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Impact of COVID-19 on domestic air transportation in China

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ABSTRACT

Assessing the impact of the coronavirus disease 2019 (COVID-19) on air transportation is essential for policymakers and airlines to prevent their widespread shutdown. The panel data observed from January 20, 2020, to April 30, 2020, were used to identify the impact of COVID-19 and the relevant control measures adopted on China's domestic air transportation. Hybrid models within negative binomial models were employed to separate the temporal and spatial effects of COVID-19. Temporal effects show that the number of new confirmed cases and the control measures significantly affect the number of operated flights. Spatial effects show that the network effect of COVID-19 cases in destination cities, lockdown, and adjustment to Level I in the early stages have a negative impact on the operated flights. Adjustment to Level II or Level III both has positive temporal and spatial effects. This indicates that the control measures adopted during the early stage of the pandemic positively impact the restoration of the aviation industry and other industries in the later stage.

1. Introduction

The coronavirus disease 2019 (COVID-19) has significantly influenced individuals' lives worldwide since 2020. According to the World Health Organization (WHO), as of December 14, 2020, there have been more than 71 million confirmed cases of COVID-19 worldwide, affecting 218 countries and regions. Considering the increasing evidence that modern transportation modes such as high-speed rail and air transportation have accelerated the spread of the pandemic (Zhang et al., 2020), urban policies including city lockdown, social distancing, and transportation shutdown have been widely adopted by cities globally. Numerous studies have shown that various control measures can reduce the spread of COVID-19 (Cowling et al., 2020; Leung et al., 2020), but the large-scale COVID-19 outbreak and the control measures adopted accordingly have affected the economy and the air transportation industry significantly. For example, the International Air Transport Association (IATA) predicts that global passenger transport revenues between $ 63 billion and $ 113 billion in 2020 will be lost due to air travel reduction during the COVID-19 outbreak (IATA, 2020a). In such cases, understanding the correlation between air traffic and COVID-19 is important for air transportation.

Despite being one of the hardest-hit countries in early 2020, China has seen a significant decrease in the new confirmed cases of COVID-19 and an increase in the number of flights since March 2020. In June 2020, the domestic passenger volume in China fell 35.5% compared to the year-ago period, which was lower than the global average of 67.6% (IATA, 2020b). One reason is that China adopted strong control measures in the early stage of the pandemic, which prevented the spread of COVID-19 and provided favorable conditions for the recovery of the aviation industry. After the market-driven consolidation and deregulated competition that began in the 2000s in China, airlines are playing an increasingly important role in adapting to the market (Wang et al., 2016). Thus, market demand and mandatory policies, such as those pertaining to travel restrictions, affect the supply of flights. The rapid recovery of China's aviation industry under the influence of market demand and control measures provides a good reference for other countries.

Currently, most studies have only used historical aviation data to study the changes in air traffic post COVID-19 outbreak; limited studies have observed the quantitative relations between the pandemic and air traffic. Furthermore, although the control measures adopted to combat the outbreak may have had different effects on air traffic, previous studies have not fully examined them. By instigating the research question raised within the Chinese context, this study explores the

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quantitative relationship between the COVID-19 pandemic, the resulting control measures adopted, and the number of flights operated.

The rest of the paper has been organized as follows. Section 2 provides a literature review on the determinants of air travel demand and air traffic volumes. Section 3 presents a brief overview of the COVID-19 outbreak and the relevant control measures adopted in China. Section 4 introduces China's aviation response to the COVID-19 outbreak and domestic flight dynamics. Section 5 discusses the methodology and data used as well as empirical results obtained. Finally, we discuss our main findings and conclusions of the study.

2. Literature review

Air traffic forecasts are the foundation of the aviation industry, which are conducive to long-term planning and risk reduction (Akinyemi, 2019). It is essential to identify the determinants of air travel demand and air traffic to improve the accuracy of air traffic forecasts. In general, these determinants can be divided into two categories: geo-economic factors and service-related factors (Boonekamp et al., 2018; Dziedzic et al., 2020; Hofer et al., 2018).

In terms of geo-economic factors, the most commonly used indicators are population, income, and gross domestic product (GDP) (Chen et al., 2019). Vedantham and Oppenheimer (1998) found that population size was a key factor in maintaining the growth of the aviation industry. Economic growth in the form of GDP, GDP per capita, foreign direct investment (FDI), and consumer price index (CPI) is a principal determining factor of air transportation (Valdes, 2015; Wang et al., 2018). For example, a 1% increase in GDP was associated with a 1.53% increase in air passenger traffic in China (Wang et al., 2014). Other studies used the unemployment rate (Carson et al., 2011) or the exchange rate (Chi, 2014). In addition, Zhang and Zhang (2016) found that employment in the financial sector and local government expenditures on science increase the demand for business travel in China. Moreover, there is an unambiguous relationship between tourism and air traffic. Jankiewicz and Huderek-Glapska (2016) found that tourism has a significant role in generating air traffic volumes.

Regarding service-related factors, it is found that airport size and hub airport, which are often measured by direct connectivity (Boonekamp et al., 2018), indirect connectivity (Huang and Wang, 2017), and the Herfindahl-Hirshman Index (Hofer et al., 2018; Wang et al., 2018), have a positive effect on air passenger traffic. In China, the dominance of several major hubs in the national network is undeniable. Wang and Jin (2007) found that the triangular axis formed by the three top hubs of Beijing–Shanghai-Guangzhou generates about one-third of the overall air travel demand. As Chengdu plays an increasingly important role as a new hub in the western region, this triangular structure is gradually transformed into a diamond structure (Chen, 2017). The distance (or time) between departure and destination airports also influences air passenger traffic, which has two conflicting effects: longer route distance discourages social and commercial interactions, but it has a comparative advantage in time-saving compared to other transportation modes (Jorge-Calderón, 1997). For instance, Boonekamp et al. (2018) found that the effect of distance on air passengers first appears to be positive and then appears to be negative, with a turning point at 500 km in Europe. In China's case, Wang and Jin (2007) found that the turning point occurs at 1200 km. Similar results were found in Yang et al. (2018). Another related variable is airfare, which is often omitted to avoid multicollinearity due to its high correlation with distance or travel time (Grosche et al., 2007).

