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COVID-19, traffic demand, and activity restriction in China: A national assessment

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ABSTRACT

The global COVID pandemic of 2020, affected travel patterns across the world. The level of impact was influenced not only by the virus itself, but also by the nature, extent, and duration of governmental restriction on commerce and personal activity to limit its spread. This paper focuses on the interaction between COVID-19 transmission and traffic volume and further explores the impact of traffic control policies on the interaction. Roadway traffic volume was used to quantify and assess the Chinese response to the pandemic; specifically, the relationship between government restrictions, travel activity, and COVID-19 progression across 29 provinces. Space and time distributions of traffic volume across China during the first half of 2020, were used to quantify the response and recovery of travel during the critical initial onset period of the virus. Most revealing of these trends were the impact of the Chinese restriction policies on both travel and the virus as well as the relationship of traffic trends during the closure period with the speed and extent of the recovery “bounce” across individual provinces based on location, economic activity, and restriction policy. These suggest that the most significant and rapid declines in traffic volume during the restriction period resulted in the most pronounced returns to normal (or more) demand levels. Based on these trends a Susceptible Infection Recovery model was created to simulate a range of outbreak and restriction policies to examine the relationship between COVID-19 spread and traffic volume in China.

1. Study motivation and goals

By January 2021, the COVID-19 outbreak that began in December 2019 in Wuhan, China, had impacted 191 countries around the world (Johns Hopkins University and Medicine, 2020). By December 2020, the COVID-19 virus infected more than 90,000 people and killed more than 4,700 people in China (Johns Hopkins University and Medicine, 2020). COVID-19 not only impacted healthcare systems but also reshaped personal mobility. Prior research showed that COVID-19 travel restriction policies implemented by the Chinese government restricted the movement of more than five million people in Hubei Province including the complete prohibition of travel out of the province; including during the 2020 Spring festival (Tian et al., 2020; Zhang et al., 2020a, 2020b).

In the early stages of the COVID-19 outbreak, the Chinese government implemented strong traffic control policies to limit personal travel. Those traffic control policies include passenger traffic suspension measures on the municipal level, such as closing highway entrances and exits and suspending trains and other transportation facilities between cities, and traffic control measures within a city, such as limiting public transport and closing the community. Those policies are differentiated between cities, and they are strict at the outbreaking duration and then gradually loosen and lifted after the infection spread eased (Jia et al., 2022). Later, in April 2020, after fear of infection lessened, the Chinese government implemented free toll policies to stimulate traffic demand and the economy. It has been theorized that although the Chinese policies were highly restrictive compared to other countries in the world, they were also highly effective in limiting the spread of COVID-19 and the re-booting of the Chinese economy. The focus of this research is to use the relationships between traffic volume and COVID-19 transmission in China during the initial onset period of the virus to examine the Chinese policies and their effects more closely.

This research fills the knowledge gap in understanding highway

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travel trends and the governmental response to the outbreak of the COVID-19 virus in China. As it is often assumed that transportation increases the likelihood of person-to-person interaction, it would be logical to assume that, by association, there would be a similar relationship between highway traffic and the spread of COVID-19 (Tian et al., 2020; Jia et al., 2020). The outbreak of COVID-19 prompts the government to develop related traffic control policies, and the reduction of traffic volume promotes the pandemic to be controlled quickly. These two aspects coincide and should be quantified. Therefore, this paper first quantifies the highway traffic trends during the outbreak of COVID-19 in China based on the traffic volume data, then uses them to assess correlations between highway traffic volume and COVID-19 transmission. The SIR model is established to imitate COVID-19 transmission. Based on this model, how traffic restriction policies affect the spread of COVID-19 and how effective they are can be explored meticulously. These two parts constitute a complete framework for the interaction between the COVID-19 transmission and traffic volume in terms of the preliminary exploration at the data level and accurate expression at the model level.

Traffic volume data in the study was collected by the Ministry of Transport of the People’s Republic of China. The data set included the daily traffic volume of mainland China’s 29 provincial administrations from January 1st through May 30th in 2019 and 2020. It should be noted that the classification of vehicle types is challenging to collect for the macroscopic analysis at the provincial level. It is assumed that the proportion of vehicle types is consistent in provinces and dates, so it is not considered in this paper. And then, the daily traffic volume for 2019 and 2020 are adjusted to align with the date of the Spring Festival, as the Spring Festival causes significant changes in the traffic volume. Among the performance indicators used to compare the various dependent variables are the “bounce level” of traffic (i.e., how quickly traffic volume decreased and increased due to governmental restriction) and the rate of new COVID-19 infections. The effects of the governmental traffic control policies on the spread of COVID-19 were assessed using a time-discrete SIR model. As an additional measure of analysis, the study also examined two theoretical restriction policies to evaluate their impact on COVID-19 transmission, highway traffic volume, and economy.

