra-city movement intensity [r=–0·52, p<0·0001], inflow intensity [–0·42, p<0·0001], and outflow intensity [–0·37, p<0·0001]; appendix p 6).

There were 41 cities in the high SEI category, 74 in the high–middle SEI category, 150 in the middle SEI category, and 88 in the low SEI category. There were regular changes in intra-city movement intensity for each of the four SEI groups. Intra-city movement data show an abrupt shift after the national emergency response for all four SEI



A Intra-city movement

	Univariate analysis: Estimate	95% CI		p value	Multivariable analysis: Estimate	95% CI		p value
Fiscal capacity								
Expenditure for education	1·20	–0·15	2·56	0·0821				
Expenditure for science and technology	–3·32	–4·64	–2·01	<0·0001				
Public budget expenditure	0·45	–0·91	1·81	0·5178				
Public budget revenue	–4·32	–5·60	–3·04	<0·0001				
Economy								
Service sector (per capita)	–5·08	–6·33	–3·83	<0·0001				
Industrial sector (per capita)	–4·63	–5·90	–3·36	<0·0001				
Agricultural sector (per capita)	2·02	0·68	3·36	0·0034	–0·33	–1·41	0·76	0·5558
GRP per capita	–5·09	–6·34	–3·84	<0·0001				
GRP	–4·44	–5·72	–3·17	<0·0001				
Demographics								
Education level	–6·43	–7·61	–5·24	<0·0001	3·36	–4·91	–1·82	<0·0001
Urbanisation rate	–5·32	–6·56	–4·07	<0·0001				
Population growth	0·51	–0·85	1·87	0·4631				
≥60 years (%)	0·69	–0·66	2·05	0·3168				
40–59 years (%)	–2·20	–3·54	–0·86	0·0014	–1·35	–2·79	0·08	0·0658
20–39 years (%)	–3·77	–5·07	–2·47	<0·0001	–3·04	–4·64	–1·44	0·0002
Population density	–3·99	–5·29	–2·70	<0·0001				
Population	–3·87	–5·16	–2·57	<0·0001				
COVID-19								
Lockdown	–11·37	–14·92	–7·83	<0·0001	–4·74	–7·92	–1·55	0·0038
COVID-19 cases	–6·84	–8·00	–5·69	<0·0001	–5·03	–6·27	–3·80	<0·0001

B Movement inflow

	Univariate analysis: Estimate	95% CI		p value	Multivariable analysis: Estimate	95% CI		p value
Fiscal capacity								
Expenditure for education	1·12	0·34	1·90	0·0051	0·45	–0·51	1·40	0·3590
Expenditure for science and technology	–0·28	–1·07	0·50	0·4794				
Public budget expenditure	0·70	–0·09	1·49	0·0818				
Public budget revenue	–0·72	–1·51	0·06	0·0721				
Economy								
Service sector (per capita)	–1·04	–1·82	–0·26	0·0096				
Industrial sector (per capita)	–1·12	–1·90	–0·34	0·0051				
Agricultural sector (per capita)	–0·02	–0·81	0·77	0·9589				
GRP per capita	–1·19	–1·97	–0·42	0·0028				
GRP	–0·46	–1·25	0·33	0·2532				
Demographics								
Education level	–1·18	–1·96	–0·40	0·0032	–0·60	–1·33	0·13	0·1070
Urbanisation rate	–1·41	–2·19	–0·64	0·0004				
Population growth	–0·64	–1·43	0·14	0·1094				
≥60 years (%)	–0·22	–1·01	0·57	0·5815				
40–59 years (%)	–0·78	–1·56	0·00	0·0522				
20–39 years (%)	–0·26	–1·04	0·53	0·5250				
Population density	–0·41	–1·19	0·38	0·3136				
Population	–0·43	–1·22	0·35	0·2808				
COVID-19								
Lockdown	–7·90	–9·91	–5·89	0·0001	–5·23	–7·40	–3·07	<0·0001
COVID-19 cases	–3·14	–3·86	–2·42	<0·0001	–1·98	–2·83	–1·12	<0·0001

