sustainability

MDPI

Article

The Impacts of COVID-19 and Policies on Spatial and Temporal Distribution Characteristics of Traffic: Two Examples in Beijing

Weiwei Guo [1], Yan Feng [1], Wenxiu Luo [1], Yilong Ren [2,]*, Jiyuan Tan [1], Xiaobei Jiang [3] and Qingwan Xue [1]

1 Beijing Key Lab of Urban Intelligent Traffic Control Technology, North China University of Technology, Beijing 100144, China; guoweiwei@ncut.edu.cn (W.G.); f_yann@163.com (Y.F.); lwx19970801@163.com (W.L.); tanjy@ncut.edu.cn (J.T.); qwxue@ncut.edu.cn (Q.X.)
2 School of Transportation Science and Engineering, Beihang University, Beijing 100191, China
3 School of Mechanical Engineering, Beijing Institute of Technology, Beijing 100081, China; Jiangxiaobei@bit.edu.cn
* Correspondence: yilongren@buaa.edu.cn

Abstract: The global closure policy to limit the spread of the new coronavirus (COVID-19) in 2020 was based on public safety and health considerations. In the implementation of arrangements to prevent the epidemic, the function of the transportation system as a basis for securing cities has been severely affected. After summarizing the domestic and international literature on epidemic policies and travel, this study analyzes the changes of the spatial and temporal distribution characteristics of people's travel and the impacts in the context of the two epidemic phases in Beijing and abroad. During the epidemic, traffic volume into and out of Beijing showed a downward trend. In our study, we found that total travel volume in Beijing during the Spring Festival in 2020 was down by about 70% year-on-year, the distribution of daily traffic trips during the day was not affected by the outbreak, and six urban areas in the center of Beijing experienced greater declines in travel volume compared to other urban areas. The conclusions of the study can provide a reference for the sustainability and recovery of urban areas and formulation of policies in the subsequent pandemic era in terms of the relationship between public travel and epidemic control.

Keywords: COVID-19; policy; travel volume; spatiotemporal distribution characteristics; sustainability

check for updates

Citation: Guo, W.; Feng, Y.; Luo, W.; Ren, Y.; Tan, J.; Jiang, X.; Xue, Q. The Impacts of COVID-19 and Policies on Spatial and Temporal Distribution Characteristics of Traffic: Two Examples in Beijing. *Sustainability* **2022**, *14*, 1733. https://doi.org/10.3390/su14031733

Academic Editor: Elżbieta Macioszek

Received: 14 January 2022
Accepted: 29 January 2022
Published: 2 February 2022

1. Introduction

COVID-19 swept the world, causing severe effects on the socioeconomic, energy–environment, and transport sectors globally [1]. Since the global outbreak of COVID-19 [2,3], the epidemic situation at home and abroad has continued to evolve and change. As of June 2021, nearly 180 million confirmed cases of COVID-19 globally were reported to the WHO, and the uneven pattern of epidemic development is obvious, with the situation in the Americas, Europe, and Southeast Asia still not optimistic. The United States lacked experience in fighting such an outbreak in the early stages of the epidemic; there are currently more than 30 million confirmed cases and 690,000 deaths in that country. India has a huge population base, a lack of health and medical security conditions, and low testing levels. There has been an explosive growth of 400,000 new confirmed cases every day. As in the United States, the cumulative number of confirmed cases has exceeded 30 million. Brazil's infection rate and number of deaths have increased again compared to before, with nearly 80,000 newly diagnosed cases every day (data source: https://www.who.int/zh (accessed on 29 June 2021)). China was the first country to discover the new coronavirus and suffer the impact of the epidemic. The first outbreak of COVID-19 in Wuhan at the end of December 2019 coincided with the peak of people returning home during the Spring Festival. For the sake of public safety and to minimize losses, in the early days, Wuhan had to implement tactics of blocking the city to reduce the flow of people, but the impact of the city blockade measures is huge, and this is a measure used only for emergencies.

Provinces and cities initiated first-level responses to the public health emergency—primary and secondary schools closed, and many enterprises adopted a policy of online office and home work in response to the government's epidemic policy. Concerning COVID-19 prevention and control, China controlled the epidemic as quickly as possible, and restarted social activities by controlling the transportation system.

Among the various social sectors responding to COVID-19, aside from the medical sector, the transportation sector is the one most closely linked to outbreak prevention and control. The transportation system, while ensuring basic human and logistic transport, also facilitates the spread of the virus due to its special vector nature, but it is also severely affected by the slowdown of socioeconomic activities and restrictions on social interactions. Transportation consumption is closely associated with the output of all industries. As a pandemic worsens, the output of all sectors declines more [4]. Many domestic and international studies have shown that the development of the epidemic and its prevention and control measures have had a significant impact on transportation systems [5–7], with the air transport sector being the most severely affected [8,9]. Occurrences such as reduced population mobility, continued decline in airline orders, flight groundings, and company layoffs created a critical situation for the air transport industry during COVID-19, and according to ICAO (2020) data, the number of passengers dropped by 2.9 billion, and the economic loss was about 390 billion USD for the year 2020. In addition to the aviation sector, the negative impact of COVID-19 on railroads, waterways, and urban public transport activities is also more serious [3]. At the same time, owing to the reduced number of vehicles being operated in cities, the COVID-19 pandemic had a positive impact on air pollution [10].

Today, with increasing globalization, travel activities and freight traffic derived from economic trade activities and tourism are on the rise. The efficiency, speed, and coverage of modern transportation networks expose people to the risk of emerging new strains of common diseases or completely new diseases [11], and these epidemics and their vectors can spread faster, farther, and more violently than ever before with today's well-established transportation networks [12]. The expanding global transportation networks by land, sea, and air created extremely high accessibility among regions worldwide, which led to the COVID-19 outbreak sweeping through multiple countries since late 2019, with hundreds of millions of confirmed cases to date. In most of the past, people and regions were mostly separated from each other, and the imperfection of transportation systems did not create conditions to fuel viral spread. According to historical data, the first pandemic of the Black Death in Europe was a localized outbreak that infected two-thirds of the European population. As a result of renewed population growth and increased travel activity, the Black Death outbreak expanded geographically and posed a threat to previously unaffected areas [13], resulting in hundreds of cases in at least 14 countries (World Health Organization, 2003).

COVID-19 led to a global depression. The most detrimental of these widespread and severe mitigation strategies is the forced shutdown of nonessential businesses in order to reduce social contact and transmission of the virus [14], such as SARS [15]. These measures have a restrictive effect on transportation activities, and the transportation system affects the spatial distribution of the population. Currently, the development of the epidemic is normalized and long-term, and the epidemic abroad mostly involves cross-infection and has not been effectively controlled, although there have been epidemic outbreaks in many places in China, such as Wuhan, Beijing Xinfadi Market, Dalian, Shijiazhuang, Guangzhou, etc. While precise control of the epidemic has been achieved through the strict implementation of various effective prevention and control measures, many areas, after going through the complete process—zero infection, emergence of cases, transmission, and case clearance—can be analyzed for the impact of the epidemic and control policies on traffic and travel activities independently.

This study examines the changing characteristics of transportation demand during the various stages of the epidemic under various prevention and control measures, and two development processes are selected as the subjects of the study. In order to simplify the follow-up work, we named the first outbreak the Spring Festival epidemic and the second the Xinfadi epidemic, both of which went through the complete process—zero infection, transmission, cases zero again—to analyze the impact of the epidemic and control policies on transportation and to determine the recovery and sustainable development of the post-pandemic era. These two phases were in the early stages of the epidemic. During the Spring Festival, when the epidemic was in its early stages and involved the spatial movement of large numbers of people, it was characterized by simultaneous outbreaks at multiple points; in the case of Xinfadi, after 56 consecutive days of zero confirmed cases in the local area, the epidemic rebounded with a single local outbreak and then spread to the periphery, but the spread was quickly interrupted based on previous control experience. Based on these observations, this paper examines the changes in traffic travel in Beijing during the Spring Festival outbreak and at various stages of the Xinfadi outbreak.

2. Literature Review

The COVID-19 epidemic has spread worldwide, and herein we review and organize some of the research completed and progress made from 2020 to the present.

The various restrictions introduced by countries in response to COVID-19 led to a significant drop in traffic in many countries and regions. For example, the State of Qatar took measures to prevent and control COVID-19 by closing all educational institutions, closing public parks, restricting international travel from a few countries, and limiting international flights from some countries [16]. The Spanish government issued a lockdown to contain the virus, closing all commercial establishments (except pharmacies and food stores), cab services, and public transportation and banning the admission of international travelers from all countries [17]. The UK government introduced measures directly related to residential travel on 16 March 2020, with a "recommendation" not to leave the house unless necessary (UK Government, 2020). In addition, Transport for London announced restrictions on services on its transport network on 18 March 2020 (TFL, 2020), and a full (national) lockdown was implemented on 23 March 2020, with "guidance and advice" to avoid unnecessary travel and maintain social distance [18].

According to statistics provided by Google (Google 2020), the total global traffic volume decreased in the range of 40 to 65% as a result of the COVID-19 epidemic. The output of the passenger sector in China declined more than that of the freight sector; the output of the freight sector was expected to decline by 1.03–2.85%, and that of the passenger sector by 3.08–11.44% [19]. The outbreak in Wuhan, China, in early 2020 coincided with the peak of spring transportation and the city's special location as a "thoroughfare through nine provinces", necessitating a citywide lockdown policy to block the transmission route of the epidemic, which directly led to a reduction in traffic and residential activities by more than 50% [20], and there was a trend of declining physical activity and well-being among adults during the second COVID-19 outbreak blockade in Germany [21]. In 2017, 2018, and 2019, the movement of Spring Festival passengers in China was 2.981 billion, 2.971 billion, and 2.981 billion, respectively. The outbreak coincided with the eve of the Spring Festival in 2020, which had been expected to see a peak of about 3 billion travelers, but due to the epidemic, passenger movement dropped significantly to 1.319 billion.

