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Exploring the dynamic impacts of COVID-19 on intercity travel in China

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ABSTRACT

Many studies have explored the effects of transportation and population movement on the spread of pandemics. However, little attention has been paid to the dynamic impact of pandemics on intercity travel and its recovery during a public health event period. Using intercity mobility and COVID-19 pandemic data, this study adopts the gradient boosting decision tree method to explore the dynamic effects of the COVID-19 on intercity travel in China. The influencing factors were classified into daily time-varying factors and time-invariant factors. The results show that China’s intercity travel decreased on average by 51.35% from Jan 26 to Apr 7, 2020. Furtherly, the COVID-19 pandemic reduces intercity travel directly and indirectly by influencing industry development and transport connectivity. With the spread of COVID-19 and changes of control measures, the relationship between intercity travel and COVID-19, socio-economic development, transport is not linear. The relationship between intercity travel and secondary industry is illustrated by an inverted U-shaped curve from pre-pandemic to post-pandemic, whereas that with tertiary industry can be explained by a U-shaped curve. Meanwhile, this study highlights the dynamic effect of the COVID-19 on intercity mobility. These implications shed light on policies regarding the control measures during public health events that should include the dynamic impact of pandemics on intercity travel.

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1. Introduction

Since December 2019, COVID-19 has significantly affected daily life and economic development all over the world (Acuto et al., 2020; Kim and Kwan, 2021). Considering human-to-human nature of COVID-19 transmission, urban lockdown and travel restrictions are major policies to counter its spread (Zhang et al., 2020; Beck and Hensher, 2020). The implementation of these policies greatly reduced human mobility. The COVID-19 became severe in China when the Chinese Chunyun, travel season during Chinese New Year, began from Jan 10, 2020. Chunyun is regarded as the largest annual human migration in the world (Xu et al., 2017). According to statistics provided by China’s Ministry of Transport, approximately 29.8 billion trips were made during the 40-day Chunyun in 2019. Before Chinese New Year, most people return to their hometowns from cities where they currently live and work, and then return to cities after the New Year. Against the background of the superposition of spring festival and major public health events, understanding how intercity population mobility is affected by COVID-19 and other determinants is of particular importance for policymakers to better designing and effectively implementing COVID-19 or other pandemics control policies.

A growing number of studies have investigated how intercity mobility has affected the spread of COVID-19. For instance, the frequency of flights and high-speed train services out of Wuhan played a key role in the spread of COVID-19 (Zhang et al., 2020). Its spreading process in China can be divided into intercity diffusion before Chinese New Year and intracity diffusion after Chinese New Year (Mu et al., 2020). In India, 72% of newly emerged COVID-19 cases were mainly brought about by migrant worker movement (Pal et al., 2020). These studies are quite useful for understanding the effects of intercity mobility on the spread of COVID-19 and for initiating effective containment measures.

However, a complementary question, what is the dynamic relevance of COVID-19 and other determinants for intercity travel, especially for situations where holidays and major public health emergencies merge, is still unknown. Therefore, the objective of this paper is to explore the...
temporal dynamics impacts of the COVID-19, socioeconomic factors, transport factors on intercity travel in China. To this end, intercity travel was analyzed between Jan 1 and Apr 7, 2020 and the driving factors were classified into time-varying factors and time-invariant factors. More specifically, this study attempted to answer two questions: (1) How important are COVID-19 and other time-varying and invariant variables in explaining intercity travel? (2) What are the temporal dynamics among COVID-19, intercity travel, and other variables between cities?

The remainder of this paper is organized as follows. The next section reviews the literature on intercity travel and long-distance travel, and Section 3 briefly describes the data and methodology. The empirical results are subsequently presented and discussed. Finally, an overview of the key findings and some avenues for further study are presented in the conclusion.

2. Literature review

As a key concept in the field of transportation and regional science, the terms “intercity travel” or “long-distance travel” are interchangeably used and differentiated from short distance travel based on the distance threshold (Arbues et al., 2016). Long-distance trips are traditionally defined as being longer than a threshold between 50 km and 100 km (Kuhnminhof et al., 2009; Dargay and Clark, 2012). Intercity travel, which refers to trips between cities, is used to avoid arbitrariness in the selection of the threshold. Municipal boundaries are used to distinguish intercity travel from the intra-city journey. Moreover, intercity travel has a considerable influence at the regional level, while intra-city journeys mainly affect transportation at the city or local level.

2.1. Intercity travel pattern

The activity space of human activity has expanded considerably with the rapid development of regional integration and transport technology (Frandsberg and Vilhelmsen, 2003; Li et al., 2020). One consequence of these processes is the increase in the number of people traveling between cities. Some studies have explored the spatial pattern of intercity travel by means of traffic flows (De Montis et al., 2010; Limtanakool et al., 2006). Meanwhile, a growing number of studies have investigated patterns of urban networks through the lens of intercity travel or intercity connectivity (Neal, 2014; Xu et al., 2018). The development of high-speed rail networks has reshaped urban networks at different scales (Yang et al., 2018; Zhu et al., 2018). Intercity travel with different travel modes (air, train, and coach) can reveal urban networks on different spatial scales and illustrate different spatial organization modes (Wang et al., 2020).

Recently, “Big Data” sources have played a key role in exploring spatio-temporal patterns of population mobility and their determinants. With respect to the various data sources from location-based services focusing on population mobility in China, Tencent and Baidu have been found to be more accurate than other sources (Li et al., 2016). Many studies have used migration data from these two sources to explore the spatial patterns of population flow networks during the Chinese holidays (Xu et al., 2017; Pan and Lat, 2019). The laborer-absorbing cities along the east coast and cities in the central and western regions are laborer-exporting areas in China. Characteristic of rich-club-style oligarchy and hub-and-spoke were revealed in the population flow network during China’s Spring Festival (Wei et al., 2018).

