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Analyzing COVID-19’s impact on the travel mobility of various social groups in China’s Greater Bay Area via mobile phone big data

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ABSTRACT

The COVID-19 outbreak has significantly impacted people’s mobility in terms of travel, which is directly related to regional economic vitality and individuals’ well-being. This study conducted research on the COVID-19 epidemic’s impact on travel mobility in China’s Greater Bay Area, utilizing mobile phone big data. The overall influence of COVID-19 was measured by investigating the impact between different income and migration groups in three core cities: Shenzhen, Guangzhou, and Foshan. Individuals’ weekly travel frequency and activity space area between December 2019 and May 2020 were calculated, and the average values between the different cities and various social groups were compared. The results showed that travel mobility declined during the epidemic’s peak, followed by a recovery based on the overall trend. The start and end of strict law enforcement had a significant impact on the initial decline and subsequent recovery of travel mobility in the core cities. COVID-19 had a larger impact on core cities than peripheral areas, and on non-commute travel frequency, compared to commute travel frequency. Compared to advantaged groups, socially disadvantaged groups experienced a steeper decline in travel mobility during the epidemic’s peak, but a more significant recovery afterwards. These findings indicate that discretionary activities have not yet recovered and remain below the pre-epidemic level, and that disadvantaged social groups had limited access to superior precautionary measures for avoiding infection. Based on the findings, we provide several policy suggestions regarding the recovery of travel mobility.

1. Introduction

The novel coronavirus (COVID-19) outbreak has become a pandemic, infecting 183 million people by the end of June 2021 (Johns Hopkins University, 2021). The outbreak has significantly impacted living patterns, especially human travel patterns, including the execution of travel bans and the promotion of social distancing, which curtailed people’s capacity to travel in order to control the disease’s spread (Espinoza et al., 2020; Daoust, 2020; Tian et al., 2020). As a result, people have spent more time inside their homes, where they participate in learning, working, and entertainment instead of going out. Travel mobility has been reduced due to objective restrictions on travel and subjective fears of becoming affected (Hoque et al., 2020; Wen et al., 2020; S. Zhang et al., 2020; Lades et al., 2020).

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Since individuals’ social participation is positively related to their travel mobility and corresponding activity space (Stanley et al., 2011; Lin and Wang, 2014; Stanley et al., 2019), the reduction of travel mobility has led to a decline in social interaction and participation, which may negatively affect individuals’ well-being (Qian et al., 2020; Newby et al. 2020). These effects may differ between different income and migrant groups (Qian et al., 2020). Moreover, since travel mobility embodies the economic vitality of a region (Wong et al., 2020), its reduction denotes a subsequent decline in economic vitality. Research concerning travel mobility changes within different groups and among various cities during the COVID-19 outbreak will significantly contribute to knowledge about individual changes in well-being and shifts in a region’s economic vitality.

Thus far, there have been increasing studies about travel mobility since the COVID-19 outbreak, including changes in travel frequency, distance, and so on. In these studies, the travel mobility data before and after the outbreak were obtained through questionnaire surveys or mobile phone data before being compared. These studies show that the trips with non-mandatory objectives were more significantly reduced than those with mandatory objectives (Arimura et al., 2020; de Haas et al., 2020; Meena, 2020), while residents with disadvantaged social conditions, such as lower income groups (Hotlie et al., 2020), migrants (Pullano et al., 2020), and the elderly (de Haas et al., 2020) tended to have a more significant reduction in travel mobility than those with advantaged social conditions. However, ample room remains for further understanding COVID-19’s impact on travel mobility.

We have identified three gaps in the current research. First, research on COVID-19’s impact on the travel mobility of different social groups is limited, and some findings still need further verification. Second, most studies are based on traditional surveys and seldom utilize mobile phone big data, which allows for a much larger sample size and a broader coverage of the disease’s impact in terms of population, geography, and time span (Wang et al., 2018). Third, existing research mainly focuses on travel frequency but seldom investigates activity space area, which not only reflects the amount of travel mobility but also its degree (Zenk et al., 2011; Sherman et al., 2005; Vich et al., 2017). To address these gaps, we intend to study COVID-19’s impact on travel mobility by comparing different social groups via mobile phone data. In addition to travel frequency, we will adopt a supplementary indicator of travel mobility: activity space.

This study’s aim is to focus on China’s Greater Bay Area (GBA) in Guangdong Province, China. The GBA is one of the most advanced areas in China with large population mobility. It consists of nine cities in Guangdong Province of mainland China (Guangzhou, Shenzhen, Foshan, Dongguan, Zhongshan, Zuhuai, Huizhou, Jiangmen, and Zhaoqing) plus Hong Kong SAR and Macau SAR. Due to different border control policies and mobility cultures in Hong Kong and Macau than those in mainland China, our study will focus on the nine mainland cities of GBA rather than the whole GBA. As the GBA is the most popular migration destination for people originating from Hubei Province (Jia et al., 2020), where the epidemic was first reported and the largest number of infections existed among the populace, the epidemic’s trend in the GBA followed that of the whole country (Xu et al., 2020), affecting a broad range of income groups and a significant portion of migrants. Therefore, this is an adequate representative area for investigating COVID-19’s impact on the travel mobility of different social groups in China.

Our analysis consists of two main parts. First, we will examine the overall impact of COVID-19 on the travel mobility of the GBA across all its cities by conducting a comparison between different periods of the epidemic (e.g., before the epidemic occurred, during its peak, and after its peak) between December 2019 and May 2020. Travel frequency and activity space area were selected as the two aspects that measure travel mobility, which will be compared between different periods to investigate the overall impact of the epidemic on travel mobility (see Section 4). Second, we will focus on the three largest cities in the GBA (i.e., Shenzhen, Guangzhou, and Foshan) to investigate the impact of COVID-19 on the travel mobility of different income groups (i.e., high, middle, and low) and various migration status groups (i.e., those from outside Guangdong or other cities in Guangdong as well as local residents) in the same city to obtain a detailed view of the impact variation among a variety of social groups (see Section 5). Based on the results, we will propose related policy implications on the travel mobility of low income and migrant workers in China.

2. Literature review
2.1. Impact of COVID-19 on travel patterns around the world

Scholars from different countries have studied the impact of COVID-19 on travel patterns, including research regarding changes in travel distance, travel modes, and frequency for different purposes. This review is grouped into two types according to the data source: questionnaire survey and mobile phone data.

The research conducted using questionnaire surveys was mainly aimed at investigating changes in the travel distance and frequency of different purposes, travel and changes in transport modes. De Haas et al. (2020) in the Netherlands show that the frequency of travel for personal care, education, and visiting friends dropped the most among all the reasons for travel. Meanwhile, based on a combination of data from active questionnaire surveys via email, social media, and professional networks, Mogaji (2020) finds that the frequency of travel in Nigeria for economic, social, and religious activities has significantly reduced, and the epidemic had the strongest impact on travel for economic activities. Similarly, in India, Meena (2020) shows that non-mandatory travel frequency and travel length were both reduced, and people became more dependent on personal transport modes (e.g., walking, driving a car, and riding a bicycle or two-wheeler) instead of public transportation due to the fear of infection. However, another study conducted by Pawar et al. (2020) shows that although people believe public transportation to pose a higher risk of infection, there is not a significant change in travel modes due to lack of commuting alternatives and less awareness about COVID-19’s ill effects during the epidemic’s early stages. Furthermore, in Japan, Parady et al. (2020) reveal that the reduction in travel frequency of most activity types was associated with the degree of self-restriction (except for shopping frequency, where the effects of self-restriction were rather small).

