Impacts of COVID-19 and anti-pandemic policies on urban transport—an empirical study in China

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ABSTRACT

The COVID-19 pandemic that began in the last quarter of 2019 seriously impacted the transportation industry. Countries around the world adopted various restrictions and policies to prevent the spread of the pandemic, which resulted in a sharp drop in the demand for transportation. China was the first country to detect the pandemic and the fastest to recover. Existing policies and impacts were reviewed to analyze the impact of the pandemic on China's urban transportation sector and propose measures that may be taken to reduce the impact of COVID-19. This study reviews the impact on urban transportation system operations and how government should respond to a viral pandemic. The recovery measures during and after the pandemic and their hierarchical response system are analyzed. Furthermore, to empirically explore the effect of the recovery measures, this study adopted the Event Study Methodology (ESM) to quantitatively analyze the impact of the epidemic as well as anti-pandemic policies on the traffic flow sequence in the resurgence of COVID-19 in Beijing. The research findings provided solid policy implications and experiences for constructing sustainable urban transportation system and improve flexibility, reliability, and resilience of traffic governance in post-pandemic era.

1. Introduction

The COVID-19 pandemic created a devastating social and economic impact on the entire world (Huang et al., 2020). In China, it brought major changes to people's life, work, business, and trade. Since the transportation system is the primary carrier of almost all social activities, the system is also the first to bear the brunt of the negative impact.

The urban transportation system affects the spatial distribution of population and economic activities. It promotes social and economic activities through transportation connectivity, but also generates negative externalities like increased carbon dioxide emissions and environmental global warming (Raicu et al., 2019). Despite the pandemic, the rapid recovery and effective operation of the urban transportation system is vital to social and economic recovery. Therefore, it is essential to predict the impact of COVID-19 on the transportation system and to analyze the short-term and long-term impact on the socio-economic system.

Furthermore, because of the globalized lockdowns, social distancing, and telework strategies, urban transportation systems face huge challenges created by COVID-19 and the future is uncertain. Assessing the impact of COVID-19 has gained the attention of professionals at the academic and policy level. Empirical studies have analyzed the impact of the pandemic on a particular country's economy or impact on specific industries through analysing various economic indicators (Yang, 2020; Nicola et al., 2020; Workie et al., 2020).

Despite these efforts, there is still lack of overall impact analysis from the perspective of the urban transportation sector in China. China was the first country to be hit by the COVID-19 virus and it quickly recovered from the pandemic. China's rapid response benefits from its previous experience learned from fighting the SARS virus in 2003; which is also a type of coronavirus with shorter incubation period but higher fatality rate (Oberholtzer et al., 2004). China's response to the coronavirus epidemic has important significance in determining best practices for other countries.

Recent research contributions analyzed the impact of COVID-19 on the urban transportation system based on the stated preference (SP) survey (Zhang and Hayashi, 2020; Mogaji et al., 2020). However, survey-based data cannot avoid subjective bias (Loomis, 2011). A revealed preference (RP) based approach is called for to complement the experiences gained from SP data and adds new insights to the impact analysis and policy recommendation.

This research summarizes and analyses impacts of COVID-19 on the

urban transportation system in China. It analyses the short-term and long-term impact of the pandemic on the transportation system and envisions effective policy measures that may be taken during the recovery phase. This provides important decision support and lessons learned for follow-on operations and future similar pandemics.

Furthermore, to provide a closer perspective for the impact analysis, based on the COVID-19 pandemic data in Xinfadi, Beijing, the event research method (ESM) (Yu and Huarng, 2020) was used for empirical analysis to uncover the net effect of COVID-19 and anti-pandemic policies. Moreover, the Empirical Mode Decomposition algorithm (EMD) (Foued and Messaoud, 2020) is used to decompose the original time sequence of traffic volume into different scales according to its composition characteristics. The EMD method is combined with the ESM framework to eliminate the periodicity of traffic flow data, therefore obtaining the pure effect of major events (new crown, anti-pandemic policies) on traffic flow time series.

Choosing the Xinfadi resurgence as the object of empirical research is of great significance to understanding the pandemic and the impact of control policies on the urban transportation system. First, from outbreak to complete control (0 new cases), the resurgence of COVID-19 in Xinfadi has gone through a complete infection-spread-control cycle. This provides a chance to capture the factors of overall development. Second, the timing of Xinfadi resurgence coincided with the resumption of work and schooling (June–July 2020). It was impossible and unnecessary to lockdown again. Third, the development trend of the resurgence in Xinfadi was similar to that of Wuhan in the early stage, but it was quickly controlled by the rapid response system based on the experience of Wuhan. Finally, considering the repeated global spread of COVID-19, the experience of Xinfadi resurgence can provide important references for not only China but also other countries in the world.

All the above areas need to be addressed using a scientific approach. The remainder of this report is organized as follows. Section 2 is the literature review. Section 3 discusses the impacts of the COVID-19 pandemic on urban transportation systems. This is followed by Section 4 where during-pandemic policy measures are analyzed. Section 5 presents the empirical analysis based on data obtained from COVID-19 resurgence in Beijing and lessons learned from the during-pandemic measures are provided in Section 6. Finally, findings and future research opportunities are discussed in Section 7.

2. Literature review

2.1. Anti-virus experiences and policies in transport system

Prior to COVID-19, most of the lessons used to deal with the pandemic in China were learned during the SARS outbreak in 2003. Adopting the G-Cubed model, Beijing's transportation and hotel occupancy rates and resident's consumption during SARS were analyzed (Oberholtzer et al., 2004). It was found that leisure activities, transportation, and tourism were negatively impacted by the SARS epidemic. The irreparable losses in the tourism industry were estimated at approximately US $1.4 billion, which was 300 times the cost of treating SARS cases in Beijing (Beutels et al., 2010). The loss of railway passenger traffic caused by SARS was assessed by using monthly data from TRAMO/SEATS (Gui and Han, 2011). It showed the SARS epidemic caused irreversible financial losses to China's transportation industry.

As for COVID-19, place-based activity is compared in response to COVID-19 policies across different countries (Zhang et al., 2020; Zhang et al., 2020; Oum and Wang, 2020). The similarities and differences between countries were analyzed (Mckenzie and Adams, 2020). Keywords based on Baidu's intelligent search engine were selected to calculate and analyze the search trend, demand map, and information index. Therefore, the key points and changing laws of traffic public opinion during the epidemic were analyzed (Sun and Yu, 2020). In the United States, Google mobility data was used to identify the determinants of social distancing during the COVID-19 pandemic. The

findings indicate that much of the decrease in mobility was voluntary, driven by the number of confirmed cases and greater awareness of risk (Maloney and Taskin, 2020).

The existing literature of COVID-19 can be roughly divided into the following four categories as shown in Table 1.

The impact of the COVID-19 has been discussed world-widely. A risk index has been proposed to measure one country's imported case risk from inbound international flights in China (Zhang L. et al., 2020). By analyzing the factors influencing the number of imported cases from Wuhan. It is found that frequencies of air flights and high-speed train (HST) services out of Wuhan are significantly associated with the number of COVID-19 cases in the destination cities (Zhang, 2020). The extent of grounded aircraft at UK airports due to COVID-19 has been explored and the challenges, from an airfield operations perspective, of resuming flights post-COVID has been discussed (Adrienne et al., 2020). A mixed geographically weighted regression model was estimated to accommodate both local and global effects of Built Environment attributes. It is found that spatial clusters are mostly related to low infections in 28.63% of the cities (Li et al., 2021).

Some literature focused on the anti-pandemic policy measures. E.g., the recovery pattern influenced by the Chinese government's aviation policy choices has been reviewed (Czerny et al., 2021). Oum and Wang (2020) examines the socially optimal lockdown and travel restriction policies for communicable virus including COVID-19. Budd and Ison (2020) pointed out that the unprecedented global shutdown that resulted from the COVID pandemic presents an opportunity to reconfigure future transport policy and practice for the benefit of the global environment and individual citizens as well.

In the people's behavioral responds aspect, Various studies explore the influence and people's reaction to the COVID-19. E.g., Zhang J. (2020) made an initial attempt to assess how people responded to the COVID-19 outbreak during its early stages in Japan. The characteristics of individuals with voluntary behavioral changes (cancellation and postponement of bookings) during the early stages of the COVID-19 outbreak in Japan has been evaluated (Kashima and Zhang, 2021). A PASS (P: Prepare-Protect-Provide; A: Avoid-Adjust; S: Shift-Share; S: Substitute-Stop) approach for policymaking that accounts for COVID-19 and future public health threats has been proposed (Zhang J., 2020).

There is still a research gap for the impact analysis of COVID-19 and the anti-pandemic policy framework as it applies to urban transportation systems, especially human transportation systems. Moving forward from this previous literature, this paper aims to provide a contribution to the research body in three areas. First, we present overall impact analysis from the perspective of the transportation sector in China, which has important significance in determining best practices for other countries and regions. Second, this study analyzes and summarizes the policy measures taken by the Chinese government and empirically investigates the impact of the anti-pandemic policy frameworks. In doing so, we also discuss the changes COVID-19 may bring to transportation systems, travel methods, and business customs in China. Finally, current empirical analyses are mainly based on SP data or general statistical analysis, while this study utilizes an ESM + EMD hybrid model to empirically analyze the impact of COVID-19 and corresponding anti-pandemic policies based on RP data. It complements the experience and lessons learn from SP surveys and provides new empirical evidence on the impact of COVID-19 and anti-pandemic policy measures which have not been addressed by existing literature.

2.2. Empirical mode decomposition and event study methodology

The empirical mode decomposition method (EMD) (Lin and Hongbing, 2009) processes non-stationary and non-linear data series. EMD reveals the inherent characteristics of the data by analyzing the Intrinsic Mode Function (IMF). Empirical mode decomposition is a better method to extract the trend of data sequences (Wang et al., 2018).

The two models have been used for quantifying the impacts of major

Table 1
Literature and gap analysis.