Furthermore, some scholars have studied the impact on air transportation from a policy perspective, mainly focusing on aviation policy and climate-related policies. Aviation policies, often related to liberalization, affect air traffic by reducing fares. For instance, EU external aviation policy leads to a 27% increase in demand through a 6%–23% fare reduction (Abate and Christidis, 2020). Similarly, the cross-strait aviation policies continuously impacted air passenger flow between the Mainland and Taiwan (Wu et al., 2018). Other studies focus on climate-related policies such as the carbon tax incentive policy, which indirectly affect demand by influencing fares (Nava et al., 2018; Pagoni and Psaraki-Kalouptsidi, 2016; Qiu et al., 2020). Due to these policies, changes in air traffic occur over a long-time scale. As a result, these studies use annual passenger flow data to serve long-term rather than short-term forecasts. In an emergency that requires rapid strategy adjustment to minimize risks, short-term forecasts may be more practical (Kim and Shin, 2016). For instance, the outbreak of COVID-19 and the implementation and adjustment of relevant control measures require aviation forecasting systems to improve their adaptability to the ever-changing external environment. In this regard, it is more practical to use daily or monthly data to study the impact of changing policies or control measures on air traffic.

Before Covid-19, although infectious diseases such as SARS significantly impacted air traffic, there were few relevant studies. Most studies had only focused on the effect of air travel on the spread of infectious diseases, not the other way around (Findlater and Bogoch, 2018; Grais et al., 2003). This may be due to its short-term global impact and the limited number of affected countries. However, the outbreak of COVID-19 changed this trend, and several studies have begun to emerge. Most studies use historical aviation data to analyze the change in air traffic after the pandemic and found that the impact of the pandemic on aviation was caused by travel restrictions and the psychological impact (Arellana et al., 2020; Forsyth et al., 2020; Suau-Sanchez et al., 2020; Wilder-Smith, 2006). Despite a non-negligible amount of research, few studies have examined the statistical relation between COVID-19 and air traffic, and even fewer have examined the impact of control measures against COVID-19 on air traffic. It is worth noting that control measures are often adapted to the dynamics of the pandemic. Therefore, studying the impact of dynamic changes in pandemic and control measures on aviation is necessary to forecast and improve its adaptability.

3. COVID-19 spread and the Chinese government response

There is growing evidence that the large-scale COVID-19 outbreak and containment efforts have significantly impacted air transportation. The outbreak's impact on air traffic volumes is partly due to reduced supply as a result of the government response and, in part, to reduced demand for travel as a result of the outbreak (Fig. 1).

Since the COVID-19 outbreak, the government has adopted a variety of control measures. First, a nationwide investigation has been carried out on confirmed, suspected, feverish, and close contacts of confirmed patients to control the source of infection. Second, to break the chain of COVID-19 transmission, temperature checks and masks have been mandatory, and "No face-to-face" services have been promoted. Third, a household-based outdoor restriction and closed-off community management have been implemented. Household-based outdoor restriction means that only one person per household is allowed to go out for food every two days. Under closed-off community management, villages, communities, and units in most closed-off areas only retain one entrance and restrict the access of each household. Fourth, hierarchical, classified, dynamic, and accurate prevention and control have been implemented. These measures include public health emergency response and risk regionalization. The strictest lockdown and traffic control were implemented in Hubei Province and Wuhan City, differentiated traffic control was implemented in areas outside Hubei Province, and effective measures were taken to avoid crowd and cross-infection. In addition, the government extended the Spring Festival holiday, canceled or postponed gathering activities, and postponed the opening of various schools.

Fig. 1 shows how the air traffic volume is affected by the pandemic, government response, and aviation response. These factors mainly affect the air traffic volume based on supply and demand. First, the government response has a twofold impact on air traffic volume: on the one hand, the most stringent policy, such as city lockdown, directly cut off

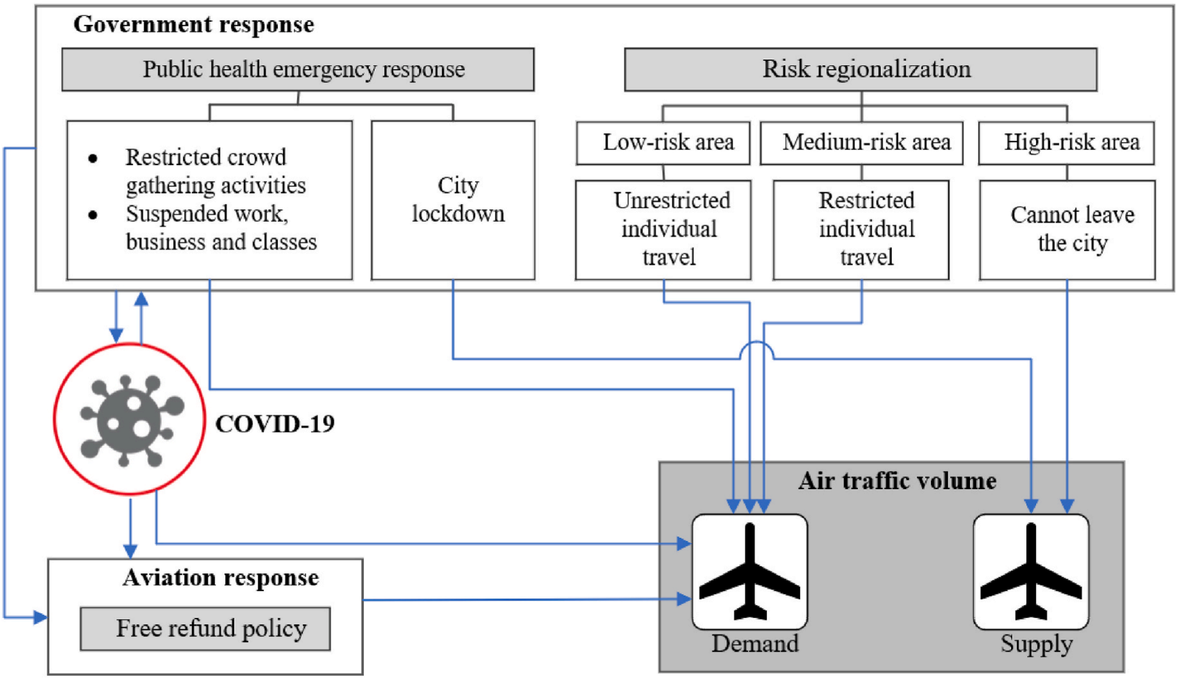

Fig. 1. Relationship between COVID-19, government response, aviation response, and air traffic volume.