2.2. Determinants of intercity travel

Generally, the literature suggests that decisions on intercity travel are determined by a combination of socio-demographic factors, urban economic and spatial attributes, and transport service factors. First, socio-demographic factors play a vital role in decision-making within intercity travel. Previous studies show that intercity travel is affected by income, gender, age, work, education level, car availability, and household types (Dargay and Clark, 2012; Kuhnminhof et al., 2012; Arbues et al., 2016). Second, urban size and economic attributes also affect intercity travel. Population, the number of jobs, certain differences between rural and urban areas, and accessibility to the transport network typically affect intercity travel (Garmendia et al., 2011; Yang et al., 2018; Zhang et al., 2020b). Limtanakool et al. (2006) found that the overall structure of the urban system, the size of the country, and the local population density all affected the frequency of medium- and long-distance travel. Third, transport service factors are also significant variables in intercity travel. The travelers from cities located around a HSR station tend to choose trains more frequently than cars for intercity travel (Garmendia et al., 2011).

Uncovering the spatial pattern of urban networks and their determinants through the lens of intercity travel is also an important mean for understanding the correlates of intercity travel. For instance, Yang et al. (2018) found that urban networks characterized by HSR passenger flow can be explained by the socio-economic attributes of cities, including tertiary employment, GDP per capita, and connectivity in HSR networks. The empirical analysis carried out by Xu et al. (2017) also indicated that the socio-economic development level of cities was positively correlated with intercity travel. Cui et al. (2020) examined the spatial-temporal dynamics of daily intercity mobility in the Yangtze River Delta and found that urban attributes, including the average wage, housing price, industrial enterprise, employment, and distance between cities were all related to intercity mobility.

These studies are extremely useful for understanding the determinants of intercity travel. More importantly, studies on linear relationships between short-distance travel and its correlates have been assumed for decades. Recent studies have uncovered the nonlinear relationships between short-distance travel and its influencing factors at an intra-city level (Ding et al., 2018; Zhang et al., 2020c). Some studies on intercity travel also concluded that correlations between intercity trips and some factors (travel cost, individual attributes) follow a non-linear pattern (Liptanakool et al., 2006). More fundamentally, since intercity travel passengers are the key resources for cities, the notion of allometric scaling, namely a system’s consumption of resources is a non-linear function of its size, has been proved effectively in urban science (Neal, 2018). Many of the effects of aforementioned influencing factors on intercity travel could be expected to be non-linear rather than linear. However, existing literatures generally assume a linear relationship between intercity trips and their associated factors, the issue is ignored in most of the existing literatures.

2.3. Infectious diseases and population movement between cities

Population movement can impact the spatio-temporal patterns of infectious diseases (Mu et al., 2020). The rapid development of modern transport modes has accelerated the spread of infectious diseases. Most studies have explored the impacts of population movement, including migration, intercity travel by high-speed trains, air, and coaches, and intracity travel on the spread of epidemic diseases (Findlater and Bogoch, 2018; Zhang et al., 2020c; Wei et al., 2020). Zhang et al. (2020c) explored the roles of HSR, air, and coach services in the spread of the COVID-19 in China and found that the presence of an airport or HSR station in a city was significantly related to COVID-19 diffusion. Chinese cities have shown a correlation between the number of confirmed cases and the time taken to restrict mobility after the first case of COVID-19 (Bai et al., 2020). Mu et al. (2020) used synchronized epidemic data and population mobility data to examine the interplay of the spatial spread of COVID-19 and human mobility. Overall, the existing literature on infectious diseases and population movement primarily attributed the spread of the pandemic to human travel, with less focus on the dynamic effects of the pandemic and other important driving factors on population movement. Pullano et al. (2020) evaluated how COVID-19 impacts on mobility in France under lockdown and
concluded that mobility reduction were moderately associated with the socioeconomic level of the regions. Beck and Hensher (2020a) investigated the impact of COVID-19 on household travel and activities in Australia during the early week of easing restrictions. They observed that working from home is an important strategy for reducing travel. Kim and Kwan (2021) examined changes of human mobility over a 7-month period in the U.S. and concluded that political partisanship, poverty level, and mobility restriction policies are associated with mobility changes. Some studies also examined the impacts of COVID-19 on transport mode use (Zhang and Fricker, 2021; Eisenmann et al., 2020).

Despite their work contributes to a better understanding of the impacts of COVID-19 on intercity mobility, these studies ignoring the dynamic effects of pandemics and other important factors on intercity travel. Specifically, intercity travel is determined by a combination of pandemic, socioeconomic factors, and transport service factors during the COVID-19. These influencing factors can be further classified as time-varying factors—such as the COVID-19, connectivity—and time-invariant factors—such as socio-economic, industry development, road accessibility and location factors. Few studies have attempted to differentiate spatio-temporal differences in intercity travel into stable and varying factors.