Category	Content	Data type	Methodology	Reference
Estimate the impact of COVID-19 on the economy	The impacts of COVID-19 on energy demand and consumption.	Time series of GDP and energy demand data	Descriptive analysis	Jiang et al. (2021)
	The effect of the COVID-19 on sharing economy activities.	Trend analysis	Descriptive analysis	Nicola et al. (2020)
	The assessment of the effect of COVID-19 on food security and agriculture of society	Farming and food supply data from word bank	Descriptive analysis	Workie et al. (2020)
	How COVID-29 refactor fast-food environment, food banking and emergency food aid industry	Trend analysis	Descriptive analysis	Cummins et al. (2020)
	Evaluate the impact of COVID-19 prevention policies on supply chain under uncertainty	Simulation data	Best Worst Method (BWM) and TOPSIS decision analysis	(Mohamed Grida et al., 2020)
Policies to improve the prevention system	Evaluates the impact of various policies adopted by US states on the growth rates of confirmed Covid-19 cases and deaths	Google mobility report and COVID-19 tracking project	SIR regression and Casual Model with structural equations	Chernozhukov et al. (2021)
	Establish the passenger flow model to monitor passenger density thereby preventing the pandemic	Simulation data	Iris recognition and Fuzzy system optimization	Liu & Huang (2020)
	Analysis of COVID-19 lockdown policy impact on economy	Trend analysis	Descriptive analysis	Mahammed (2020)
	Literature review of how transport sector influences the pandemic and epidemic mitigation	Review article	Literature analysis	(Kim, 2021)
Explore the role of transport in epidemic mitigation	Focused on the present and long-term impact of COVID-19 on transportation in Nigeria.	SP survey	ANOVA analysis and descriptive analysis	Mogaji (2020)
	Estimation of the medium- and long-term impacts of COVID-19 on the aviation industry	Monthly industry data	Descriptive analysis	Suau-Sanchez et al. (2020)
	Analysis of the impacts of COVID-19 on transport and how to mitigation pandemic in transportation	SP survey of experts in transport sector	Descriptive analysis	Zhang et al. (2021)
	The impact of lockdown policy on transport and its effectiveness to fight against the pandemic	COVID-19 confirmed case data	Modified SIR regression model	Peng et al. (2020)
Impact analysis of anti-pandemic policies and COVID-19 on transport sector	Examine the impact of policy tools during the pandemic in the road transport industry in Poland	SP survey based on	Multinomial logit regression	Osinska and Zalewski (2020)
	Analyze the impact and effectiveness of COVID-19 and anti-pandemic policies on transport sector in China	RP big data + COVID-19 confirmed case data	ESM + EMD model analysis	This paper

event shocks on transportation system, (Joshi and Hadi, 2015). This research utilizes the event study methodology (ESM) framework to estimate the impact of a pandemic on a system. It is usually used to analyze the impact of emergencies on stock market prices. It is appropriate for recognizing key trends in time series data and judging structural change point, therefore suitable for this research scenario (Ju et al., 2014).

A hybrid EMD-ESM algorithm is developed and adopted to empirically investigate the impact of COVID-19 and anti-pandemic policy packages on urban transportation system.

3. Impacts of the COVID-19 pandemic on urban transportation

After January 23rd, as COVID-19 was spreading, major provinces and cities imposed different levels of policy prevention and control requirements, such as bans and restrictions on various transportation methods entering and leaving the provinces and cities.
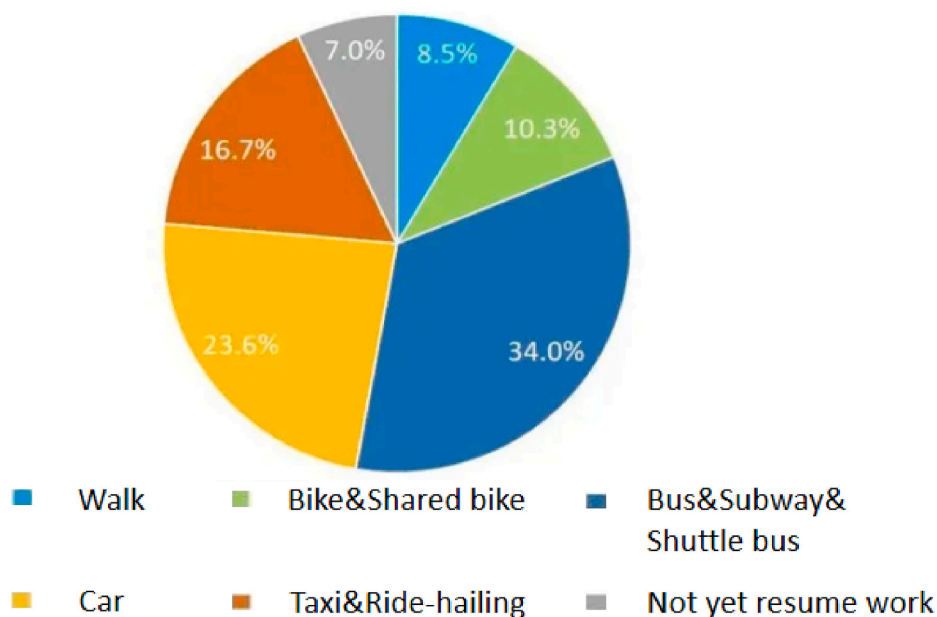

Fig. 1. Travel priority of commuter after resuming work
(Data source: ITDP epidemic travel choice survey).

As subway and public transportation users resumed working, 34% maintained their original transportation mode and 40% of switched to motor vehicles (private cars, taxis, and ride-hailing services) as shown in Fig. 1 and Fig. 2, according to the ITDP (Institute of Transportation and Development Policy) epidemic travel choice survey. It appears that for car owners who usually choose private cars, they prefer to travel by car after resuming work, and decrease usage of all other travel modes. For people without cars, more than half said they have plans to buy cars after the pandemic.

The epidemic has also triggered people's demand for car purchases. As shown in Fig. 3, those who tended to use public transportation in the past are also considering buying a car. (Data Source: "Survey of China's Auto Consumption Trends under the Epidemic" by the China Automobile Finance Laboratory, with 3021 valid samples nationwide.)

When the epidemic was the worst in February, the data from the Ministry of Transport shows the total passenger volume of public transportation was less than 15% of the passenger volume of the same period last year, while the public bus and tram and rail transit were only 12.0% and 14.7% of the passenger volume of the same period last year, as shown in Fig. 4. In addition to the policy on restricting traffic, the citizen's concerns about the safety of high-density public transportation is a larger influence.

As shown in Fig. 5), with the effective control of the domestic epidemic, the resumption of work and production has progressed steadily. On April 3, the national driving rate exceeds the average level of last year. On April 30, affected by the peak of the May Day holiday, the driving rate reached 140.8% (compare to historical level), setting the highest value in the first half of the year.

In the second half of the year, as the number of confirmed diagnoses across the country was gradually cleared, the public travel enthusiasm reignited, and the national driving rate rose steadily. The driving rate reached their peaks on June 25, July 19, and October 1. Among them, on October 1, the national holiday, driving rate reached 157.7%, becoming the most congested day of the year.

Compared with the first half of year 2020, the public's willingness to travel has changed significantly in the second half of the year. In the second half of the year, the top five travel destination categories with the highest increase in user search became restaurants, scenic spots, shopping malls, train stations, and budget hotels. Among them, the hottest search term throughout the year is "Guangzhou South Railway Station", which implies that the intercity travel has also revived. According to the official data of Guangzhou South Railway Station, on October 1, 2020, Guangzhou South Railway Station sent 437,000 passengers, with a record high. We can also see that the national driving rate for major cities in China has been restored to historical level (100% recovery) since April 2020 in general.

4. During-pandemic policy measures

As shown in Fig. 6, in the short term the spread of the epidemic had a greater impact on the needs of industries that require people to gather, such as catering, retail, entertainment, and the transportation system. The impact of COVID-19 caused short-term unemployment and economic recession, which have a negative impact on the production, transportation, and employment of the manufacturing industry. As shown in Fig. 8, various policy measures have been used in response to the impact of the COVID-19 on the transportation system.

Although the pandemic has been adequately controlled in China, and companies have successfully resumed work as planned, it should be noted that in the long run, the long-term and far-reaching impact of COVID-19 still needs further exploration. The impact of the COVID-19 pandemic on traffic may be short-lived, and as the pandemic diminishes, various transportation modes can be restored gradually. However, its potential impact on people's lifestyle and consumption habits may continue. Stimulated by a series of new policy measures emerged during the pandemic, the current mode of travel may accelerate the evolution of the future transportation system. Prior to the outbreak of COVID-19 China had already established a public health emergency response system with 4 response levels of emergency as shown in Appendix Table A1.

In response to COVID-19 and to sustain the public transportation system during the pandemic, China implemented central and local governmental transportation management policies to reduce the number of passengers including the following policy measures as a package.

[1] **Mandatory mask-wearing on public transportation.** Metro/bus stations require passengers to wear masks throughout the journey, and conduct temperature checks on incoming passengers, and require those with abnormal body temperature to wait for disease control personnel.

[2] **Regulate demand from the source.** Based on the different working hour schedules, qualified companies implemented policies such as flexible work schedule, work at home, online meetings, etc., to reduce total transportation demand from at the source.

[3] **Physical protection of drivers and frequent disinfection.** Drivers working for the public transportation system must wear masks throughout the day. Special cleaning personnel are scheduled daily to perform thorough disinfection of all vehicles at regular intervals. They focus on cleaning and disinfection of air-conditioning filters, seats, armrests, ground, car windows, coin boxes, credit card equipment, and other high traffic parts.

[4] **Keeping social distance by setting lower occupancy rates on public transportation.** Based on the previous experience, the occupancy rate on subway and bus transportation was restricted
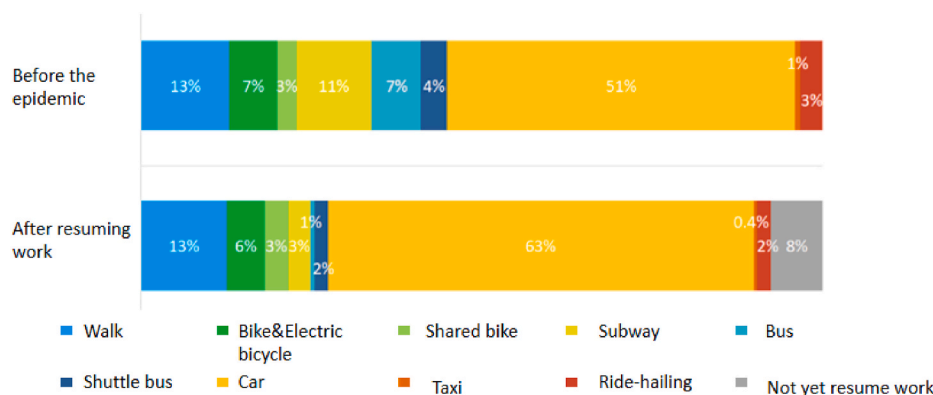

Fig. 2. Changes in travel mode (Car owners)
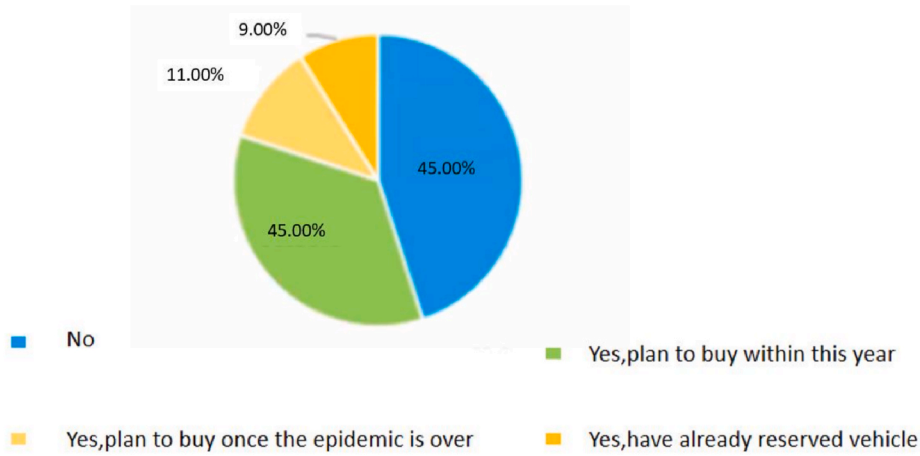(Data source: ITDP epidemic travel choice survey).