Research utilizing mobile phone data has been primarily conducted in developed countries, and has been concerned with...
comparing changes in total travel frequency or distance in different regions and at various times. Gao et al. (2020a, 2020b) conducted a study on daily mobility changes at the county level, measured by comparing the maximum travel distance to a location from the day’s initial location. Their results show that among most states in the Pacific Coast, Midwest, and East Coast, the reactions to a declaration of national emergency and daily mobility quickly declined, while a few states did not actively react, so the daily mobility did not drop until two weeks after a national emergency was declared. In other words, in states where the confirmed cases were growing more rapidly, people responded more actively and rapidly by reducing their daily travel distance. Badr et al. (2020) show a similar tendency regarding a change in the travel frequency between different regions in the United States. In France, Pullano et al. (2020) show larger reductions in travel frequency among regions that were more severely hit by the epidemic as well as that of long distance trips over a hundred kilometers. In Sapporo, Arimura et al. (2020) show that the population reduction in commercial areas was more significant during the nighttime than daytime and over holidays, compared to weekdays, implying a stronger impact on discretionary trips compared to commuter trips.

2.2. Impact of COVID-19 on travel patterns in China

It should be noted that the research discussed above was mainly conducted in the respective countries before the epidemic had reached its peak; thus, changes in travel mobility after the peak remains unknown. China is one of the few countries where the epidemic was quickly controlled, passing its peak, and the change in travel mobility during the whole process (both before and after the epidemic’s peak) has been studied by scholars.

From December 2019 to May 2020, China underwent the process of the disease being spread widely, reaching its peak, and finally controlled. In December 2019, the epidemic was first reported in Wuhan, and the city’s subsequent lockdown on January 23 denoted the beginning of travel restriction. Daily new cases of infection reached a peak of over 6000 by February 11, and then reduced to only two by May 30 (National Health Commission of the People’s Republic China, 2020). To further promote disease control and prevention, the mainland Chinese Government imposed stringent travel restrictions and encouraged potentially infected individuals to self-quarantine (Aleta et al., 2020). Overall, the response strengthened before the epidemic’s peak and then weakened afterwards, but the response differed at provincial level.

In Guangdong Province, for example, the first-level response to the pandemic was issued on January 23, indicating the closure of indoor public places, and enforcing strict registration measures and examination upon entry to residential areas. On February 24, the response to the pandemic had changed to the second level, indicating the limited opening of indoor public places and relatively diminished control of residential areas (Hu et al., 2020). The start and end dates of regulation enforcement in different cities are presented in Table 1. Since China is one of the few countries in the world that has controlled the epidemic to such a large extent and lightened restrictions (Zou et al., 2020), the changes in travel mobility trends can be considered unique, and has significance for related research.

Several scholars conducted research regarding COVID-19’s impact on travel mobility in China. Wu et al. (2020), for example, collected a questionnaire survey in several Chinese cities (Beijing, Shanghai, Guangzhou, Shenzhen, and Chongqing), which shows that people reduced the frequency of their travel for eating out, shopping, touring, and taking public transportation during the epidemic’s peak in early February, as compared to the pre-COVID-19 period. In late April, the frequency of these travels had recovered somewhat (compared to the peak period), but remained less than the pre-COVID-19 period. The research of Gibbs et al. (2020), Fang et al. (2020) and Wang et al. (2020) compared travel mobility before and after the outbreak of COVID-19 using the Baidu Mobility Index, which is calculated from mobile phone data. Their results show that travel mobility had significantly reduced in Chinese cities after the epidemic’s outbreak. Specifically, Wuhan’s travel mobility experienced the largest reduction, and the mobility trough occurred around early February, before it started to pick up.

2.3. Impact of COVID-19 on travel patterns among different social groups

Studies have been conducted regarding COVID-19’s impact on travel patterns among various social groups (e.g., those related to income, migrants, and age). These studies were primarily aimed at comparing the epidemic’s varied impacts on the travel mobility of advantaged and disadvantaged groups. For example, based on questionnaire survey data, de Haas et al. (2020) indicate that older

| City       | Prohibition of eating in restaurants | Closure of indoor public places | Resumption of eating in restaurants | Reopening of indoor public places |
|------------|--------------------------------------|--------------------------------|-------------------------------------|----------------------------------|
| Shenzhen   | Jan 23                               | Jan 23                         | Feb 26                              | Mar 21                           |
| Guangzhou  | Jan 23                               | Jan 23                         | Feb 22                              | Mar 17                           |
| Foshan     | Jan 23                               | Jan 23                         | Feb 29                              | Mar 17                           |
| Dongguan   | Jan 23                               | Jan 23                         | Mar 13                              | Mar 17                           |
| Zhongshan  | Jan 23                               | Jan 23                         | Mar 9                               | Feb 21                           |
| Zhuhai     | Jan 23                               | Jan 23                         | Mar 3                               | Mar 13                           |
| Huizhou    | Jan 23                               | Jan 23                         | Mar 12                              | Mar 17                           |
| Jiangmen   | Jan 23                               | Jan 23                         | Feb 23                              | Mar 18                           |
| Zhaoqing   | Jan 23                               | Jan 23                         | Mar 10                              | Mar 23                           |

Data from: Health Commission of Guangdong Province, 2020a, Health Commission of Guangdong Province, 2020b.
people experienced a larger decline in their travel frequency and distance after the outbreak due to their stronger fear of becoming affected. Shamshiripour et al. (2020) conducted research on individuals’ economic vulnerability in Chicago’s metropolitan area and find that people’s frequency of travel for work and shopping trips had both been reduced as a result of working from home and online shopping. However, this study was primarily aimed at the economically vulnerable, while a comparison between this group and non-vulnerable groups is still lacking in the literature. Thus, the impact of the epidemic on different income groups remains unknown. In relation to income-related grouping, Hotle et al.’s (2020) study shows that higher income groups were more capable of making purchases to reduce their risk of getting infected during their trips. Thus, their travel frequency was supposed to have a smaller reduction than lower income individuals during the epidemic (as compared to before), but since there still lacked an actual measurement of their travel frequency, this needs further verification.

Very few studies using mobile phone data have investigated travel mobility across social groups. Pullano et al.’s (2020) results, obtained from mobile phone data, show that foreigners suffered a more severe reduction in travel frequency than native residents. This indicates that the lockdown caused a stronger disruption in long-distance tourism, especially international tourism, compared to short-distance or domestic tourism.