the city's external connections with other cities, thereby affecting the supply of flights. On the other hand, some policies, including travel restrictions, suspended work, business, and class, affect individual travel demand and thus affect flights from the demand side. Second, in response to the change in travel demand caused by the above-mentioned policies, airlines have proposed a free refund policy, which further affects flight demand. Third, the number of flights is affected by the pandemic. A pandemic would reduce the desire or demand to travel, thereby reducing the demand for flights. The decrease in travel demand is attributed to people's behavioral changes resulting from fear of exposure to an infectious disease (World Bank, 2014).

3.1. Spread process of the COVID-19 pandemic

Since the first case was reported in Wuhan, China has experienced a rapid increase, then a slow decline in new confirmed cases. On March 12, 2020, the National Health and Welfare Commission stated that the current peak of the pandemic had been controlled. Fig. 2 outlines the COVID-19 outbreak from January 17, 2020, to March 12, 2020. During this period, the pandemic in China can be broadly divided into five stages. In the first stage (before January 19), no new cases have been confirmed in other cities except Wuhan. Insufficient understanding of COVID-19 at this stage has prevented the government from imposing effective measures to contain the spread of COVID-19. There was a nationwide outbreak in the second stage (January 19 to January 26). The first confirmed case in other cities occurred on January 19, and the number of cities with confirmed cases rose sharply thereafter. In the third stage (January 27 to February 4), there was an increasing number of daily new confirmed cases, resulting in a gentle upward curve for new confirmed cases and the number of cities. Early control measures began to have a positive impact in the fourth stage (February 5–February 18), and the number of new cases gradually decreased. In the fifth stage (February 19–March 1), daily new cases continued to decline, and the number of cities affected by the pandemic has dropped to less than ten, and China's pandemic situation is basically under control. In the sixth stage (March 1–March 12), the number of new cases continued to

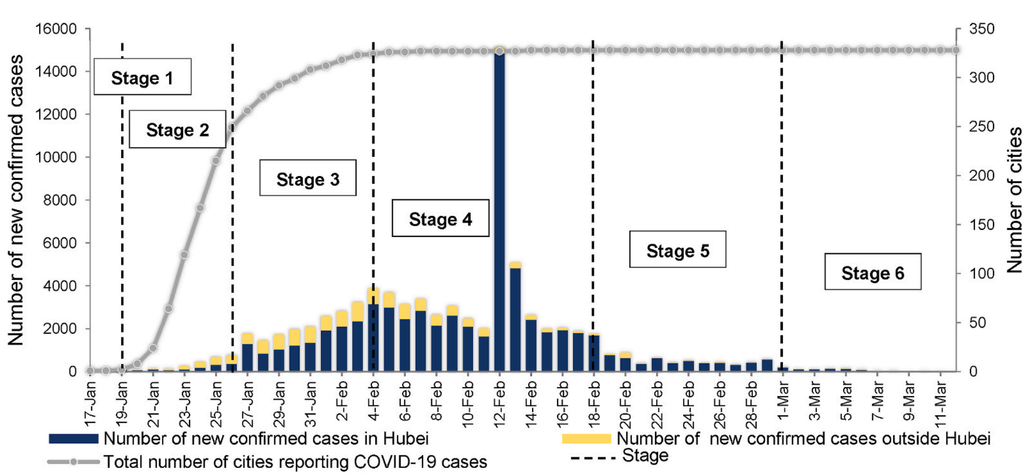

Fig. 2. Different stages of COVID-19 in China, 2020). Note: National Health Commission of the People's Republic of China changed its diagnostic guidelines on February 12, leading to a sharp rise on February 12.

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decline. On March 12, the National Health and Welfare Commission officially announced that the peak of the pandemic has been controlled.

3.2. Public health emergency response

To contain the outbreak, the government responded immediately. According to the National General Plan for Public Emergencies and the National Public Health Emergency Plan, public health emergency is classified into four levels: I, II, III, and IV, with severity reduced from Level I to Level IV. The emergency response measures at all levels of government include measures related to population movements, and the governments can delimit the control area and impose a lockdown within its administrative areas. For example, Hubei implemented the strictest lockdown measures since the outbreak. Governments can also limit or stop crowd gathering activities and suspend work, business, and classes.

Hubei took the lead in launching the Level II emergency response to public health emergencies on January 22 and adjusted it to a Level I emergency response on January 24. Since then, other provinces initiated a Level I emergency response and downgraded their response levels as the pandemic gradually came under control (Fig. 3). After the lockdown in Wuhan on January 23, the public transportation system in other cities in Hubei Province was suspended. By January 28, all jurisdictions of Hubei Province except the Shennongjia Forest Region—one of the World Natural Heritage Sites with a sparsely populated area— adopted border shutdown measures, and all modes of transportation were suspended. Lockdown time for most cities in Hubei began on January 24 and ended on March 25. As the pandemic eased, some provinces began to lower their response levels to Level II or even Level III in late February. As of March 1, 13 provinces maintained a Level I response, nine provinces were adjusted to a Level II response, and ten were adjusted to Level III. (Fujian adjusted the medium-risk area to the Level II response, and the low-risk area to the Level III response). The 13 first-level response provinces were mainly concentrated in the surrounding areas of Hubei Province. Most northwest and south China provinces were downgraded to a Level III response.