The paper is organized into five sections. Section 2 provides readers with a review of recent COVID-related transportation research undertaken since the start of the pandemic in 2020. In Section 3, traffic trends in China are assessed using resilience metric and analysis techniques. Section 4 describes the development of a mathematical model to simulate the spreading process of COVID-19 in China. This section also includes an application to assess theoretical control policies to constrain COVID-19 and restart the national economy. Finally, Section 5 describes the primary outcomes of this research and how they could be used to inform future policy and research.

2. Prior research

In the first year of the COVID-19 pandemic, a significant amount of researches were undertaken to assess its impact on transportation. An interesting aspect of those researches was also the wide variety of types and sources of information to measure travel activity. A study by Jia et al. (2020) used mobile phone roaming data to compute Wuhan’s population movements to the rest of mainland China. This data was then used to predict the spread rate and patterns of COVID-19 throughout China. Zhang et al. (2020a, b) used traffic volume to assess the spread of the COVID-19 pandemic by applying an improved Susceptible-exposed-Infected-Removed (SEIR) model. Lee et al. (2020) analyzed the change in traffic volume from 2019 to 2020. The researchers concluded that traffic volume increased the risk of COVID-19 spreading.

Zhang et al. (2020a, b) explored the correlation between international travel and COVID-19 spread and suggested that policymakers focus attention on restricting movement into and out of hotspot areas with high infection rates. Farzegan et al. (2020) used global tourism data and virus spread patterns in more than 90 countries to demonstrate a correlation between international tourism and COVID-19 severity (as measured by number of cumulative COVID-19 confirmed cases). The researcher also showed that countries with the highest global tourism were most prone to new COVID-19 cases and deaths. Additionally, Ortiz and Askin (2020) found a statistical relationship between higher airline passenger traffic and higher numbers of patients with COVID-19 in countries around the world. Similar findings were also evident in other related studies, including Sokadjo and Atchadé (2020).

Other research on the relationship between road and air traffic on COVID-19 severity was also proceeded, including a study by Joseph et al. (2020). As a part of this work, the researchers used a regression model to analyze the relationship between COVID-19 case counts, neighborhood characteristics, and transit accessibility at the census tract level to assess virus progression in the American state of Louisiana. A key finding of the study was that densely populated neighborhoods with higher public transit ridership had larger per-capita COVID-19 infection rates. From this, it was suggested that governments should increase public transport capacity to maintain increased social distancing to reduce COVID-19 spread in large cities. Asweto et al. (2020) studied the correlation between COVID-19 infections and population mobility across 26 African countries using community mobility data. This study showed that COVID-19 spread was negatively correlated to residential mobility and positively correlated to public place mobility change. From this the authors suggested that governments should restrict public transit mobility during the initial onset stages of COVID-19.

Another key consideration in the implementation and relaxation of activity restriction policies in countries around the world was their impact on economic activity. The importance of this is also evident in research that examined such policies on national economies (Yen et al., 2020; Arellana et al., 2020). He et al. (2020) showed that travel bans and “active isolation” policies that limited the spread of COVID-19

![Fig. 1. Research framework.](image-url)
significantly impacted daily inter-city transportation demand and festival related travel in China. Research by Parr et al. (2020) investigates the effect of COVID-19 lockdowns on traffic volume in ten US states. The research team found that the decline in traffic volume is heterogeneous across space and time and was closely linked to closures of many commercial businesses. Loske (2020) studied freight impacts of COVID-19. The study showed that retail freight movement was relatively unaffected throughout the COVID-19 pandemic. Arellana et al. (2020) analyzed the impacts of COVID-19 on air transport, freight transport, and urban transport networks. This research showed that decreased traffic demand during COVID-19 lockdowns leads to lower levels of traffic congestion and declines in transit ridership. Forsyth et al. (2020) examined air traffic demand related to COVID-19 and Amankwah-Amoah (2020) developed a framework to study the airlines’ response to the virus. Sun et al. (2020) explored spatial-temporal evolutionary dynamics of COVID-19 in air transport networks from a complex system perspective. This research suggested that the aviation industry response to the pandemic had a two-month lag.

Sun et al. (2020) also analyzed the impacts of COVID-19 on air transport, freight transport, and urban transport networks. This research showed that decreased traffic demand during COVID-19 lockdowns leads to lower levels of traffic congestion and declines in transit ridership. Forsyth et al. (2020) examined air traffic demand related to COVID-19 and Amankwah-Amoah (2020) developed a framework to study the airlines’ response to the virus. Sun et al. (2020) explored spatial-temporal evolutionary dynamics of COVID-19 in air transport networks from a complex system perspective. This research suggested that the aviation industry response to the pandemic had a two-month lag.