C Movement outflow

	Univariate analysis: Estimate	95% CI		p value	Multivariable analysis: Estimate	95% CI		p value
Fiscal capacity								
Expenditure for education	–0·45	–1·17	0·28	0·2290				
Expenditure for science and technology	–1·14	–1·85	–0·42	0·0021	–0·67	–1·46	0·13	0·1023
Public budget expenditure	–0·55	–1·27	0·18	0·1392				
Public budget revenue	–0·74	–1·47	–0·02	0·0442				
Economy								
Service sector (per capita)	–0·83	–1·55	–0·10	0·0256				
Industrial sector (per capita)	–0·99	–1·71	–0·27	0·0074	–0·56	–1·22	0·10	0·0958
Agricultural sector (per capita)	0·42	–0·30	1·15	0·2518				
GRP per capita	–0·93	–1·65	–0·21	0·0118				
GRP	–0·87	–1·59	–0·15	0·0185				
Demographics								
Education level	–0·61	–1·33	0·12	0·1007				
Urbaniasation rate	–0·52	–1·24	0·21	0·1608				
Population growth	–0·78	–1·51	–0·06	0·0340				
≥60 years (%)	1·13	0·41	1·85	0·0022	1·43	0·81	2·05	<0·0001
40–59 years (%)	0·54	–0·19	1·26	0·1476				
20–39 years (%)	–1·11	–1·83	–0·39	0·0026				
Population density	–0·61	–1·34	0·11	0·0984				
Population	–0·61	–1·33	0·12	0·1020				
COVID-19								
Lockdown	–7·62	–9·46	–5·79	<0·0001	–4·21	–6·06	–2·36	<0·0001
COVID-19 cases	–3·17	–3·82	–2·52	<0·0001	–3·30	–4·16	–2·44	<0·0001

Figure 2: **Univariate and multivariable analyses for the association between socioeconomic factors and changes in population mobility following the COVID-19 national emergency response among 358 cities in China**
Univariate and multivariable analysis for intra-city movement intensity (A), movement inflow intensity (B), and movement outflow intensity (C). Solid circles represent significant (ie, p<0·05) values. Bars show the 95% CI. GRP=gross regional product.