3. Data and methodology

3.1. Intercity population mobility data collection

Daily intercity mobility data at the city level were obtained from the Baidu Huiyan (https://qianxi.baidu.com/), which has been used in previous studies (Gibbs et al., 2020; Mu et al., 2020). This website publishes the intercity mobility index (IMI) data for each city. The IMI index is the relative measure of the volume of daily inbound and outbound passengers. Estimates of the data are based on nearly 120 billion service enquiries every day from over 1.1 billion mobile phones. In 2020, there were 932 million mobile internet users, accounting for 64.54% of the total population in China (China Internet Network Information Center, 2020). Daily intercity travel flow data between each pair of cities can be calculated through the IMI of inflows and the proportion of them from origin cities. For instance, Guangzhou’s IMI of inflows on Jan 23 in 2020 is 4.88 and the proportion of them from Wuhan is 0.83%, so the relative volume of flow from Wuhan to Guangzhou on Jan 23 is 4.88*0.83% = 0.04. The data were collected during the 14-week COVID-19 period between Jan 1 and Apr 7 in 2020 (about 100 days). Considering Chunyun around Chinese Lunar New Year is the main body of intercity travel during study period. The IMI data was also collected for the corresponding period by Chinese Lunar Calendar in 2019 to construct the counterfactual status of the intercity travel. The data covers 362 cities in mainland China, including 4 municipalities, 331 prefecture-level cities, and 27 county-level cities.

3.2. Selection of variables

Five categories of explanatory variables were included in this study based on the spatial interaction model and previous studies (Zhang et al., 2020b; Yang et al., 2018). As mentioned previously, these influencing factors included time-varying and time-invariant factors (Fig. 1).

Socio-economic factors include GDP, population, and the urbanization ratio, which represents the basic size of cities from the socioeconomic perspectives. Industry development factors include the gross product of secondary industry (GPS) and tertiary industry (GPT), which reflects the industrial development size of cities. Both socio-economic factors and industry development factors were collected from the Provincial Statistical Yearbooks of 2019 and City Statistical Yearbook of 2019. Location factors include spatial distance and cultural distance, where spatial distance is defined as the average great circle distance from one city to the rest of all cities (Zhang et al., 2020c). Since spatial disparities of dialects in China are pronounced and play a potential in intercity mobility (Wu et al., 2016; Zhang et al., 2020b), the cultural distance is also chosen as a location factor to indicate whether the two cities belong to the same dialect zones. The original data was collected from the Atlas of Chinese Dialects (the year of 2010 is the latest accessible data) (Xiong and Zhang, 2012), wherein 18 dialect zones are delineated within China. Noting that the distribution of dialects is almost spatially constant in China, the data of 2010 is in line with the present situation.

Transport factors are designed with three intercity travel modes in China, including the road transport, civil aviation and high-speed rail. Given the data limitation of the frequency of coach during the study period, the well-developed expressway network, and the increasing car ownership in China, we selected travel time, which refers to the average shortest travel time to other cities by private car, as the surrogate measure of road transport accessibility factor. The shortest travel time for each city pair was acquired from the Baidu online map services. The connectivity data includes the number of daily departure and arrival domestic flights (flight frequency) and the number of daily operating high-speed trains (HST frequency) of each city. The connectivity of a city in the airline and HSR networks is measured by the flight frequencies and HST frequencies going through the city, respectively (Chen and Hall, 2012; Xu et al., 2018). The data was obtained from the Airsavvi travel data platform (https://maptemp.airsavvi.com/) and the Railway’s booking website (https://www.12306.cn/index/), respectively. Notably, flight frequency and HST frequency varied daily during the
### 3.3. Method

The GBDT model iteratively constructs $M$ different individual decision trees $h(x; \alpha_m)$, where $\alpha_m$ is the mean of split locations and the terminal node for each splitting variable in an individual decision tree $h(x; \alpha_m)$. The GBDT model then estimates the function $F(x)$ as an additive expansion of $f(x)$ based on the basis function $h(x; \alpha_m)$:

$$F(x) = \sum_{m=1}^{M} f_m(x) = \sum_{m=1}^{M} \beta_m h(x; \alpha_m)$$

where $\alpha_m$ is the mean of split locations and the terminal node for each splitting variable in an individual decision tree $h(x; \alpha_m)$, and $\beta_m$ represents the weights given to the nodes of each tree. $\beta_m$ is determined by minimizing a specified loss function, which is defined as follows:

$$L(y, F(x)) = (y - F(x))^2$$

Friedman (2001) proposed the gradient boosting approach to estimate the parameters $\alpha_m$ and $\beta_m$. Its algorithm can be referenced by Ding et al. (2018) and Friedman (2001). The learning rate $\xi$ ($0 < \xi \leq 1$), also called shrinkage, is used to scale the contribution of each base tree model to overcome the overfitting problem (Friedman, 2001). The final model $F(x)$ is derived when $m$ reaches a preset number of iterations, $M$.

$$F_m(x) = F_{m-1}(x) + \xi \beta_m h(x; \alpha_m), \text{ where } 0 < \xi \leq 1$$

Generally, a smaller learning rate leads to a more accurate estimation of the residual when given a fixed $M$, but more trees are needed for computing.

The relative importance ($I_{R}$) of each variable $(x_i)$ can be computed based on the variation in intercity population mobility, which is necessary to quantify the relative importance or contribution of each independent variable. For each tree, the change in the squared error $d_j$ can be calculated if $x_i$ is set as the $j$th split node. The squared importance for $x_i$ can be derived by summing these changes (Hastie et al., 2009):