In the face of the rampant spread of the global COVID-19 epidemic, attention has also been given to constructing applicable models to analyze and predict the links between the epidemic and transportation networks in the context of epidemic transmission mechanisms and development patterns. Studies have shown that the spread of the epidemic has a strong positive correlation with population movement and migration, and that transportation contributes to the spread of the epidemic and accelerates the spread of viruses and diseases [22–25], Browne et al. compared SARS, MERS, and coronavirus and found that air transportation accelerated and amplified influenza transmission [24]. Zhu et al. used a random effects panel data model and a reverse difference (DDR) model and found that Wuhan's high-speed rail and airline had a significant positive impact on the number of new confirmed cases, with a 25.5% higher daily average of new confirmed cases in cities directly connected to Wuhan than in cities not directly connected. Air transport was less affected than high-speed rail transport [26]. Zhang et al., in their study on the impact of cross-regional outbreaks of COVID-19 on controlling its spread, found that city closures were not the best strategy to contain outbreaks; in fact, a purely urban closure might not mitigate the effects of the virus without accompanying nonlockdown measures such as conditional isolation, as occurred in Italy, Spain, and New York [27]. In this paper, we focus more on COVID-19 and the connection between epidemic prevention and control measures and traffic, so the research work on epidemic spread is not covered here.

In a review of 418 policy measures adopted in Australia, Canada, Japan, New Zealand, the United Kingdom, and the United States, Zhang et al. concluded that policy measures to combat COVID-19 with regard to public health and transportation were not associated with a decline in either cumulative deaths or cumulative infections, and the continued increase in global confirmed cases from 2020 to the present may support their findings [28]. At the same time, it is noteworthy that people's travel patterns have changed significantly over the course of the epidemic, with many scholars [29,30] finding that COVID-19 has had a significant impact on public transportation services, travel behavior, and travel mode preferences worldwide, with public transport use declining sharply. Results based on such studies can help authorities give some consideration to people's travel preferences in the context of the epidemic when formulating policies.

The results of the abovementioned studies suggest that in the post-epidemic era we should take advantage of the role of the transportation system as a link and transmitter in the normal functioning of all sectors of society. The two cases of the epidemic in Beijing selected for this paper provide a database for studying the impact of epidemic prevention and control measures on transportation activities, which can be used to study the mechanism of the impact of such strategies on travel during COVID-19. Based on the description of data sources in Section 3, the spatiotemporal distribution characteristics of the development of the Spring Festival and Xinfadi epidemics and their impact on traffic are discussed in Section 4, and the conclusions and limitations of this paper are presented in Section 5. Figure 1 shows the content structure of this study.

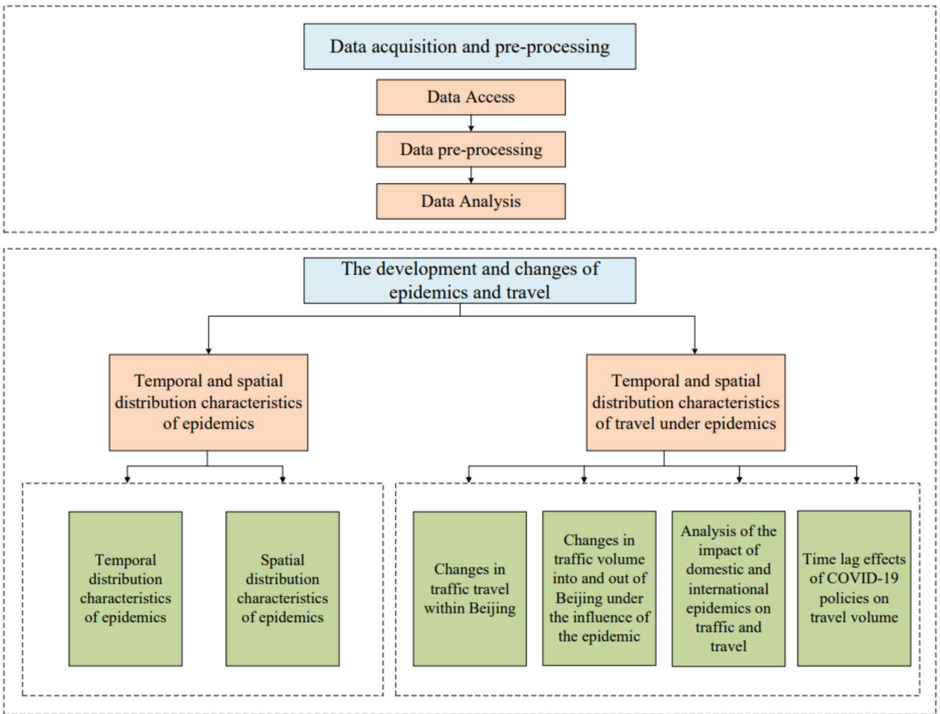

Figure 1. Content structure of this study.

3. Data Description

The scope of this study is Beijing Municipality as a whole, and the data include reported cases of COVID-19 during the Spring Festival pandemic, reported cases during the Xinfadi cluster outbreak, and the series of control measures issued by the government during each time period, including case data and various control measures from the Beijing Municipal Health Commission (http://wjw.beijing.gov.cn/ (accessed on 29 June 2021)), the National Health Commission (http://www.nhc.gov.cn/ (accessed on 29 June 2021)), and statistics published by the Beijing Municipal Government (http://www.beijing.gov.cn/ (accessed on 29 June 2021)). The time span of the Spring Festival phase of the study was 20 January to 30 March 2020 and the time span of the Xinfadi phase was 1 June to 6 August 2020, with the cumulative confirmed cases counted for each district in Beijing.

Beijing cell phone signaling data from a certain mobile phone operators, obtained as the original traffic data, were converted into traffic data according to the mobile phone signaling data processing method [31]; the dataset does not contain user identification information and does not extract the specific travel trajectories of users. Since failed signaling data do not necessarily reflect users' real location information and cannot be used to analyze travel OD, such data were filtered in the process. For the problem of missing data in some time periods, the missing values were completed based on the proportion of travel volume in each time period under normal conditions.

The steps to obtain the traffic volume in and out of Beijing were as follows:

1. Divide Beijing into eight directions: north, northeast, east, southeast, south, southwest, west, and northwest, based on the main roads into and out of the city.
2. When obtaining the traffic volume into Beijing, 5 km of the boundary line is area O, and the remaining part within the boundary line is area D.

The opposite was true for the regional division of outbound traffic to obtain OD.

The traffic demand data were obtained after processing the raw cell phone signaling data, which covered 89 days under normal conditions without the outbreak, 60 days during the resumption of work and production after the Spring Festival was affected by the pandemic, and 30 days during the Beijing Xinfadi outbreak.

4. The Development and Changes of Epidemics and Travel

Spring Festival marks the Lunar New Year, accompanied by a travel rush causing massive transportation stress. During this period, traffic congestion occurs as the number of passengers rises across the country as people return to their hometowns and go out for activities. The initial phase of the outbreak coincided with the Spring Festival period. The widespread movement of people accelerated the spread of the pandemic.

The epidemic outbreak in June 2020 was highly related to the city's largest wholesale market, Xinfadi Market. It was the source of the local pandemic, which is known as the "vegetable basket of the capital", is located in the Huaxiang area; it is 21 times larger than Wuhan's south China seafood market and responsible for more than 90% of Beijing's supply of vegetables and fruits, and has the highest trading scale in Beijing. The market is densely populated and highly mobile, with many sources of people coming and going. In view of the nature of the Xinfadi market and its impact on Beijing, if the spread of the Xinfadi epidemic had not been contained, the impact would have been catastrophic.

The following is a summary of some important time points during the development of the epidemic cluster in Xinfadi market and the measures introduced (Figure 2).

4.1. Temporal and Spatial Distribution Characteristics of Epidemics

4.1.1. Temporal Distribution Characteristics of Epidemics

Figure 3a shows the development of the novel coronavirus in Beijing from 20 January to 30 March 2020, including the current number of existing confirmed cases and the number of new cases in Beijing. Figure 3b shows the current number of confirmed cases, obtained after removing imported cases shown in Figure 3a.

