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Unraveling the dynamic impacts of COVID-19 on metro ridership: An empirical analysis of Beijing and Shanghai, China

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ABSTRACT
The outbreak of coronavirus disease 2019 (COVID-19) has had severely disruptive impacts on transportation, particularly public transit. To understand metro ridership changes due to the COVID-19 pandemic, this study conducts an in-depth analysis of two Chinese megacities from January 1, 2020, to August 31, 2021. Generalized linear models are used to explore the impact of the COVID-19 pandemic on metro ridership. The dependent variable is the relative change in metro ridership, and the independent variables include COVID-19, socio-economic, and weather variables. The results suggested the following: (1) The COVID-19 pandemic has a significantly negative effect on the relative change in metro ridership, and the number of cumulative confirmed COVID-19 cases within 14 days performs better in regression models, which reflects the existence of the time lag effect of the COVID-19 pandemic. (2) Emergency responses are negatively associated with metro system usage according to severity and duration. (3) The marginal effects of the COVID-19 variables and emergency responses are larger on weekdays than on weekends. (4) The number of imported confirmed COVID-19 cases only significantly affects metro ridership in the weekend and new-normal-phase models for Beijing. In addition, the daily gross domestic product and weather variables are significantly associated with metro ridership. These findings can aid in understanding the usage of metro systems in the outbreak and new-normal phases and provide transit operators with guidance to adjust services.

1. Introduction

The first coronavirus disease 2019 (COVID-19) pandemic was identified in late 2019 in Wuhan, China, and became prominent in January 2020. The pandemic spread rapidly throughout the country and was close to the Spring Festival, which resulted in the largest annual human movement in China (Gibbs et al., 2020). Normal life and public health have been severely challenged by the COVID-19 pandemic worldwide. Over 220 million cases were confirmed and 4.5 million deaths occurred by September 6, 2021 (WHO. Weekly operational update on, 2021).

Disasters, such as earthquakes (Lu et al., 2012), diseases (Castillo-Chavez et al., 2016; Walters et al., 2018), and hurricanes (Bian et al., 2019), can significantly change people’s travel patterns. Unlike most previous disasters, the impact of the COVID-19 pandemic is seen worldwide, and it has lasted more than 30 months (Li, 2020; Nieuwenhuijsen, 2020). It may even last for a longer period. Many studies have been conducted to investigate the influence of COVID-19 on different fields, such as logistics (Srivatsa Srinivas and Marathe, 2021; Yang et al., 2021), economics (Hu et al., 2021b; Ahmed and Sarkodie, 2021; Wang and Zhang, 2021), air quality (Pandey et al., 2021; Yumin et al., 2021; Benchrif et al., 2021), and travel behavior (Abdullah et al., 2020; Shakibaei et al., 2021; Hara and Yamaguchi, 2021; Luan et al., 2021).

Mobility has decreased significantly worldwide owing to the COVID-19 pandemic. In the Netherlands, 80% of people reduced outdoor activities temporally, and the number of trips and average travel distance...
were reduced by 55% and 68%, respectively (de Haas et al., 2020). In India, Pawar et al. (2020) applied a decision tree approach and observed that 41% of commuters stopped traveling, 51.3% maintained previous modes, and 5.3% shifted from public transit to private modes. In Australia, over a 50% reduction in weekly household trips occurred, and private cars had the largest reduction. In addition, bike sharing usage declined by 50% in Beijing (Shang et al., 2021), daily metro ridership declined by 42% in Hong Kong (Zhang et al., 2021), and public transport ridership declined by 80% in Budapest (Bucsky, 2020) and 90% in Switzerland (Molloy et al., 2021). Furthermore, Sahraei et al. (2021) validated that the lockdowns in 12 countries caused a dramatic decline in human movements and public transit use by 90%. Additionally, psychological reactions to the pandemic have an essential role in mode choice. Campisia et al. (Campisi et al., 2022) observed that anxiety and fear were significantly associated with daily walking. People tended not to use public transit because of fear and anxiety during the pandemic. Moreover, studies have indicated that attitudes toward the pandemic and related measures differed by group (Bannak et al., 2022; Chen et al., 2022).

This study aims to deepen the understanding of the impact of the COVID-19 pandemic on the use of metro systems. This study selects the largest cities in China (Beijing and Shanghai) to conduct the analysis. The daily metro ridership data for the two cities are collected from official websites and Weibos. COVID-19 data are obtained from various official websites of provincial and municipal health organizations. These datasets are used to analyze the changes in metro ridership due to the COVID-19 pandemic. In addition, generalized linear models are applied to explore the impact of the COVID-19 pandemic on metro ridership. The relative change in metro ridership is the dependent variable, and the independent variables include COVID-19, socio-economic, and weather variables. While previous studies have validated that the COVID-19 pandemic has had a significantly negative effect on metro ridership (Zhang et al., 2021; Chang et al., 2021), this study conducts further analysis and contributes in the following aspects:

(1) This study uses generalized linear models, as well as socio-economic, weather, and other variables, to quantify the impact of the COVID-19 pandemic on metro ridership in Beijing and Shanghai, China.