To quantify traffic changes under the COVID-19 outbreak in China, R is defined as the “accumulated highway traffic volume difference with the normal level” during time range \( t_1 \) and \( t_2 \), which is calculated as below.

\[
R = \int_{t_1}^{t_2} (Q_{2020}(t) - Q_{2019}(t)) dt
\]

where \( t_1 \) is the start time, and \( t_2 \) is the end time of the quantization period. \( Q_{2020}(t) \) and \( Q_{2019}(t) \) are the highway traffic volume in 2020 and 2019 (benchmark group), respectively, which are depicted in Fig. 2. It should be noted that the traffic volume in 2019 is considered to be the normal traffic volume. The horizontal axis represents the date of 2020, and the vertical axis is the highway traffic volume in ten thousand vehicles. It is worth noting that the national highway traffic volume is the sum of total highway traffic volumes from 29 provincial-level administrative regions in mainland of China. A V-shape curve exits in the 2020 China national highway traffic volume. This V shape curve depicts a giant drop in national highway traffic volume at the beginning of the COVID-19 outbreak since January 23, 2020, followed by a rise in national highway traffic volume since February 16, 2020. Therefore, three stages are defined as the response stage, recovery stage, and bounce stage for China. The accumulated highway traffic volume difference for these three stages is calculated as below.

\[
R_{\text{response}} = \int_{t_1}^{t_2} (Q_{2020}(t) - Q_{2019}(t)) dt
\]

(2)

\[
R_{\text{recovery}} = \int_{t_2}^{t_3} (Q_{2020}(t) - Q_{2019}(t)) dt
\]

(3)

\[
R_{\text{bounce}} = \int_{t_3}^{t_4} (Q_{2020}(t) - Q_{2019}(t)) dt
\]

(4)

In which \( t_1 \) (Jan 23, 2020), \( t_2 \) (Feb 16, 2020), and \( t_2 \) (Mar 9, 2020) are the start date of the response stage, recovery stage, and bounce stage. Furthermore, \( t_3 \) (May 12, 2020) is the end day of the bounce stage.

The sketch map of the three stages is illustrated in Fig. 2. The area with orange and green colors represent \( R_{\text{loss}} \) and \( R_{\text{bounce}} \), respectively. Because there is a significant drop in national highway traffic volume in 2020 compared to 2019, the accumulated highway traffic volume difference in the response and recovery stage is negative. Therefore, “accumulated highway traffic volume loss” is defined as below.

\[
R_{\text{loss}} = |R_{\text{response}}| + |R_{\text{recovery}}|
\]

(5)

It is worth noting that \( t_2 \) was when the 2020 highway traffic volume surpassed the 2019 highway traffic volume. If the 2020 highway traffic volume never surpassed the 2019 highway traffic volume, the bounce stage would not exist. If the 2020 highway traffic volume surpassed the 2019 highway traffic volume one day, the bounce stage would exist. But the \( R_{\text{bounce}} \) could be negative if the cumulative highway traffic volume never surpassed the cumulative highway traffic volume in the same period of 2019.

The exact date of \( t_1 \) and \( t_2 \) for all the 29 provinces are recorded in Table 1, which demonstrates that 27 of the 29 provinces except for Beijing and Shanghai has the bounce stage.

According to the different stages, bounce level \( n_0 \) is defined as the ratio of \( R_{\text{bounce}} \) and \( R_{\text{loss}} \) to represent the bounce of traffic volume compared to the loss of traffic volume in the total research period calculated in Eq. (6). This indicator aims to present the recovery characteristics of traffic volume from a long-term perspective, as traffic volume may fluctuate between adjacent days. Calculating bounce level based on daily/weekly traffic volume may cause biased results.

\[
n_0 = \frac{R_{\text{bounce}}}{R_{\text{loss}}}
\]

(6)

A higher bounce level means better bounce performance of highway traffic volume after the response stage, which illustrates that traffic has a good recovery performance. Based on the calculated bounce level, all the 29 provinces were divided into three categories: Category 0 (no bounce), Category 1 (low bounce level less than 100 %), and Category 2 (high bounce level greater than 100 %) in Table 2. Category 0 represents provinces with slower recovery and has not yet recovered to pre-pandemic levels by the end of May. And Category 1 indicates that the
Fig. 2. Daily highway traffic volume (2019 vs 2020) in China.