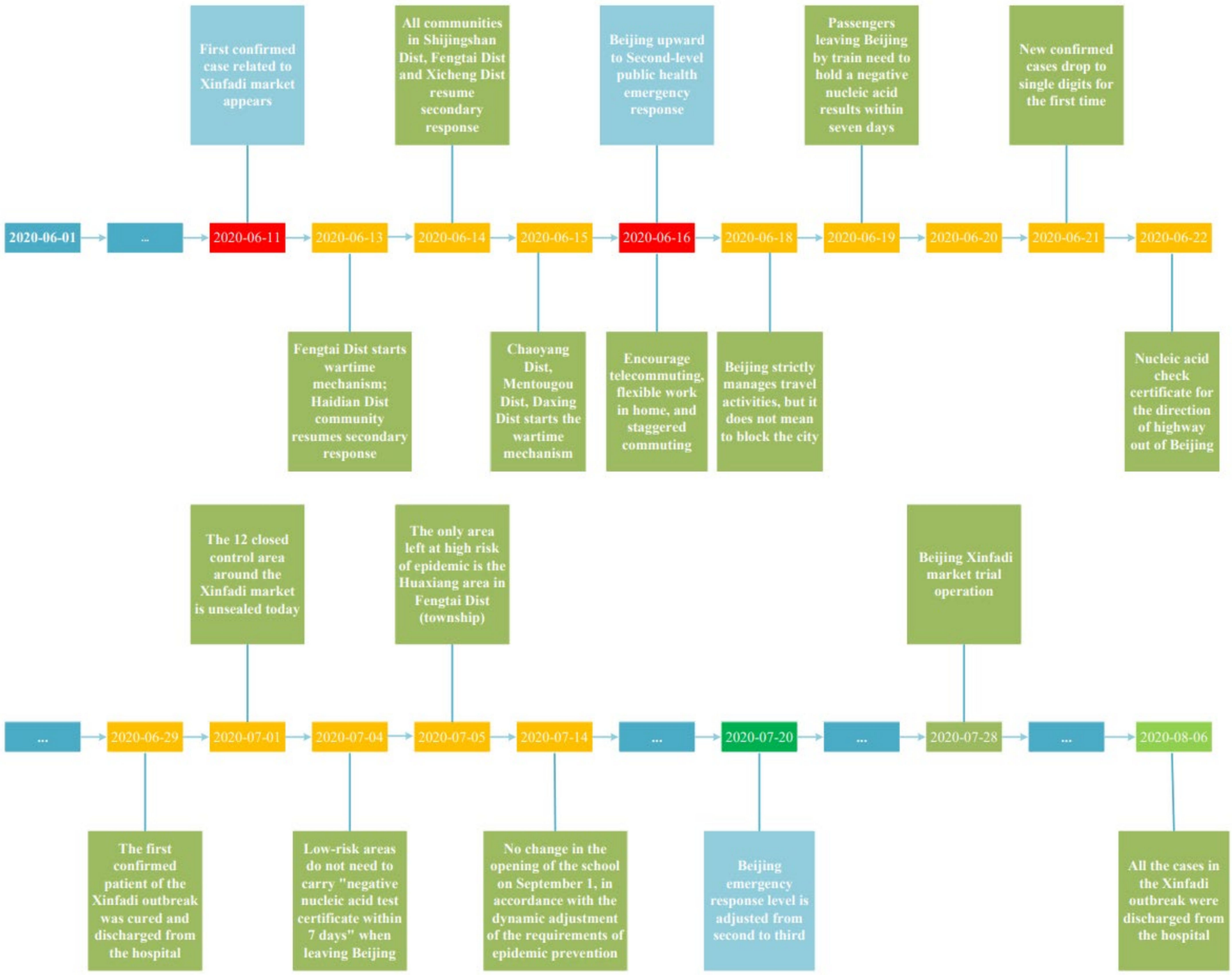

Figure 2. Xinfadi outbreak prevention and control measures.

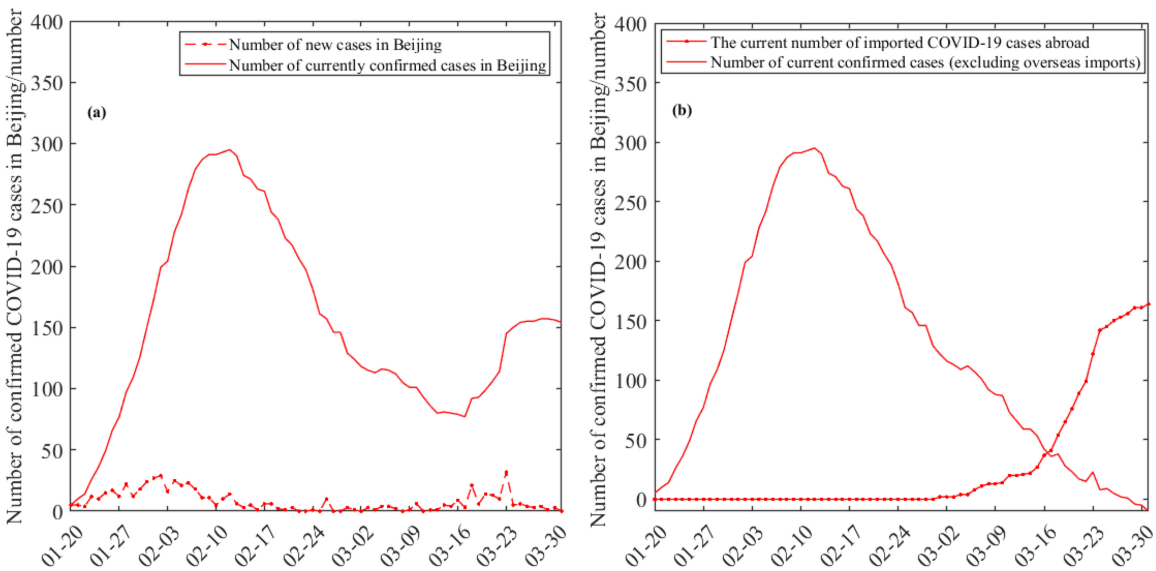

Figure 3. (**a**) New and cumulative confirmed cases in Beijing, and (**b**) overseas imported and cumulative confirmed cases in Beijing (excluding overseas imported).

Compared to the COVID-19 outbreak during the Spring Festival, the Xinfadi outbreak spread rapidly, with clusters of cases appearing within a short period of time; it took only 5 days from the first to the 100th new case (Figure 4).

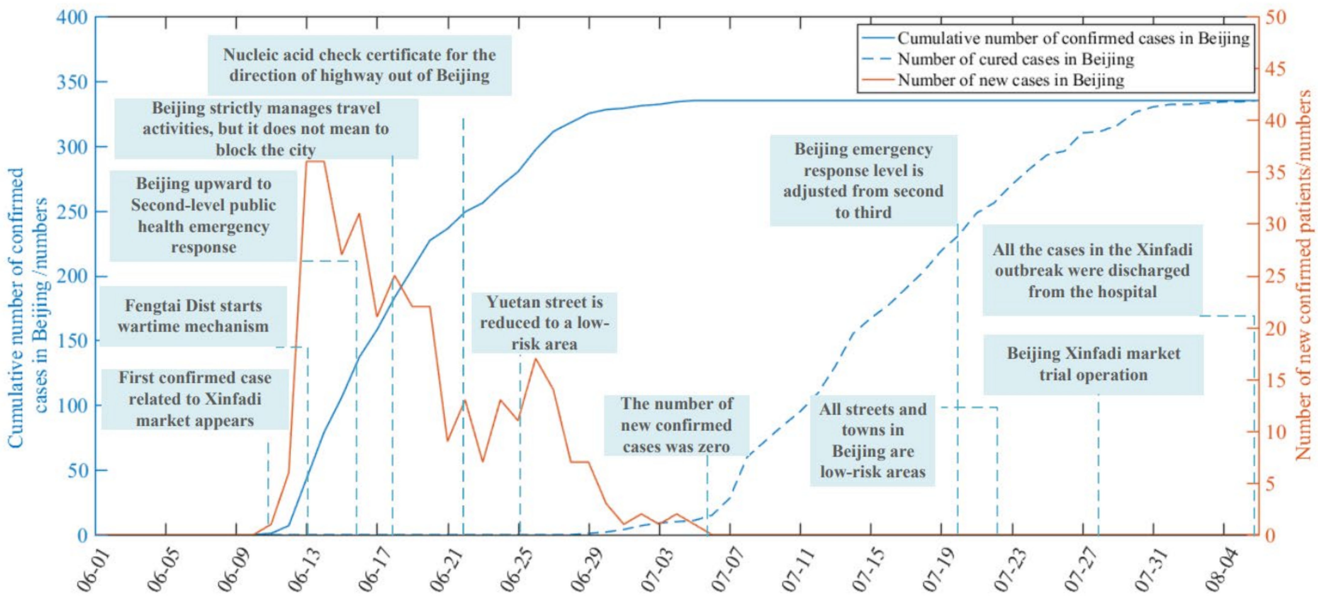

Figure 4. Trend in number of reported cases during Xinfadi epidemic over time.

4.1.2. Spatial Distribution Characteristics of Epidemics

Figure 5a shows the distribution of the number of confirmed novel coronavirus diagnoses by region in Beijing from when the first case appeared until the end of March 2020, with Haidian and Chaoyang Districts recording the highest numbers of confirmed cases. There were 335 clustered cases in the Xinfadi epidemic and the distribution of the confirmed cases in each district of Beijing in the Xinfadi outbreak is shown in Figure 5b. The spread of the epidemic was centered on the Xinfadi market; 221 cases (66%) were within 5 km, 270 cases (80.6%) within 10 km, and 314 cases (93.7%) within 15 km. This shows that this was a single-point localized outbreak of an aggregated epidemic, which later spread to 11 districts.

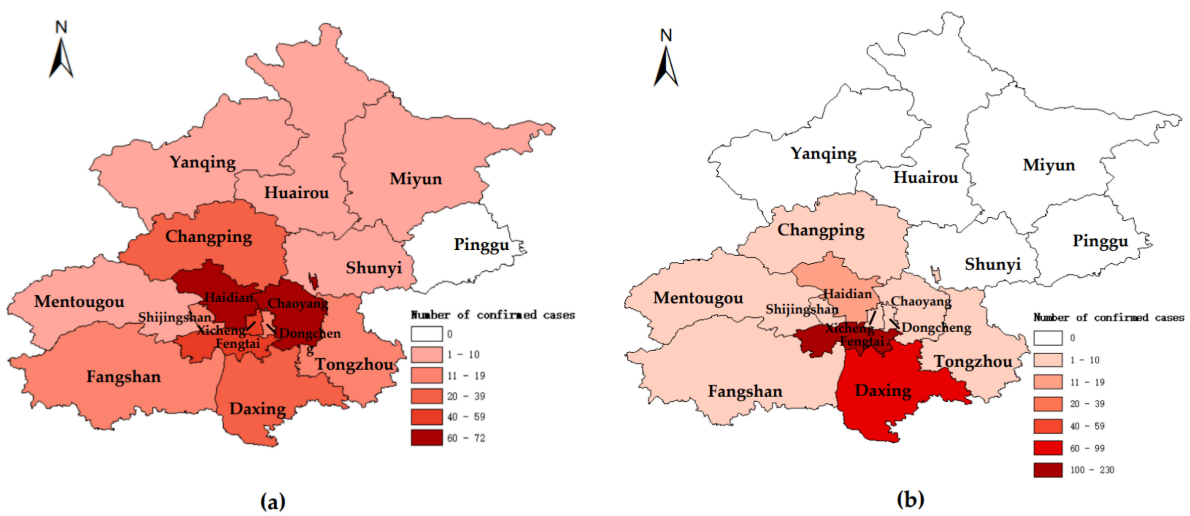

Figure 5. (**a**) Distribution of the number of confirmed cases of COVID-19 in Beijing by region in the Spring Festival pandemic, and (**b**) distribution of the number of confirmed cases of COVID-19 in Beijing by region in the Xinfadi epidemic.