Fig. 3. Car purchase plan for those without cars
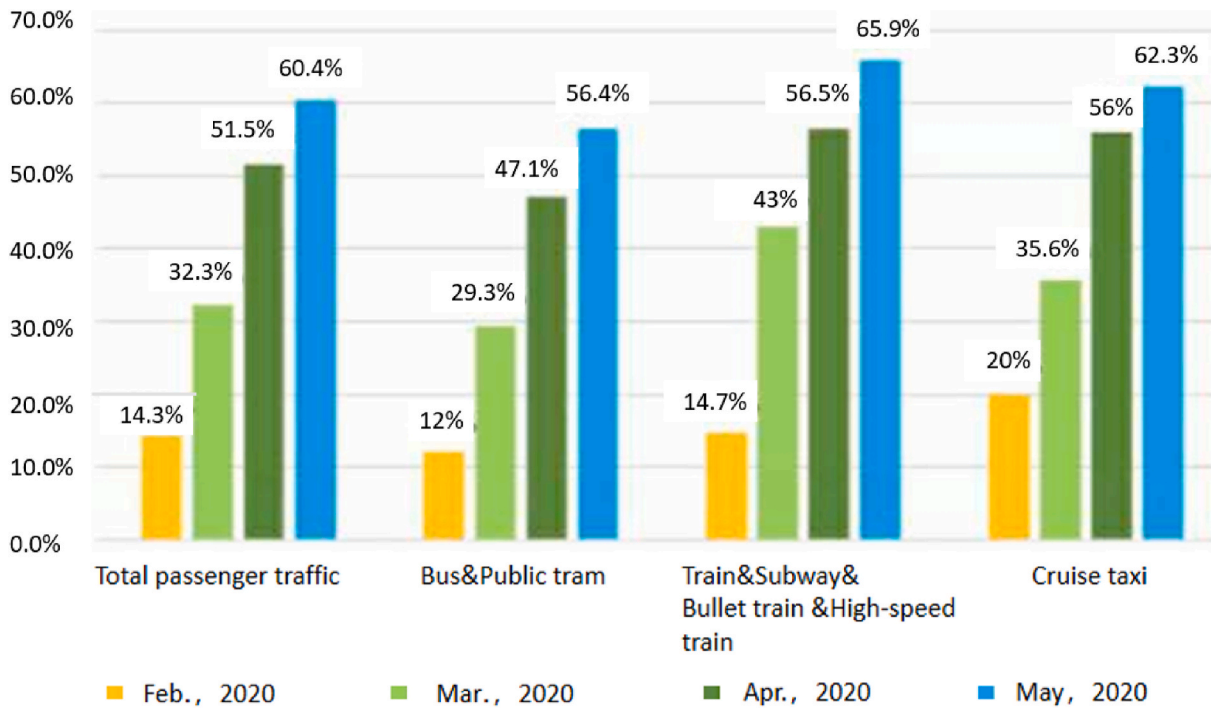(Data source: Survey of China's Auto Consumption Trends under the Epidemic).

Fig. 4. Passenger traffic from Feb. to May 2020 compared with the same period last year
(Data source: ITDP epidemic travel choice survey).

to 50% during the pandemic. Real time occupancy rate information of each bus/subway was provided to reduce perceived risks to passengers.

[5] **Travel by reservation**: A refined passenger flow control method was utilized. Before entering a subway station, passengers needed to make a reservation using an on-line QR code. The station then gave the passenger a precise arrival time, reducing their queueing time and avoiding overcrowding. It transformed queuing into waiting at home and arranged transportation capacity according to real-time changes in passenger demand. Passengers using reservations can save an average of 3–5 min of queuing time outside the station. Using Shahe Station as an example, during May 20th -May 28th, the average daily time savings was 221 h, and the maximum daily time savings was 287 h.

[6] **Increase Customized Bus Routes**: Launched the "Beijing Bus Customization" WeChat Mini Program to serve the public's need

to resume business. Individuals and companies can both apply for it. During the pandemic period, it provided passengers with online reservations, one seat per person, fast direct access, and mass public transportation services that generated customized routes. Customized bus services transported 400,000 passengers during the pandemic in Beijing.

[7] **Health code and national wide green code pass**: The health code is based on data submitted online by citizens. After the background review, a personal QR code is generated, which can be used as an electronic voucher for entry and exit to public places and transportation systems. It integrates the static data that would have been presented on paper questionnaires with the internet public security database, CDC database, community electronic passes, etc. to form a dynamic data link. It is combined with all transport modes and has become management
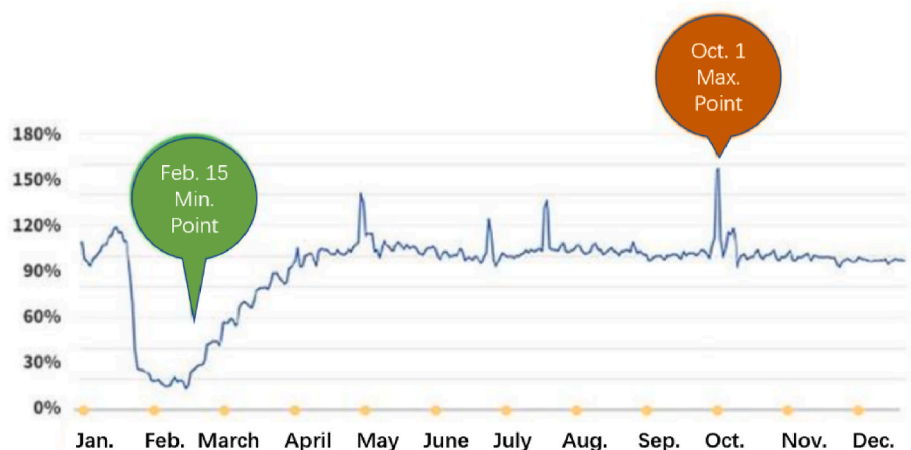
Fig. 5. National driving rate for major Chinese cities in 2020 (Compared to historical data in the same date) (
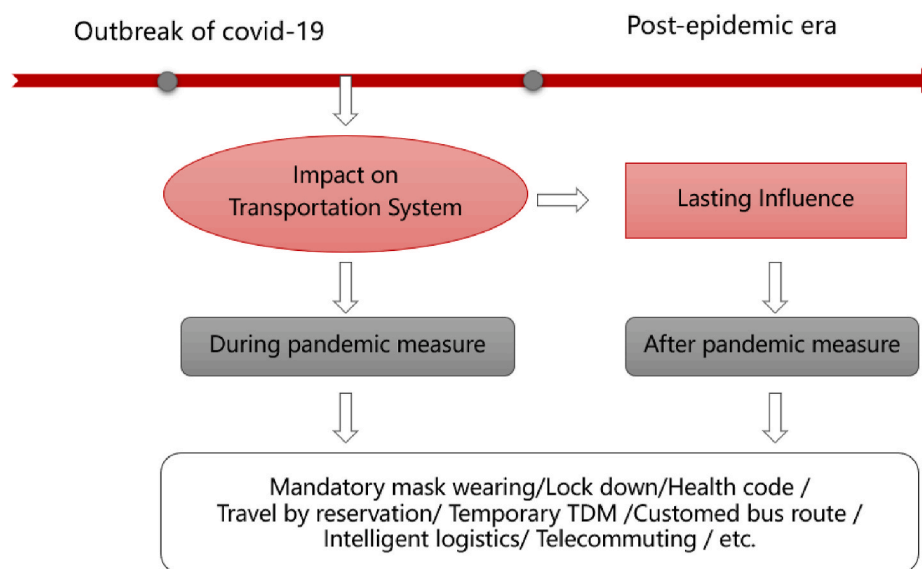Data source: Amap urban travel data platform).

Fig. 6. Policy measures during/after COVID-19 pandemic.

departments' first source to identify and cut down the infection chain and enhance traceability if an infection occurs.

Furthermore, to mitigate transportation modal shifts to cars, motorcycles, and other private motorized modes in response to the perceived COVID-19 infection risk in public transport the following policies were utilized together:

[1] **Temporarily cancel the restriction on private cars and encourage traveling by private vehicles:** To minimize the spread of COVID-19 during the pandemic, the restrictions on private cars were suspended and will be reinstated after the pandemic is under control. Temporary parking discounts were provided for public parking spaces. The transportation management office extended the free parking time at key transportation stations. The Ministry of Commerce also encouraged relaxation of private vehicle purchase restrictions and encourages automobile purchase and use.

[2] **Develop the non-motorized traffic system:** Encourage citizens to commute by cycling to public transportation stations or walking/jogging to public transportation stations. This will

reduce the passenger flow density on buses and subways and help alleviate urban congestion.

[3] **Issue guidelines to encourage commuting by sharing transportation during pandemic:** During the pandemic, many experts and government offices issued prevention and control guidelines on commuting. It was recommended that people can choose modes such as shared bicycles and shared cars to commute. Policies promoted the increase in the construction of non-motorized transportation lanes in various places. These policies ensure the reasonable usage of shared bicycles and promotes the integration of shared bicycles with existing public transportation systems such as buses, subways, taxis, and online car-hailing. Shared cars are disinfected every time they change passengers.