3.3. Risk regionalization

To control the pandemic more effectively, the government proposed the concept of risk regionalization on February 25, 2020. The administrative units of risk regionalization are smaller than emergency response measures and therefore easier to manage and control. Based on the pandemic's severity, regions are divided into low-risk, medium-risk, and high-risk areas at the county level. According to the risk regionalization promulgated by the State Council, a high-risk area means that there are disease clusters within 14 days and the cumulative number of confirmed cases exceeds 50. In this case, the government's primary task is to control the pandemic rather than to resume production and living activities. In high-risk areas, regional traffic is controlled and external traffic links are cut off. A medium-risk area is defined as areas with new confirmed cases within 14 days and the cumulative confirmed cases do not exceed 50, or the cumulative confirmed cases exceed 50 and no disease clusters occur within 14 days. The government is committed to orderly resuming production and living activities. In medium-risk areas, individual travel may be limited to a certain extent; A low-risk area means that there are no confirmed cases within their administrative areas or no new confirmed cases within 14 days (Peng et al., 2020). In these areas, production and living activities should be fully restored. The low-risk area adopts strict import prevention, and individual travel is not strictly controlled. Since this study used the city as the basic unit, the county-level risk area cannot be used in our study.

4. Aviation response and flight dynamics

The aviation industry also responded quickly to the pandemic and its control measures. A free refund policy has been proposed in response to changes in aviation demand. Under the combined effect of the pandemic, the government's response, and the airline's response, the domestic aviation industry has undergone a process of first decline and then recovery.

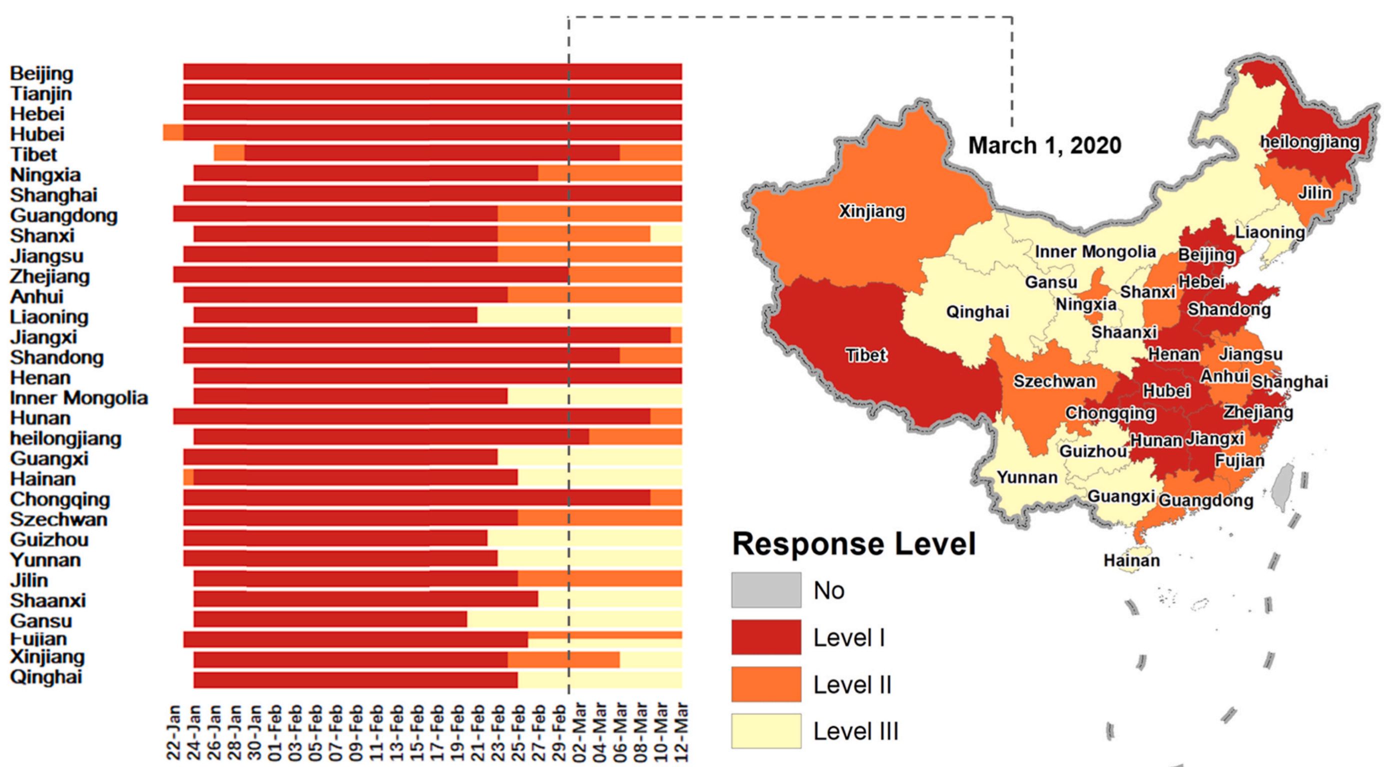

Fig. 3. Emergency response levels in provinces and municipalities.

4.1. Free refund policy

On January 21, the Civil Aviation Administration of China (CAAC) issued guidelines on preventing and controlling civil aviation, airlines, and airports. In the ensuing days, the CAAC issued a set of ticket refund policies for various groups and regions, including passengers to Wuhan or other cities, student passengers, medical professionals, and passengers affected by entry restrictions. Since a small number of medical staff and passengers affected by entry restrictions have a limited impact on domestic flights, they will not be discussed in detail in this study. Three types of refund policies can be summarized: 1) Free refund policy to Wuhan (January 21). On January 21, the CAAC requested all airlines to refund tickets free of charge for flights involving Wuhan (tickets purchased before January 31, 2020, and traveling from January 1, 2020, to March 29, 2020); 2) Free refund policy to all cities (January 28). On January 24, the CAAC required all airlines to refund tickets free of charge purchased before January 24, 2020. After four days, the CAAC extended the ticket purchase date to January 28, 2020; 3) Free refund policy for students (February 11). To cope with the ticket refunds caused by delays in school start dates, the CAAC required that students who had purchased tickets before February 11 and traveled between February 11 and March 31 could refund or reschedule their tickets for free. This policy, coupled with the delay in school start dates, increased canceled flights.