Compared with the epidemic during the Spring Festival, the Xinfadi epidemic was not affected by the mass migration caused by special factors such as the Spring Festival travel rush. Therefore, in Beijing, the confirmed cases occurred in 11 districts, while cases occurred in 15 districts during the Spring Festival.

A total of 46 medium-risk and high-risk streets (towns) were involved in the whole epidemic outbreak in Xinfadi Market, as shown in Figure 6 (only partly marked). The area marked red is the range of five high-risk streets.

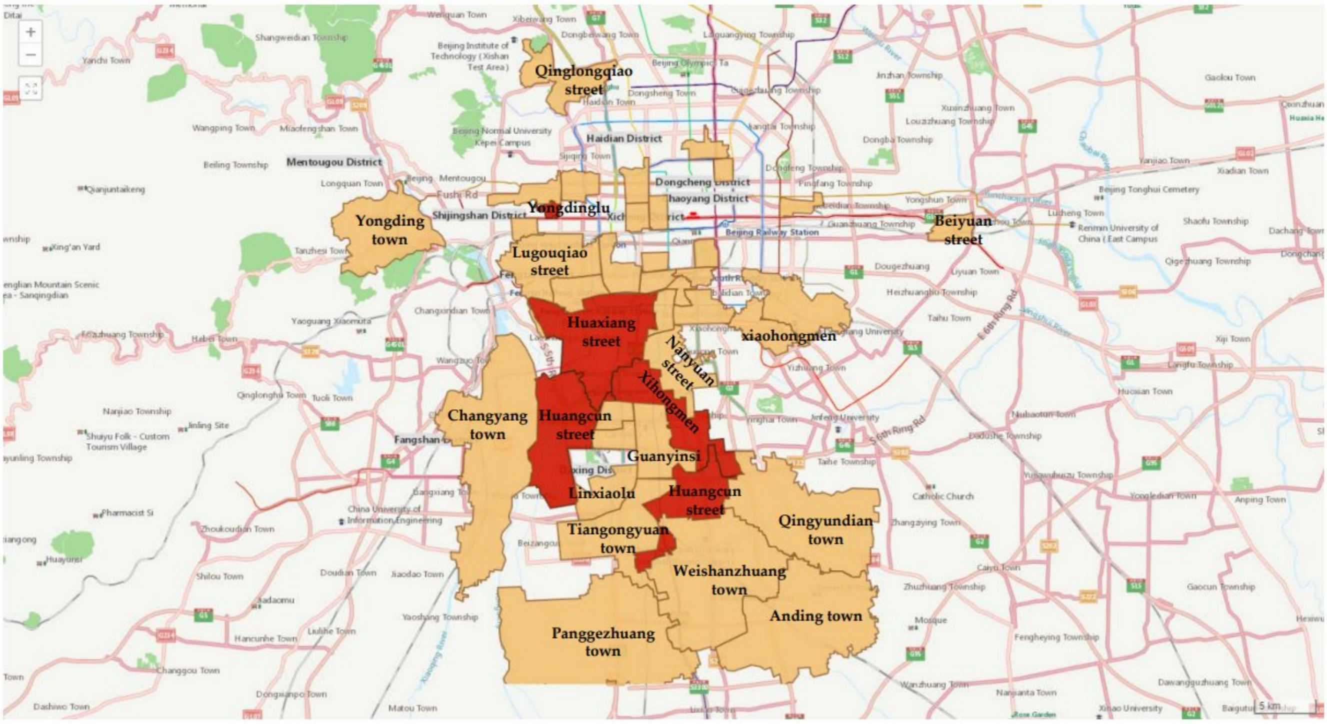

Figure 6. Distribution of epidemic-risk neighborhoods (townships).

Considering the delay in the release and dissemination of information about the epidemic among the general public, a correlation analysis was conducted between traffic volume decline and the related epidemic factors after n days, and the results are shown in Table 1. It can be seen that decreased traffic volume is significantly correlated with the numbers of cumulative confirmed cases and medium- to high-risk streets when compared to a delay of one day in the release of epidemic-related information.

Table 1. Correlation analysis of epidemic-related factors and reduced traffic volume.

Factors		N(t + 0)	N(t + 1)	N(t + 2)	N(t + 3)	N(t + 4)
Cumulative number of confirmed cases	Pearson correlation	0.880	0.879	0.87	0.844	0.823
	Sig. (bobtail)	0.000	0.000	0.000	0.000	0.000
	Number of cases	28	28	28	27	26
Number of new confirmed cases	Pearson correlation	0.196	0.361	0.519	0.545	0.476
	Sig. (bobtail)	0.316	0.059	0.005	0.003	0.014
	Number of cases	28	28	28	27	26
Medium- to high-risk street numbers	Pearson correlation	0.866	0.887	0.866	0.848	0.826
	Sig. (bobtail)	0.000	0.000	0.000	0.000	0.000
	Number of cases	28	28	28	27	26

4.2. Temporal and Spatial Distribution Characteristics of Travel under Epidemics

4.2.1. Changes in Traffic Travel within Beijing

This section examines the characteristics of changes in traffic demand within Beijing's districts and in and out of the city relative to 2019 under the influence of the dual factors of the Spring Festival holiday and the novel coronavirus outbreak.

Due to the epidemic prevention measures, the traffic volume within Beijing during the Spring Festival showed a downward trend compared to the same period the previous year. We can see that the total traffic volume in February 2020 had a year-on-year decrease of 67.8%. Additionally, the total travel volume in Beijing in the first two weeks of June 2020 under normal conditions was lower than in the same period the previous year. The total travel volume for the entire Beijing Municipality decreased by 25.3% during that period.

On the 23rd day of the first lunar month of 2019, the total traffic volume in Beijing was between 13 million and 14 million (Figure 7a). On the 23rd day of the first lunar month of 2020, the total traffic volume was only about 3 million (Figure 7b). The return trend of the Spring Festival tourist season in 2020 is the same as that in 2019. However, due to the impact of the epidemic, it was orders of magnitude smaller than the trend of traffic volume during the return journey in 2019.

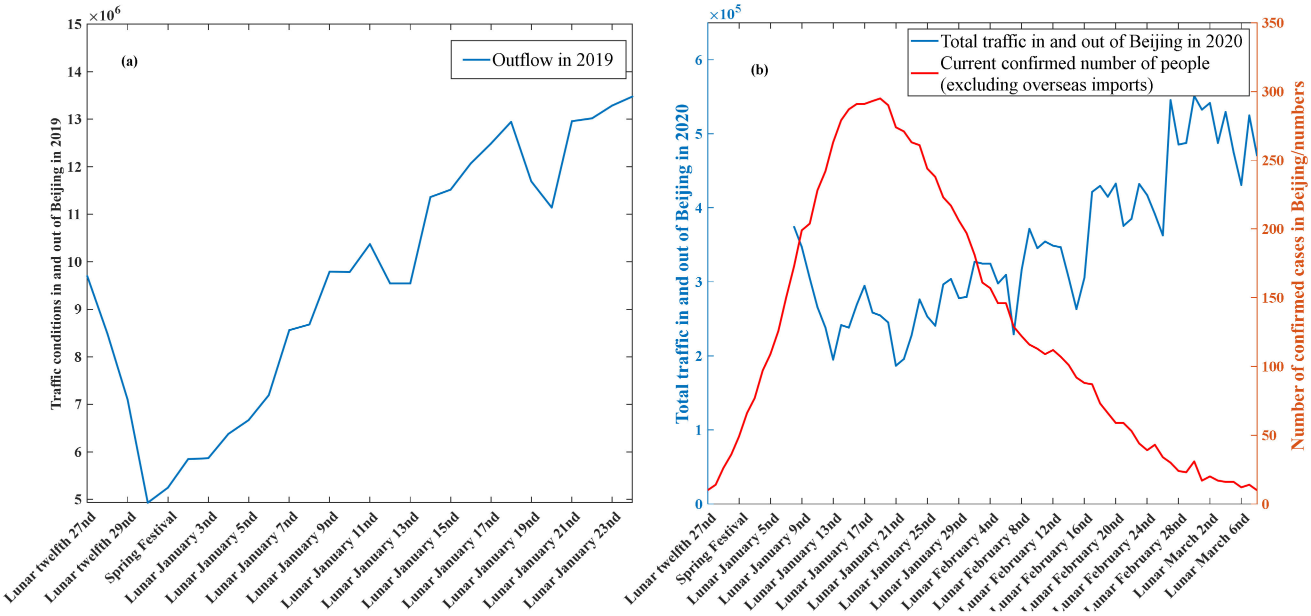

Figure 7. (**a**) Normal traffic volume trend within Beijing in February 2019 and (**b**) comparison of traffic volume and confirmed coronavirus cases in Beijing.

As shown in Figure 8, during the two epidemics in Beijing, the districts and counties with larger decreases in travel volume are represented by Chaoyang, Haidian, Dongcheng, Xicheng, and Fengtai Districts, so it is believed that both outbreaks had a large impact on traffic in the central city.

During the period of the Xinfadi outbreak, due to the implementation of restrictions such as booking and restriction of traffic during time slots and distant evacuation under the secondary response to major public health events, Dongcheng and Xicheng Districts, with a higher concentration of celebrities' residences and places of interest in Beijing, experienced the greatest decrease in travel volume, 40.76 and 33.37%, respectively, compared to the same period in 2019. Fengtai District accounted for 68.7% of confirmed cases reported in the outbreak, with a 31.37% decrease in travel volume, and Daxing District ranked second in the number of confirmed cases, with a 26.06% decrease in travel. Shijingshan District, one of the central urban areas involved in the epidemic at that time, saw a 19.41% drop in travel volume due to its small footprint, small population base, and low percentage of cross-district travel volume (Figure 9).