[4] **Support the decreased travel demand by improved intelligent logistic system:** Smart logistics technologies such as unmanned delivery robots and smart warehouses, played an important role during the pandemic. For the transportation of medical supplies and daily necessities, the priority traffic policy was implemented. It dictated a "no parking, no inspection, no charge" for related smart technology vehicles to ensure the

smooth passage of these smart transportation vehicles. **Contactless home delivery service**: Although the COVID-19 pandemic keeps many people at home and isolated, it also allows online shopping businesses to reach more customers, which in turn drives the express logistics industry to grow in market share. By reducing face-to-face contact, the safety of users and delivery man during the process is guaranteed.

5. The impact of anti-pandemic policy on traffic in COVID-19 resurgence in beijing

The empirical analysis evaluates the impact of anti-pandemic policy measures and COVID-19 on the transportation system using the Beijing Xinfadi resurgence case (Pang et al., 2020). To test the former synthesized experience and account for anti-pandemic policy influencing human mobilities in the transport sector, an Event Study Methodology (ESM) (Yu and Huarng, 2020) was used to capture the true influence of COVID-19, as well as the anti-pandemic policy measures.

5.1. Research area and policy measures

After more than two months of fewer confirmed cases, an unexpected increase in COVID-19 cases in Beijing in June 2020 attracted a lot of attention. It started from the city's largest wholesale market, Xinfadi market. The spread of the pandemic was fast, and many cases appeared in a short period of time. From June 11 to June 23, a total of 256 confirmed cases were reported in Beijing. It took only 5 days from the first to the hundredth new case. There are 253 cases of clustered epidemics that are clearly related to Xinfadi market, accounting for 98.8%. The spread of the pandemic in the first five days of the Xinfadi market is similar to the Wuhan outbreak.

Xinfadi market is Asia's largest agricultural products wholesale market, with annual trading volume of 17.49 million tons. It is responsible for 90% of Beijing's supply of agricultural products and its size and influence is 21 times that of Wuhan's south China seafood market. If the spread of the Xinfadi resurgence could be controlled, its potential impact would be catastrophic. Researchers have concluded that imported food via cold chain from high-risk areas overseas was the origin of the COVID-19 resurgence. The resurgence in Xinfadi market suggests the virus could be reintroduced via cold chain transportation of contaminated items and initiate an outbreak.

The distribution of confirmed cases and risk-level was as shown in Fig. 7, after the outbreak, 45 street blocks in Beijing were upgraded to code-red and code-orange areas and packaged epidemic control measures were implemented (according to the emergency responds system in Table 2). This round of epidemic spread centered on the Xinfadi market. 70% of the confirmed cases were concentrated within 5 km of Xinfadi, indicating that the initial stage was a local outbreak. Most of the confirmed cases are along the rail transit lines around key areas such as the market in Figs. 7 and 8. Due to the high traffic volume and long distance of rail transit, although there were not many cases in the initial stage of spread, the spread distance was long and the potential impact was wide. And there was spread from market to market as shown in Fig. 8. Along the city's main ring road, the epidemic in Xinfadi markets quickly spread to Tiantao Honglian market on the second ring road and Yuquandong market on the fourth ring road. The risk of infection in places such as markets was high, which were potential outbreak points.

The anti-pandemic policy packages are implemented within the code-red and code-orange areas as introduced in section 4. Furthermore, within 48 h of the discovery of a new epidemic, Beijing government
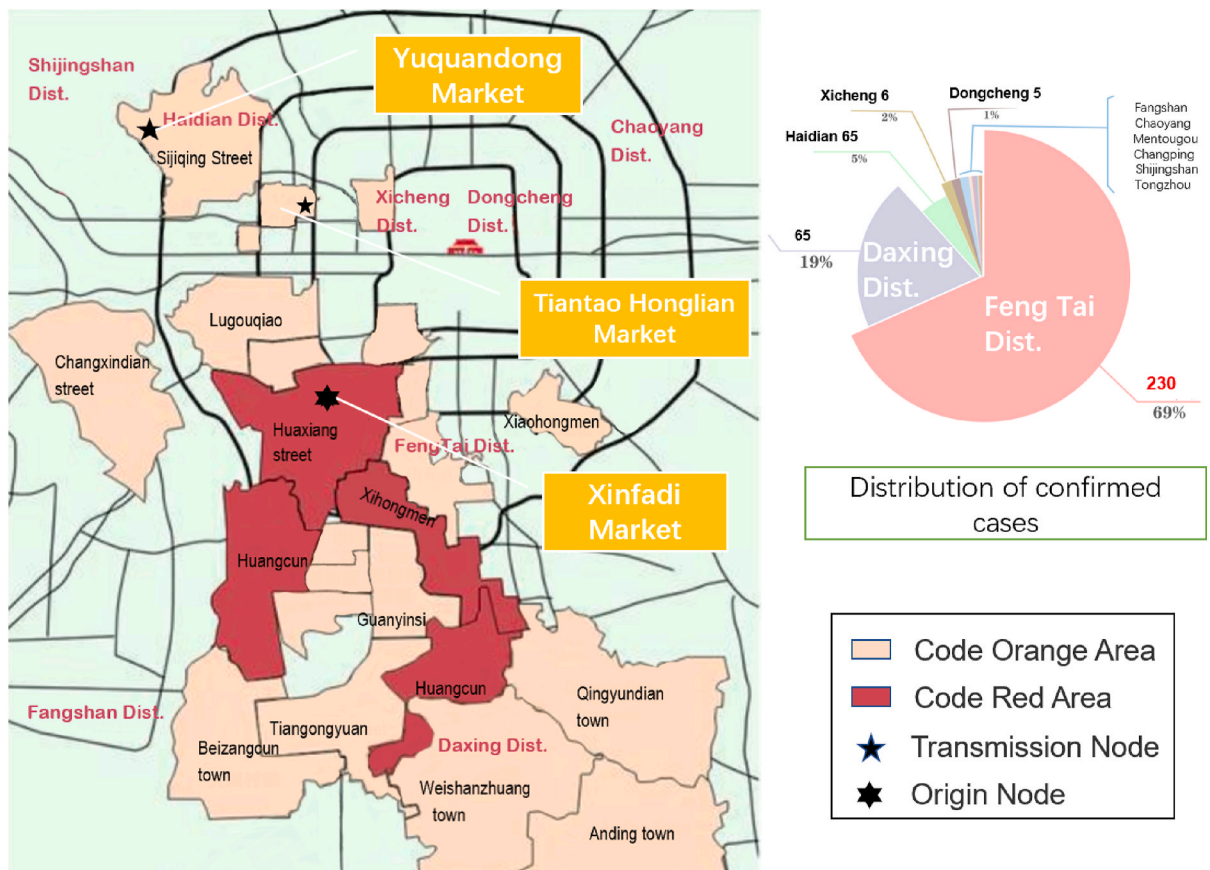

Fig. 7. The distribution of confirmed cases and risk-level areas in Beijing Covid-19 resurgence (Data source: AkShare COVID-19 data set).
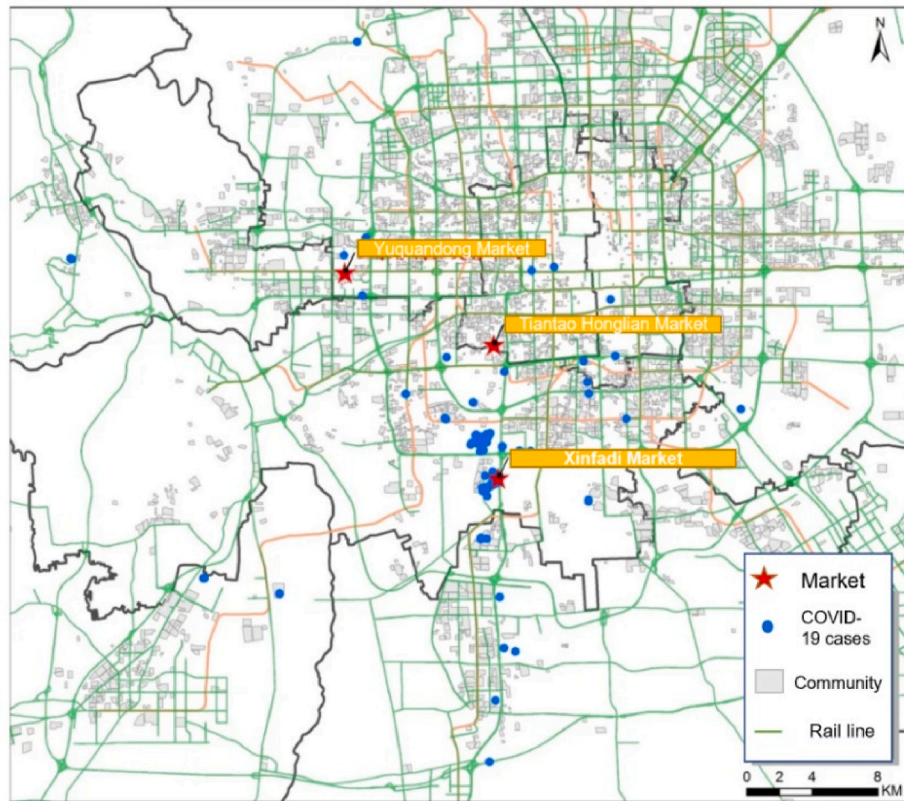
Fig. 8. Confirmed cases spread along rail transit and surrounding markets (Data source: AkShare COVID-19 data set).

Table 2
Analysis of the correlation and source of variance between the IMF, residual function, and traffic flow ratio data.

	Cycle	Kendal coefficient	Pearson coefficient	Variance	% of original Variance
Original				0.0387	
IMF 1	7	0.204*	0.462**	0.0146	36.85%
IMF 2	45	0.612*	0.793**	0.0238	60.07%
IMF 3	45	0.341*	0.423**	0.0011	2.78%
Residual		0.212*	0.401**	1.17e-4	0.30%
All					100%

* Significantly correlated under the 0.1 level, **, significantly correlated under the 0.05 level.

located all the potential contacts which may have been to the Xinfadi market utilizing big data technology and cell phone signaling data. A text message reminding everyone who went to the Xinfadi market to quarantine was sent. Those impacted were kept at home for 14 days. Social workers would contact them as soon as possible to help them isolate and provide appropriate supplies. The notification message can be used to ask for leave from work and request approval to work from home. At the beginning of the pandemic, speed is essential and key to reducing a lot of potential social costs in the future.

5.2. Data source

Traffic volume rate data has been selected as the proxy variable of human mobility. The travel volume rate data for 16 districts of Beijing area starting from Jun 1st,2020, was provided by Amap, a map navigation company in China. Amap has its own electronic map database, with leading digital map content. It provides navigation and location-based services (LBS) which covers more than 90% of traveler's

mobility data in China. The travel volume rate data compares the current traffic volume on each section with historical traffic volume records, and represent the relative fluctuation using a percentage ratio. As shown in Fig. 9, 0.86 travel volume means current traffic volume is 86% of the historical records. From Fig. 9, we can see how travel volume reduced according to the daily confirmed cases. There is a certain time lag between the two, indicating that it takes a certain amount of time for people to perceive travel risks at the beginning of the epidemic.