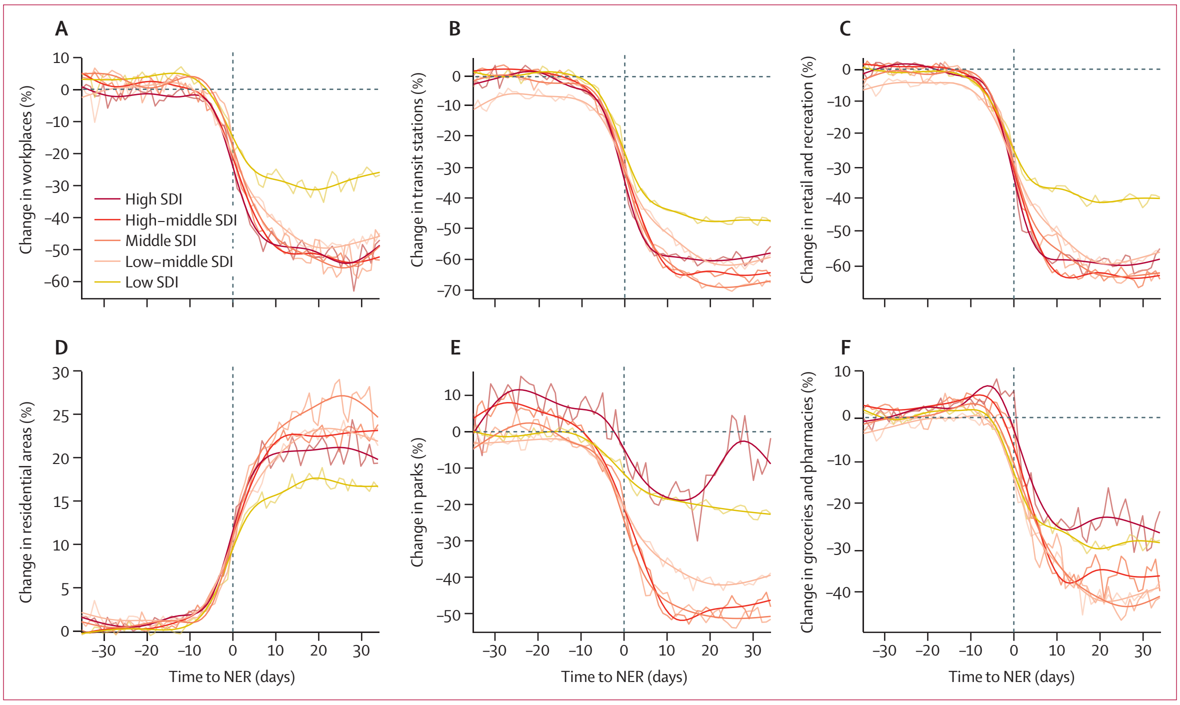


Figure 3: **Change in daily mobility before and after implementation of NERs across 121 countries worldwide**

Change in daily mobility before and after NERs in workplaces (A), transit stations (B), retail and recreation areas (C), residential areas (D), parks (E), and groceries and pharmacies (F). Thin lines represent raw data. Thick lines represent smoothed values from a generalised additive model. Global population mobility data were obtained from Google Community Mobility Reports. The selected observation time period was the first 35 days after the NER was declared. The baseline is the median value for the corresponding day of the week from Jan 3 to Feb 6, 2020. NER=national emergency response. SDI=sociodemographic index.

groups (figure 1D). Cities with a higher SEI had a greater reduction in intra-city movement intensity than did cities with a lower SEI (figure 1E). We found a highly negative correlation between SEI and mobility change ($r=-0\cdot47$, $p<0\cdot0001$). However, there was no similar variation in inflow or outflow intensity between different SEI groups (appendix p 7).

To identify the specific factors associated with changes in population mobility, we did univariate and multivariable linear analyses for the three types of movement (figure 2). In univariate analysis, the average reduction in intra-city movement intensity in each city increased with the number of reported COVID-19 cases and implementation of lockdown. We also observed significant associations between changes in population mobility (ie, reduction in intra-city movement intensity) and socioeconomic factors (figure 2A). For example, for age groups between 20 and 39 years and between 40 and 59 years, there was a negative correlation with change in intra-city movement intensity (ie, the greater the proportion of the population with these age groups, the greater the decrease in intra-city movement intensity).

The percentage of the population with a post-secondary education qualification also correlated negatively with the change in intra-city movement intensity. Other factors significantly associated with changes in intra-city movement intensity in the univariate analysis included urbanisation rate, gross regional product, gross regional product per capita, and factors related to industry and public service (ie, agricultural sector per capita, industrial sector per capita, service sector per capita, public budget revenue, and expenditure for science and technology). Considering the collinearity among the various socioeconomic indicators, we selected six variables on the basis of variance inflation factor for inclusion in the multivariable linear regression. Most of the variables were significantly associated with changes in intra-city movement intensity, except agricultural sector (per capita) and proportion of people in the 40–59 years age group (figure 2A).

Changes in movement inflow intensity correlated negatively with cumulative number of confirmed COVID-19 cases and lockdown status (figure 2B). Similar results were seen for change in movement outflow intensity (figure 2C). However, we did not observe consistent associations with socioeconomic factors for these two types of movement, except for an association between the proportion of people aged 60 years and older and change in outflow intensity.