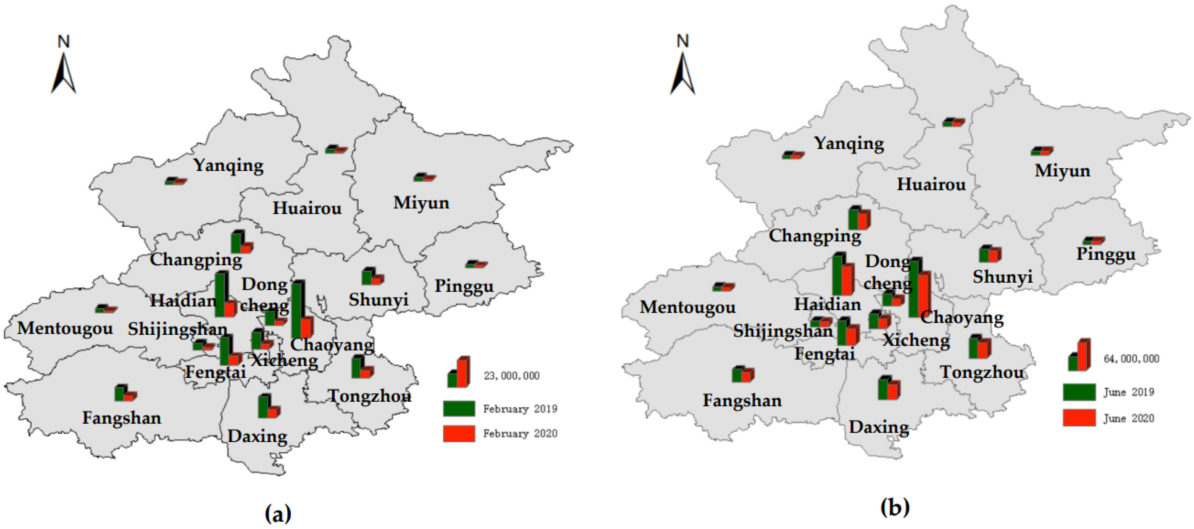

Figure 8. Comparison of traffic volume in each district of Beijing in February 2019 and 2020: (**a**) Spring Festival epidemic and (**b**) the Xinfadi epidemic.

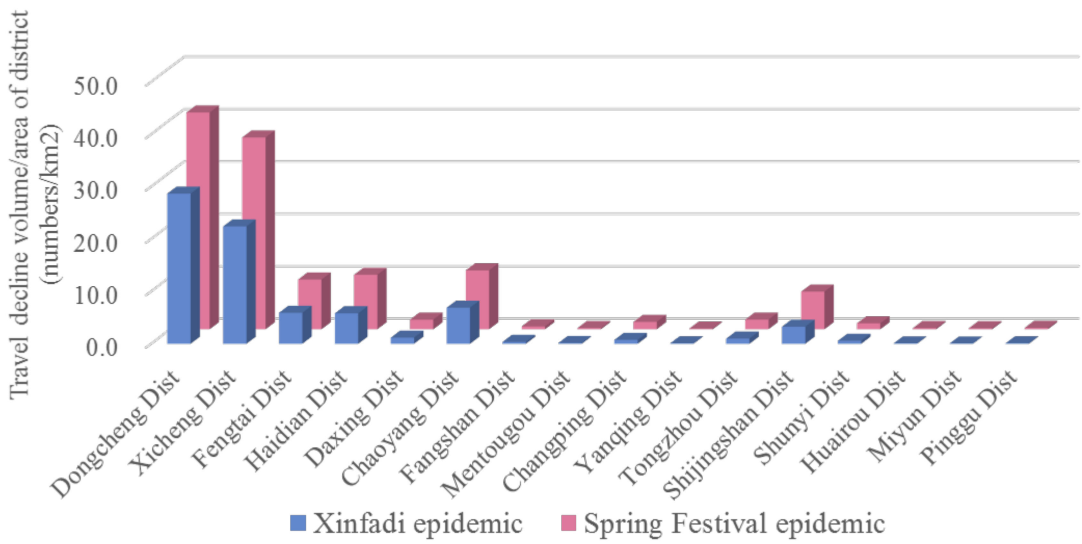

Figure 9. Decline in travel volume per unit area in Beijing, by district and county.

The traffic conditions in Beijing were basically consistent with the economic, population, and development level of each district. Within the scope of Beijing, Chaoyang, Haidian, Fengtai, Dongcheng, and Xicheng Districts, all have relatively well-developed economic and cultural industries. The travel population is relatively concentrated. As a consequence, the degree of decrease in each district was influenced by the development characteristics of the epidemic itself and the control measures; the geographic location and development level of each district were also among the influencing factors.

The travel recovery after the epidemic is also affected by many of the same factors. After the Spring Festival, the travel conditions (the average of the occurrence of the morning peak) in each district were as follows (Figure 10). Traffic activity was gradually restored from the central six districts to the outer districts.

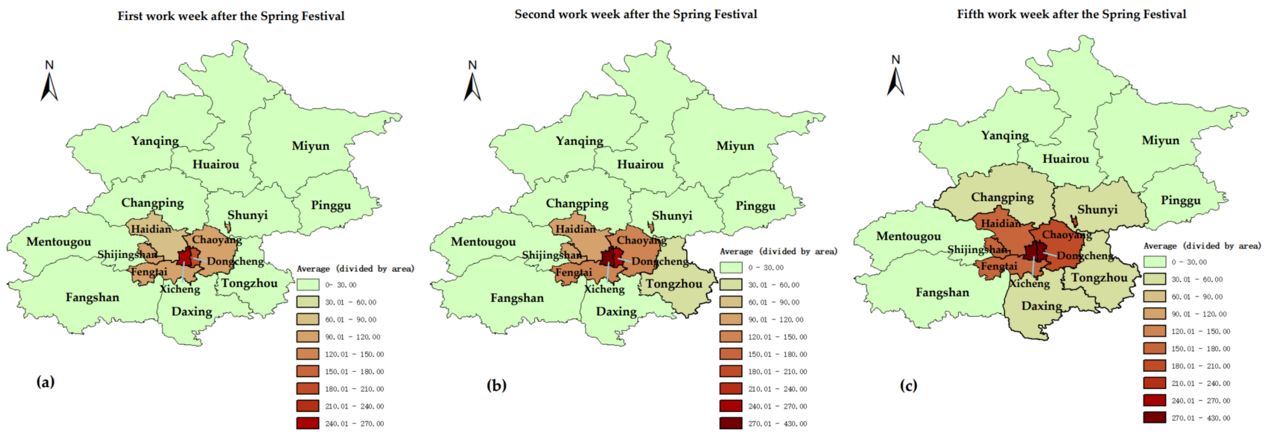

Figure 10. Morning peak recovery in Beijing from 7:00–9:00 a.m.: (**a**) the first working week after Spring Festival 2020 (10–14 February), (**b**) the second working week after the Spring Festival in 2020 (17–21 February), and (**c**) the fifth working week after the Spring Festival in 2020 (9–13 March).

The daily travel cycle in the Huaxiang area under normal conditions includes significant morning and evening peak patterns during weekdays; the maximum of morning and evening peaks dropped significantly in the first week after the epidemic, but overall, significant commuting characteristics were retained, and commuting was weaker during weekdays in the second week after the epidemic (22 to 28 June 2020), as shown in Figure 11.

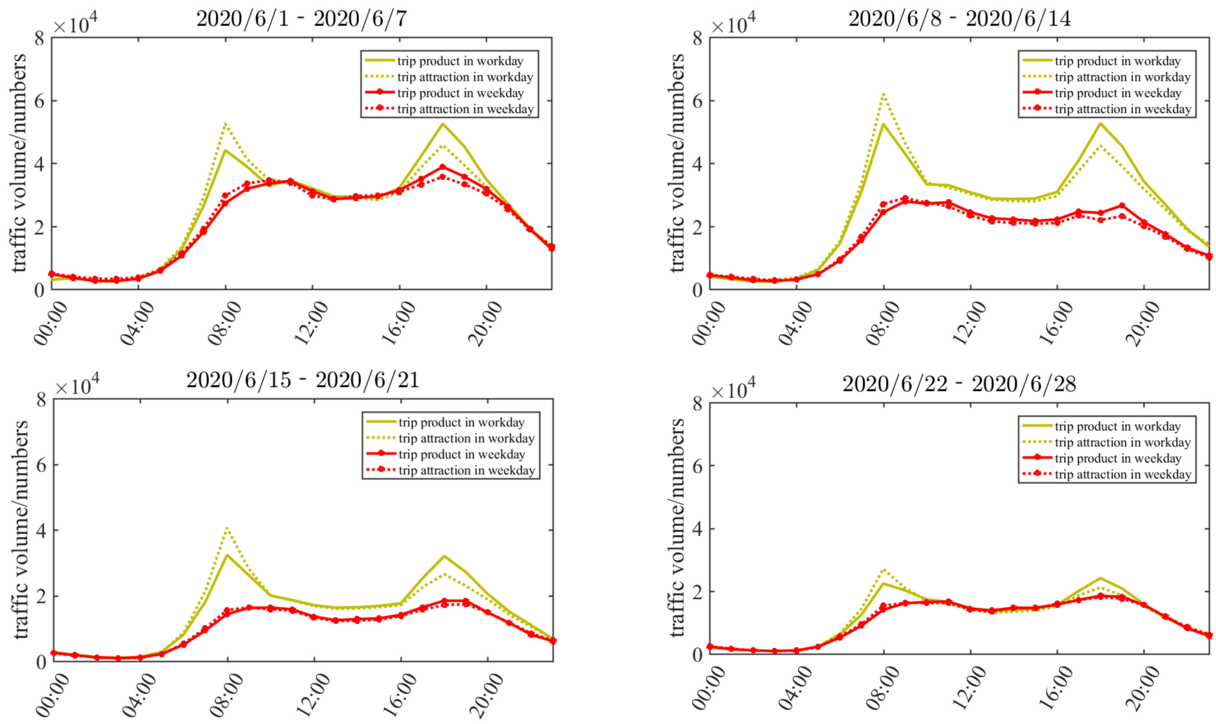

Figure 11. Change in travel volume in the Huaxiang area for four weeks in June 2020.