4.2. Flight reduction and recovery

Fig. 4 provides an overview of daily domestic flights during and after the six stages of the pandemic. The flight data was obtained from VariFlight (https://www.variflight.com/en/) and covers 100% of China's domestic flights. Domestic flights are severely affected by the outbreak of COVID-19, and the state of canceled flights is highly consistent with the six stages of the pandemic. No measures were imposed to control the pandemic in the first stage, and aviation was not affected. As the outbreak in other cities intensified in the second stage, the number of operated flights began to decrease. Since the lockdown in Wuhan on January 23, the activation of the Level I response, and the free refund policy on January 24, daily operated flights have shown a downward trend. On January 26, the State Council extended the Spring Festival holiday to February 2, and some provinces and cities further extended it to February 10. However, people returning to work on the original schedule led to a rebound in the number of flights on January 26. In the third stage, the downward trend of daily operated flights is exacerbated. The pandemic and the resulting prevention measures in each city were the most severe in this stage. At the end of the third stage, both new confirmed cases and canceled flights reached a peak. In the fourth stage, the operated flights showed a trend of fluctuation. From February 6 to February 9, the flight execution rate had a slight upward trend with the end of extended holidays in some cities. Since then, it began to decline again, reaching a trough on February 13, with fewer than 1900 daily operated flights. In the fifth stage, the operated flights rose with fluctuations. With the initial control of the pandemic, daily flights began to rise. On March 1, daily operated flights exceeded 6500, half of the average daily flight volume during the usual period. Since then, daily operated flights have continued to increase, returning to the level of 70% of planned flights by the end of April.

Fig. 5 presents the network of flights canceled on February 14, 2020, when the number of canceled flights reached its maximum. The average flight cancellation rate was 83%, and about 10,000 flights were canceled. In general, cities with larger average scheduled flights tend to have higher cancelation rates. Although major cities still play the role of transportation hubs, flights in these cities have been severely affected by the pandemic. The cancelation rate of some main routes has reached between 75% and 90%, including Shanghai-Qingdao, Shanghai-Beijing, Shanghai-Guangzhou, Shanghai-Shenzhen, Shanghai-Chongqing, Beijing-Shenzhen, and Beijing-Chengdu, forming a diamond structure. However, the impact on the thin routes cannot be underestimated. Approximately 1600 pairs of cities have a cancellation rate of 100%, with an average of 3 scheduled flights, indicating that non-closely connected routes have been disconnected. The origin cities with the largest number of cancelations of the thin routes are Chongqing, Xi'an, Wuhan, Zhengzhou, Yinchuan, Changsha, Shanghai, and Urumqi.

5. Empirical analysis

5.1. Model description and variables

After North Korea temporarily banned the entry of Chinese citizens on January 27, other countries began to impose travel restrictions against China. According to the China National Immigration Bureau, 139 countries imposed several travel restrictions against China as of March 4, causing numerous cancellations of international flights. Since the international market was canceled during the study period, this study only examined the impact of COVID-19 on China's domestic air transportation, not international flights. This study employed panel regression analysis in examining the impact of COVID-19 on China's domestic air transportation. The observation unit is the daily air service (sum of departure and arrival flights) for each city. Socio-economic data was obtained from the China City Statistical Yearbook. The flight data obtained from VariFlight (https://www.variflight.com/en/) includes flight data from January 01, 2020, to December 31, 2020. However, we chose the study period from January 20, 2020, to April 30, 2020, due to the following reasons. First, the human-to-human transmission was confirmed on 20 January 2020, thus beginning to have an impact on aviation. Second, at the end of April, the flight operated had recovered to 70% and maintained a stable trend, and the epidemic has been basically under control. Since all of our independent variables are city-level, we combined airport-level flights into city-level flights. After data processing, a total of 16,731 observations with 169 cities were retained.

As our dependent variable—the number of operated flights—is a non-negative count variable, Poisson regression, and negative binomial regression are our primary choices (Aguiléra and Proulhac, 2015). We examined whether the mean value of the dependent variable changes for each independent variable and found that in all cases, the conditional variance of the dependent variable is much greater than its conditional mean. It shows the existence of over-dispersion, and thus the negative binomial regression is more appropriate (Cameron & Trivedi, 2013).

We have adopted a between-within model (also known as a hybrid model), whose major advantage is that it can decompose the relationship between COVID-19 and flights into temporal effects (within-effects) and spatial effects (between-effects) (Sjölander et al., 2013; Yang et al., 2018). Another advantage is that it allows the inclusion of time-invariant variables, which are often omitted in the fixed effects model (Torres-Reyna, 2007; Yang et al., 2018). Our between-within model is based on the following equations:

$$Flown_{it} = \alpha_0 + \alpha_1(X_{it} - \overline{X_i}) + \alpha_2\overline{X_i} + \alpha_3 Z_i + U_i + \varepsilon_{it} \tag{1}$$

where the dependent variables are the number of operated flights of the city i on day t. The coefficient α_1 represent the temporal effects (within effects), while the coefficient α_2 represent the between effect (spatial effects). α_3 is the coefficient of the time-invariant variable.

We used COVID-19, control measures, and geo-economic elements as our independent variables (see Table 1). Several lines of evidence suggest that COVID-19 has resulted in a severe loss of global passenger transport revenue (Gössling et al., 2020; IATA, 2020a). Although the government proposed the concept of risk regionalization at the end of February, the county-level risk areas were not taken as the independent variable because this study took cities as the basic unit. As a complement, we combine the concept of risk regionalization based on whether there are new confirmed cases within 14 days—a very critical indicator—to generate new variables related to the COVID-19.