3. Research gaps

Based on the literature review, we have identified several research gaps. First, the epidemic’s various impacts on the travel mobility across different social groups have been understudied. Only a few studies focus on the socio-spatial equity issues that are related to COVID-19’s impact on travel mobility. Second, few papers have used location-based “big data,” such as mobile phone data or geo-tagged social media data, to investigate the travel mobility impact. Third, existing research has studied the pandemic’s impact on travel mobility at different times and for different purposes, and the results imply that the epidemic had a stronger impact on trips for discretionary purposes, as compared to those with a commute purpose. However, few have differentiated between commute and non-commute travel. Fourth, when measuring travel mobility’s impact, existing research primarily adopted indicators such as travel frequency. While other indicators have been utilized, especially activity space area, one of the most common dimensions of activity space measurements that directly captures the degree or amount of mobility (Hasanzadeh et al., 2019), has seldom been investigated. Individuals’ activity space area deserves more research attention as it not only embodies people’s ability to reach their destinations during a certain period under various constraints (Gesler and Meade, 1988), but also reflects their accessibility of environmental exposure and different opportunities (Zenk et al., 2011; Sherman et al., 2005; Vich et al., 2017). Fifth, existing studies have mostly

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**Fig. 1.** Study area: The Greater Bay Area, China.
been conducted in countries where regulation enforcement was not as strict as in China, and were still recording a high number of cases, such as the United States (Truong and Truong, 2021), India (Meena, 2020), Canada (Fatmi, 2020), and Ireland (Shokouhyar et al., 2021). Countries with strict regulation enforcement, such as China, provide useful contexts for empirical research to derive possible lessons and policy implications for other countries.

4. Method and data sources

4.1. Study area: China’s GBA

China’s GBA in the south is one of the most advanced areas in the country and consists of nine cities in the Guangdong Province: Guangzhou (GZ), Shenzhen (SZ), Foshan (FS), Dongguan (DG), Zhuhai (ZH), Zhongshan (ZS), Huizhou (HZ), Jiangmen (JM), and Zhaoqing (ZQ) (Fig. 1). The total population of the GBA is sixty-three million, which includes 26.7 million migrants outside of the local Hukou system (Statistical Bureau of Guangdong Province, 2020). Table 2 presents basic information about these nine cities.

Fig. 1 and Table 2 show that Shenzhen, Guangzhou, and Foshan are located in the GBA’s core, and have the highest GDP and income. Moreover, they have a large population, comprising different portions of migrants. Shenzhen is a sub-provincial city, where migrants are the majority, consisting of 8.02 million people (outside of the Hukou system) among the population’s total of 13.44 million. Guangzhou is the capital city of the Guangdong Province, where local residents are the majority, including 9.54 million people within the Hukou system and a total population of 15.31 million. Foshan, on the other hand, is a city where the local residents and migrants are equally represented, with 4.61 million people within the Hukou system and a total population of 8.16 million. Therefore, in the second part of this paper (Section 5), the cities of Shenzhen, Guangzhou, and Foshan have been selected for a detailed comparison and analysis regarding the impact of COVID-19 on the travel behavior among different income and migrant groups.

4.2. Data source

This research utilized mobile phone data provided by the China Mobile Communications Corporation (CMCC). The data encompasses the base station in the Guangdong Province that an individual stays in for the longest time, based on every hour over the last two years, including a user’s number, the base station’s longitude and latitude, and personal information that correlates with the user’s number (e.g., the longitude and latitude of their living and workplace locations, as well as their hometown, and even the price of their mobile phone). The longitude and latitude of a user’s living and workplace locations can be detected through the most frequently used cell tower location during both night and day (Demissie et al., 2016; Phithakkitnukoon et al., 2012), and it is processed by the CMCC. The hometown of the mobile phone user is available due to China’s regulations. Since September 1, 2015, all mobile phone users need to provide their personal information (e.g., an identifying card number), and from this information, their hometown is detected, allowing their migrant status to be inferred. (Jiang, 2015). Regarding the mobile phone user’s income level, the correspondent price of the mobile phone’s type can be inferred, as various research shows that a mobile phone’s price is positively correlated with the user’s income (James, 2016; Ramachander, 2016; Lai et al., 2019). Similarly, the type of mobile phone can be detected through the International Mobile Equipment Identity (IMEI) number, which correlates to the user number and market price for the mobile phone’s type, so this information can also be obtained (Alsunaidi and Almuhaideb, 2019).

The resolution of the positioning can reach between 100 and 500 m in an urban area. According to Guangdong mobile’s official WeChat account (2020-08-15), the number of people that use CMCC’s mobile phones in the Guangdong Province has reached a hundred million, which accounts for 86% of the Guangdong Province’s total population. Therefore, the data adequately represents the residents of both Guangdong and China’s GBA. The number of valid individuals (N) in different cities in the CMCC dataset analyzed in this study is shown in Table 3.

In the current study, we selected a study period of 26 weeks (from December 1, 2019 to May 30, 2020), which covers the period before the outbreak, its peak, and afterward.

Table 2
Basic information on the cities in China’s GBA.

| City            | Total population (million) | Residents in local Hukou system (million) | GDP (billion CNY) | Personal annual income (CNY) |
|-----------------|-----------------------------|-------------------------------------------|-------------------|--------------------------------|
| Shenzhen (SZ)   | 13.44                       | 5.42                                      | 2692.7            | 62,522                         |
| Guangzhou (GZ) | 15.31                       | 9.54                                      | 2362.8            | 60,074                         |
| Foshan (FS)     | 8.16                        | 4.61                                      | 1075.1            | 54,043                         |
| Dongguan (DG)  | 8.46                        | 2.51                                      | 948.2             | 53,657                         |
| Zhongshan (ZS) | 3.38                        | 1.83                                      | 310.1             | 50,478                         |
| Zhuhai (ZH)     | 2.02                        | 1.33                                      | 343.6             | 52,495                         |
| Huizhou (HZ)    | 4.88                        | 3.90                                      | 417.7             | 37,160                         |
| Jiangmen (JM)   | 4.63                        | 4.00                                      | 314.6             | 32,323                         |
| Zhaoqing (ZQ)   | 4.19                        | 4.50*                                     | 224.9             | 26,122                         |

Data: Statistical Bureau of Guangdong Province, 2020.
Note: * The residents in the Hukou system of Zhaoqing is greater than the city’s total population because the city has a relatively large amount of outmigration population, as compared to other major cities within the GBA.
4.3. Measurements of travel mobility

Travel mobility measures the character of people’s movement through time and space, which includes the travel time, frequency, safety, and transportation accessibility (Vella-Brodrick and Stanley, 2013). In this study, travel frequency and activity space area were selected to measure travel mobility, covering both geometrical and non-geometrical measurements.

4.3.1. Travel frequency

Travel frequency is a kind of non-geometrical measurement, which focuses on how often an individual goes to other places (Hasanzadeh et al., 2019; Leung and Le, 2019). In this research, the number of trips per week was recorded as travel frequency. Specifically, a trip was either recorded when an individual moved from one location to another that was beyond 1000 m and stayed there, or if they moved within 1000 m for over an hour (Calabrese et al., 2013). The total number of trips that an individual conducted in a week is regarded as the individual’s total travel frequency.