Under normal conditions, they have obvious commuting characteristics and cyclical properties. Travel on nonworking days after the outbreak was more sluggish than normal. This shows that in the middle and late stages of the epidemic, the decline in travel volume was not as sharp as that in the early stages.

While people responded positively to the prevention and control policies during the epidemic, they also reduced their travel activities during the concentrated travel time-out so that they would not increase their risk of infection. The overall distribution of daily travel during the day is not affected by the measures.

4.2.2. Changes in Traffic Volume into and Out of Beijing under the Influence of the Epidemic

Under normal circumstances, Beijing has the largest amount of traffic from inside and outside the city to the south, southeast, and east (Figure 12). The provinces with the widest population distribution and frequent economic and trade exchanges are mainly located in the southeast coastal cities and south of Beijing. The traffic volume in and out of the city in February 2020 dropped significantly compared to the same period in 2019, but the proportion of traffic activity in all directions did not change. Among the eight directions, the traffic volume is still mostly east, southeast, and south.

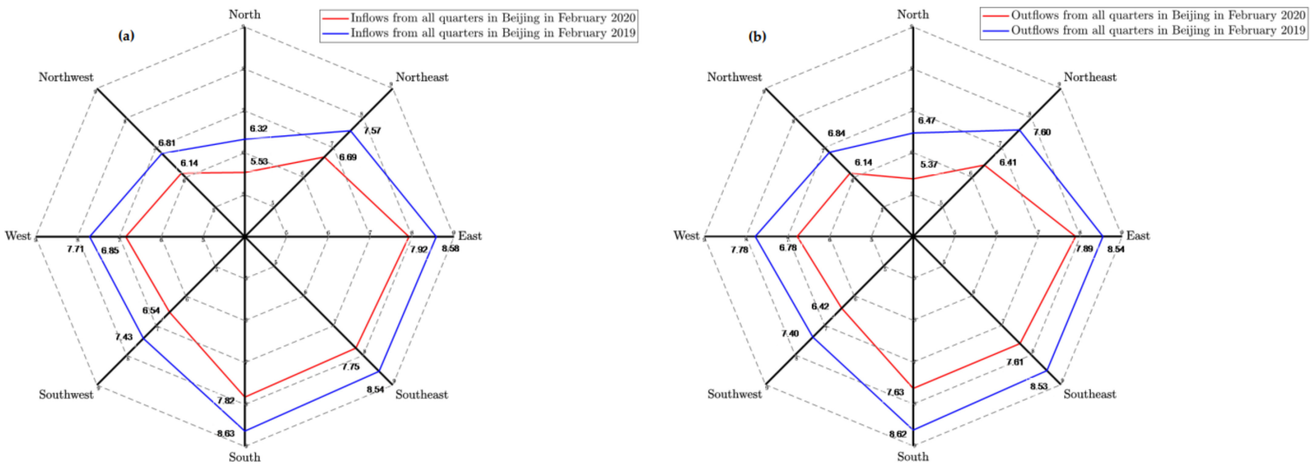

Figure 12. (**a**) Beijing's inflow volume in 2019 compared to 2020. (**b**) Beijing's outflow volume in 2019 compared to 2020.

During the Xinfadi epidemic, from 11 June to the end of the month, the inflow and outflow of the city generally both showed the same downward trend (Figure 13), except for travel fluctuations due to weekday and off-day reasons. Compared with the same period in 2019, in 2020 the total inflow to Beijing decreased by about 6.24 million trips and the total outflow decreased by about 10.27 million.

4.2.3. Analysis of the Impact of Domestic and International Epidemics on Traffic and Travel

To reduce the spread of infection, many other countries have imposed strict travel restrictions on people's travel and business. Some countries gradually or suddenly resorted to imposing restrictions that have resulted in partial or complete embargoes (https://www.gco.gov.qa/en/media-centre/press-release/ (accessed on 27 June 2020)). The embargo measures have limited the amount of travel and activity people can engage in globally, which has had a direct impact on people's travel characteristics. In the same way that the two outbreaks in Beijing had a limiting impact on total travel, travel activity in the UK has gradually decreased since 8 March 2020 with the introduction of a series of prevention and control measures and stabilized at around 80% after the implementation of the blockade [18]. During the same period, traffic during the Spring Festival fell by about 70% year-on-year due to the impact of the epidemic and prevention policies, and total travel in Spain fell by more than 40% in 2020 [32]. Because of the different points in time when restrictions were implemented in each country, some countries gradually implemented restrictions on travel, and some suddenly implemented restrictions that resulted in partial or complete blockades, and these restrictions changed the amount of travel on a global scale [16].

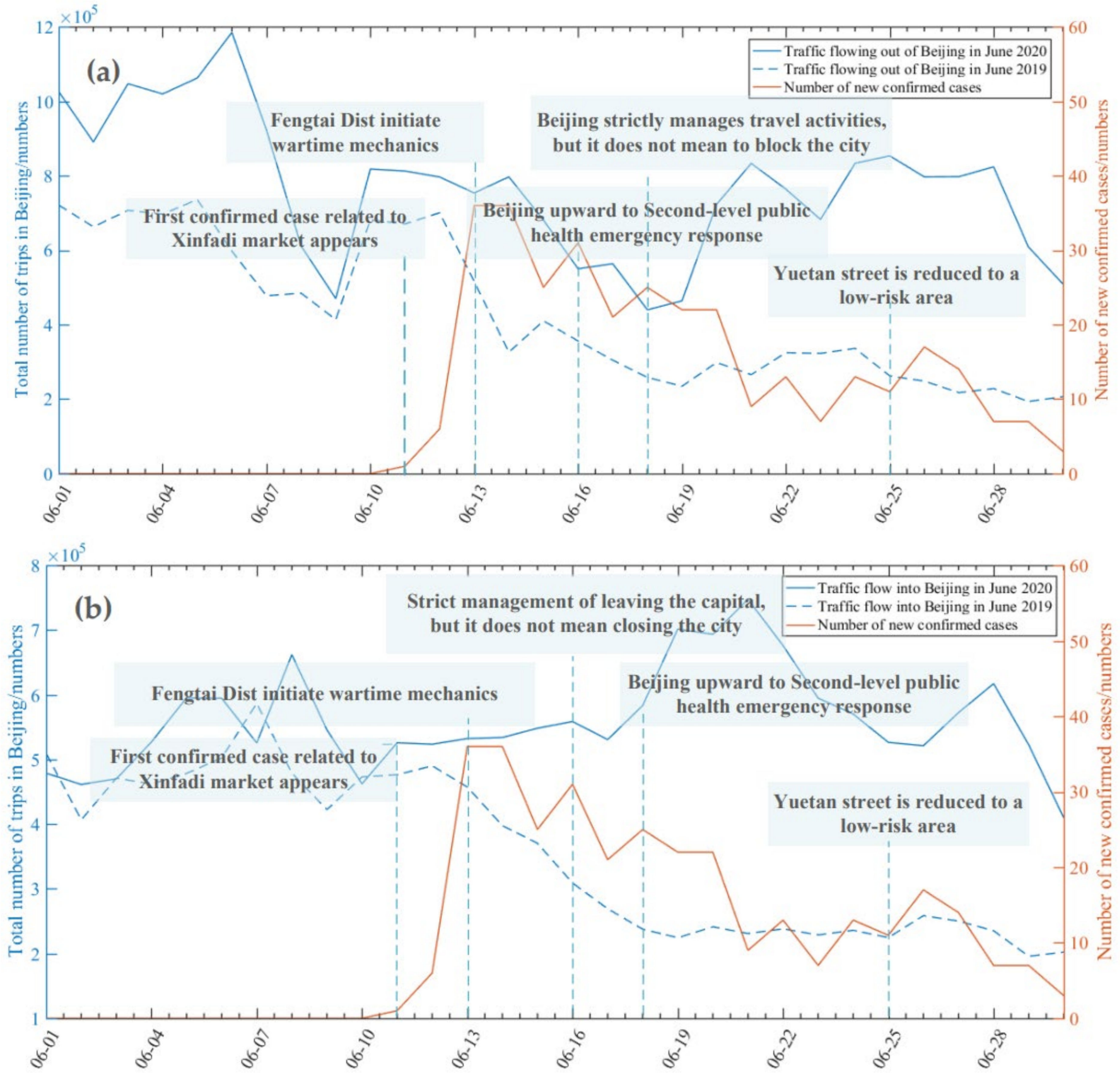

Figure 13. (**a**) Relationship between traffic volume to and from Beijing and new confirmed cases, and (**b**) relationship between traffic volume into Beijing and new confirmed cases.

Meanwhile, there was also a shift in people's travel mode choices during and after the epidemic. Combining the results of two samples from Beijing during the epidemic and the Spanish government [32] during the pandemic, people limited their choice of public transportation and more often chose to drive individually. According to data from the Ministry of Transport (Figure 14), passenger traffic in Beijing showed a significant decline in February when the epidemic was severe, dropping 83.8% compared to the same period the previous year. Total passenger traffic in Beijing in June was down 46.7% compared to the same month the previous year. After the implementation of restrictions in Spain, the proportions of people choosing private cars and walking greatly increased, and the proportion of people choosing public transportation was greatly reduced. People's consideration of factors such as the safety of the transportation mode and the possibility of infection was an important component of the decline in public transportation use.