Fig. 3. Three stages of highway traffic volume and resilience.
impact of COVID-19 outbreak has been recovered or compensated. In addition, provinces in Category 2 have rebound traffic volumes that exceed their total loss of traffic volume. We set the classification threshold as 100% because this indicates whether the total loss of traffic volume was compensated in the later bounce stage. The bounce level for all the 29 provinces in China is calculated and depicted in Fig. 4, which clearly shows that the bounce level varies significantly from province to province, ranging from –32% to 484%. It should be noted that Shanghai’s 2020 traffic volume exceeded the 2019 traffic on April 30th (2020/4/30), but it was only exceeded for one day and remained low all the time, which is very similar to the trend of Beijing’s traffic volume. Therefore, Shanghai does not have a bounce stage like Beijing.

The highway traffic volume in 2019 and 2020 of three provinces, i.e., Beijing of Category 0, Jiangsu of Category 1, and Shandong of Category 2 are drawn in Fig. 5 to illustrate the characteristics of each category. Beijing’s highway traffic volume in 2020 dropped and never came back to the state in 2019, which is attributed to strict control policies in Beijing. It is also noted that there has been a big drop in highway traffic volume since May 1, 2020, which is attributed to the second outbreak of COVID-19 in Beijing. While Jiangsu province of Category 1 has a recovery of highway traffic volume since Feb 12, 2020, and finally, the highway traffic volume in Jiangsu recovered to the normal state in 2019. The Shandong province of Category 2 reveals more promising results: its highway traffic volume has a much shorter recovery time and much higher magnitude than its normal state in 2019.

There are only two provinces in Category 0, Beijing and Shanghai, China’s capital city and the economic center of China. Both regions are under strict control and isolation rules. Thus, the highway traffic volume never goes back to the normal state as in 2019. Category 1 includes most developed provinces (such as Zhejiang province and Jiangsu province) or provinces adjacent to the Hubei province in China (such as Chongqing and Hunan province). Regions in Category 1 obtain a better recovery performance than Beijing and Shanghai, and their \( r_0 \) values are less than 100%. While Category 2 contains 11 provinces, most of these provinces are either under-development provinces (such as Jilin and Gansu) or provinces located far away (such as Shandong, Inner Mongolia, or Xinjiang) from Hubei province, the COVID-19 outbreak center. Areas in Category 2 all have high bounce levels, meaning that COVID-19 had less impact on these provinces, and their highway traffic volume bounced quickly and even surpassed the same period in 2019. The difference in highway traffic volume and bounce level among provinces indicates that such difference may be attributed to control policies and province geographic location.
The geographic location and bounce level of all the provincial administrative regions are shown in Fig. 6. The three most developed provinces, Jiangsu, Zhejiang, and Guangdong provinces, are all in Category 1 and have bounce levels: 4%, 24%, and 31%, meaning that COVID-19 has worse impacts on the three most developed provinces than most of the other regions. It is demonstrated that provinces bordering Hubei have relatively small bounce levels, which indicates that the impact of COVID-19 on these provinces was much worse than regions far away.

The bounce level and the recovery time ($t_2 - t_1$) are further investigated. The scatters of bounce level and recovery time for each province are illustrated in Fig. 7, which demonstrates a log relationship between bounce level and recovery time. A shorter recovery time leads to a higher bounce level, and this pattern is particularly evident in provinces with short recovery times. This may be due to the fact that the provinces with shorter recovery times are more active in economic and social activity, making up for the production losses in other provinces. Thus, the stimulation on the economy and transportation of these provinces generates higher rebounds than their normal level. Therefore, to gain a high bounce level, implementing traffic resume policies such as "free toll of the highway" as long as the pandemic severity reached a minimum would be beneficial for both economy and transportation.

### 3.2. Loss & bounce comparison

Further, *loss rate* and *bounce rate*, which are calculated by the division of their accumulated traffic volume difference and the corresponding time duration, are used to quantify the loss and bounce speed.
of traffic volume in 2020 in the loss stage and the bounce stage, as below.

\[
r_{\text{loss}} = \frac{\int_{t_1}^{t_2} Q_{2020}(t) dt}{t_2 - t_1} = \frac{\int_{t_1}^{t_2} Q_{2020}(t) dt}{(t_2 - t_1) \int_{t_0}^{\infty} Q_{2020}(t) dt}
\]

(7)

\[
r_{\text{bounce}} = \frac{\int_{t_1}^{t_2} Q_{2020}(t) dt}{t_2 - t_1} = \frac{\int_{t_1}^{t_2} Q_{2020}(t) dt}{(t_2 - t_1) \int_{t_0}^{\infty} Q_{2020}(t) dt}
\]

(8)

Based on the definition of loss rate and bounce rate, the linear or nonlinear relationship between loss rate and bounce rate for all China provinces is tested. As there are only two provinces in Category 0, linear regression is implemented to investigate the relationship between the bounce rate and loss rate for provinces in Category 1 and 2, respectively. It is noted that there exists a strong linear relationship between bounce rate and loss rate for provinces in Category 1 and 2, respectively. In contrast, there exists a weak or no linear relationship between bounce rate and loss rate for provinces in Category 2 (Fig. 8a). All provinces of Category 2 have a considerable stable bounce rate, meaning that the loss of highway traffic volume does not significantly impact these provinces’ highway traffic volume.