### Table 1

| Variable name          | Variable description                                      | Mean   | St. dev. |
|------------------------|----------------------------------------------------------|--------|----------|
| Intercity mobility index (IMI) | Daily inflow and outflow population movement for each city | 2.17   | 2.96     |
| GDP (100 million $)$  | Total population                                         | 47.15  | 93.67    |
| Population (10,000)   | Percentage of the population living in the urban area     | 62     | 15       |
| Urbanization (%)      |                                                          | 538.52 | 468.30   |
| Industry development  |                                                          | 1688.71| 1958.87  |
| Secondary industry    | Gross product of secondary industry                       | 2365.44| 3694.63  |
| Tertiary industry     | Gross product of tertiary industry                        |        |          |
| Location              |                                                          |        |          |
| Spatial distance (km) | Average great circle distance to other cities             | 1484.18| 407.79   |
| Cultural distance (scale) | Assigning a fixed number to each dialect area ranging from 1 to 18 | 7.84   | 4.60     |
| Transport             |                                                          |        |          |
| Road accessibility (h) | Average shortest travel time to other cities by private car | 21.92  | 6.22     |
| Flight frequency (count) | Number of daily domestic operating flights               | 47.15  | 93.67    |
| HST frequency (count) | Number of daily operating high-speed trains              | 195.92 | 233.22   |
| COVID-19 epidemic     |                                                          |        |          |
| Total confirmed cases (case) | Number of cumulative confirmed COVID-19 cases          | 48.45  | 103.37   |
| Total recovered cases (case) | Number of cumulative recovered COVID-19 cases        | 30.22  | 70.18    |
| Existing cases (case) | Number of current existing COVID-19 cases for each city  | 17.99  | 52.11    |

Notes: 1-Beijing dialect, 2-Wu dialect, 3-Yue dialect, 4-Xinan dialect, 5-Jilu dialect, 6-Jianghual dialect, 7-Jiaoliao dialect, 8-Xiang dialect, 9-Zhongyuan dialect, 10-Min dialect, 11-Dongbei, 12-Gan dialect, 13-Jin dialect, 14-Lanyni dialect, 15-Qiong dialect, 16-Kejia dialect, 17-Zang dialect, 18-Mongolia dialect.
The partial dependence plot depicts the nonlinear relationship between explanatory variables and intercity population mobility after controlling for the average effect of other variables. Let $\mathbf{x}$ represent other independent variables in the model. The partial dependence function $F(s)$ for an independent variable $x_s$ is the expected marginal average of $F$:

$$F_s(x_s) = E_{x_c}[F(x_s, x_c)]$$

The partial function $F_s(x_s)$ as follows can be estimated by the averages of the training data,

$$F_s(x_s) = \frac{1}{N} \sum_{i=1}^N F(x_s, x_{si})$$

The “gbm” package in the R programming language designed by Greg (2020) was used to execute the GBDT algorithm. The study period was grouped into weekly intervals and the GBDT algorithm was executed for each week to reveal the dynamic effects of these driving factors on intercity travel. A five-fold cross-validation procedure was applied to the developed GBDT model (Ding et al., 2018). The dataset was split into five distinct subsets consisting of 20% of the data. Each subset was used as test data, while the remaining subsets were used to train the model. Following Ding et al. (2018), the final model was set at a maximum of 10,000 trees, the learning rate was kept at 0.001, and a ten-way interaction was chosen. The range of Pesudo R-square for these 14 models is between 0.93 and 0.96.

3.3.3. Recovery rate of IMI

The recovery rate of IMI ($R^I_i$) as follows was used to study the spatio-temporal variations of intercity mobility during the COVID-19.

$$R^I_i = \frac{V_{t1} - V_{t0}}{V_{t0}} \times 100\%$$

If the passenger reflux exists, the value of $R^I_i$ of a city is positive. Otherwise, the $R^I_i$ value of a city is negative, indicating that the city has more outflow than inflow.

4. Results

4.1. Intercity travel patterns and changes

4.1.1. Temporal variations in intercity travel patterns

Fig. 3 illustrates the temporal evolution of IMI in 2020 and the corresponding period in 2019 for China and Wuhan, respectively, as well as the year-on-year difference between the two years. Intercity mobility was observed to drop significantly after the Jan 25, 2020 due to the Chinese New Year and COVID-19. The daily IMI in China was reduced by 51.35% from Jan 26 to Apr 7, 2020, compared with the corresponding period in 2019 by lunar calendar. More specifically, the study period can be separated into the following three phases. (1) The normal period before Chinese New Year (Jan 25, 2020): China’s IMI was...
observed to slightly increase by 10.01% compared with the corresponding period in 2019. (2) The period of rapid decline in IMI from Jan 26 to Feb 13, 2020, when the year-on-year difference was the most distinct. During this period, the IMI declined by 74.56% compared with the corresponding period in 2019. (3) The IMI recovery period starting from Feb 14, 2020. During this period, the year-on-year difference gradually decreased. However, the overall level of intercity travel was only half of the corresponding period in 2019. With respect to Wuhan (Fig. 3b). Starting from Jan 23, 2020, IMI was significantly lower than that in the same period of 2019 and greatly reduced to nearly 0 after the
Jan 25, 2020. As we know, to counter the spread of the COVID-19, the city lockdown policy was imposed in Wuhan on Jan 23, 2020 and then extended to 13 cities of Hubei Province on Jan 24, 2020.

Fig. 4 maps the intercity travel networks on the three selected dates which corresponding to before, during and after the COVID-19. These three snapshots demonstrate the IMI between cities. Obviously, the IMI for the second period was the most seriously affected by the COVID-19 than other two periods. This result demonstrates the rationality of the above phase division.

Note: The region demarcation of Eastern China, Central China, and Western China based on Li et al. (2016).

4.1.2. Spatial variations in intercity travel pattern

In this section, the IMI of the whole country is compared in different periods (Fig. 5). The IMI in China’s three major regions is also compared. Regarding the decline of IMI, central China was the most affected by the pandemic, followed by the eastern and western regions. During the rapid decline period, the median IMI value for cities located in central China decreased by 76.98%, followed by eastern China (73.28%) and western China (37.56%). During the recovery period, eastern China and central China had the largest reduction (47.86% and 46.31%, respectively), followed by western China (37.56%).