To get a broader understanding of the effects of socioeconomic factors on reduction of movement at the city level in China, we did univariate and multivariable analyses for each SEI group (appendix p 8). These analyses show that the cumulative number of confirmed COVID-19 cases was significantly associated with intracity movement intensity in the middle and

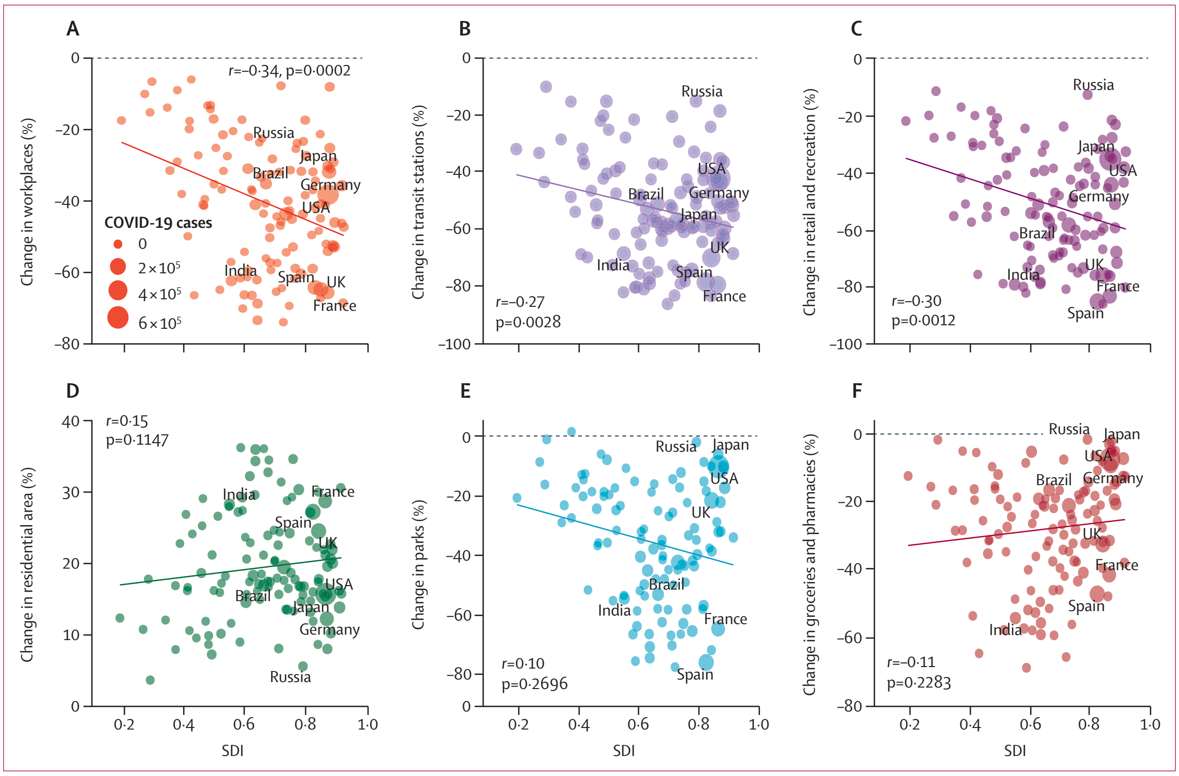


Figure 4: **Association between change in population mobility and sociodemographic index at a global scale**
The association between changes in population mobility and SDI at a global scale that were significant (A–C), including workplaces (A), transit stations (B), and retail and recreation (C), and not significant (D–F), including residential areas (D), parks (E), and groceries and pharmacies (F). The size of the dot represents the cumulative number of confirmed COVID-19 cases up to 35 days after implementation of the national emergency response. SDI=sociodemographic index.

high-middle SEI groups. In the high SEI group and the low SEI group, the cumulative number of confirmed COVID-19 cases was not significant, meaning that the number of COVID-19 cases was not significantly associated with changes in movement intensity in these SEI groups. The proportion of people with a post-secondary education qualification was significantly associated with changes in intra-city movement intensity in the middle and low SEI groups, but not in the high or high–middle SEI groups.

The percentage of the population with a post-secondary education qualification was 28·36% (95% CI 26·86–29·86) in the high and high–middle SEI groups, compared with 17·50% (16·85–18·15) in the middle and low SEI groups. In multivariable analysis, the effect size of education level was –11·04 in the low SEI group and –5·51 in the middle SEI group. To test whether the coefficients of education level differed significantly between different SEI groups, pairwise SEI group comparisons were done using multivariable regression with the interaction term between SEI group and education level. No significant differences were observed between the low SEI group and the middle SEI group (p=0·14). We did not find an association between socioeconomic factors and reduction in inflow and outflow intensities in the four SEI groups (appendix pp 9–10).