4.3.2. Activity space

Activity space area is a direct measurement of the degree or amount of mobility. In this research, the weekly standard deviation ellipse (SDE) is applied for the activity space’s measurement of its size that is based on an individual’s activity points in a week, which is a statistical approximation of an abstract activity space’s size. It embodies the dispersion and orientation of activities from a global perspective through an elliptical polygon (Fig. 2) (Donaldson, 1973; Vich et al., 2017; Herminghaus, 2019; Tao et al., 2020). The advantage of an SDE is that it excludes the outliers, making the results less sensitive to them (Kerstens, 1996; Buliung and Kanaroglou, 2006; Mattioli et al., 2016). In addition, an SDE reflects the structure of the activity space at two anchor points: the home and workplace (Modarres, 2003; Järv et al., 2014).

The size of an individual’s weekly activity space, which is calculated by an SDE, can also be calculated via Eq. (1): (Donaldson, 1973).

$$S = \frac{1}{4} \pi ab$$

(1)

In this equation, $S$ is the activity space area, which is calculated by an SDE, while $a$ and $b$ are the lengths of two axis’, which can be calculated in Eqs. (2) and (3) respectively:

| City       | $N$     |
|------------|---------|
| Shenzhen   | 11,625,545 |
| Guangzhou  | 12,789,254 |
| Foshan     | 5,692,279   |
| Dongguan   | 7,563,048   |
| Zhongshan  | 3,082,581   |
| Zhuhai     | 1,790,779   |
| Huizhou    | 3,954,674   |
| Jiangmen   | 3,073,257   |
| Zhaoqing   | 2,258,485   |
In these equations, \( n \) is the total number of points that an individual has travelled in a week, while \( x_i \) and \( y_i \) are the latitude and longitude, respectively, in radian of the \( i \)th point. Also, \( \bar{x} \) and \( \bar{y} \) are the average values of the latitude and longitude, respectively, in radian of all the points that week, while \( \theta \) is the rotation angle that can be calculated in Eq. (4):

\[
\theta = \arctan \left( \frac{\sum_{i=1}^{n} \bar{x}_i^2 - \left( \sum_{i=1}^{n} \bar{y}_i \cos^2 \varphi \right)}{\sum_{i=1}^{n} \bar{y}_i^2 \cos \varphi + 4 \cos \varphi \sum_{i=1}^{n} \bar{x}_i \bar{y}_i} \right)
\]

For this equation, consider the following:

\[
\bar{x}_i = x_i - \bar{x}
\]

\[
\bar{y}_i = y_i - \bar{y}
\]

After the calculation, weekly travel frequency and activity space area at the individual level can be obtained among different groups (e.g., those based on cities, incomes, and/or migration status). The comparison for travel frequency and activity space was conducted based on the average value of different groups.

4.4. Commute vs. non-commute travel

Since the travel mobility of different trip purposes can vary considerably, we will differentiate a trip’s purpose into two types: commute and non-commute travel. Since the latitude and longitude coordinates of an individual’s home and workplace are

![Fig. 3. Impact of COVID-19 on travel frequency in China’s GBA over time (from December 2019 to May 2020).](image-url)
documented by CMCC with corresponding mobile phone numbers, it is possible to distinguish between commute and non-commute trips. The trips between the home (or within 1000 m of their home’s coordinates) and workplace (or within 1000 m of the workplace’s coordinates) are regarded as commute trips (Calabrese et al., 2013; Vich et al., 2017), while other instances of travel are regarded as non-commute trips.

4.5. Hypothesis

In the next section, we will conduct a group comparison of travel mobility and test the following hypotheses, which we propose based on our literature review:

1. The epidemic had a stronger impact on the frequency of non-commute trips than that of commute trips (Arimura et al., 2020; de Haas et al., 2020; Meena, 2020).
2. The epidemic had a stronger impact on the travel mobility of lower income groups than that of higher income groups (Hotle et al., 2020; Shamshiripour et al., 2020).
3. The epidemic had a stronger impact on the travel mobility of migrants than that of local residents (Pullano et al., 2020; Jauhiainen, 2020).

5. The overall impact of COVID-19 on the travel mobility of China’s GBA

5.1. Travel frequency and travel mobility

In this section, we present the weekly travel frequency and activity space area for the residents of the aforementioned nine cities between December 1, 2019 and May 30, 2020 (note that our weekly value was calculated from Sunday to Saturday; therefore, strictly speaking, May 31, 2020 [Sunday] was not included in our study period). The changes in their travel frequency and size of their activity space are shown in Figs. 3 and 4. As a reference and cross-validation, we also collected the data of new COVID-19 cases in China’s GBA from the Health Commission of Guangdong Province, and then, we plotted these numbers in the lower panel for the same figures.

To generate these figures, we first calculated the average value of weekly travel frequency ($F_0$) and activity space area ($S_0$) before the epidemic’s outbreak (December 1, 2019 ~ January 18, 2020). Then, we calculated the ratios for travel frequency ($F$) and activity space area ($S$) across different weeks to determine the average value before the epidemic, namely $F/F_0$ and $S/S_0$. For the several vertical dashes of key dates during China’s pandemic, we plotted the ratios of $F/F_0$ and $S/S_0$ over time in Figs. 3 and 4, respectively, to present

Fig. 4. Impact of COVID-19 on activity space in China’s GBA over time (from December 2019 to May 2020).
COVID-19’s impact on travel mobility. The reference line of 1.0 represents the average value of weekly activity space area and travel frequency before the outbreak. It is important to note that not every city in the GBA began from a 1.0 reference point because the average value for weekly activity space area and travel frequency before the outbreak may not equal the weekly values of these factors during the single week from December 1 to 7, 2019.

In general, Figs. 3 and 4 show a marked temporal variation in the travel mobility of residents in the GBA, which can be attributed to the pandemic. This also coincided with the Chinese New Year (Spring Festival). From the figures, we can observe a period of sharp decline after the outbreak, which is followed by a slow recovery and the decrease of new COVID-19 cases. Before the outbreak, the total travel frequency almost stabilized, while the activity space area reached a small peak in the week from December 29, 2019 to January 4, 2020 due to the New Year holiday. This indicates that although COVID-19 cases had been reported in Wuhan, it did not significantly raise public awareness in the GBA (or even in China as a whole); thus, scant effects were seen on people’s travel mobility. In the week from January 19 to 25, 2020, activity space area reached a large peak, showing that a large number of the population were returning their home for the Spring Festival (i.e., Lantern Day and the Chinese traditional festival), from the evening of January 24 to February 8. While this may have produced an enlarged activity space on their way home, the level of travel mobility sharply decreased that week, indicating that the beginning of the travel restriction, which was characterized by the lockdown at Wuhan on January 23, 2020, had already led to a decline in travel mobility.

Travel frequency reached a valley during the week of January 26 to February 1, 2020, which saw the largest increasing rate of COVID-19 cases and the strictest lockdown strategy. As workers gradually returned to work after February 10 (Song et al., 2020), both travel frequency and activity space had picked up. However, it should be noted that the travel frequency had exceeded the average level before the outbreak (by early April), while the activity space remained below the average level, suggesting that people chose short-distance trips over long-distance trips, as compared to the period before the outbreak. The figures also show that the travel mobility of residents had not completely recovered until late May of 2020. This is particularly true in terms of activity space, as most cities in the GBA were affiliated with a ratio of $S/S_0$ being less than one (Fig. 4).