Fig. 6 shows the spatial pattern of the cumulative net inflow index for the normal IMI period and the IMI recovery rate for Chinese cities on different dates, respectively. During the normal IMI period, the cumulative net inflow index showed a similar pattern to the Chinese migration pattern before Chinese New Year, during Chunyun (Xu et al., 2017). Most of the passengers departed from metropolises in developed eastern regions to the periphery of developed areas in eastern China or to developing areas in central and western China. More specifically, high positive values mostly appeared in central and western China, with the highest value of 52.93 located in Zhoukou, Henan Province. Negative values appeared in Beijing, Tianjin, the Pearl River Delta, the Yangtze River Delta, Shandong Peninsula, Zhejiang Province, and other provincial capital cities. Shenzhen yielded the lowest value of –204.51. Cities in the Qinghai-Tibetan Plateau and Xinjiang Province also had negative values.

The spatial pattern of the IMI recovery rate showed a different pattern, which was also in line with the trend observed in Chunyun after Chinese New Year (Xu et al., 2017). As of Feb 13, 2020, only about 14% of the cities had a recovery rate of more than 25%. The level of IMI gradually recovered during the post COVID-19 period, where work resumed, and confinement measures were gradually lifted in most cities of China, aside from Hubei Province. As of Apr 7, about 50% of the cities’ recovery rates exceeded 80%. Compared with the level of intercity mobility during the pre-Chinese New Year, half of the cities’ intercity travel demand of post-Chinese New Year had already recovered much of the ground lost due to the lockdown.

### Table 2: Relative importance of independent variables in predicting intercity mobility.

| Variable | Overall ranking | Relative importance (%) | Total (%) |
|----------|-----------------|-------------------------|-----------|
| Socio-economic factors | GDP | 5 | 8.19 | 16.99 |
| | Population | 6 | 5.71 | |
| | Urbanization | 9 | 3.09 | |
| Industry development factors | Gross product of secondary industry (GPS) | 3 | 15.38 | 39.08 |
| | Gross product of tertiary industry (GPT) | 1 | 23.70 | |
| Location factors | Spatial distance (km) | 7 | 3.97 | 5.33 |
| | Cultural distance | 13 | 1.36 | |
| Transport factors | Road accessibility (h) | 10 | 2.31 | 31.54 |
| | Number of daily domestic operating flights | 2 | 19.43 | |
| | Number of daily operating high-speed trains | 4 | 9.80 | |
| COVID-19 factors | Total number of daily confirmed cases | 8 | 3.13 | 7.05 |
| | Total number of daily recovered cases | 11 | 2.30 | |
| | Number of current daily existing cases | 12 | 1.63 | |

4.2. Determinant dynamics

4.2.1. Relative importance of independent variables

Table 2 presents the average value of the relative importance of independent variables in predicting intercity mobility during the study periods. The total relative influences of the studied variables added up to 100%. Among the variable categories, industry development factors and transport factors collectively accounted for 39.08% and 31.54% of the prediction, respectively. This shows that intercity mobility was significantly affected by industrial and transport service. In addition, socio-economic factors were the third most important variable in predicting intercity mobility, with a relative contribution of 16.99%. It is worth noting that daily flights and high-speed rail operation plans were arranged according to the COVID-19 control policies and greatly reduced intercity travel demand (Wang et al., 2021). Despite the relative contribution of COVID-19 was 7.05%, COVID-19 factors had some indirect effects via transport connectivity in intercity population mobility. Location factors had a relatively limited influence, with a contribution of 5.33%.

Regarding the individual variables, GPT had the largest contribution in predicting intercity population mobility, with a relative importance of 23.70%, followed by flight frequency (19.43%), GPS (15.38%), HST
frequency (9.80%). Airlines in China is less regulated and can arrange their flight plan more flexible based on market demand during the COVID-19. By the contrary, HST sector in China is still highly regulated and responded to the demand slowly (Wang et al., 2021). Therefore, flight connectivity is closer to travel demand than HST and represented a bigger contribution during the COVID-19.

4.2.2. Temporal trend of relative importance

According to Fig. 7, temporal analysis for the 14-week period revealed that the relative importance of all variables showed obvious fluctuations. The impacts of independent factors on intercity travel were observed to be dynamic due to the change in the COVID-19 situation and the implementation of relevant policies, such as urban lockdown, travel restrictions and the work resumption policy.

Industry development factors played a dominant role in shaping intercity mobility in most weeks. This is plausible because cities with a strong industry foundation can impact the demand and supply of intercity connectivity and are more attractive for intercity travel. This finding is also consistent with most existing literature (Zhang et al., 2020b). Moreover, the predictive contribution of secondary and tertiary industries to intercity mobility showed an opposite trend. For the tertiary industry, its effect was illustrated by a U-shape curve with a 31.54% contribution in the first week, whereas its relative contribution was reduced to 1.10% in the eighth week, and then increased to 40.82% in the final week. In contrast, the effect of the secondary industry was illustrated by an inverted U-shape curve, with a 7.15% contribution in the first week, which had risen to 37.17% by the fifth week. The relative contribution was reduced to 4.34% in the final week. Generally, tertiary industry played a more key role in predicting intercity mobility than secondary industry (Zhang et al., 2020b; Cui et al., 2020). However, the predictive contribution of tertiary industry was observed to gradually decline, while secondary industry gradually increased during the COVID-19. This is because rebound activities were undertaken by some key secondary industries in the national economy (e.g., the

**Fig. 7.** Changes in the relative importance of explanatory variables pre-, during, and post the COVID-19.
manufacturing, construction, and processing sectors) for economic resurgence during the most severe COVID-19 periods. In contrast, labor-intensive service industries such as hotels, supermarkets and tourism are still under serious control (Xinhua News, 2020).