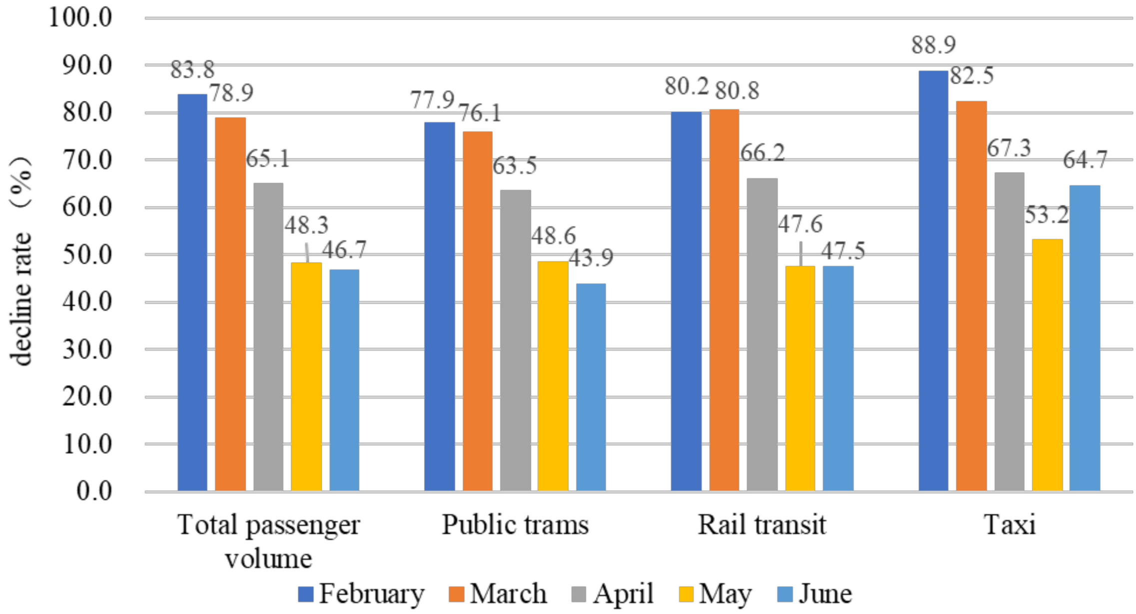

Figure 14. Comparison of passenger traffic in Beijing for the same period in 2020.

4.2.4. Time Lag Effects of COVID-19 Policies on Travel Volume

As shown in the previous analysis, during the spread of the epidemic, local governments or institutions may implement a series of prevention and policies to slow the spread of the epidemic, and the implementation of these policies will bring a certain degree of effect to the transportation system. However, these changes will not be reflected in liquidity immediately, but will be reflected in some future period.

We use change point detection to identify changing points in traffic volume to quantify the time lag effects of the COVID-19 pandemic and policies. Change point detection goes through model selection and chooses the appropriate segmentation to minimize the objective function. Formally, linear penalties are linear functions of the number of change points, meaning that:

$$pen(\omega) = \beta(\omega) \tag{1}$$

The computationally efficient PELT algorithm is chosen here, with the main assumption that the number of change points increases linearly with the size of the data, and that the change points are not limited to a portion of the data [33,34]. Precisely, for two indexes t and s ($t < s < T$), the pruning rule is written as:

$$\text{if}\left[\min_{\omega} V(\omega, y_{0..t}) + \beta|\omega|\right] + c(y_{t..s}) \geq \left[\min_{\omega} V(\omega, y_{0..s}) + \beta|\omega|\right] \tag{2}$$

If this relationship holds, then t cannot be the last change point prior to T.

The length of the lag is calculated as the difference between the policy's implementation date and the date detected by the change point detection algorithm. Based on the model calculation results, combined with the actual background and policies, the date of the change point screened out is shown in Figure 15.

Each section between the two change points is in a stable trend. Due to the severity of the epidemic and the activation of the wartime mechanism in Fengtai District, and from 16 June to 21 June, Beijing announced that the public health level was raised to Level two, resulting in a continuous decline in traffic volume for five days. For example, after the outbreak began on 11 June, traffic began to drop on 12 June, with a lag of 1 day. From 11 to 13 June, a series of measures was introduced, such as suspending classes, closing a number of residential areas around the market, launching a wartime mechanism in Fengtai District, and flexible work from home, these led to a precipitous 50% drop in travel volume from the norm in the Huaxiang area. These drastic changes are uncommon in our transportation system. Understanding the delay effects over time can inform how long it takes for the impact of COVID-19 policies to be reflected in various transportation systems, and when transportation systems should prepare to adapt to these changes.

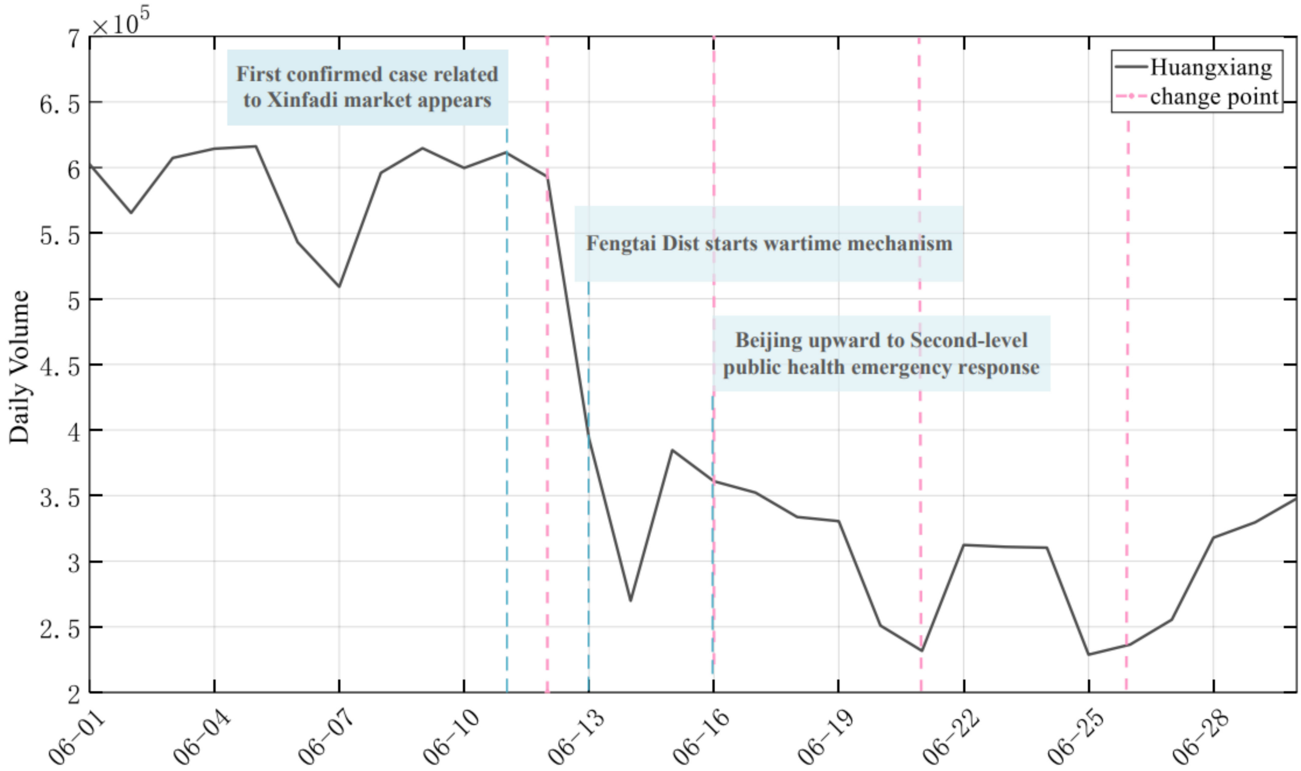

Figure 15. Detection results of daily volume change points for Huaxiang Street.

5. Conclusions and Limitations

This paper studies and analyzes the impact of COVID-19 on changes in traffic demand in Beijing and summarizes the relevant measures introduced in the city during the pandemic. In the context of domestic and foreign epidemics, we analyzed the impact of the epidemic and its corresponding policies on transportation.

COVID-19 has had a great impact on the transportation needs of people around the world. Compared with the normal situation, the overall traffic volume inside and outside Beijing during the two epidemics showed a significant downward trend. This decline in traffic volume is the result of multiple factors involving regional population, economic development level, etc. In addition, under the control of government measures and based on their own willingness to travel, people have changed. Compared with other urban areas, the traffic volume in the central city of Beijing has fallen to a greater extent, but the overall distribution characteristics of daytime transportation have not been affected. The number of medium- and high-risk streets, the cumulative number of confirmed cases, and the degree of decline in traffic volume show a significant correlation. In the choice of travel mode, people have also limited their choice of public transportation in order to reduce infectivity. Therefore, it is precisely because the transportation system plays a role as a link in various sectors of society, so in the period after the COVID-19 epidemic, discussing the mechanism of the role of the epidemic and various measures on transportation activities has a significant impact on the normal operation of society and the restoration of social functions. The results of the analysis above can provide a reference for how to coordinate the work of various sectors of society through traffic management, in order to achieve the purpose of not only blocking the spread of the epidemic, but also for maintaining people's daily routine during the epidemic.

This study only uses traffic volume in Beijing and official data from the Ministry of Transport as research data. Although it can directly reflect the trends and directions of changes in traffic demand with the spatial and temporal characteristics of the development of the epidemic and the prevention and control policies, further specific studies are needed to examine the mechanism of the profound impact of the epidemic on transportation demand. This study does not focus on the prediction of traffic volume and the propagation mechanism of the epidemic by transportation mode. Finally, the change point detection model is only used for the change detection of traffic volume, and it is analyzed in combination with the policy. In-depth modeling and derivation are not carried out. We will continue to address these issues and improve the analysis in future work.