5.3. Methodology

As shown in Fig. 10. A hybrid EMD-ESM algorithm is developed and adopted to empirically investigate the impact of COVID-19 and anti-pandemic policy packages on urban transportation system. Here, the EMD method is used to decompose the time series data into several time series with different inherent characteristics (different frequencies and periods). Therefore, the periodic(cyclic) fluctuations of the time series can be excluded from the following analysis process (Yu and Huarng, 2020).

Second, The ESM framework applies the ARIMA time series forecasting method to predict what the traffic flow should be if the COVID-19 does not occur, and then uses this counterfactual inference data (The COVID-19 did happen, so this is a counterfactual inference) to compare with the real traffic trend data. The difference between them is defined as abnormal traffic flow (Foued and Messaoud, 2020), which can be attribute to the influence of COVID-19 and its corresponding anti-pandemic policy package.

As previously discussed, EMD is a method for processing non-stationary and non-linear data sequence for any given time series signal $S(t)$. Firstly, all the extreme points on $S(t)$ are determined, using cubic spline curve Connect all maximum points to form the upper envelope, and the same method to form the lower envelope. The difference
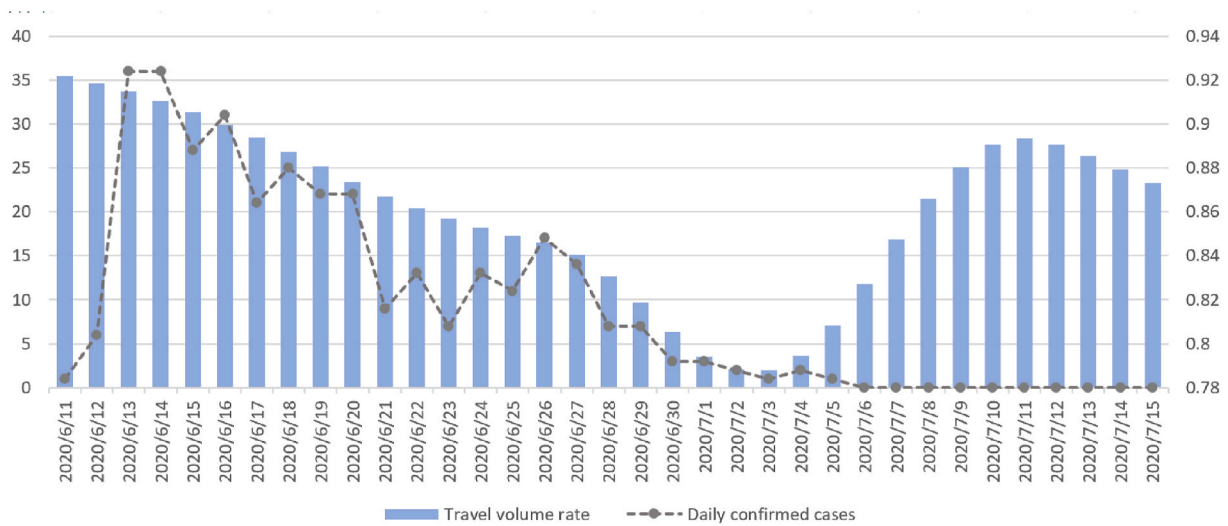
Fig. 9. Confirmed cases and Travel volume rate data
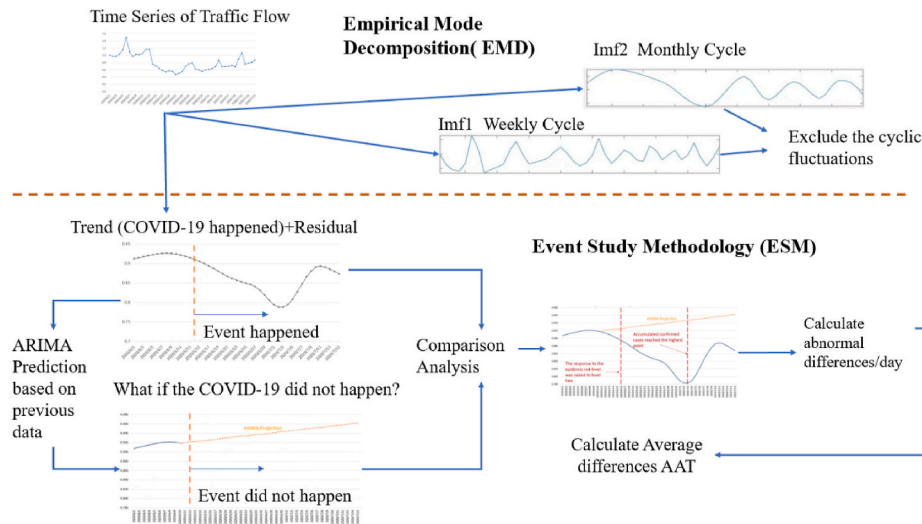(Data source: Amap Company).

Fig. 10. Methodology framework.

between the data $S(t)$ and the mean value m1 of the upper and lower envelopes is recorded as h_1, namely:

$$h_1 = S(t) - m_1 \qquad (1)$$

Using h_1 as the new $S(t)$ to be decomposed, repeat the above process until h_1 meets the two conditions of IMF, then it becomes the first-order MF filtered from the original signal, denoted as IMF_1, usually the first-order IMF component IMF_1 contains the highest frequency component of the time series. Separate IMF_1 from $S(t)$ to get a difference sequence with high frequency components removed, which has:

$$R(t) = S(t) - IMF_1 \qquad (2)$$

Taking the $R(t)$ as a new signal, repeat the above-mentioned screening process until the residual signal of the nth order becomes a monotonic function, and the IMF component can no longer be screened out. So far, the original time series can be expressed as the sum of n IMF components and a residual term, that is

$$S(t) = \sum_{i=1}^{n} IMF_i(t) + r_n(t) \qquad (3)$$

where $r_n(t)$ is residual $r_n = r_{n-1} - IMF_n$, represents the average trend in time

series. Each IMF component $IMF_i(t)$ represents the components of the signal from high to low in different frequency bands. The frequency components contained in each frequency band are different. In the same IMF component, the instantaneous frequency at different times is also different. In summary, the EMD method obtains simple IMF components through multiple screenings, which can be used to identify the trends of the original traffic flow ratio sequence. The EMD method is used to decompose and eliminate the cyclical trends of traffic flow data, leaving only intrinsic trends, so that we can further analyze the net effect of the epidemic on traffic flow.

To further deconstruct the impact of new outbreaks and corresponding anti-pandemic measures on traffic flow, this study adopts the Event Study Methodology (ESM) framework (Andres et al., 2014) to analyze changes in traffic flow caused by changes in traveler behavior after the outbreak of COVID-19. The ESM framework first divides the time series into three period, the estimation window, the event window, and post-event window.

Due to the characteristics of the data set, this study chose to use the ARIMA time series forecasting model (Abuhasel et al., 2020) to train the estimation window, thereby making counterfactual inferences to forecast the development of the original time series when COVID-19 did not

occur. The difference between the actual situation and the counterfactual situation will be further calculated as the abnormal traffic rate. As a result, the abnormal traffic rate can be statistically tested by calculated the different variances between the two situations.

According to ESM framework, we further define the daily abnormal traffic volume as $AT_{i,t} = ARIMA(p,d,q)_{i,t} - T_{i,t}$, where i represents the district id and t stands for the date index, d is the order of the time series, p and q are respectively the lag order selected by the information criterion for autoregressive and moving average.

5.4. Model analysis and result

The proposed EMD-based traffic flow ratio fluctuation analysis is initially driven by data, and the analysis of the decomposition results is closely integrated with the transport economic theory, overcoming the shortcomings of theoretically-driven or data-driven research. After EMD decomposition, it identified the influencing factors of the cyclical fluctuations of the urban traffic flow ratio include medium and long-term trends related to traffic demand fundamentals, traffic control policies and the impact of COVID-19 pandemics, and random fluctuations caused by short-term factors. The traffic flow ratio is the superposition of these three aspects. The decomposition result is as follows:

At the top of Fig. 11 is the original data of the traffic flow ratio data in Beijing. From this, it can be inferred that the impact of the COVID-19 epidemic is not readily obvious, but it also shows that the residual function is a U-shaped line, reaching a minimum value around the 35th time unit, and then slowly recover, this trend converges with the trend of IMF 3.

Further analysis of the correlation coefficient shows that the volatility of many intrinsic characteristics is composed of IMF 1 and IMF 2. However, from the perspective of correlation coefficient analysis, IMF 3 and the residual series have significant correlations, and the correlation coefficient is close to IMF 1.

Do a mean test for all IMFs. The null hypothesis: the mean value of each IMF function is not significantly different from 0. The test result is shown in Table 2. The smaller the two-tailed probability (Sig.2-tailed), the more significant the mean of the IMF. It is different from 0. It can be

seen from Fig. 12 that there are significant structural changes starting from IMF 3. IMF 1 and IMF 2 can be considered as a group of high-frequency modes with intrinsic characteristics, and another group of common properties appears after IMF 3.

Combined with the estimated cycle(period) shown in Table 2, we can see that the original time series is periodic. IMF1 represents weekly cycle (7 days) of traffic volume fluctuation, where trip volume peaks on weekends and starts to fall back on Monday. And IMF 2 is approximately monthly cycle of traffic volume fluctuation. The traffic volume is high in the first half of the month and fell back in the second half of the month, showing a relatively regular sine wave shape. Therefore, we removed the influence of the week and the monthly cycles and reconstructed time series as IMF3+residule, and this waveform reflecting the impact of the emergency event on the traffic flow is extracted as shown in Fig. 13.

The time window for defining the event is as shown in Fig. 13. Set the day of the epidemic release conference as the event start date ($t = 0$) until July 5, and a total of 24 days as the event window. After July 5th, when $t\varepsilon[23,33]$, no new confirmed cases were diagnosed, and traffic flow data began to recover slowly, so it was defined as the post-event window.

The result is shown in Fig. 14. Starting from June 11, the actual travel volume has dropped significantly (two-tailed significance: 0.000), which deviates greatly from the predicted value, with maximum decrease of 15% at the day when the accumulated confirmed cases in Beijing almost reached the highest point.