It is also presented that bounce rate and loss rate are positively related to each other, which means that a province with a high loss rate will have a high bounce rate in the bounce stage. High traffic loss in response and recovery stages may get compensation in the future bounce stage and then get a head start in economic and social activities. Like retaliatory consumption in the economy, the more stringent restrictions in the response stage will depress people’s desire to consume and travel; the consumption and travel demand will rapidly rise once the restrictions are lifted.

Based on the above discussions, the government could implement a strict traffic control policy to constrain traffic demand in the early stage of the COVID-19 outbreak (high loss rate) so that traffic demand will be dramatically released as long as the COVID-19 severity is relieved. However, the relationships between the COVID-19 transmission parameter and highway traffic volume are still unknown. Therefore, a virus transmission mode is built to investigate the quantitative relationship between highway traffic volume and the epidemic parameters in the next section.

4. Traffic control policies

The linear relationship between loss rate and bounce rate indicates that strict highway traffic control policies may constrain highway traffic volume in the response and recovery stage and stimulate highway traffic volume in the bounce stage. The highway traffic volume and COVID-19 infected population are plotted in Fig. 9, demonstrating that the inflection points for highway traffic volume and the infected population appeared on the same day, i.e., Feb 16, 2020. Therefore, it is assumed that a strict traffic control policy could bring forward the inflection point of highway traffic volume and infected populations. Only the data in the response and recovery stages are included because the traffic volume has already increased and surpassed its normal stage since the bounce stage. Thus, controlling the spread of the virus before the bounce stage is necessary. What should be illustrated is that the traffic control policies of various provinces in China have certain similarities after the outbreak in Hubei province (Fig S1), such as the published dates for the first-level emergency response policies for provinces are mainly concentrated between Jan 23, 2020, and Jan 25, 2020. Therefore, the national traffic data is used to model and analyze the spread of COVID-19.

4.1. COVID-19 transmission model

To assess this assumption, a COVID-19 transmission model is built to simulate the outbreak and spreading process of COVID-19 in China. Existing researches demonstrate that the spread of COVID-19 followed Susceptible-Infected-Removed (SIR) dynamic. Moreover, the modified model, such as Susceptible-exposed-Infected-Removed (SEIR) model, needs to make additional assumptions compared with the SIR model. In
\[ \frac{dI}{dt} = \mu I \tag{9c} \]

The differential equations can be solved at each discrete time step \((dt/\Delta t)\), as Eqs. (10) show below.

\[ ds = S_i - S_i = -\lambda \Delta t S_i I_i \tag{10a} \]

\[ dl = I_i - I_i = \lambda S_i \Delta t I_i - \mu \Delta t l_i \tag{10b} \]

\[ dR_i = R_i - R_i = \mu \Delta t l_i - \tag{10c} \]

Fig. 10 (b) shows how the three compartments evolve in a typical epidemic spreading process. The size of the total population \(N = 10,000\), spreading rate \(\lambda = 0.3\), recovery rate \(\mu = 0.1\), and \(I = 1\) (the first infected people). In Fig. 10 (b), \(R\) monotonically increases, and \(S\) decreases. The size of \(I\) increases in the first stage and then reaches a maximum, followed by a decrease, representing the spreading process of pandemics that \(S = N\) during the onset phase of a pandemic. In this stage, the increase of infected compartment \(dl = I_i - I_i = \lambda S_i \Delta t I_i - \mu \Delta t l_i \) is always positive. As long as \(S\)’s size is reduced until \((\lambda S_i - \mu) \Delta t I_i < 0\), the size of \(I\) will decrease and eventually dissipate, as shown in Fig. 10 (b).

Based on the epidemic evolution process, an epidemic will eventually dissipate even though no virus control/constrain policies are implemented, i.e., a constant value of \(\lambda\) and \(\mu\) will lead to a dissipation of epidemic. However, as Fig. 10 (b) shows, a vast amount of people (the number of total infections is equal to the area under the orange curve) will be infected, even though most of them (95% in Fig. 10(b)) will eventually be healthy.