Transport factors were the second most important variable for predicting intercity mobility. Regarding individual variables, flight frequency had the largest contribution but showed a declining trend. The HST frequency also had a significant effect on intercity mobility and showed a slightly increasing trend for the prediction contribution. The more severe the spread, the more flights and HST services were canceled (Wang et al., 2021). Thus, flight frequency played a more significant role than HST frequency during the COVID-19. As control measures were relaxed, the previously suspended HST services were gradually resumed, and the predictive power of the HST frequency featured an increasing trend. After the 10th week (Mar 4–10, 2020), its relative contribution exceeded that of flight transportation. Road accessibility is unimportant compared with connectivity factors.

Socio-economic factors were the third most important variable in predicting intercity mobility, and GDP has a dominant role among all socio-economic factors. This finding is in line with previous studies and the nature of the spatial interaction (Wu et al., 2016). Intercity connectivity is always proportional to the urban size and inversely proportional to the distance between them. The relative contribution of industry development factors is greater than that of socio-economic

Fig. 8. The dynamic relationships between socio-economic factors and intercity mobility. Note: Relative importance of the independent variable is shown in the label of the horizontal axis, same for the following figures.
factors, which shows the efficacy of industry development on intercity travel.

The COVID-19 factors ranked fourth in predicting intercity mobility. It is worth noting that the dynamic role of the COVID-19 in determining intercity mobility during the research period. Among the COVID-19 factors, the total confirmed cases, total recovered cases, and existing cases successively became the main influencing factors for intercity mobility. During the period between Jan 8 and Feb 04, 2020, the total number of confirmed cases was the most important independent variable. Between Feb 5 and Mar 3, 2020, with the COVID-19 under control, the contribution of the total recovered cases surpassed the total confirmed cases and played a vital role in intercity mobility. After Mar 3, 2020, the existing cases became the dominant variable.

Location factors ranked fifth among the five variables with a 5.33% contribution. The relative contribution of spatial distance gradually increased after the seventh week. This is reasonable because, for most people, intercity travel within provinces was the primary travel areas as the lockdown was lifted firstly within the province. The cultural distance was unimportant during the research period, but also showed an increasing trend.

4.2.3. Nonlinear associations between independent variables and intercity travel

A partial dependence plot was used to demonstrate the marginal effect of independent variables in predicting intercity mobility, after controlling for all other variables. Three typical weeks were selected for analysis (the third, fifth, and eleventh week), which corresponding to the aforementioned normal, rapid decline and recovery period.
respectively. Small fluctuations still appeared in the plots because of the model’s overfitting issue (Tao et al., 2020).

Socio-economic variables including GDP, population, and urbanization presented nonlinear and positive relationships with intercity mobility (Fig. 8). Take the third week as an example, the IMI increased slightly by about 1.2 units within the GDP range of 1000 billion RMB. Subsequently, the effects of the further increase in GDP became stable when it exceeded 1000 billion RMB. The IMI increased substantially when GDP grew from 2000 to 2300 billion RMB. For the eleventh week, the effective range decreased to around 0–500 billion RMB. Beyond this range, the IMI did not change much, and the marginal effect of GDP also declined. With respect to population, once the population exceeded the threshold of 10 million persons in the third week, it had no additional influence on intercity mobility. Notably, once the population exceeded 8 million in the fifth week and eleventh week, intercity mobility kept stable. This may be due to the reduction in intercity travel of megacities resulting from COVID-19 confinement. In terms of urbanization, when urbanization grew from 70% to around 90% in the third week and 80% in the fifth and eleventh week, the IMI increased to about 0.8, 0.3, and 0.4 for three weeks respectively. Some fluctuation was observed as urbanization above these thresholds, whereby the relationship became almost stable.

Similarly, industry development variables showed nonlinear and positive relationships (Fig. 9). The predicted intercity mobility was approximately 4, 1.1, and 1.7 when the GPS was smaller than 500 billion RMB in these three weeks. The intercity mobility increased to 12, 3.3,
and 2.1 when the GPS grew to around 600 billion RMB in all three weeks, respectively. However, the IMI decreased when GPS exceeded 600 billion RMB in eleventh week. This effect is consistent with the association between the GPT and intercity travel.

Transport variables also showed a nonlinear relationship with intercity mobility (Fig. 10). Road accessibility in terms of shortest travel time had a negative association with IMI, consistent with the previous studies (Zhang et al., 2020b). It is noteworthy that for eleventh weeks, road accessibility had a positive association with intercity travel within the range of 17–20 h. This is reasonable because, for most people, intercity travel within provinces was the primary destination as the COVID-19 lockdown was lifted from within the province. With respect to connectivity, the two factors all showed a positive association with the IMI. During the third week, within the daily frequency of 230, the IMI increased by about 1 unit. Subsequently, the IMI increased substantially when the flight frequency increased from 230 to 380, and this effect became stable when the flight frequency exceeded 380. During the fifth and eleventh weeks, the effective flight frequency range decreased to approximately 50–100 and 100–200, respectively. Beyond this range, the IMI was not observed to change much. The effect of the HST frequency varied within the range of 400 in the third week. After that, its effect size was small compared to other weeks. The effect of HST...
gradually decreased due to the COVID-19 confinement measures and the halt in the operations of some HST services. After this critical value, the HST frequency had a small and diminishing return. During the eleventh week, the IMI increased substantially (by about 1.3 units) when the HST frequency increased from 200 to around 400, but the increase was smaller when it exceeded 400.