Author Contributions: Methodological theory and article structure design, W.G. and J.T.; data acquisition and analysis, Y.F. and W.L.; writing—original manuscript preparation, Y.F. and W.L.; writing—review and editing, Y.F.; language organization and review, Y.R. and X.J.; proofreading, Q.X. All authors have read and agreed to the published version of the manuscript.

Funding: This research was supported by the National Key Research and Development Program of China (2018YFB1601100), the National Natural Science Foundation of China (51805034), the Youth Top Talent Training Program of Beijing (CIT&TCD201904013), and the General Program of Science and Technology Plan of Beijing Municipal Education Commission (KM202010009007).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The case data and various measures of the COVID-19 epidemic are from the official websites of the government and relevant institutions. The website links are given in the article. The cell phone signaling data used in this article are from the Ji Smart Platform, which is an online data platform that cannot be shared, and we currently do not have login access. Although we cannot share raw cell phone signaling data, we present the results of the analysis of the data in this paper.

Acknowledgments: We thanks for all the funding support for the research, the data provided by the Ji Smart Platform and related websites, and the authors listed in the references for the important research content and conclusions.

Conflicts of Interest: We declare that we have no financial and personal relationships with other people or organizations that can inappropriately influence our work; there is no professional or other personal interest of any nature or kind in any product, service, and/or company that could be construed as influencing the position presented in this manuscript or in its review.

References

1. Munawar, H.S.; Khan, S.I.; Ullah, F.; Kouzani, A.Z.; Mahmud, M.A.P. Effects of COVID-19 on the Australian Economy: Insights into the Mobility and Unemployment Rates in Education and Tourism Sectors. *Sustainability* **2021**, *13*, 11300. [CrossRef]
2. Nundy, S.; Ghosh, A.; Mesloub, A.; Albaqavy, G.A.; Alnaim, M.M. Impact of COVID-19 pandemic on socio-economic, energy-environment and transport sector globally and sustainable development goal (SDG). *J. Clean. Prod.* **2021**, *312*, 127705. [CrossRef]
3. Rothengatter, W.; Zhang, J.; Hayashi, Y.; Nosach, A.; Wang, K.; Oum, T.H. Pandemic waves and the time after COVID-19—Consequences for the transport sector. *Transp. Policy* **2021**, *110*, 225–237. [CrossRef]
4. Zhang, Q.; Tong, Q. The economic impacts of traffic consumption during the COVID-19 pandemic in China: A CGE analysis. *Transp. Policy* **2021**, *114*, 330–337. [CrossRef] [PubMed]
5. Zhang, J.; Hayashi, Y.; Frank, L.D. COVID-19 and Transport: Findings from a World-wide Expert Survey. *Transp. Policy* **2021**, *103*, 68–85. [CrossRef]
6. Li, J. Impact of the novel coronavirus pneumonia outbreak on transportation travel in New York City. *Highw. Eng.* **2020**, *45*, 91–98.
7. Xiaomin, D.; Zhigang, G.; Yuru, W.; Chen, J. Analysis of the impact of the new crown pneumonia epidemic on the transportation industry and policy recommendations. *Road Traffic Technol.* **2020**, *16*, 337–340.
8. Gudmundsson, S.V.; Cattaneo, M.; Redondi, R. Forecasting temporal world recovery in air transport markets in the presence of large economic shocks: The case of COVID-19. *J. Air Transp. Manag.* **2021**, *91*, 102007. [CrossRef]
9. Zhu, C.; Wu, J.; Liu, M.; Wang, L.; Li, D.; Kouvelas, A. Recovery preparedness of global air transport influenced by COVID-19 pandemic: Policy intervention analysis. *Transp. Policy* **2021**, *104*, 54–63. [CrossRef]
10. Vichova, K.; Veselik, P.; Heinzova, R.; Dvoracek, R. Road Transport and Its Impact on Air Pollution during the COVID-19 Pandemic. *Sustainability* **2021**, *13*, 11803. [CrossRef]

11. Guimera, R.; Mossa, S.; Turtschi, A.; Amaral, A.N. The worldwide air transportation network: Anomalous centrality, community structure, and cities' global roles. *Proc. Natl. Acad. Sci. USA* **2005**, *102*, 7794–7799. [CrossRef]
12. Tatem, A.J. Global transport networks and infectious disease spread. *Adv. Parasitol.* **2006**, *62*, 293–343.
13. Gage, K.L.; Kosoy, M.Y. Natural history of plague: Perspectives from more than a century of research. *Annu. Rev. Entomol.* **2005**, *50*, 505–528. [CrossRef]
14. Verikios, G. The dynamic effects of infectious disease outbreaks: The case of pandemic influenza and human coronavirus. *Socio-Econ. Plan. Sci.* **2020**, *71*, 100898. [CrossRef]
15. Smith, R.D. Responding to global infectious disease outbreaks: Lessons from SARS on the role of risk perception, communication and management. *Soc. Sci. Med.* **2006**, *63*, 3113–3123. [CrossRef]
16. Muley, D.; Ghanim, M.S.; Mohammad, A.; Kharbeche, M. Quantifying the impact of COVID-19 preventive measures on traffic in the state of qatar. *Transp. Policy* **2021**, *103*, 45–59. [CrossRef]
17. Saladie, O.; Bustamante, E.; Gutierrez, A. COVID-19 lockdown and reduction of traffic accidents in Tarragona province, Spain. *Transp. Res. Interdiscip. Perspect.* **2020**, *8*, 100218. [CrossRef]
18. Hadjidemetriou, G.M.; Sasidharan, M.; Kouyialis, G.; Parlikad, A.K. The impact of government measures and human mobility trend on COVID-19 related deaths in the UK. *Transp. Res. Interdiscip. Perspect.* **2020**, *6*, 100167. [CrossRef]
19. Cui, Q.; He, L.; Liu, Y.; Zheng, Y.; Wei, W.; Yang, B.; Zhou, M. Measuring the impacts of the COVID-19 pandemic on China's transport sectors based on the CGE model coupled with a decomposition analysis approach. *Transp. Policy* **2021**, *103*, 103–115. [CrossRef]
20. Zhou, H.; Wang, Y.; Huscroft, J.R.; Bai, K. Impacts of COVID-19 and anti-pandemic policies on urban transport—An empirical study in China. *Transp. Policy* **2021**, *110*, 135–149. [CrossRef]
21. Füzéki, E.; Schröder, J.; Reer, R.; Groneberg, D.A.; Banzer, W. Physical Activity and Well-Being during the Second COVID19-Related Lockdown in Germany in 2021. *Sustainability* **2021**, *13*, 12172. [CrossRef]
22. Zhang, Y.; Tian, W.; Wu, Z.; Chen, Z.; Wang, J. Transmission mechanism of COVID-19 epidemic along traffic routes based on improved seir model. *J. Traffic Eng.* **2020**, *20*, 150–158.
23. Colizza, V.; Barrat, A.; Barthelemy, M.; Vespignani, A. The role of the airline transportation network in the prediction and predictability of global epidemics. *Proc. Natl. Acad. Sci. USA* **2005**, *103*, 2015–2020. [CrossRef]
24. Annie, B.; Sacha, S.; Beck, C.R.; Nguyen-Van-Tam, J.S. The roles of transportation and transportation hubs in the propagation of influenza and coronaviruses: A systematic review. *J. Travel Med.* **2016**, *23*, tav002.
25. Fei, X.; Mccluskey, C.C.; Cressman, R. Spatial spread of an epidemic through public transportation systems with a hub. *Math. Biosci.* **2013**, *246*, 164–175.
26. Zhu, P.; Guo, Y. The Role of High-speed Rail and Air Travel in the Spread of COVID-19 in China. *Travel Med. Infect. Dis.* **2021**, *42*, 102097. [CrossRef]
27. Zhang, X.; Ji, Z.; Zheng, Y.; Ye, X.; Li, D. Evaluating the effect of city lock-down on controlling COVID-19 propagation through deep learning and network science models. *Cities* **2020**, *107*, 102869. [CrossRef]
28. Zhang, J.; Zhang, R.; Ding, H.; Li, S.; Liu, R.; Ma, S.; Zhai, B.; Kashima, S.; Hayashi, Y. Effects of transport-related COVID-19 policy measures: A case study of six developed countries. *Transp. Policy* **2021**, *110*, 37–57. [CrossRef]
29. Abdullah, M.; Ali, N.; Javid, M.A.; Dias, C.; Campisi, T. Public Transport versus Solo Travel Mode Choices during the COVID-19 Pandemic: Self-reported Evidence from a Developing Country. *Transp. Eng.* **2021**, *5*, 100078. [CrossRef]
30. Cartenì, A.; Di Francesco, L.; Henke, I.; Marino, T.V.; Falanga, A. The Role of Public Transport during the Second COVID-19 Wave in Italy. *Sustainability* **2021**, *13*, 11905. [CrossRef]
31. Li, Z.; Yu, L.; Gao, Y.; Wu, Y.; Song, G.; Gong, D. Identifying Temporal and Spatial Characteristics of Residents' Trips from Cellular Signaling Data: Case Study of Beijing. *Transp. Res. Rec.* **2018**, *2672*, 81–90. [CrossRef]
32. Echaniz, A.; Rodriguez, A.; Cordera, R.; Benavente, J.; Alonso, B.; Sanudo, R. Behavioural changes in transport and future repercussions of the COVID-19 outbreak in Spain. *Transp. Policy* **2021**, *111*, 38–52. [CrossRef]
33. Wambui, G.D. The Power of the Pruned Exact Linear Time (PELT) Test in Multiple Changepoint Detection. *Am. J. Theor. Appl. Stat.* **2015**, *4*, 581. [CrossRef]
34. Truong, C.; Oudre, L.; Vayatis, N. Selective review of offline change point detection methods. *Signal Processing* **2019**, *167*, 107299. [CrossRef]