For the spatial variation of travel mobility among the GBA’s nine cities, we observe that the most significant decline in activity space area occurred in Shenzhen, Guangzhou, and Foshan within the GBA’s core. In particular, Shenzhen had the largest reduction, at $-18.2\%$ during the trough week from February 9 to 15, 2020, as compared to the value before the epidemic. Meanwhile, in the peripheral areas of Huizhou and Zhaoqing, there was a relatively smaller reduction in activity space area, which was at $-4.4\%$ and $-5.8\%$, respectively. However, the activity space area in Jiangmen did not see a significant reduction.

In terms of travel frequency, Shenzhen also experienced the largest decline at $-36.2\%$ during the trough week that spanned from January 26 to February 1, 2020, as compared to the value before the epidemic. Other cities in the GBA’s core, including Guangzhou and Foshan, experienced a decline that was close to the average level ($-24.2\%$) of the whole GBA. The cities’ decline in travel frequency between the core and peripheral areas (i.e., Zhongshan, Zuhai, and Zhaoqing) was also close to the average level of the whole GBA. Regarding those in the GBA’s periphery, Jiangmen and Huizhou experienced a decline in travel frequency that was close to the average level of the whole GBA, while Zhaoqing experienced a smaller decline ($-15.3\%$) that was less than the average level.

After the epidemic’s primary period, cities of different population sizes underwent various rhythms of recovery. For example, Shenzhen experienced an adequate recovery that was comparable to the GBA’s average level. Taking the last week of the study period (from May 24 to 30, 2020) as an example, Shenzhen observed a slightly larger increase ($8.1\%$) in travel frequency, as compared to the period before the outbreak and the average level ($7.9\%$). It also experienced a smaller decrease in activity space area ($-0.9\%$) within the GBA (including Guangzhou and Foshan), and it experienced a smaller rate of recovery than the average level in the GBA. Changes in activity space area during the week from May 24 to 30, as compared to the value before the outbreak, were $-5.9\%$ and $-7.2\%$ in Guangzhou and Foshan, respectively. These values were below the average level in the GBA ($-3\%$).

Moreover, in the week from May 24 to 30, 2020, the increase in Guangzhou’s travel frequency ($4.6\%$) was below the average level ($7.9\%$), while that of Foshan was even less than the value before the outbreak. Zhongshan and Zuhai, cities between the core and peripheral areas, experienced recovery to a smaller extent in terms of travel frequency ($-3.3\%$ and $-3.1\%$, respectively) than the average level ($7.9\%$), but they also observed a larger activity space ($2.5\%$ and $1.4\%$, respectively) than the average level ($-3\%$), when compared to the pre-epidemic value. Meanwhile, Dongguan experienced recovery to a larger extent in terms of both activity space area ($0.1\%$) and travel frequency ($19.1\%$), as compared to the GBA’s average level. In the peripheral area, the travel frequency of Zhaoqing and Huizhou was larger ($34.5\%$ and $17\%$, respectively) than the GBA’s average level ($7.9\%$), while compared to the pre-epidemic value. Meanwhile, Jiangmen’s level of recovery approximated the GBA’s average level. In terms of activity space area, Jiangmen and Huizhou had a more substantial ($-2.3\%$ and $0.1\%$) recovery than the GBA’s average level ($-3\%$), when compared to the value before the epidemic, while Zhaoqing experienced less recovery than this average.

In terms of travel frequency, there was a sharp increase in the week of February 23 to 29, 2020 ($17.9\%$) in Shenzhen, compared to the week before. This surge coincided with the resumption of eating in restaurants. In addition, there was a relatively larger increase in travel frequency in the week of March 22 to 28 in Guangzhou ($2.5\%$), Foshan ($5.1\%$) and Dongguan ($2.2\%$), compared to the week before. This change coincided with the reopening of indoor public places, on March 17. As to the activity space, in larger cities such as Shenzhen, Guangzhou and Foshan, there was a relative larger increase in activity space area in the week of February 23 to 29 ($5.8\%$, $4.7\%$, and $6.5\%$, respectively) and in the week of March 22 to 28 ($3.9\%$, $2.6\%$, and $6.9\%$, respectively) compared to the week before. These changes coincided with the resumption of eating in restaurants and reopening of indoor public places (see Table 1), respectively. Moreover, in Dongguan, there was a relatively larger increase in activity space ($2.2\%$) in the week from March 29 to April 4, compared to the week before, which was about two weeks lagging behind the date of resumption of eating in restaurants (March 13) and reopening of indoor public places (March 17). However, in smaller cities, such as Zuhai, Zhongshan, Jiangmen, Huizhou, and Zhaoqing, the increase of both travel frequency and activity space in the weeks around the regulation end dates were all below $2\%$. 

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Our empirical data illustrates that the epidemic had a strong effect on travel mobility in the GBA’s core rather than in its peripheral areas. This may be due to a relatively larger number of infections in these cities, which led to a more pronounced fear among residents about becoming infected. Moreover, after the epidemic’s primary period, the core cities in the GBA, especially Guangzhou and Foshan, experienced less recovery than other cities. This may be due to the international airport in Guangzhou and the nearby city, Foshan, which suffered an increasing number of untimely, isolated imported COVID-19 cases from abroad in late March and mid-April before the country began to restrict entry (Ren et al., 2020; L. Zhang et al., 2020). This increased residents’ fears and impeded the recovery of travel mobility. Furthermore, the start of strict regulation enforcement had a significant effect on the initial decline in travel mobility, while the end of strict enforcement had a great impact on the subsequent recovery of travel mobility in larger cities such as Guangzhou, Shenzhen, Foshan, and Dongguan. However, in smaller cities in the GBA area, this effect was not very significant, possibly because travel mobility in these cities was impacted by the epidemic to a lesser extent.

5.2. Commuting and non-commuting trips

To obtain a better understanding of the epidemic’s impact on travel frequency, the trips were divided into commute and non-commute trips, according to the travel purpose. Based on the method described in Section 3.4, this was determined by whether the trip was between the designated home and workplace (commute trip) or not (non-commute trip). The average value of commute and non-commute travel frequency ($F_{c,0}$ and $F_{n,0}$) before the epidemic’s outbreak (December 1, 2019 ~ January 18, 2020) was calculated. Afterward, the ratios were obtained of commute and non-commute travel frequency ($F_c$ and $F_n$) during different weeks, as compared to the average value before the epidemic ($F_c/F_{c,0}$ and $F_n/F_{n,0}$). Changes over time of $F_c/F_{c,0}$ and $F_n/F_{n,0}$ are shown in Figs. 5 and 6, respectively.

Fig. 5 shows that the commute travel frequency in the GBA declined (~20.2%) during the Spring Festival after the outbreak. After this holiday, the commute travel frequency quickly picked up and remained stable at a level that was close to what it was before the outbreak since mid-February. Fig. 6 shows a sharp decline (~35.6%) in non-commute travel frequency, which was experienced after the outbreak. Specifically, Shenzhen experienced the largest reduction at ~65.8%. From the Spring Festival to mid-April, non-commute travel frequency slowly picked up but remained less than the pre-epidemic value. Afterwards, non-commute travel frequency remained stable at a level that was close to the pre-epidemic value.