Further analysis was employed using the same methodology (ESM + EMD) based on the data of all 16 urban districts in Beijing respectively. The average abnormal traffic volume for day t can be further defined as follows:

$$AAT_{i,t} = \frac{\sum_{i=1}^{n} AT_{i,t}}{n} \quad (3)$$

The result in Table 3 shows that the average abnormal traffic flow per day for Beijing is −8.65%, and the maximum impact on urban traffic flow for all districts in Beijing does not exceed −44.3% (Fengtai district −44.3% and Haidian district −43.6%). The AAT is negative and has passed the significance test, indicating that the overall traffic flow in Beijing has been significantly reduced by the impact of the COVID-19.
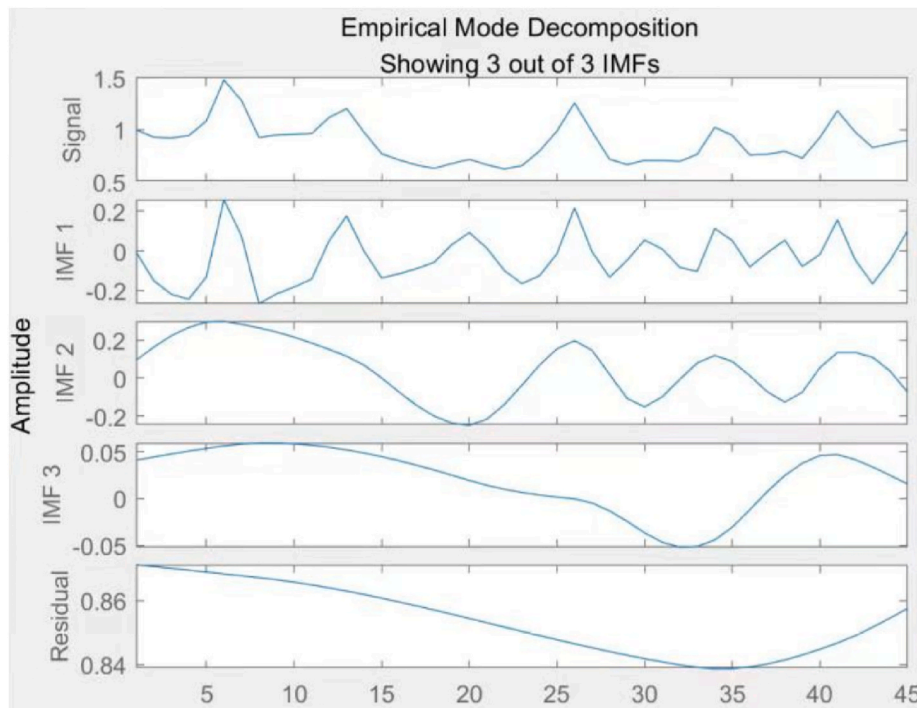

Fig. 11. IMF functions of different frequencies obtained after EMD decomposition.
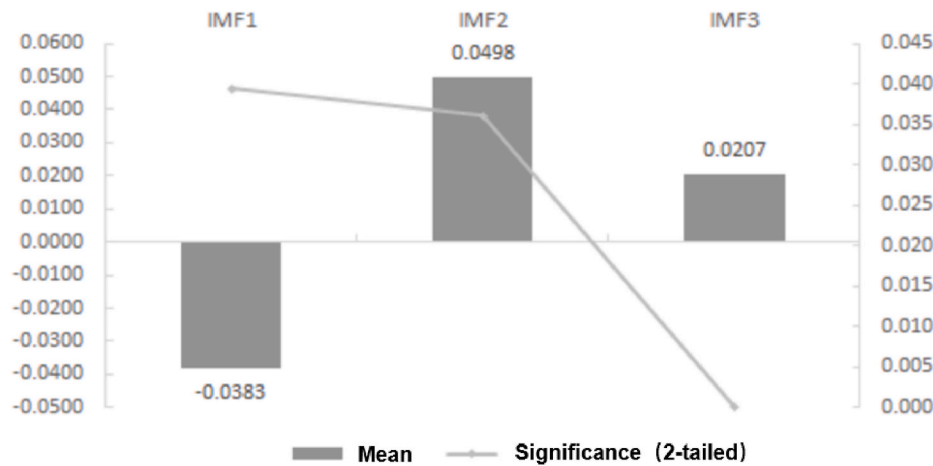
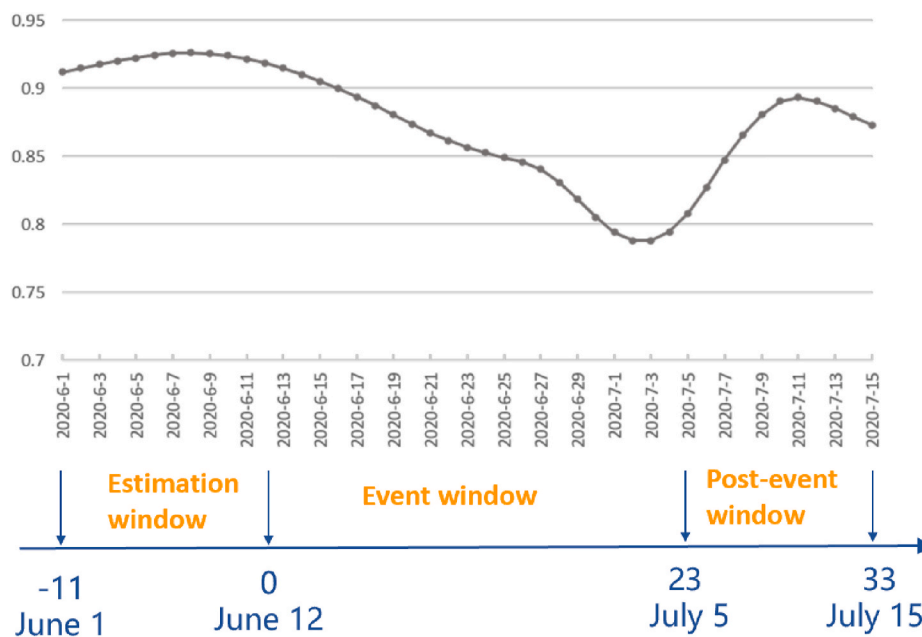**Fig. 12.** The mean of each IMF and the T test result with mean zero.

Fig. 13. Reconstructed time series and event window.

(Please note that the overall AAT cannot be calculated by simply average of all AAT of 16 districts, since AAT it's a ratio data which evaluates its changed ratio according to its original level, and different districts have quite different original traffic flow volumes, therefore cannot be directly summarized).

Fig. 15 plots the comparison between AAT and the cumulative number of confirmed cases in various districts of Beijing. The result shows that the average abnormal flow rate (AAT) in different district areas has a correlation with the degree of epidemic risk, as well as the confirmed cases. The higher the risk, the larger the decrease of AAT, especially for Fengtai, Haidian and Xicheng district. For Miyun and Huairou District, since their confirmed case is 0, their AAT is relatively high. Especially for Miyun District, AAT is positive, indicating a slight increase in travel flow.

Comparative research shows that the city-wide blockade policy at the beginning of 2020 reduced traffic flow/human resident activities by more than 50%. Although the outbreak time was sudden, due to well-prepared Hierarchical response control, only a maximum of 15% traffic reduction was required. Compared to lockdown the whole city, the traffic reduction is significant but not too high, with good virus prevention effect.

As far as the transportation system is concerned, one of the biggest impacts of the COVID-19 pandemic is it severely reduced people's travel needs, resulting in a sharp decline in human mobility, and some people voluntarily reduced their outings. More importantly, to meet the needs of pandemic prevention and control measures at all levels, people's travel was restricted by policy measures such as work at home, close the school, lockdown, etc. It can be seen from the horizontal comparison of Fig. 16 that human mobility has been reduced in various cities during the outbreak of COVID-19.

Instead of lockdown again with huge economic cost, a precise anti-pandemic policy and hierarchical response system provide a viable alternative to fight COVID-19 in the Xinfadi COVID-19 resurgence case. It could have evolved into a disaster, but it was handled promptly by precise prevention and control measures. The prevention and control measures adopted in this round have low social costs (maximum traffic reduction 15%), but the results achieved are positive for everyone.

Prompt response and technology support at the early stage are the first keys to success in this case. The precise anti-pandemic policy is impossible without the technical support of the health code, signaling
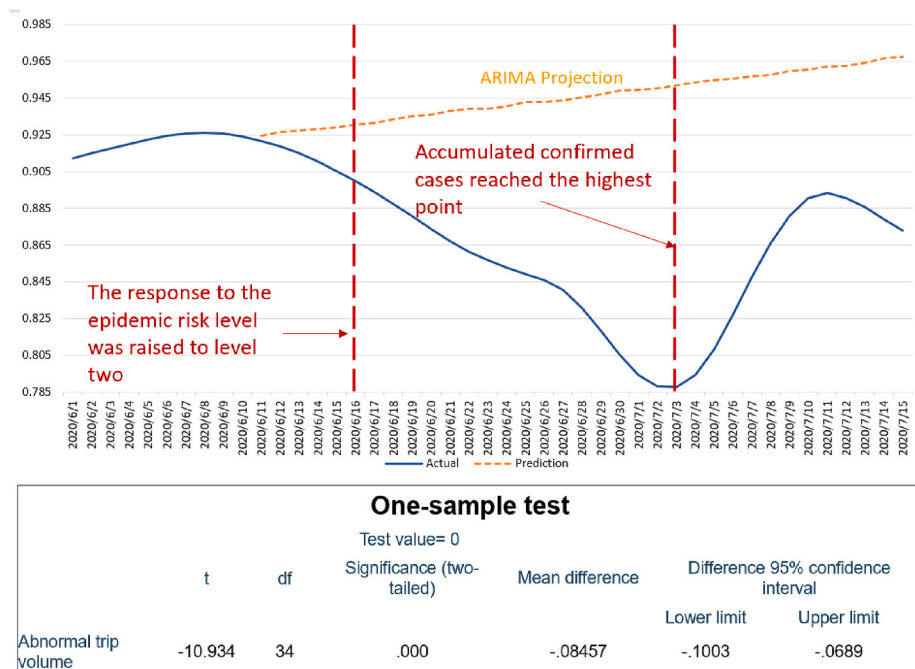
One-sample test

Test value= 0

	t	df	Significance (two-tailed)	Mean difference	Difference 95% confidence interval	
					Lower limit	Upper limit
Abnormal trip volume	-10.934	34	.000	-.08457	-.1003	-.0689

Fig. 14. ESM analysis result.

Table 3
ESM + EMD analysis result for 16 Districts in Beijing.