COVID-19 pandemic variables include total confirmed cases, total recovered cases and total existing cases (Fig. 11). In the third week, total confirmed cases showed nonlinear and positive relationships with IMI, indicating that the impact of the COVID-19 on IMI is not significant during the normal Chunyun period at this stage. Conversely, although the effect of total confirmed cases varied within the range of 150, it showed a negative association with IMI on the whole in the fifth week. The total recovered cases, which reflected how the pandemic was brought under control, featured nonlinear and negative relationships with IMI in the fifth week. As expected, the total number of recovered cases was positively associated with IMI in the eleventh week during the recovered period. With respect to total existing cases, its association with IMI showed a negative trend in the fifth and eleventh week.

Location variables featured nonlinear and negative relationships during most of the study periods (Fig. 12). Spatial distance, an indicator of geographical location, had a negative relationship with intercity travel. This finding is in line with Tobler’s first law. In the eleventh weeks, spatial distance had a positive association with intercity travel within the range of 1100–1500 km. This is congruent with the finding of road accessibility.

Fig. 12. The dynamic relationships between location factors and intercity mobility.
5. Conclusion and discussion

This study employs the GBDT model to explore the dynamic effects of COVID-19, socio-economic, industry development and transport services on intercity travel in China from Jan 1 to Apr 7, 2020. Overall, the intercity travel of Chinese cities experienced three phases evaluated by IMI index: the normal period, rapid decline period, and recovery period. Due to the COVID-19 and a series of pandemic prevention measures adopted by the government of China, i.e., urban lockdown and decreasing intercity transport connections, the intercity population mobility decreased by 51.35% from Jan 26 to Apr 7, 2020. Central and eastern China were more affected than western China. It was also found that the attractiveness of many cities on the eastern coast and the provincial capital cities, or the population-absorbing areas in normal periods, had decreased substantially.

The COVID-19 reduces intercity travel directly and indirectly by influencing industry development and transport connectivity. With the spread of COVID-19 and changes of control measures, the relationship between intercity travel and COVID-19, socio-economic development, and transport connectivity is not linear. The predictive contribution of secondary and tertiary industries on intercity mobility showed opposite trends. The relationship between intercity travel and secondary industry is illustrated by an inverted U-shaped curve from pre-pandemic to post-pandemic, whereas that with tertiary industry can be explained by a U-shaped curve.

This study highlights the dynamic effect of the COVID-19 in influencing intercity mobility. The total number of confirmed cases was the most important independent variable for intercity mobility firstly. With the COVID-19 under control, the contribution of the total recovered cases surpassed the total confirmed cases and played the most significant role in the study of intercity mobility. In the post COVID-19 period, the existing cases became the dominant variable.

The contribution to the literature of our study is twofold. First, it includes the time-varying and time-invariant variable and explicitly examines the dynamic effect of COVID-19 on intercity mobility. Most previous studies largely focused on changing travel patterns during the COVID-19 (Gibbs et al., 2020). Second, it examines the explicitly amines the non-linear effect of the COVID-19 on intercity mobility. Few studies investigated this issue. Specifically, this study found that socioeconomic factors, industry development factors, accessibility and connectivity, location factors, COVID-19 factors, and intercity population mobility had nonlinear relationships with different patterns. This finding extends and embraces the discussion about nonlinear relationships in intra-urban or short-distance travel (Ding et al., 2018). Some policy implications can be obtained from this study. First, transportation planners should pay attention to the nonlinear relationships between intercity travel and their influencing factors, particularly in transport demand prediction. Second, the control measures during public health events should include the dynamic impact of pandemics on intercity travel.

Moreover, our study also has several limitations, which also suggest avenues for further research. First, we assume that socio-economic and industry development are time-invariant. In fact, these factors can also be affected by COVID-19 and changed by time. Future studies should consider time-varying socio-economic variables for more reliable analysis. Secondly, it would be worthwhile to quantify the causal effects of COVID-19 on intercity mobility at the city pairs level. Third, the inflow and outflow are not symmetrical because of COVID-19. Future studies can further distinguish the inflow and outflow to better reveal the spatial pattern of intercity travel. Finally, since COVID-19 is unprecedented in terms of long-lasting effect (Vickerman, 2021), the results would be more reliable and comprehensive if a longer-term data is adopted for the recovery analysis of intercity mobility from resilient perspective.

CRediT authorship contribution statement

Tao Li: Conceptualization, Methodology, Formal analysis, Writing – original draft, Writing – review & editing. Jiaoe Wang: Conceptualization, Formal analysis, Writing – original draft, Writing – review & editing, Funding acquisition. Jie Huang: Formal analysis, Writing – original draft. Wenyue Yang: Formal analysis. Zhuo Chen: Formal analysis.

Declaration of Competing Interest

The Authors declare no conflict of interests.