Our results suggest that the epidemic had a stronger impact on non-commute trips than on commute trips, which confirms Hypothesis 1 from Section 3.5. According to Figs. 5 and 6, not only did non-commute travel frequency experience a sharper declination than commute travel frequency, but the recovery of non-commute travel frequency was also slower. The quicker recovery of commute travel frequency suggests that the process for workers to resume work was rapid after the Spring Festival due to the sufficient precaution measures that were provided by the government and relevant companies (Tang et al., 2020). By contrast, the sharp decline and slow recovery of non-commute travel frequency combined with the continuing downturn of related industries’ status (e.g., touring, tourism, retail, and transportation services), as depicted in Fig. 6, contributed to the prolonged decline in non-commute travel. This decline continued until mid-May, even after the epidemic had subsided in the region.

Fig. 5. Changes in commute travel frequency over time in the GBA (from December 2019 to May 2020).
catering, off-line retailing, and so on) indicates that the fear of becoming infected continued to restrain the residents’ discretionary activities. In other words, people were continuing to attempt social distancing and avoid unnecessary trips (e.g., Rieger and He-Ulbricht, 2020).

5.3. The impact of COVID-19 on travel mobility in different social groups

After examining the general travel mobility patterns in China’s GBA that were a result of COVID-19, we will focus on a few selected cities to gain a more nuanced understanding of the impact among different social groups in this section. Since the cities of Shenzhen, Guangzhou, and Foshan in the GBA’s core had a large proportion of migrants and the epidemic’s impact on travel mobility was relatively stronger in these cities (as compared to others), they have been chosen for further study in terms of COVID-19’s impact on travel mobility among different social groups. In addition, according to the results of this research, as shown in Section 4.1, the epidemic’s impact on travel frequency is larger on non-commute travel. Therefore, non-commute travel frequency and activity space area were selected as the two main factors for travel mobility in the following analysis.

The three cities consist of a significant proportion of migrants, who went home during the Spring Festival and gradually returned to their city afterwards to work. Therefore, we will focus on the period after the Spring Festival in the following analysis. We further divided the dates after the Spring Festival, which was named from February 9 to May 30, 2020, into four periods of four weeks each: February 9 to March 7, March 8 to April 5, April 6 to May 2, and May 3 to 30. These periods correspond to those that occurred in the domestic epidemic’s later stage as well as the import epidemic’s earlier stage and later stage, ending with the achievement of its control. In each period, the average weekly non-commute travel frequency and activity space area were calculated across four weeks for different social groups. Afterward, the rates of change for the average weekly values of non-commute travel frequency and activity space area were calculated across four weeks for different social groups. Finally, the rates of change for the average weekly values were compared with the average value before the epidemic (December 1 to January 18) ($F_0$ and $S_0$), which was namely $F_1/F_0 \sim F_4/F_0$ and $S_1/S_0 \sim S_4/S_0$, and between different social groups.

5.4. Income groups

In this study, individual income was inferred by the price of the mobile phone that correlated to its number. Specifically, these prices (for all the valid individuals) were obtained and ranked in a descending order. Then, the individuals were equally divided into three groups based on the ranking of the mobile phone prices: “high income group,” “middle income group,” and “low income group.” The individuals whose prices for their mobile phone ranked in the first 1/3 of the total number of valid individuals were regarded as part of the “high income group,” while those with mobile phone prices that ranked between 1/3 and 2/3 of the total number of valid individuals were regarded as the “middle income group.” Lastly, those whose mobile phone prices ranked in the bottom one third of the

![Fig. 6. Change in non-commute travel frequency in China’s GBA over time (from December 2019 to May 2020).](image-url)
transportation and non-commute travel frequency and activity space area were compared with the values before the outbreak. The results were displayed in Figs. 7 and 8. In addition, for each city, a t-test was conducted to determine the significant level in terms of the differences in activity space area and travel frequency between various income groups. The results are shown in Tables 4 and 5. It is important to note that since the data for the corresponding mobile phone price is missing for some mobile phone users, the number of valid individuals in this section is smaller than it was in Section 4.

As observed in Figs. 7 and 8 as well as in Tables 4 and 5, during the primary period of the epidemic (February 9 to March 7), the lower income groups suffered a significantly larger decline in both non-commute travel frequency and activity space area than the higher income groups. According to Hypothesis 3 in Section 3.5, which is based on the research of Hotle et al. (2020), the higher income groups had more accessibility to superior protective measures, such as private vehicles or masks of higher quality, which provided them with a lower risk of becoming infected than lower income groups. The results of this research demonstrate that this difference finally led to a significantly smaller reduction for them in terms of travel mobility.

In addition, it should be noted that after the epidemic’s peak, the lower income groups had a significantly more prominent recovery than higher income groups in terms of both non-commute travel frequency and activity space area. The quick recovery—and even rebound—of lower income groups’ travel mobility illustrates the phenomenon of retaliatory travel, which especially occurred during the following holidays: Qingming Festival (April 3 to 5) and Labor Day (May 1 to 3). In other words, the residents tended to conduct more trips than usual after the lockdown period, which is when their demand and desire for travel (as well as various other activities) were suppressed. The lower income groups were less rational and more likely to conduct retaliatory consumption behavior, including impulsive retaliatory travel (Lu et al., 2020); thus, they had a more significant recovery in terms of travel mobility. While retaliatory travel can improve economic recovery on one hand, it could also lead to an unnecessary gathering of the population that can increase the risks associated with a new wave of the epidemic. Therefore, it needs to be rationally dredged.

5.5. Migration groups

For migration, we divided the residents of each city into three groups, which included migrants from other provinces, migrants from other cities in Guangdong Province, and local residents. We inferred immigration status based on a mobile phone user’s hometown, which is directly linked to each mobile phone number in the CMCC dataset. Then, for each migration group per city, the changes in non-commute travel frequency and activity space area across different periods were calculated in comparison with the pre-epidemic period, and the results were displayed in Figs. 9 and 10. In each city, a t-test was also conducted to determine the significant level in terms of changes in activity space area and travel frequency according to immigration status. The results are shown in Tables 6 and 7. Please note that since the data of the corresponding hometown is missing for some mobile phone users, the number of valid individuals in this section is smaller than that in Section 4.

It can be observed, from Figs. 9 and 10 as well as Tables 6 and 7, that local residents experienced a significantly smaller reduction in the size of their activity space than the migrants in all periods that followed the Spring Festival, which confirms Hypothesis 4 in Section 3.5. However, concerning the non-commute travel frequency, after early March, local residents experienced recovery to a significantly smaller extent than the migrants did. Therefore, it can be inferred that local residents may have accessibility to superior precautionary measures, especially that of a private vehicle, allowing them to have a larger activity space. However, after the epidemic’s peak, local residents may also have been more rational than migrants and less likely to conduct impulsive retaliatory travel, leading to a slower recovery of travel frequency.