District Name	Abnormal Travel Rate (AT)	Average Abnormal Travel Rate (AAT)	Sig. Two-tailed (P-value)
Changping Dist.	−7.531077193	−21.52%	0.000***
Chaoyang Dist.	−4.878891757	−13.94%	0.000***
Daxing Dist.	−6.055480207	−17.30%	0.000***
Dongcheng Dist.	−7.00047346	−20.00%	0.000***
Fangshang Dist.	−10.87323249	−31.07%	0.000***
Fengtai Dist.	−15.505	−44.30%	0.000***
Haidian Dist.	−15.26172735	−43.60%	0.000***
Huairou Dist.	−2.094791421	−5.99%	0.000***
Mengtougou Dist.	−9.5823562	−27.38%	0.000***
Miyun Dist.	−9.479246297	−27.08%	0.000***
Pinggu Dist.	0.450861732	1.29%	0.000***
Shingjingshan Dist.	−8.447487903	−24.14%	0.000***
Shunyi Dist.	−8.608088075	−24.59%	0.000***
Tongzhou Dist.	−4.836302224	−13.82%	0.000***
Xicheng Dist.	−12.90058944	−36.86%	0.000***
Yanqin Dist.	−5.281059367	−15.09%	0.000***
Overall	−3.028768057	−8.65%	0.000***

Note: *** represents significance at 99% confidence level.

data, processing, and tracking. The health code prohibits people who have contact with confirmed cases from entering public places and transportation systems. At the same time, the analysis of mobile phone signaling data provides accurate information to identify who should quarantine at home.

The packaged hierarchical emergency response system with precise anti-pandemic provides feasible solutions to deal with the challenge of COVID-19. It allows cities and nations to be better prepared and provides a way to achieve bigger success with less cost.

The experience of Xinfadi COVID-19 resurgence is also a reminder, Xinfadi market is not an isolated case, cities and nations should be prepared for the future other resurgence of COVID-19. It may come from cold-chain packaging materials, contaminated water, or animals, etc. Cities should remain vigilant, and prepare for the longer post pandemic

period.

6. Lessons learned from the policy measures and experience

The spread of the pandemic is not directly related to population density of a city, but it is significantly related to the degree of population crowding (Sun and Yu, 2020). Whether in cities, suburbs, or rural areas, the risk of infection is often closely related to gathering places. From the perspective of urban traffic management, temporarily reducing urban mobility will help control the spread of the pandemic and reduce the risk of infection. However, reducing urban mobility brings about a series of social and economic problems. Effective policy governance measures are needed to guide and change public behaviors and promote new transportation modes.

[1] **Comprehensive information dissemination policy is the key to mitigating the spread of the pandemic.** As discussed in Section 4 and 5, within 48 h, the management office has collected all the infection data and continue to release it to the public. This is also the basic requirement stated in Table A1 part, public release is a prerequisite. The public has increasingly diversified channels for obtaining and disseminating information. Therefore, for the public to have a correct understanding, the most important thing is to announce the pandemic information in a timely, objective, and comprehensive manner. Therefore, timely broadcast of information and exchange of opinions to the public will help promote citizens' self-discipline behavior and increase the level of cooperation among the people in pandemic prevention and control, but also help adjust people's expectations regarding government policy governance and medical measures.

[2] Although **digital infrastructure** cannot completely replace the face-to-face experience, compared with the SARS epidemic, policies to invest in information technology, such as artificial intelligence (AI) and big data analytics, has become a powerful weapon in this battle against COVID-19. This investment provides a solid backing for pandemic prevention and control. Without the help of big data technology and cell phone signaling data, it will be a mission impossible to locate all the potential infected cases within 48 h.
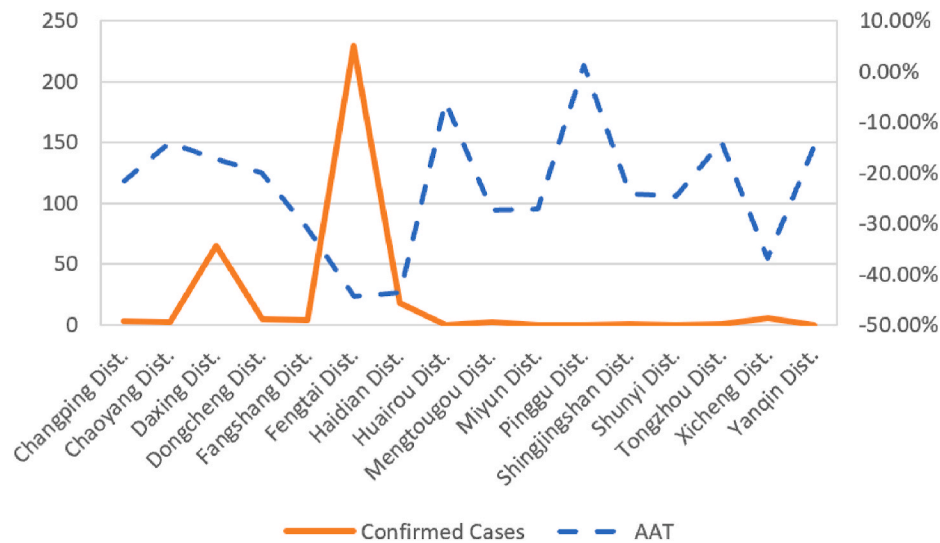
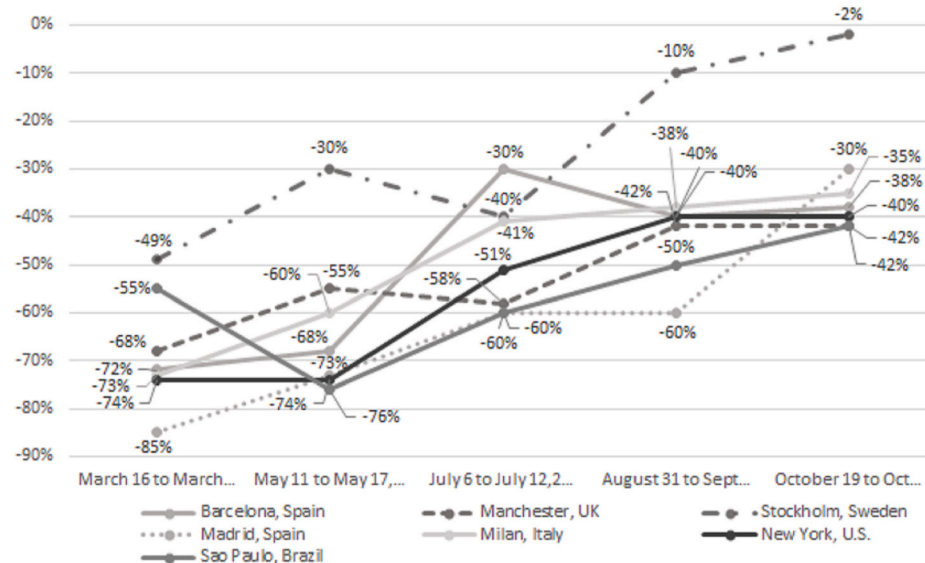**Fig. 15.** AAT and confirmed cases for each district in Beijing.

Fig. 16. Traffic volume reduction related to coronavirus in selected cities in 2020 (Data Source: Statista).

[3] **Policies and related measures have been implemented to address the social distancing needs in the transition period.** For example, in Appendix A.1, from code red to code blue part, it all require drivers to wear masks, frequently sanitize the vehicles, and maintain appropriate ventilation flow. The occupancy rate in subways and buses were restricted to 50% during the pandemic (they will be gradually increased to 70% during the transition period). Telework measures help to alleviate the commuting demand. On-line shopping with smart logistic system reduces citizens' need to go shopping outside of their home.

[4] **Preventive preparation and precise anti-pandemic measures are the key to ensuring rapid response and reducing the social costs of anti-pandemic measures.** The empirical research in this article shows that compared with the Wuhan epidemic and the epidemics around the world, the Xinfadi resurgence of COVID-19 have been effectively controlled in just over a month, and at the same time, the resumption of work and production has been maintained. Only some districts with large number of confirmed cases have had severe impact. Thanks to precise anti-

epidemic measures as shown in section 4, the overall social cost of epidemic prevention measures is controllable, and the spread of the epidemic is accurately prevented and the chain of infection is cut off, thereby avoiding greater potential losses. With the former experience of hierarchical anti-pandemic policy package and Big Data technology support, the precise anti-epidemic will be an important mean for us to fight the epidemic in the future.

7. Conclusions, policy recommendations and future research

In this research, the impacts of COVID-19 were investigated as it pertains to China and impacts on transportation systems. First, China's preparation for a pandemic before the outbreak of COVID-19 was reviewed based on literature and lessons learned from the SARS epidemic. Although SARS brought huge economic and life loss to society in 2003, the SARS epidemic prompted China to vigorously build a sanitation and epidemic prevention system. The accumulated experiences laid a solid foundation for the fight against COVID-19.

During-pandemic measures and after-pandemic recovery measures

were analyzed and reviewed with related impact analysis. Working from home, travel by reservation system, health codes, customized bus routes, and intelligent logistic technologies have attracted increasing attention. Transportation management under the pandemic is like traffic management under abnormal conditions; it tests the flexibility, reliability, and resilience of the traffic governance system.

In the post-pandemic era, it is necessary to analyze and reevaluate urban transportation planning, policy governance, and operation services. The goal is to position the transportation system to efficiently and effectively handle both normal and abnormal transportation scenarios. Strategies such as improving the intelligent transportation system in response to the emergencies; build an ecological and green transportation system dominated by walking, bicycles, and door-to-door high-quality public transportation services; construct more walking and bicycle road systems; advocate walking, bicycle priority, public transportation priority; and focusing on smart logistics are important and recommended management and governmental strategies.

This empirical study only adopts the time series of traffic flow data. Although it can reflect the direct impact of the epidemic and corresponding anti-pandemic policies, it does not further consider the adjustment effects of the built environment, weather, and traveler behavior on related impacts, and it also did not conduct mid- and long-term predictive analysis, we will further improve these aspects in the next step of the research.

Further research is needed to explore whether this trend will be sustained and continue to impact people's long-term choices (work choices, education choices, daily routine, etc.). Many questions have been answered in this study, yet various more need to be explored to face the uncertainty in the post-pandemic era.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.tranpol.2021.05.030.