(2) We conduct an analysis to compare the impact of the two specifications of local COVID-19 cases on metro ridership. This study indicates that the cumulative model performs better in generalized linear models, and we can infer that there is a time lag effect of the COVID-19 pandemic.

(3) We perform a heterogeneity analysis on the effect of the COVID-19 pandemic, such as weekdays versus weekends and outbreak phase versus the new normal phase. For example, an interesting observation is that the reduction in metro ridership is larger on weekdays, whereas the marginal effects of COVID-19 and the first-level response are larger on weekdays.

(4) We further test the impact of the number of imported COVID-19 cases and observe that it is only significant in the weekend and new-normal-phase models for Beijing.

The remainder of this paper is organized as follows. Section 2 briefly reviews studies on the determinants of public transit ridership and the impact of the COVID-19 pandemic on urban mobility. Section 3 describes the study area and utilized data. Section 4 introduces the study’s analytical framework. Section 5 presents the metro ridership changes and estimation results. Section 6 discusses the findings and recommendations for planning and policies. Finally, section 7 presents the conclusions and limitations of the study.

2. Literature review

2.1. Determinants of public transit ridership

Generally, the determinants of public transit ridership can be divided into four main types: built environment, socio-economic characteristics, service attributes, and others (Xin et al., 2021). Built environment factors have a significant role in public transit usage. The widely used descriptors of the built environment include population density, employment density, and land use variables. For example, Li et al. (2020) used direct ridership models to investigate the associations between metro ridership and fine-scale built environment factors and observed that the transfer dummy and number of entrances or exits have a positive influence on station ridership. In addition, An et al. (2019) validated that commercial land use, metro system factors, tourist spots, and healthcare factors have a positive effect on metro ridership on both weekdays and weekends; however, land use related to jobs is only significant on weekdays. Social and economic characteristics can reflect the economic development level of cities, such as income and auto ownership (Xin et al., 2021). Chakraborty and Mishra (2013) used ordinary least squares and spatial error modeling approaches to determine the determinants of ridership in different regions, which validated that land use, income, transit accessibility, and density are significantly related to transit ridership. Vasudevan et al. (2021) investigated the impacts of socio-economic, demographic, and travel characteristics on mode shift behavior and observed that low-income group travelers are more sensitive to price changes. Service attributes include service coverage, service frequency, feeder services, and transfer possibilities, which are positively associated with public transit ridership. Typically, these three determinants are stable in the short term, and they are used to predict public transit ridership in a normal scenario.

However, some factors can change the operation of the system and the choice of passengers, such as weather, public transit strikes, and special events. Wei et al. (2019) highlighted that the effect of weather on ridership varies by mode and time of day and observed that metro ridership is less sensitive to weather variables (such as rain and wind) than ferries and buses. Jiang et al. (2021) confirmed that precipitation, the comprehensive comfort index, and the wind-chill index are significant for metro ridership. Zhang et al. (2019) assessed both instantaneous and accumulated human mobility perturbations during extreme weather events. Moreover, Spyropoulou (2020) used generalized linear models to demonstrate the influence of public transport strikes on traffic conditions, including average speed, travel times, and traffic flow.

2.2. Impacts of COVID-19 on urban mobility

After the COVID-19 outbreak, many scholars have explored the impact of the pandemic on urban mobility. Public transit in particular has experienced a dramatic decrease in ridership. Sahraei et al. (2021) validated that the lockdowns in 12 countries caused a dramatic decline in human movements and public transit use by 90%. Based on a Global Positioning System (GPS) tracking trajectory in Switzerland, Molloy et al. (2021) observed reductions of 60% in the average travel distance and 90% in public transit. Based on cell phone and GPS data in Metro Manila, Hasselwander et al. (2021) demonstrated that passengers relying on public transit were severely affected by lockdowns. In Budapest, Bucsky (2020) observed that public transport had the greatest reduction of 80%. In Sweden, the ridership decrease in public transport was more severe than in other modes (Jenelius and Gebeecauer, 2020). Furthermore, controlling for the confounding effects of trends, holidays, seasonality, and weather, Hu and Chen (2021) adopted a Bayesian structural time-series model to prove that COVID-19 had significant effects on transit stations and resulted a reduction in ridership. In addition, Oroz et al. (2020) compared the urban mobility during three periods and observed that public transit had a larger impact than general traffic during the lockdown period. Finally, lockdowns were observed to...
stimulate a shift from public transit (Hasselwander et al., 2021) and private motorized (Hook et al., 2021) modes to active modes, but no significant shift occurred from public transit to private modes (Hook et al., 2021).