During the onset and transmission process of COVID-19 in China, the Chinese government has issued strict control policies such as travel restriction, isolation of suspected people, “stay and home,” etc. Therefore, the spreading rate \(\lambda\) and recovery rate \(\mu\) vary day by day. Also, \(\frac{S_i}{N}\) as most people in China have never been infected (\(S_i = 139,162,423, N = 139,244,149\) and \(\frac{S_i}{N} = 0.9994\) on March 29, 2020). Under such conditions, the time-discrete SIR model is revised as below.

\[ S_i - S_i = -\lambda \Delta t S_i I_i = -\lambda S_i I_i \tag{11a} \]

\[ I_i - I_i = \frac{S_i - I_i}{N} \Delta I_i - \mu \Delta I_i = \lambda S_i \Delta I_i - \mu \Delta I_i = (\lambda S_i - \mu) \Delta I_i \tag{11b} \]

\[ R_i - R_i = \mu \Delta I_i - \tag{11c} \]

According to Eq. (11b), \(I_i - I_i = (\lambda S_i - \mu) \Delta I_i\). This Equation denotes that one infected individual infects \((\lambda S_i - \mu)\) persons on day \(t\). Thus, the variable \(\Phi_i\) is calculated as below.

\[ \Phi_i = \lambda S_i - \mu \tag{12} \]

This variable is defined as effective spreading rate (Dehning et al., 2020) on day \(t\), which represents the intensity of infection and the strength of control policy, i.e., the smaller \(\Phi_i\) is, the stricter control policy is. According to Eqs. (11) and (12), the values of \(\lambda S_i - \mu\) and \(\Phi_i\) of China are calculated and depicted in Fig. 11.

To find the relationship between traffic control policy and highway traffic volume, national highway traffic volume and variable \(\Phi_i\) are plotted as scatters in Fig. 12. These scatters can be clustered into two parts. The solid circles represent the period from Jan 24, 2020, to Feb 16, 2020, while the hollow circles denote the date between February 17, 2020, and Mar 29, 2020. The scatters of highway traffic volume and variable \(\Phi_i\) show a skewed V shape in Fig. 12.

According to Fig. 12, highway traffic volume \(Q\) and \(\Phi_i\) show a strong linear relationship (\(|\text{Pearson coefficient}| > 0.8\)) in the response stage.
and recovery stage, respectively. The highway traffic volume is fitted as a linear function of the effective spreading rate for the response stage and recovery stage, the equations for the response stage and recovery stage are shown in Eqs. (13) and (14),

$$Q = 1796.6\Phi + 454.75$$  \hspace{1cm} (13)

$$Q = -21443\Phi + 1177.4$$  \hspace{1cm} (14)

In the response stage, highway traffic volume decreases as the effective spreading rate $\Phi$ decreases, while in the recovery stage, highway traffic volume increases as the effective spreading rate $\Phi$ decreases. Besides, the decrease-rate of highway traffic volume in the response stage is much lower than the increase-rate of highway traffic volume in the recovery stage. Such the difference in decrease-rate and increase-rate means that a decline in the effective spreading rate will lead to a slight decrease in highway traffic volume and a rapid increase of highway traffic volume in the response and recovery stage. Because more highway traffic volume means more economic activities, implementing policies to decrease the effective spreading rate $\Phi$ will eventually constrain the spreading of COVID-19 in the response stage and boom traffic and economy in the recovery stage.

The E-Divisive with Medians (EDM) (James et al., 2014) is further used to detect the dynamic evolution of the effective spreading rate $\Phi$. 

Fig. 9. Line chart of infected population and highway traffic flow.

Fig. 10. Illustration of standard SIR

Fig. 11. $\lambda$, $\mu$, and $\Phi$ of each day.
The EDM method is a statistical technique that automatically detects breakouts in time series datasets by assuming that the dataset before and after a breakout point shows different statistical distributions. The time series of $\Phi_t$, as well as breakouts detected by EDM, are shown in Fig. 13. It is inspiring to find out that there exist three different periods: Jan 24, 2020, to Jan 30, 2020, Jan 31, 2020, to Feb 17, 2020, and Feb 18, 2020, to Mar 29, 2020. The three periods coincide with the response time of the Chinese government. On Jan 30, 2020, the Chinese government stopped almost all the passenger traffic and issued an “isolation at home” order. Later in late February, most provinces in China began to reduce emergency response levels since no new cases appeared in many days. The exact time for each province to reduce its response level is shown in Fig. 14.

The trend of variables $\Phi_t$ between Jan 25, 2020, to Mar 29, 2020, shows the COVID-19 outbreak and spreading process characteristics. Period 1 and period 2 coincide with the response stage, and period 3 contains the recovery stage. Period 1 is within one week after the COVID-19 outbreak on Jan 23, 2020. Thus, period 1 can be described as the “active transmission” period of COVID-19 and period 2 is the “transmission” period of COVID-19. It is worth noting that the values of $\Phi_t$ in period 1 are high and then decrease in period 2. Finally, $\Phi_t$ in period 3 reaches a stable and low weight. Thus, the best time for COVID-19 constrain seems to lie in period 1 since the effective spreading rate $\Phi_t$ of this period is relatively high that strict traffic control policy would decrease the effective spreading rate and achieve the most significant decline of infected people. Most people were not aware of the importance of self-isolation and went out without wearing a mask in period 1. It is essential to implement a strict traffic control policy during this period to avoid the wide spreading of COVID-19.