We plotted the scatter plot between SEI and change in intra-city movement intensity across cities in China from Feb 19 to March 6, 2020 (appendix p 11). SEI negatively correlated with mobility change. There was a greater reduction in mobility in cities with higher SEI. We also did a similar analysis for change in intra-city movement intensity between Feb 19 and March 6, 2020, and found that education level was negatively associated with mobility change (appendix p 12).

In the country-level analysis, five of the six types of movement analysed (ie, movement occurring in parks, workplaces, retail and recreation, transit stations, and groceries and pharmacies) showed a reduction in mobility intensity in response to COVID-19, with movement in residential areas showing increased mobility intensity (figure 3). Population mobility responses were heterogeneous between countries (figure 4, appendix p 13): countries with a higher SDI showed a greater reduction in mobility in transit stations (*r*=–0·27, p=0·0028), workplaces (*r*=–0·34, p=0·0002), and areas of retail and recreation (*r*=–0·30, p=0·0012) than those with a lower SDI. Moreover, those countries with a higher UHC index had a higher reduction in mobility (appendix p 15) in transit stations (r=–0·44, p<0·0001), workplaces (r=–0·45, p<0·0001), retail and recreation (r=–0·51, p<0·0001), parks (r=–0·39, p<0·0001), and groceries and pharmacies (r=–0·20, p=0·0449) than those with a lower UHC index, but had increased level of staying at home (r=0·33, p=0·0011).

We also compared mobility changes between country groups (appendix p 14). The average reduction in population mobility in transit stations in high, high–middle, and middle SDI groups was 56·04% (95% CI 52·61–59·47), which was 1·2 times larger than that measured in the low–middle and low SDI groups (47·04%; 40·47–53·62). For workplaces, the average reduction in population mobility in the high, high–middle, and middle SDI groups was 44·10% (40·67–47·5), which was 1·32 times larger than that in the low–middle and low SDI groups (33·40%; 27·06–39·73). For retail and recreation areas, the average mobility reduction in the high, high–middle, and middle SDI groups was 54·63% (50·82–58·44), which was 1·24 times larger than that in the low–middle and low SDI groups (43·96%; 37·27–50·66). For residential areas, parks, and groceries and pharmacies, we did not observe a significant association between change in mobility and SDI.

Similarly to the previous analysis at the city level, a linear regression was done for the six categories of movement reduction (appendix pp 23–24). Changes in mobility in each country were not significantly associated with the cumulative number of confirmed COVID-19 cases. Here, we considered two variables: stay-at-home order and SDI. Considering the biases in mobile data and the limited number of NPIs implemented in the 121 countries analysed, additional analyses were done (appendix pp 4, 23–24) to check whether our conclusion still held or not. The results from these analyses showed that our conclusion was consistent with the previous one (ie, that the SI and SDI are negatively associated with the mobility reduction in workplaces, transit stations, and areas of retail and recreation).

49 countries had an interval of more than 1 week between the date of the COVID-19 outbreak and the introduction of a first NPI. Univariate linear regression showed that higher SDIs were significantly associated with greater mobility reduction in park areas (*r*=0·34, p<0·0001) and groceries and pharmacies (*r*=0·33, p<0·0001), whereas there were no significant differences for the other four categories of movement in the week before the first NPI. For the UHC index, we did not observe a significant association with mobility changes in any of the six movement categories in the week before the introduction of the firt NPI (appendix p 25).

Discussion

Using empirical data from 358 cities in China and 121 countries globally, we analysed population mobility data before and after emergency responses were introduced to mitigate the spread of COVID-19 and identified socioeconomic factors related to reduced population mobility. A large number of studies have found an association between decreased levels of mobility and reduced transmissibility of COVID-19 worldwide.[8,20] Population mobility data should therefore be taken into account to inform future policy on containing the ongoing COVID-19 pandemic. Our findings provide additional evidence that can inform policy relating to COVID-19 containment.