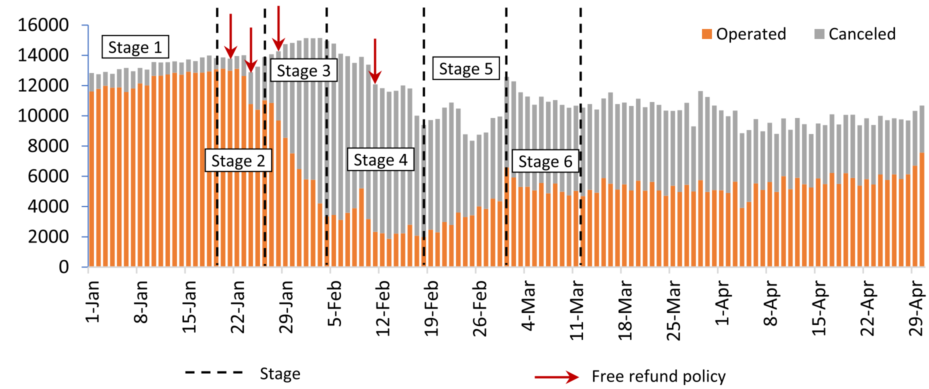

Fig. 4. Daily domestic flights in China during and after the six stages of COVID-19 (Note: only domestic flights in mainland China are included. The stages are the same as Section 3.1. The timeline of the free refund policy is the same as Section 4.1.).

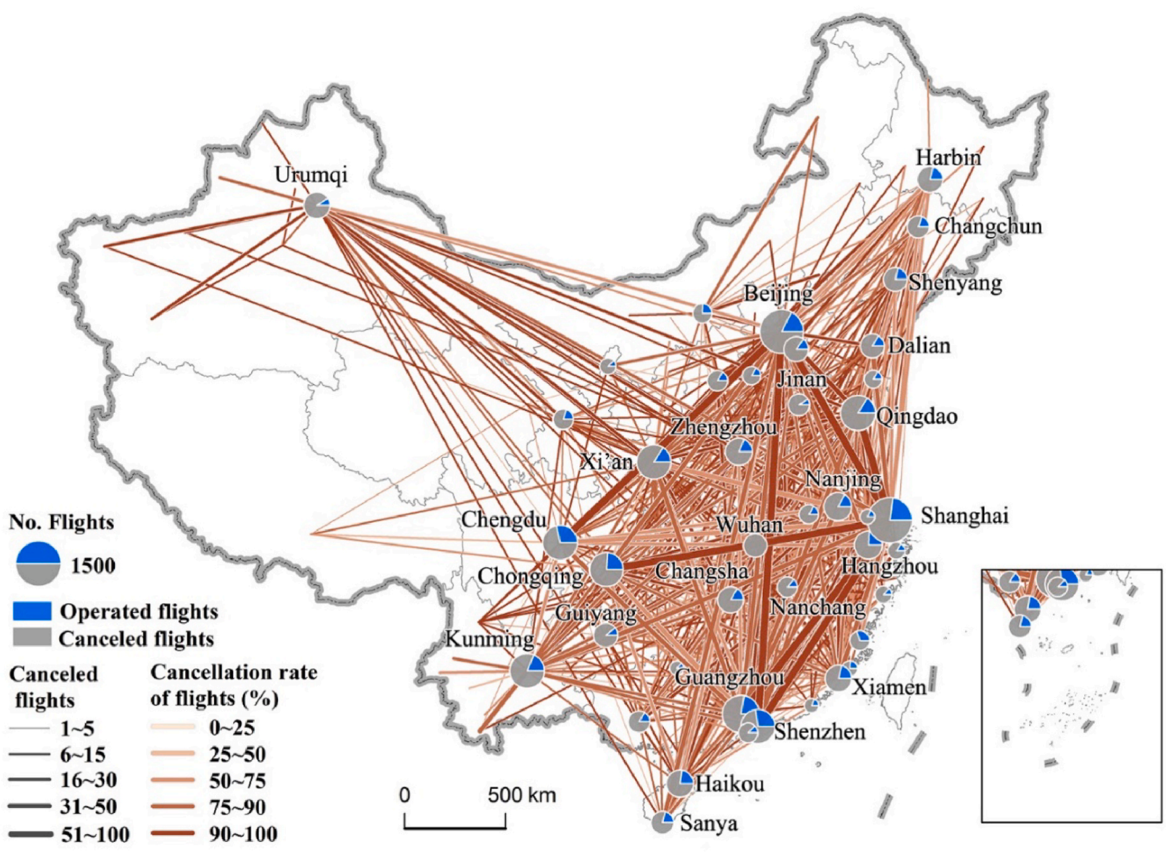

Fig. 5. Operated and canceled flight network on February 14.

$$\text{COVID14}_{it} = \begin{cases} 1\ ,\ if \sum_{t-15}^{t-1} COVID_{it} > 0 \\ 0\ ,\ if \sum_{t-15}^{t-1} COVID_{it} = 0 \end{cases} \tag{2}$$

Where $COVID14_{it} = 1$, if the departure city i has confirmed cases in the past 14 days; 0, otherwise. $COVID_{it}$ refers to the number of new confirmed cases at origin city i on day t.

Furthermore, the COVID-19 outbreak in destination cities may have affected the operated flights. Since our data is at the city level rather than the air route level, we cannot directly use the number of COVID-19 cases in destination cities. Based on the air route data in 2019, we inferred the corresponding destination cities of each origin city during the study period. Here, we examined the presence of new confirmed cases within 14 days in the destination city with reference to the definition of risk regionalization. The network effect of COVID-19 cases in destination cities was calculated as follows:

$$D\_COVID14_{it} = \sum_{j} COVID14_{jt} Weight_{ij} \tag{3}$$

where $COVID14_{jt} = 1$, if the destination city j has confirmed cases in the past 14 days; 0, otherwise.

$$\text{Weight}_{ij} = \frac{Flown_{ij}}{\sum_j Flown_{ij}} \tag{4}$$

Table 1
Summary statistics of explanatory variables.