4.2. Policy and effects

There are two approaches to planning a strict control policy in period 1: the first approach is to decrease $\Phi_t$, while the second way is to shorten...
Thus, Policy 1 is built as below.

**Policy 1:** constrain the average value of effective spreading rate to 0.3 (the real average value of effective spreading rate is 0.48, and the lowest effective spreading rate is 0.3 in Fig. 13). This new control policy means that the government issued a “wearing mask” or “stay-at-home” order and raise the public’s attention to the epidemic during the onset period. Then, people wear a mask and reduce travel demand to reduce the probability of being infected.

Policy 2 is built as below.

**Policy 2:** shorten the duration of period 1 from 5 days to 2 days. Although the Chinese government has already made an effort to prevent the spreading of COVID-19, like issuing a travel ban in Wuhan on Jan 23, 2020, until the end of period 1 (Jan 30, 2020), Chinese citizens began to quarantine themselves at home. So, Policy 2 means the government could issue a travel restriction policy earlier.

The real observed value of $\Phi_t$ and the value of $\Phi_t$ under policies 1 and 2 are plotted in Fig. 15 (a). Using the time-discrete SIR model (Eq. (11)), the infected population’s size under the two control policies can be predicted. The changing trend of the number of infected people under both approaches is depicted in Fig. 15 (b), which promises that the maximum active infected population was 35,809 and 19,450 under policy 1 and policy 2, respectively. Besides, the inflection point under policy 2 is brought forward by two days.

Using the linear relationship between highway traffic volume and $\Phi_t$ (Eqs. (13) and (14)), the highway traffic volume under different policies can be predicated. As shown in Fig. 16, highway traffic volumes in the response stage are reduced under policies 1 and 2. The inflection point appeared on February 15, 2020, and February 13, 2020, under policies 1 and 2, respectively. It is observed that the highway traffic volume before the inflection point day does not change a lot compared to the observed data. However, highway traffic volume rises rapidly after the inflection point day. A much more significant rise in highway traffic volume is observed under policy 2 compared to policy 1. Finally, highway traffic volume obtains a reduction of 12 million vehicles under policy 1 and an increase of 56 million cars under policy 2.

The scatter of cumulative highway traffic volume and GDP (National Bureau of Statistics, 2020) for all the provinces of China in the first half of 2020 are plotted in Fig. 17. It is exhibited that there exists a robust linear relationship between cumulative highway traffic volume and GDP. The linear regression results are shown in Table S1.

Transportation activity embodies people’s active economic activity. For instance, more highway traffic volume represents people traveling more often than when highway traffic volume is low. Thus, implementing policies to stimulate more highway traffic volume may lead to higher economics such as GDP.

In general, policy 1 is conservative, and policy 2 is strict. Both approaches can constrain the spreading of COVID-19. However, the impacts of policies 1 and 2 on highway traffic volume are different. Choosing one of the two approaches is a big challenge as it needs knowledge about the pandemic’s transmission process. At the outbreak stage of an unknown pandemic, the government should monitor this pandemic’s evolution process and calculate the virus spreading rate, recovery rate, and effective spreading rate dynamically. Based on such information, government administrators can simulate and predicate this pandemic’s evolution process and then make the right decision about control policy, such as travel restriction, “stay at home” order, wearing a mask, etc. If the unknown pandemic has a fast-spreading rate, government administrators should order strict control strategies such as “travel restriction” and “stay at home” immediately. But if the epidemic is not so bad, the officers may order conservative orders such as constraining transit ridership, and so on. Meanwhile, the government should dynamically change policies based on the spreading process of this pandemic.

In addition to traffic control policies, the development of biological and medical technologies will also contribute to the control of COVID-19. For instance, the normalization of COVID-19 has led to the inevitable of some traffic activities (Kim and Kwan, 2021). Promoting the COVID-19 vaccine could reduce the spreading rate ($\lambda$). Moreover,
improvements in treatment techniques could increase the recovery rate ($\mu$). Those measures will weak the spread of COVID-19 based on the established SIR model. Furthermore, those measures also open up the horizon for our future research on how the advances in technological developments affect pandemic control.