Appendix

A.1 Response levels of public health emergencies

Levels	Code	Possible Policy Measures
Level 1 **Particularly important event**	**Code Red**	1) The central state council is responsible for decision-making and deployment and unified command and coordination of emergency response in the region 2) Restrict or stop markets, assemblies, theater performances, and other crowd gathering activities 3) Suspension of work, business, and classes 4) Emergency measures such as closing or securing public drinking water sources, food and related items contaminated by infectious disease 5) Temporary expropriation of houses, vehicles, and related facilities and equipment 6) Lockdown contaminated area 7) Take measures of on-site isolation, observation, and treatment of patients and suspected patients, and centralized or home medical observation for close contacts according to the situation 8) Organize railway, civil aviation, quality inspection, and other departments to set up temporary transportation sanitation and quarantine points at stations and entry/exit ports to conduct quarantine on areas. Quarantine inspection of vehicles entering and exiting epidemic areas and in operation, as well as their passengers, materials, and host animals 9) Information release: after a public health emergency occurs, the relevant departments must do a good job of information release in accordance with relevant regulations 10) Maintain social stability: organize relevant departments to ensure the supply of goods, stabilize prices, and prevent looting 11) All public places, business places, and public transportation that are open for business must reasonably control the density of people and take preventive measures such as masks, ventilation and disinfection on a regular basis. 12) Maintain social distancing
Level 2 **Important Event**	**Code Orange**	1) The central ministry is responsible for decision-making and deployment and unified command and coordination of emergency response in the region. 2) Public places should set up warning reminders at entrances to remind shoppers to take personal protection and indicate personnel entry and exit requirements and crowd control standards 3) Strengthen the management and control of public places and continue to suspend the operation of closed entertainment and leisure places 4) Strict prevention and control in the hotel and catering industry. Control the number of diners and recommend the implementation of meal delivery and split meal methods 5) Reduce social events and reduce unnecessary crowds 6) All public places, business places, and public transportation that are open for business must reasonably control the density of people and take preventive measures such as masks, ventilation and disinfection on a regular basis. 7) Strictly enforce centralized observation and testing for all visitors to the region and implement control measures for entering from high-risk areas 8) Information release: after a public health emergency occurs, the relevant departments must do a good job of information release in accordance with relevant regulations 9) Maintain social distancing
Level 3 **Major Event**	**Code Yellow**	1) The province government is responsible for decision-making and deployment and unified command and coordination of emergency response. 2) All types of enterprises have fully resumed production and operation activities on the premise of doing a good job in the prevention

(*continued*)

Levels	Code	Possible Policy Measures
		and control of the epidemic. 3) Strictly prevent and control key places such as markets, restaurants, construction sites, factories, etc. 4) Inspection and quarantine of food and animals at ports and comprehensively strengthen the supervision of imported cold chain food. 5) Strictly enforce centralized observation and testing for all visitors to the city and implement control measures for entering from high-risk areas 6) All public places, business places, and public transportation that are open for business must reasonably control the density of people and take preventive measures such as masks, ventilation and disinfection on a regular basis. 7) Information release: after a public health emergency occurs, the relevant departments must do a good job of information release in accordance with relevant regulations 8) Maintain social distancing
Level 4 Normal Event	**Code Blue**	1) The local government is responsible for decision-making and deployment and unified command and coordination of emergency response in the area 2) It is recommended that residents do personal protection and monitor their health status 3) Information release: after a public health emergency occurs, the relevant departments must do a good job of information release in accordance with relevant regulations 4) It is recommended that residents avoid public places and gatherings; maintain social distancing

References

Abuhasel, K.A., Khadr, M., Alquraish, M.M., 2020. Analyzing and Forecasting Covid-19 Pandemic in the Kingdom of saudi arabia Using Arima and Sir Models. Computational Intelligence.

Adrienne, N., Budd, L., Ison, S.G., 2020. Grounded aircraft: an airfield operations perspective of the challenges of resuming flights post-COVID. J. Air Transport. Manag. 89, 101921.

Andres, C., Betzer, André, Doumet, M., Theissen, E., 2014. Open Market Share Repurchases in germany - a Conditional Event Study Approach. Schumpeter Discussion Papers.

* Kashima, S., Zhang, J., 2021. Temporal trends in voluntary behavioural changes during the early stages of the COVID-19 outbreak in Japan. Publ. Health 192, 37–44.

Beutels, P., Jia, N., Zhou, Q.Y., Smith, R., Vlas, S.J.D., 2010. The economic impact of sars in beijing, China. Trop. Med. Int. Health 14 (s1), 85–91.

Budd, L., Ison, S.G., 2020. Towards Responsible Transport: a post-COVID agenda for future transport policy and practice. Transportation Research Interdisciplinary Perspectives 6, 100151.

Chernozhukov, V., Kasahara, H., Schrimpf, P., 2021. Causal impact of masks, policies, behavior on early covid-19 pandemic in the U.S. J. Econom. 220 (1), 23–62.

Cummins, S., Berger, N., Cornelsen, L., Eling, J., Yau, A., 2020. Covid-19: impact on the urban food retail system and dietary inequalities in the UK. Cities & Health 1–4.

Czerny, A.I., Fu, X., Lei, Z., Oum, T.H., 2021. Post pandemic aviation market recovery: experience and lessons from China. J. Air Transport. Manag. 90, 101971.

Grida, Mohamed, RM, B., ANHZ, B., 2020. Evaluate the impact of covid-19 prevention policies on supply chain aspects under uncertainty Transportation. Research Interdisciplinary Perspectives 8, 100240.

Gui, W.L., Han, Z.Z., 2011. Assessment of SARS influence on railway passenger traffic volume based on SA bottom line. J. China Railw. Soc. 33 (9), 10–18.

Huang, C., Wang, Y., Li, X., Ren, L., Cao, B., 2020. Clinical features of patients infected with 2019 novel coronavirus in Wuhan, China. Lancet 395 (10223).

Jiang, Peng, Fan, Y.V., Jíí, J.K., 2021. Impacts of Covid-19 on energy demand and consumption: challenges, lessons, and emerging opportunities. Appl. Energy 285, 116441.

Joshi, M., Hadi, T.H., 2015. A review of network traffic analysis and prediction techniques. Computer Science.

Ju, K., Zhou, D., Zhou, P., Wu, J., 2014. Macroeconomic effects of oil price shocks in China: an empirical study based on hilbert–huang transform and event study. Appl. Energy 136, 1053–1066.

Kim, K., 2021. Impacts of covid-19 on transportation: summary and synthesis of interdisciplinary research. Transportation Research Interdisciplinary Perspectives 9, 100305.

Li, S., Ma, S., Zhang, J., 2021. Association of built environment attributes with the spread of COVID-19 at its initial stage in China. Sustainable Cities and Society 67, 102752.

Lin, L., Hongbing, J., 2009. Signal feature extraction based on an improved emd method. Measurement 42 (5), 796–803.

Liu, Q., Huang, Z., 2020. Research on intelligent prevention and control of covid-19 in China's urban rail transit based on artificial intelligence and big data. J. Intell. Fuzzy Syst. 39 (21), 1–6.

Loomis, J., 2011. What's to know about hypothetical bias in stated preference valuation studies? J. Econ. Surv. 25 (2), 363–370.

Mahammed, M.A., 2020. Analysis of covid-19 lockdown policy impact by the government of the country on the economic sector and signing of working relationships (layoffs). International Journal of Law Reconstruction 4 (1), 44.

Maloney, W.F., Taskin, T., 2020. Determinants of social distancing and economic activity during covid-19: a global view. Policy Research Working Paper Series.

Mckenzie, G., Adams, B., 2020. A Country Comparison of Place-Based Activity Response to Covid-19 Policies.

Mogaji, E., 2020. Impact of covid-19 on transportation in lagos, Nigeria. Transportation Research Interdisciplinary Perspectives 6, 100154.

Nicola, M., Alsafi, Z., Sohrabi, C., Kerwan, A., Agha, R., 2020. The socio-economic implications of the coronavirus and covid-19 pandemic: a review. Int. J. Surg. 78, 185–193.

Oberholtzer, K., Sivitz, L., Mack, A., Lemon, S., Mahmoud, A., Knobler, S. (Eds.), 2004. Learning from SARS: Preparing for the Next Disease Outbreak: Workshop Summary. National Academies Press.

Osinska, M., Zalewski, W., 2020. Effectiveness of the anti-crisis policy in the period of covid-19 pandemic in the road transport industry. European Research Studies Journal XXIII (Special Issue 2), 40–57.

Oum, T.H., Wang, K., 2020. Socially optimal lockdown and travel restrictions for fighting communicable virus including COVID-19. Transport Pol. 96, 94–100.

Pang, Xinghuo, , et al.Covid-19 Field Response Group, Covid-19 Laboratory Testing Group, 2020. Cold-chain food contamination as the possible origin of Covid-19 resurgence in Beijing. National Science Review. https://doi.org/10.1093/nsr/nwaa264.

Peng, T., Liu, X., Ni, H., Cui, Z., Du, L., 2020. City lockdown and nationwide intensive community screening are effective in controlling the covid-19 epidemic: analysis based on a modified sir model. PloS One 15 (8), e0238411.

Raicu, S., Costescu, D., Popa, M., Rosca, M.A., 2019. Including negative externalities during transport infrastructure construction in assessment of investment projects. European Transport Research Review 11 (1).

Suau-Sanchez, P., Voltes-Dorta, A., Natàlia, C.E., 2020. An early assessment of the impact of covid-19 on air transport: just another crisis or the end of aviation as we know it? J. Transport Geogr. 86, 102749.

Sun, D., Yu, D., 2020. From the intelligent search of internet public opinion information to see traffic management during epidemic prevention and control. Automotive and Safety (4), 86–90 (Chinese Version).

Wang, H., Liu, L., Qian, S.Z., 2018. Empirical mode decomposition–autoregressive integrated moving average: hybrid short-term traffic speed prediction model. Transport. Res. Rec. 2460 (1), 66–76.

Workie, E., Mackolil, J., Nyika, J., Ramadas, S., 2020. Deciphering the impact of COVID-19 pandemic on food security, agriculture, and livelihoods: a review of the evidence from developing countries. Current Research in Environmental Sustainability 2, 2666-0490.

Yu, H.K., Huarng, K.H., 2020. A new event study method to forecast stock returns: the case of facebook. J. Bus. Res. 115.

Zhang, J., 2020. Transport policymaking that accounts for COVID-19 and future public health threats: a PASS approach. Transport Pol. 99, 405–418.

Zhang, L., Yang, H., Wang, K., Zhan, Y., Bian, L., 2020. Measuring imported case risk of COVID-19 from inbound international flights—A case study on China. J. Air Transport. Manag. 89, 101918.

Zhang, Y., Zhang, A., Wang, J., 2020. Exploring the roles of high-speed train, air and coach services in the spread of COVID-19 in China. Transport Pol. 94, 34–42.

Zhang, J., Hayashi, Y., Frank, L.D., 2021. COVID-19 and transport: findings from a world-wide expert survey. Transport Pol. 103, 68–85.