Variable	Description	Mean	Std Dev	Min	Max
Dependent variable					
Flown	The number of operated flights	59.88	140.77	0	2127
Time-variant variables					
COVID14	Dummy variable: 1 if the departure city has confirmed cases in the past 14 days, 0 otherwise	0.39	0.49	0	2997
D_COVID14	The network effect of COVID-19 cases in destination cities	0.59	0.34	0	1
Level 1	Dummy variable: 1 if a city imposes a level 1 response, 0 otherwise (reference)	0.39	0.49	0	1
Level 2	Dummy variable: 1 if a city imposes a level 2 response, 0 otherwise	0.17	0.38	0	1
Level 3	Dummy variable: 1 if a city imposes a level 3 response, 0 otherwise	0.40	0.49	0	1
Lockdown	Dummy variable: 1 if a city imposes a lockdown, 0 otherwise	0.02	0.14	0	1
FreerefundFeb11	Dummy variable: 1 is assigned to dates from February 11 to March 31, and 0 otherwise	0.48	0.50	0	1
Time-invariant variables					
LnPop	Logarithm of the population size (unit: 10,000)	5.96	0.78	3.73	8.05
LnGDPpercap	Logarithm of GDP per capita (unit: yuan)	1.74	0.56	0.52	3.00
HubTop10	Dummy variable: 1 if it is the city where the top ten airport hubs are located, 0 otherwise	0.05	0.22	0	1

Note: The adjustment time of the response level of each province is shown in Fig. 3.

$Flown_{ij}$ refers to the number of operated flights from the origin city i to destination city j in 2019. In a true network sense, each city affects other connected cities, which are, in turn, affected by their destination cities. Here, $D\_COVID14_{it}$ only considers the direct impacts from the destination cities of the origin city, and therefore it is a rough estimate of the true network effect.

Since severe emergency response levels can restrict population movement, we assume this variable negatively affects operated flights. When the relationship between emergency response level and the number of flights was decomposed into within effect and between effect, we found that categorical variables will lose part of the information. Therefore, we divided this variable into three dummy variables—Level I, Level II, and Level III.

Regarding municipal control measures, city lockdown is one important measure that should be considered. The severest lockdown measure, border shutdown measures in Hubei Province, was introduced. All modes of transportation were suspended during the lockdown. Shiyan, Yichang, Enshi, Wuhan, and Xiangyang were on lockdown from January 25 to March 35, January 26 to March 35, January 26 to March 35, January 24 to April 8, and January 26 to March 35 respectively.

We included the free refund policy in the model to reflect the aviation industry responses. We included all three free refund policies in the preliminary analysis. However, due to multicollinearity, we finally deleted the free refund policy variable for Wuhan (after January 21) and all cities (after January 24 and January 28). In the final model, we only used the free refund policy for students (February 11) as an independent variable.

In terms of geo-economic and service-related variables, population size, GDP per capita, and hup airports were selected as our independent variables. We performed a logarithmic transformation of population size and GDP per capita since these variables were highly skewed to the left. We used 2017 data for population size and GDP per capita, as the China City Statistical Yearbook has been updated to 2018 (data for 2017). We took the cities with the top ten hub airports as an independent variable and named it Hubtop10, which includes Beijing, Shanghai (Pudong and Hongqiao), Guangzhou, Kunming, Xi'an, Chengdu, Shenzhen, Chongqing, and Hangzhou (Huang and Wang, 2017).

5.2. Results

Table 2 shows the results of the between-within model for all periods and different stages. According to the characteristics of each stage, we re-divide the six stages into two stages. Since the first stage of COVID-19 had not yet started to affect aviation, we started with the second stage. Figs. 2 and 4 show that the period from the second stage to the fourth stage was the most severe stage of the epidemic and also the period with the greatest impact on the number of operated flights. Accordingly, we combined the second, third, and fourth stages. The fifth and the sixth stages were combined as the epidemic was largely under control and flight volumes began to recover. In addition, we examined the stages beyond the sixth stage to examine the impact of relevant variables on aviation once the epidemic was largely under control. Since the number of operated flights recovered to 70% by the end of April, our study period was up to the end of April. We did the Wald test for ln alpha equal to 1 (it corresponds to the test for alpha equal to 0) and found that all alphas of the three models are significantly different from 0, which means that using a negative binomial can better estimate.

With respect to within-effects, COVID-19 at both origin and destination negatively impacts the operated flights. Regarding emergency response, different stages have different effects. In general, compared with no response level, adjusting to Level I, Level II or Level III emergency responses will lead to a 55.2%, 44.4%, and 57.5% reduction in operated flights, respectively. From the second to the fourth stage, all the provinces adjusted from no response to Level I response, therefore Level II or Level III responses were omitted in the model. From the fifth to the sixth stage, all provinces adjusted from Level I response to Level II or Level III. Due to the multicollinearity issue, Level I responses were omitted in the model and used as reference. The results show that adjusting from Level I to Level II or Level III will increase the number of operated flights. As expected, lockdown and free refund policy negatively impact the number of operated flights throughout the stages, reducing the number of operated flights by nearly 97%.[1] It should be noted that since these variables do not change over time at some stages, they were omitted in some models.

With respect to between-effects (spatial effects), in the early stages, COVID-19 status in the origin city was positively correlated with operated flights. It is because, in the early stages, cities heavily affected by the epidemic tend to be those with a higher number of operated flights, so there is a positive correlation between the two variables. It should be noted that this is a comparison between cities, and for one city, the severity of COVID-19 will cause a decrease in the operated flights (time effects). However, this significant positive correlation disappeared after Stage 5, as almost all cities were affected by the outbreak after Stage 4 (Fig. 2). Unlike departure cities, the network effect of COVID-19 cases in destination cities has a negative impact on the operated flights. This result suggests that cities with a large number of flight connections to hard-hit cities tend to have fewer flights than those with the opposite situation. Regarding the emergency level, cities that implement Level I earlier have fewer flights than cities that implement level I later (Model

[1] The formula to compute this effect is 100%*(e^{b_i} -1), where b_i is the estimated coefficient.