5. Conclusion

The intent of this research was to analyze the interaction between the COVID-19 transmission and traffic volume, and then, examine and assess the highway traffic effect of the activity restriction measures on the onset of the COVID-19 virus across individual provinces in China. Since highway traffic volume reflects personal movement and, likely, social interaction, it was assumed that these restrictions would slow the progression of the virus. Prior related research performed for Sweden and individual US states showed somewhat mixed, though overall limited, relationships between traffic volume and the progression of the virus (Parr et al. 2021). However, the restriction policies in these two countries were more varied and far less-restrictive than those used in China, where some provinces were on near-complete home isolation with no local or inter-provincial travel permitted.

Clearly, restrictions used in China had an enormous and immediate effect on traffic with traffic volumes dropping effectively to zero in several provinces. The traffic volume remained a small fraction of its normal level for about a month until restrictions were eased at the end of February and beginning of March in the various provinces. Trends in the data also revealed several other key aspects of the COVID-19 event in China, in particular, the timing and rate of traffic decline and increase with respect to the implementation of the restrictions as well as how long they lasted, both nationally and across individual provinces.

Interestingly, the trends of traffic decline and recovery in China due to the pandemic closely resembled the classic onset, duration, and recovery trends in traffic seen during any transportation disruption. Over the past 20 years, these trends have been used by both researchers and practitioners to describe and analyze the resilience of transportation systems and their ability to respond and recover from disruptive events. While there were not any on-road incidents or infrastructure failures during the pandemic, the analytical relationships used to describe cause and effect relationships of disruptive events were applied in this research to examine the temporal and spatial trends of actions and results during the pandemic.

Among the most obvious and interesting relationships identified in the provincial traffic trends were the magnitude rate of traffic decline

![Fig. 15. Effective spreading rate and infected population under Policy 1 and 2.](image)

![Fig. 16. Highway traffic volume under policy 1 and 2.](image)
and the later rate and magnitude of traffic increase once the pandemic-related restrictions were eased. The recovery in particular in some provinces were quite rapid and, in some cases, actually resulted in traffic levels that considerably existed prior year levels. In this research, these traffic recovery trends were termed as a ‘bounce’ effect. With this in mind, the bounce characteristics both nationally and within individual provinces in China were the focus of this effort.

Among the broad findings of this analysis was the magnitude of provincial bounces. These were most apparent in the “Category 2” provinces like Inner Mongolia, Jilin, Xinjiang, Shaanxi, which are located far away from Hubei province, showed a nearly immediate return to normal traffic levels after the lifting of social restrictions. While, in contrast, “Category 1” provinces like Zhejiang, Guangdong, and Jiangsu, where nationally important transportation connections and employment centers are located and other provinces boarding Hubei. Here, the data showed much slower increases back to normal after the lifting of social restrictions. Additionally, the results revealed that relationships existed between the amount of traffic volume decline and the amount of bounce. Provinces with the most significant traffic reduction were usually followed by more rapid and significant rates of traffic increase, which is referred to here as a greater bounce stage.

Another notable finding was the relationship between highway traffic volume and COVID-19 spread rate. Once again, clear linear relationships were evident between the immediate decline in traffic and the slowing of the COVID virus in all provinces. Based on this finding, it is obvious that necessary control policies implemented in China were effective in slowing the rate of spread during the most critical early active transmission periods of COVID-19 in the provinces. This is a key finding since it would be most advantageous for countries to immediately contain the COVID-19 virus when it first appears to slow, minimize, or prevent its wider spread within the population.

Clearly, the Chinese control policies were highly restrictive compared to those used in most western countries, particularly during the most critical onset period of the virus. However, the available data used in this research suggest that they were also highly effective at slowing, if not completely stopping, the COVID-19 virus in China. While there are many metrics that could be considered when evaluating the effectiveness, health outcomes, both positive and negative would certainly be among the most important. Given the goal of attempting to limit adverse health impacts at the price of economic activity, coupled with their ability to enforce it, it was apparent that a nationwide restriction policy was the method of choice in China. The results of this study suggest that this initial “bitter pill” resulted in more rapid recovery and reduced economic loss over the longer term of the COVID-19 experience in China.

While the findings of this research are quite valuable to demonstrate important relationships between governmental policy, the progression of COVID-19 through China, and the effect of both on traffic volume, it has some limitations. The most significant of these is that it only considered roadway traffic. Travel by public mass transportation systems is quite common in major metropolitan areas of the country. Similarly, more travel between more-distant origins and destinations using air and highspeed rail was also not considered in this analysis. Based on this further research could be carried out to analyze the traffic impact associated with these other modes. Additionally, only provincial-level highway traffic counts were included in these analyses. Future research could also be focused on the analysis of the distribution of traffic and its movement both at the local level and, more broadly, nationwide.

**Declaration of Competing Interest**

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

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