In our study, we found that several factors were associated with reduced intra-city movement intensity, including a high proportion of people in age groups between 20 and 39 years, socioeconomic factors (ie, education level), and COVID-19-related factors (ie, lockdown status and number of COVID-19 cases). These findings are consistent with studies done in the USA[12,13] and France.[14] For inflow and outflow intensity, socioeconomic factors were not associated with reduced mobility. However, the sociodemographic factor of the percentage of people aged 60 years and older was associated with reduced outflow intensity.

Our study showed that the socioeconomic status of cities in China was also negatively associated with change in intra-city movement intensity. We expanded our analysis to a global level and found a similar pattern, and these results were broadly in line with previous findings[12] at a regional scale. Cities and countries with a higher socioeconomic level had a greater change in population mobility in response to COVID-19. Moreover, in regions with lower socioeconomic levels, changes in population mobility responses were weak. One reason for this finding could be that people with lower incomes rely on public transport and cannot follow population mobility guidelines as easily as people with higher incomes. People on lower incomes might also be unable to work remotely because of the nature of their work (eg, occupations in services, retail, cleaning, or agricultural labour). Moreover, it seems that cities with higher SEIs still follow the national emergency response guidelines during relaxation of control measures while the regions with lower SEIs did not (figure 1D).

The detailed analyses by SEI group at the city level also provided meaningful insights. Previous studies have shown that the number of COVID-19 cases affects risk perception, resulting in voluntary changes in population mobility.[10] When the number of confirmed cases in cities is high, members of the public are more aware of the seriousness of the epidemic and thus reduce unnecessary trips. However, these findings might not be true for regions with lower socioeconomic levels. In our analysis, we found that the cumulative number of confirmed COVID-19 cases correlated negatively with intra-city movement intensity in the high–middle and middle SEI groups, but this was not the case for the high and low SEI groups. People in regions with a lower SEI might have lacked awareness of the pandemic, or might have been affected by other lifestyle barriers preventing them from following population mobility guidelines. Further investigation is needed for high and low SEI groups. Another important finding from our study was that education level is related to population mobility in the middle and low SEI groups, but not in the high and high–middle SEI groups. Previous studies have shown that human behaviour is strongly related to level of education.[21–23] From our perspective, education level seems to be associated with response to the COVID-19 pandemic. However, there could be a threshold effect above which education level is no longer associated with COVID-19 responses. This hypothesis is supported by our finding that education level in the high and high–middle SEI groups was significantly higher than in the middle and low SEI groups. We also checked whether the effect size of education level in the low SEI group was larger than that in the middle SEI group, and no difference was found. Nevertheless, by improving public understanding of the pandemic, increasing testing availability, and providing more financial support for regions with a lower SEI, policy makers can not only contain the spread of COVID-19 more effectively at the local scale, but could also benefit other regions as a result.

Our study has several limitations. First, data from Baidu did not clarify the location properties of a trip, so we could not distinguish between low-risk trips and high-risk trips. For example, multiple trips to the park (a location associated with low risk of transmission) alone might be less risky than one trip to the mall (a location associated with high risk of transmission) alone. Second, some countries did not have a national emergency response, such as Brazil, where the authority to declare interventions was delegated to local authorities. In such cases, the intervention date varied across the country and the earliest date might have only been representative of a small region of a country, which would have resulted in an underestimation of the reduction in movement. Third, because of the low availability of data, it was challenging to obtain standardised socioeconomic factors for city-level data and country-level data. We therefore chose comprehensive indexes (SEI for cities and SDI for countries), which indicated socioeconomic level, to make conclusions derived from the city-level and country-level data comparable.