Migrants from other cities in the Guangdong Province experienced a greater reduction in activity space area than migrants outside of the Guangdong Province, and their reduction in non-commute travel frequency was nearly the same. This suggests that the epidemic...
had a stronger impact on the range of activity that migrants from other cities in the Guangdong Province experienced than that of those outside of the Guangdong Province, and the impacts from the two migration status groups’ frequency of activity were similar. However, the reasons behind this phenomenon are beyond the scope of this study and require further research.

6. Conclusions

We conducted research on COVID-19’s impact on travel mobility in China’s GBA by utilizing mobile phone data, investigating its overall influence on different social groups as well. First, as the outbreak occurred, reached its peak, and finally reduced, our results indicate a strong temporal change occurred in travel mobility alongside COVID-19 cases. Our findings (e.g., Figs. 3 and 4) portray a process of sharp decline first, which was followed by a slow recovery that went against the trends of new COVID-19 cases. In addition, the start of strict regulation enforcement had a significant impact on the decline in travel mobility, while the end of strict enforcement played a significant role in the recovery of travel mobility in larger cities in China’s GBA, such as Guangzhou, Shenzhen, Foshan, and Dongguan. The recovery of travel mobility indicates successful control over the epidemic and the recovery of daily life and activities

** denotes that the result is significant at a 1% level.

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### Table 5
Results of a t-test showing the non-commute activity space between different income groups in the selected cities of China’s GBA.

| Indicators | Groups               | Feb 9 - Mar 7 | Mar 8 - Apr 5 | Apr 6 - May 2 | May 2 - May 30 |
|------------|----------------------|---------------|---------------|---------------|---------------|
| Shenzhen   | Low                  | t-value 50.678 | 46.282        | 61.804        | 22.970        |
|            | Sig.                 | 0.000**       | 0.000**       | 0.000**       | 0.000**       |
|            | Mid                  | t-value 9.523 | 58.032        | 87.587        | 107.511       |
|            | Sig.                 | 0.000**       | 0.000**       | 0.000**       | 0.000**       |
| Guangzhou  | Low                  | t-value 153.513 | 158.147    | 218.326       | 185.498       |
|            | Sig.                 | 0.000**       | 0.000**       | 0.000**       | 0.000**       |
|            | Mid                  | t-value 40.058 | 69.296        | 45.886        | 52.923        |
|            | Sig.                 | 0.000**       | 0.000**       | 0.000**       | 0.000**       |
| Foshan     | Low (n = 1,461,035)  vs. Mid (n = 1,461,035) | t-value 17.319 | 2.821       | 1.143         | 0.181         |
|            | Sig.                 | 0.000**       | 0.005**       | 0.253         | 0.856         |
|            | Mid (n = 1,461,035) vs. High (n = 1,461,035) | t-value 32.154 | 12.926       | 10.886        | 11.101        |
|            | Sig.                 | 0.000**       | 0.000**       | 0.000**       | 0.000**       |

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**Fig. 9.** Impact of COVID-19 on non-commute travel frequency across different migration status groups in the selected cities of China’s GBA (from December 2019 to May 2020).

**Fig. 10.** Impact of COVID-19 on non-commute activity space across different migration status groups in the selected cities of China’s GBA (from December 2019 to May 2020).


Table 6
Results of a t-test showing non-commute travel frequency between different migration status groups in the selected cities of China’s GBA.

| Cities             | Groups                                              | Feb 9 - Mar 7 | Mar 8 - Apr 5 | Apr 6 - May 2 | May 2 - May 30 |
|--------------------|-----------------------------------------------------|---------------|---------------|---------------|---------------|
| Shenzhen           | Migrants from Guangdong (n = 2,758,268) vs. Migrants not from Guangdong (n = 3,997,127) | t-value       | Sig.          | t-value       | Sig.          |
|                    |                                                     | 116.549       | 0.000**       | 25.178        | 0.000**       |
|                    | Migrants from Guangdong (n = 2,758,268) vs. Local residents (n = 641,760) | value         |               |               |               |
|                    |                                                     | 26.439        | 0.000**       | 102.190       | 0.000**       |
|                    | Migrants not from Guangdong (n = 3,997,127) vs. Local residents (n = 641,760) | t-value       | Sig.          | value         | Sig.          |
|                    |                                                     | 38.349        | 0.000**       | 117.116       | 0.000**       |
|                    | Migrants from Guangdong (n = 2,951,057) vs. Migrants not from Guangdong (n = 2,626,605) | t-value       | Sig.          | t-value       | Sig.          |
|                    |                                                     | 7.115         |               | 49.213        | 0.000**       |
|                    | Migrants from Guangdong (n = 2,951,057) vs. Local residents (n = 3,922,718) | value         |               | value         |               |
|                    |                                                     |               |               | 120.878       | 0.000**       |
|                    | Migrants not from Guangdong (n = 2,626,605) vs. Local residents (n = 3,922,718) | t-value       | Sig.          | value         | Sig.          |
|                    |                                                     |               | 175.884       | 0.000**       | 106.199       | 0.000**       |
|                    | Migrants from Guangdong (n = 1,108,148) vs. Migrants not from Guangdong (n = 1,375,594) | t-value       | Sig.          | t-value       | Sig.          |
|                    |                                                     |               | 130.894       | 0.000**       | 123.535       | 0.000**       |
| Guangzhou          | Migrants from Guangdong (n = 2,951,057) vs. Local residents (n = 3,922,718) | value         |               | 78.589        | 0.000**       |
|                    |                                                     |               |               | 138.054       | 0.000**       |
|                    | Migrants not from Guangdong (n = 1,375,594) vs. Local residents (n = 1,776,388) | t-value       | Sig.          | value         | Sig.          |
|                    |                                                     |               | 24.583        | 0.000**       | 21.910        | 0.000**       |
| Foshan             | Migrants from Guangdong (n = 2,951,057) vs. Local residents (n = 3,922,718) | value         |               | 53.315        | 0.000**       |
|                    |                                                     |               |               | 9.475         | 0.000**       |
|                    | Migrants from Guangdong (n = 1,108,148) vs. Local residents (n = 1,776,388) | t-value       | Sig.          | value         | Sig.          |
|                    |                                                     |               | 24.583        | 0.000**       | 21.910        | 0.000**       |

** denotes that the result is significant at a 1% level.

Note: Since the data of the corresponding hometown city is missing for some users, the number of valid individuals in this section is smaller than in Section 4.

among residents. However, after the epidemic, residents experienced a greater recovery in travel frequency but less recovery in terms of activity space area, indicating that they tended to conduct short-distance trips rather than long-distance trips, as compared to before. The epidemic had a stronger effect on travel mobility in core cities than those in the peripheral area of the GBA (e.g., Figs. 3 and 4).

Second, the epidemic had a stronger effect on the reduction of non-commuting frequency in terms of varying travel purposes, as compared to the effect on the reduction of commuting frequency (e.g., Figs. 5 and 6). On one hand, this indicates that the process for workers to resume their work happened quickly due to sufficient precautionary measures being provided by the government and relevant companies, but on the other hand, the recovery process for discretional activity happened very slowly due to a fear of becoming infected.