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References

Acuto, M., Larcom, S., Keil, R., Ghojeh, M., Lindsay, T., Camponeschi, C., Parnell, S., 2020. Seeing COVID-19 through an urban lens. Nat. Sustain. 2.
Arbos, P., Banos, J.F., Mayor, M., Suarez, P., 2016. Determinants of ground transport model choice in long-distance trips in Spain. Transp. Res. Pt. A-Policy Pract. 84, 131–143.
Bai, X., Nagendra, H., Shi, P., Liu, H., 2020. Cities: build networks and share plans to emerge stronger from COVID-19. Nature 584, S17–S20.
Beck, M.J., Hensher, D.A., 2020a. Insights into the impact of COVID-19 on household travel and activities in Australia – the early days of easing restrictions. Transp. Policy 95, 99–119.
Beck, M.J., Hensher, D.A., 2020b. Insights into the impact of COVID-19 on household travel and activities in Australia – the early days under restrictions. Transp. Policy 96, 76–93.
Chen, C.L., Hall, P., 2012. The wider spatial-economic impacts of high-speed trains: a comparative case study of Manchester and Lille sub-regions. J. Transp. Geogr. 24, 89–110.
China Internet Network Information Center, 2020. The 46th China Statistical Report on Internet Development. Available at: http://www.gov.cn/xinwen/2020-09/29/c_558176.htm.
Cui, C., Wu, X., Liu, L., Zhang, W., 2020. The spatial-temporal dynamics of daily intercity mobility in the Yangtze River Delta: an analysis using big data. Habitat international, p. 102174.
Dargay, J.M., Clark, S., 2012. The determinants of long-distance travel in Great Britain. Transp. Res. A Policy Pract. 46, 576–587.
De Montis, A., Chessa, A., Campagna, M., Caschili, S., Deplano, G., 2010. Modeling commuting systems through a complex network analysis: a study of the Italian islands of Sardinia and Sicily. J. Trans. Land Use 2, 39–55.
Ding, C., Cao, X.Y., Naess, P., 2018. Applying gradient boosting decision trees to examine non-linear effects of the built environment on driving distance in Oslo. Transp. Res. Pt. A-Policy Pract. 110, 107–117.
Eismann, C., Nobis, C., Kolarova, V., Lenz, B., Winkler, C., 2021. Transport mode use during the COVID-19 lockdown period in Germany: the car became more important, public transport lost ground. Transp. Policy 103, 60–67.
Findlater, A., Bogoch, I.I., 2018. Human mobility and the global spread of infectious diseases: a focus on air travel. Trends Parasitol. 34, 772–783.
Frändberg, L., Vilhelmsen, B., 2003. Personal mobility: a corporeal dimension of transnationalisation.The case of long-distance travel from Sweden. Environ. Plan. A 35, 1751–1768.
Friedman, J.H., 2001. Greedy function approximation: a gradient boosting machine. Ann. Stat. 29, 1189–1232.
Garmendia, M., Urena, J.M., Coronado, J.M., 2011. Long-distance trips in a sparsely populated region: the impact of high-speed infrastructures. J. Transp. Geogr. 19, 537–551.
Gibbs, H., Liu, Y., Pearson, C.A.B., Jarvis, C.I., Grundy, C., Quilty, B.J., Diamond, C., Eggo, R.M., Grg, L.C.W., 2020. Changing travel patterns in China during the early stages of the COVID-19 pandemic. Nat. Commun. 11, 9.
Greg, R., 2020. Generalized boosted models: a guide to the gbm package, pp. 1–15.
Gu, C.L., Zhu, J., Sun, Y.F., Zhou, K., Gu, J., 2020. The inflection point about COVID-19 may have passed. Sci. Bull. 65, 865–867.
Hastie, Trevor, Tibshirani, Robert, Friedman, Jerome, 2009. The Elements of Statistical Learning: Data Mining, Inference, and Prediction. Second. Springer.
Kim, J., Kwan, M.-P., 2021. The impact of the COVID-19 pandemic on people’s mobility: A longitudinal study of the U.S. from March to September of 2020. J. Transp. Geogr. 95, 103039.
Kuhnimhof, T., Collet, R., Armoogum, J., Madre, J.-L., 2009. Generating internationally comparable figures on long-distance travel for Europe. Transp. Res. Rec. 2105, 18–27.

Kuhnimhof, T., Buehler, R., Wirtz, M., Kalinowska, D., 2012. Travel trends among young adults in Germany: increasing multimodality and declining car use for men. J. Transp. Geogr. 24, 443–450.

Li, J., Ye, Q., Deng, X., Liu, Y., Liu, Y., 2016. Spatial-temporal analysis on spring festival travel rush in China based on multisource big data. Sustainability 8, 1184.

Li, T., Wang, J., Huang, J., Gao, X., 2020. Exploring temporal heterogeneity in an intercity travel network: a comparative study between weekdays and holidays in China. J. Geogr. Sci. 30, 1943–1962.

Limtanakool, N., Dijst, M., Schwanen, T., 2006. The influence of socioeconomic characteristics, land use and travel time considerations on mode choice for medium- and longer-distance trips. J. Transp. Geogr. 14, 327–341.

Mu, X., Yeh, A.G.-O., Zhang, X., 2020. The Interplay of Spatial Spread of COVID-19 and Human Mobility in the Urban System of China during the Chinese New Year (Environment and Planning B-Urban Analytics and City Science).

Neal, Z., 2014. The devil is in the details: differences in air traffic networks by scale, species, and season. Soc. Networks 38, 63–73.

Neal, Z.P., 2018. The urban metabolism of airline passengers: scaling and sustainability. Urban Stud. 55, 212–225.

Pal, S.C., Saha, A., Chowdhuri, I., Roy, P., Chakrabortty, R., Shit, M., 2020. Threats of unplanned movement of migrant workers for sudden spurt of COVID-19 pandemic in India. Cities 103035.

Pan, J., Lai, J., 2019. Spatial pattern of population mobility among cities in China: case study of the National day plus mid-autumn festival based on Tencent migration data. Cities 94, 55–69.

Pullano, G., Valdano, E., Scarpa, N., Rubrichi, S., Colizza, V., 2020. Evaluating the effect of demographic factors, socioeconomic factors, and risk aversion on mobility during the COVID-19 epidemic in France under lockdown: a population-based study. Lancet Digital Health 2, E638–E649.

Tao, T., Wu, X.Y., Cao, J., Fan, Y.L., Das, K., Ramaswami, A., 2020. Exploring the nonlinear relationship between the built environment and active travel in the twin cities. J. Plan. Educ. Res. 16.

Vickerman, R., 2021. Will Covid-19 put the public back in public transport? A UK perspective. Transp. Pol. 103, 95–102.