Table 2
Between-within model for all periods and different stages.

	Model 1: All periods		Model 2: Stage 2- Stage 4		Model 3: Stage 5- Stage 6		Model 4: After Stage 6	
	Estimate	Std Error	Estimate	Std Error	Estimate	Std Error	Estimate	Std Error
Temporal effects (within-effects)								
COVID14	−0.146***	−0.017	−0.277***	−0.036	−0.260***	−0.028	−0.061***	−0.014
D_COVID14	−0.127***	−0.027	−0.131**	−0.064	−0.973***	−0.049	−0.449***	−0.038
Level1	−0.803***	−0.026	−0.418***	−0.037	–	–	–	–
Level2	−0.587***	−0.027	–	–	0.463***	−0.033	0.075**	−0.035
Level3	−0.857***	−0.025	–	–	0.590***	−0.041	0.125***	−0.037
Lockdown	−3.627***	−0.102	−4.504***	−0.197	–	–	−2.457***	−0.073
FreerefundFeb11	−0.605***	−0.011	−1.771***	−0.026	–	–	–	–
Spatial effects (between-effects)								
COVID19	1.467**	−0.726	2.492***	−0.627	−0.199	−0.494	0.209	−0.499
D_COVID19	−2.715***	−1.015	−5.459**	−2.372	−1.592	−1.246	−1.733***	−0.661
Level1	−16.227	−12.304	−8.031***	−2.873	–	–	–	–
Level2	−15.571	−12.275	–	–	1.375***	−0.481	0.413	−0.468
Level3	−15.584	−12.341	–	–	1.399***	−0.441	0.358	−0.413
Lockdown	−3.032***	−1.007	−4.164***	−0.526	–	–	−1.904	−1.839
FreerefundFeb11	–	–	–	–	–	–	–	–
Time-invariant variables								
LnPop	0.618***	−0.136	0.558***	−0.119	1.019***	−0.185	0.688***	−0.129
LnGDPpercap	1.192***	−0.162	1.099***	−0.148	1.201***	−0.217	1.246***	−0.17
HubTop10	1.125***	−0.412	1.346***	−0.357	1.525***	−0.558	1.372***	−0.462
Lnalpha	−1.242***	−0.015	−1.198***	−0.026	−1.853***	−0.038	−3.676***	−0.042
Constant	13.17	−11.617	7.395***	−2.704	−5.681***	−1.472	−3.337***	−0.952
Observations	16,731		4901		3887		7943	
Number of groups	169		169		169		169	

Note: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

2). In Stages 5 and 6, cities that adjust to Level II or Level III earlier have more flights than cities that adjust to Level II or Level III later (Model 3). After Stage 6, the emergency level no longer has spatial effects. As expected, cities with lockdowns have fewer flights than cities without lockdowns. After Stage 6, since most cities in Hubei were unlocked on March 25, the spatial effect of this variable disappeared. Since the free refund policy for students applies to all cities, there is no difference between them, resulting in automatic omission during the calculation process.

In accordance with previous studies (Dziedzic et al., 2020; Grosche et al., 2007), the impact of time-invariant variables is relatively stable, and population size, GDP per capita, and cities with hub airports all have a positive impact on operational flights. The elasticity of operated flights for the population size and GDP per capita ranged from 0.558 to 1.019 and from 1.099 to 1.246, respectively.

6. Conclusions

This study investigated the extent to which the COVID-19 outbreak and the relevant control measures adopted affect the aviation industry. Although there is abundant evidence that the aviation industry has been drastically affected by the COVID-19 outbreak, few studies have investigated the quantitative relationship between the pandemic and the number of flights. This study filled this gap by examining the impact of COVID-19 on China's domestic air transportation from January 17, 2020, to April 30, 2020. We adopted a between-within model to separate the temporal effects and spatial effects.

This study has shown that COVID-19 and the relevant control measures adopted have a significant negative effect on the number of operated flights, which is mainly reflected in the temporal dimension. In general, imposing lockdown measures is related to a 97% reduction in the number of operated flights. Moreover, adjustment to the Level I responses in the early stages will result in a reduction in the number of operated flights, while adjustments from Level I responses to Level II or Level III responses in the later stages (Stage 5–6) will result in an increase in the number of operated flights.

In terms of spatial effects, COVID-19 status in the origin city in the early stage was positively correlated with operated flights since cities heavily affected by the epidemic tend to be those with a higher number of operated flights. In contrast, the network effect of COVID-19 cases in destination cities has a negative impact on the operated flights. The number of operated flights in cities under a lockdown is significantly less than that observed in cities that are not under a lockdown. In terms of emergency responses, in the early stages, cities that implement Level I earlier have fewer flights than cities that implement level I later. At a later stage, cities that adjust to Level II or Level III earlier have more flights than cities that adjust to Level II or Level III later. After Stage 6, the response level has no spatial effects.

This study shows that stringent control measures will result in a decrease in the number of operated flights. However, effective control measures can contain the spread of the pandemic, which is of great significance to the rapid recovery of the aviation industry. When the outbreak is contained to a certain extent, that is when the response level is downgraded from Level I to Level II or Level III, the negative impact of the response level on operated flights is weakened. This indicates that the control measures adopted during the early stage of the pandemic positively impact the restoration of the aviation industry and other industries in the later stage. In addition, compared with provincial control measures, smaller control management units and differentiated control measures are more conducive to restoring the number of operated flights.

Credit authorship contribution statement

Yongling Li: Formal analysis, Methodology, Writing-original draft. **Jiaoe Wang**: Conceptualization, Investigation, Writing-review&editing, Funding acquisition, Project administration. **Jie Huang**: Writing-review&editing. **Zhuo Chen**: Formal analysis, Methodology, Writing-review&editing.

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