Third, under the epidemic’s impact and among various social groups, the residents of socially advantaged groups (e.g., higher income groups and local residents) suffered a smaller reduction in terms of their travel mobility during the epidemic’s peak than the socially disadvantaged groups (e.g., lower income groups and migrants) experienced due to their superior access to precautionary measures, such as a private vehicle (Wang and Zhao, 2017) or better-quality precautionary materials. After the peak, residents of socially disadvantaged groups (e.g., lower income groups and migrants) experienced due to their superior access to precautionary measures, such asismic travel practices, which had a more significant effect on the recovery of their travel mobility than that of socially advantaged groups (e.g., Figs. 7 to 10).

Based on these findings, we can draw several policy implications. First, the recovery of travel mobility is based on the epidemic’s strict control through China’s firm state orders. For instance, during the epidemic, entries to all residential estates were strictly registered, each resident’s health was examined, and masks were enforced in public spaces, including shopping malls and public transportation (Li et al., 2020). These measures curbed the epidemic’s spread and halted the increase of new cases. Since May 2020, the GBA has recorded fewer than 10 cases every week (Health Commission of Guangdong Province), and travel mobility has showed a trend toward recovery due to the epidemic’s successful control. For example, metro ridership is a typical indicator of mobility within a city. The official Weibo of Shenzhen metro and Guangzhou metro shows that the average daily ridership in Shenzhen and Guangzhou reached 4.06 and 5.70 million in May, respectively, which was 6.4 and 4.4 times the amounts in February, respectively. While in the countries where there was no strict regulation enforcement, such as the United States (Truong and Truong, 2021), India (Meena, 2020), Canada (Fatmi, 2020), and Ireland (Shokouhyar et al., 2021), the recovery in mobility after the peak of the epidemic was much slower, and its extent much smaller than that of mainland China. Therefore, it can be observed that the epidemic’s successful control prompted the recovery of travel mobility. Thus, to provide residents safer conditions for travel, prevention and control should not be loosened at critical stages of the pandemic. In addition, our results show that the discrentional activity embodied in non-commute travel frequency and activity space had still not fully recovered. This may imply a change in lifestyle, as more people opt for utilizing information and communications technology (ICT) for virtual travel, such as telecommuting, online shopping, and online education. We may need a longer period to evaluate this impact.
Table 7
Results of a t-test showing non-commute activity space between different migration status groups in the selected cities of China’s GBA.

| Cities       | Groups                                              | Feb 9 - Mar 7 | Mar 8 - Apr 5 | Apr 6 - May 2 | May 2 - May 30 |
|--------------|-----------------------------------------------------|---------------|---------------|---------------|---------------|
| Shenzhen     | Migrants from Guangdong (n = 2,758,268) vs. Migrants not from Guangdong (n = 3,997,127) | t-value       | Sig. 0.000**  | 0.000**       | 0.000**       |
|              | Local residents                                     | t-value       | Sig. 0.000**  | 0.000**       | 0.000**       |
|              | Migrants from Guangdong (n = 2,758,268) vs. Local residents (n = 641,760) | t-value       | Sig. 0.000**  | 0.000**       | 0.000**       |
|              | Migrants not from Guangdong (n = 3,997,127) vs. Local residents (n = 641,760) | t-value       | Sig. 0.000**  | 0.000**       | 0.000**       |
| Guangzhou    | Migrants from Guangdong (n = 2,951,057) vs. Migrants not from Guangdong (n = 2,626,605) | t-value       | Sig. 0.000**  | 0.000**       | 0.000**       |
|              | Local residents                                     | t-value       | Sig. 0.000**  | 0.000**       | 0.000**       |
|              | Migrants from Guangdong (n = 2,951,057) vs. Local residents (n = 3,922,718) | t-value       | Sig. 0.000**  | 0.000**       | 0.000**       |
|              | Migrants not from Guangdong (n = 2,626,605) vs. Local residents (n = 3,922,718) | t-value       | Sig. 0.000**  | 0.000**       | 0.000**       |
| Foshan       | Migrants from Guangdong (n = 1,108,148) vs. Migrants not from Guangdong (n = 1,375,594) | t-value       | Sig. 0.000**  | 0.000**       | 0.000**       |
|              | Local residents                                     | t-value       | Sig. 0.000**  | 0.000**       | 0.000**       |
|              | Migrants from Guangdong (n = 1,108,148) vs. Local residents (n = 1,776,388) | t-value       | Sig. 0.000**  | 0.000**       | 0.000**       |
|              | Migrants not from Guangdong (n = 1,375,594) vs. Local residents (n = 1,776,388) | t-value       | Sig. 0.000**  | 0.000**       | 0.000**       |

** denotes that the result is significant at a 1% level.

Note: Since the data of the corresponding hometown city is missing for some users, the number of valid individuals in this section is smaller than in Section 4.

Moreover, since the results show a larger impact of COVID-19 on the reduction of travel mobility for disadvantaged groups (e.g., lower income groups and migrants) over others, it may indicate social inequity between disadvantaged and advantaged groups, including unequal accessibility to precautionary materials, such as high-quality masks, hand sanitizers (Hotle et al., 2020; Shamshiripour et al., 2020), and private vehicles (Wang and Zhao, 2017). It is critical to contemplate how this inequity in access to resources may be narrowed to recover the travel mobility of disadvantaged groups. Therefore, this social inequality and measurements for narrowing it need to be studied further.

This study contributes to the literature on COVID-19 and travel mobility in several aspects. First, we apply mobile phone big data in this study to provide not only a larger sample size and more representative results but also a more holistic view of travel mobility across various cities and social groups in China’s GBA. Second, we depict the changes in travel mobility over an extended period (before and after the epidemic’s peak), which at first reveals a trend of mobility’s reduction and then its recovery. We referenced this against, or cross-validated with, the number of COVID-19 cases in the GBA. Third, we adopted the concept and measure of activity space as a supplementary indicator of travel mobility in addition to travel frequency. Fourth, we compared the different impacts of the COVID-19 epidemic on socially advantaged and disadvantaged groups. Our results suggest that social inequity exists, which demands more attention in future studies.

There are some limitations in this research. First, as the data’s accuracy of the time was provided by the CMCC during the study period, we limited out study’s focus to an hour, and the indicators of travel mobility in this paper were mainly limited to a weekly average of travel frequency and activity space. While this dataset is sufficient for achieving our study’s objectives, it is insufficient for providing a detailed depiction of individuals’ travel trajectories. In future studies, a detailed depiction of the travel patterns that are embodied in travel routes and modes detection should be conducted if data that contains a higher temporal frequency (e.g., that of five minutes) becomes available. Second, while our study reveals some interesting findings related to differences in travel mobility among different social groups (e.g., migrants’ activity space has been more significantly reduced for those inside of the Guangdong Province), the results’ validation and reasons behind these phenomena require different data sources and research methods (e.g., a questionnaire survey or interview). Third, this study only focuses on China, where law enforcement during the epidemic is quite strict, and the comparative study of the impact of COVID-19 on travel mobility between different countries with different levels of regulation enforcement is still very few in existing literature, and thus it deserves further investigation.

CRediT authorship contribution statement

**Yu Pan:** Methodology, Data curation, Formal analysis, Visualization, Writing – original draft. **Sylvia Y. He:** Conceptualization, Investigation, Methodology, Supervision, Writing – review & editing, Funding acquisition.
Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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