Fourth, population age groups and education level in our study came from census data, which might not reflect current demographic characteristics. Fifth, ownership of devices that were capable of location tracking is a function of resources. Therefore, the observed differences in mobility by aggregate socioeconomic status might instead have reflected regional contrasts only among individuals who were wealthy enough to contribute data. In addition, Baidu and Google do not have exactly the same market share in each region analysed in our study; studies show that Baidu has an 89·1% market share in China[24] and has 200 million daily users of its apps.[25] With more than 2·5 billion active Android devices in 2019, Google location data are available for an increasing percentage of the world.[26] We therefore believe that these two datasets are adequate to reflect population mobility for all countries included in our study. There were some biases and spatial heterogeneity in these datasets, but the effects of these biases are likely to be small. One study[27] compared two parallel datasets (one based on mobile phone data and one based on survey data) and found that mobility estimates based on mobile phone data were surprisingly robust against the substantial biases in mobile phone ownership across different geographical and socio-economic groups. We believe that our findings are also robust, but the effect sizes for socioeconomic factors could be affected by these biases.

Sixth, the extent of mobility change measured in the cities included in our study could have been related to their respective distances from Wuhan. We calculated that the number of confirmed COVID-19 cases in each city was significantly negatively correlated with the distance from Wuhan ($r=-0\cdot69$, $p<0\cdot0001$), so we did not consider this factor in the model. Seventh, within a city, socioeconomic factors might differ between communities. We did the analysis at the city level because it is difficult to obtain data on socioeconomic factors for units smaller than a city and because the mobility data were collected at the city level. Although heterogeneous socioeconomic patterns exist within cities, we believe that our conclusion that mobility reduction is greatest in regions with higher socioeconomic levels is still supported. Eighth, although it is better to compare mobility data between 2020 and 2019, country-level mobility data for 2019 were not released by Google. We also could not use the same time interval to study changes in mobility in different countries because the dates of national emergency response varied substantially among countries (eg, March 15, 2020, in Australia, *vs* March 26, 2020, in Thailand). Therefore, a better strategy was to compare mobility for a defined period after the national emergency response.

Lastly, concerning the heterogeneity in intra-city movement intensity, we compared changes in the ratio of the travelling population to the resident population in each city rather than changes in different regions within the city. In addition, workers who commuted into the city to work might not have returned to work on time after the Spring Festival holiday (also known as the Chunyun period) because of COVID-19, which could partly explain the reduction in mobility in cities with a higher SEI. According to the Ministry of Industry and Information Technology, as of Feb 26, 2020, the average operating rate of industrial enterprises with an annual main business income of 20 million yuan or more in China was 88·9% (except in Hubei),[28] indicating that a large proportion of people had returned to work. The effect of the Chunyun period on our study is likely to be small. However, future research is needed to confirm this.

Our results show that socioeconomic, demographic, and other population characteristics were associated with changes in population mobility following the national emergency response in China and other countries. Although we cannot infer causality, our study provides some insights into how NPIs could be customised on the basis of the socioeconomic characteristics of each city or country. Socioeconomic factors should be modelled to predict the risk of COVID-19 in different regions in future analyses. Intervention support could be strengthened in areas with a low socioeconomic level to reduce transmission, including deepening public understanding of the virus, improving self-health management, and increasing testing availability. Considering the high prevalence of asymptomatic SARS-CoV-2 infection[29] and the risk of additional waves of COVID-19, it is important to maximise the effects of NPIs to contain the spread of COVID-19 in regions with low amounts of funding, as well as other regions.

Contributors

HT and PZ designed the study. YL and BL collected the statistical data, drew the figures, and collected and processed the mobility data. ZW and HT wrote the manuscript. YL did the analyses. HT, ZW, BR, C-HW, JDW, NCS, ONB, and JSB edited the manuscript. All authors read and approved the manuscript. All authors had full access to all the data used in the study and had final responsibility for the decision to submit for publication. The main authors who verified the underlying data were YL and BL.

Declaration of interests

We declare no competing interests.

Data sharing

We analysed mobility data from 121 countries using Google COVID-19 Community Mobility Reports from Feb 15 to Oct 6, 2020 (https://www.google.com/covid19/mobility/). We analysed movements and relative volume of inflow, outflow, and intra-city movement intensity for each Chinese city (n=358, excluding Hong Kong, Macau, and Taiwan) from the migration flows database (http://qianxi.baidu.com/) from Jan 1, 2019, to March 6, 2020.

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