According to data from the Mass Transit Railway during the pandemic, daily commuting ridership declined by 42% in Hong Kong (Zhang et al., 2021). From the perspective of purpose, trips destined for commercial areas, entertainment areas, and borders decreased more dramatically. Similarly, Chang et al. (2021) applied the difference-in-differences model to explore the influences of confirmed cases on ridership at the station level and observed that one more confirmed case result in a decrease in ridership of 1.43%. Furthermore, Mutzel and Scheiner (2021) compared the metro ridership of Taipei from January to March in 2019 with that in 2020, which indicated that metro usage had not declined uniformly under the impact of COVID-19; instead, it was highly heterogeneous in both spatial and temporal dimensions. Considering 11 cities simultaneously, Xin et al. (2021) investigated the effect of COVID-19 on daily metro ridership using the synthetic control method and suggested that reductions in metro ridership are correlated with the duration and severity of lockdowns and restrictions.

Generally, cycling has been less influenced by the COVID-19 pandemic than other modes. Using data on bike sharing systems in Beijing, Shang et al. (2021) observed that bike sharing usage declined by 50%, whereas the average trip time increased during the COVID-19 pandemic. During the first wave, bike sharing trips in Boston, Chicago, and New York City (Padmanabhan et al., 2021) experienced different decreases, while the average duration of the trips increased. Additionally, COVID-19 was negatively associated with the number of bike sharing trips, and the correlation was even stronger during the uphill COVID-19 phase. In addition, Teixeira and Lopes (2020) declared that bike sharing was more resilient than the metro system, which has

### Table 1

Review of the impacts of the COVID-19 pandemic on urban mobility.

| Source | Study time | Region | Data | Method | Key findings |
|--------|------------|--------|------|--------|--------------|
| Gibbs et al. (Gibbs et al., 2020) | 1 Jan.–1 Mar. 2020 | Wuhan | Movement data | K-means clustering, network analysis | Network analyses indicate no sign of major changes in the transportation network. The average daily distance reduces by 60%, with decreases of over 90% for public transport. The modal share of cycling increases dramatically. |
| Molloy et al. (Molloy et al., 2021) | 2 Mar.–17 Aug. 2020 | Switzerland | GPS tracking data | Descriptive and statistical analysis | The public transport declines by 80%, while bike sharing declines by 2%. The modal share of cycling, car, public transport changes from 2%, 43%, and 43%–45%, 65%, and 18% respectively. |
| Bucsky (Bucsky, 2020) | Mar. 2020 | Budapest | Modal daily volumes | Descriptive and statistical analysis | While significant decreases are observed for all modes, public transport decreases mostly by 74.5%. |
| Haswelwander et al. (Haswelwander and Mutzel et al., 2021) | 3 Jan.–6 Feb. 2020 | Metro Manila | GPS data | Descriptive and statistical analysis | Even without strong restrictions, trips and inter-prefectural travel decreases significantly. The population density decreases by 20% and people avoid traveling to densely populated areas. |
| Harra and Yamaguchi (Harra and Yamaguchi, 2022) | Jan.–31 May. 2020 | Japan | Mobile phone location data | Descriptive and statistical analysis | Government orders and the severity of local outbreak significantly contribute to the strength of social distancing. |
| Pan et al. (Pan et al., 2020) | 2 Feb.–30 Mar. 2020 | Americas | Mobile phone location data | Mobility metrics, social distancing index | The number of bus trips and car trips decrease by 40% and 12% respectively compared with earlier weeks. The reductions of trips are more intensive during the daytime and weekends. Moreover, trips of people in wealthier areas decrease more than those in lower-priced areas, particularly bus trips. |
| Kim et al. (Kim et al., 2021) | Feb.–Apr. 2020 | Daejeon | Trips data of car and bus | Mixed-effect regression model | The metro ridership decreases by 43%, 49%, and 59% during weekdays, Saturdays, and Sundays, respectively. |
| Zhang et al. (Zhang et al., 2021) | 1 Jan.–31 Mar. 2020 | Hong Kong | Metro | Descriptive and statistical analysis | The decline in metro trips is attributed to health risks. The impacts of the COVID-19 are larger on metro stations connected to high markets, shopping centers, or colleges. |
| Chang et al. (Chang et al., 2021) | 1 Jan.–31 Mar. 2020 | Taipei | Metro | Difference-in-differences model, descriptive statistics | The impacts of COVID-19 on metro usage are not uniform but have spatial and temporal heterogeneity. The rush hours on weekdays were affected the least, whereas ridership at night decreases the most. |
| Mutzel and Scheiner (Mutzel and Scheiner, 2022) | Jan.–Mar. 2019 and 2020 | Taipei | Metro | Descriptive and statistical analysis | Most Chinese cities experienced about a 90% reduction in ridership with some variations among different cities. Metro ridership reductions are associated with the severity and duration of restrictions and lockdowns. |
| Xin et al. (Xin et al., 2021) | Jan. 2019–Sep. 2020 | 22 cities | Metro | Synthetic Control Method | The metro ridership decreases by 69.7%. Areas with lower income, greater percentage of non-white people, and greater percentage of essential and health-care workers, have more mobility during the pandemic. |
| Sy et al. (Sy et al., 2021) | Jan.–Apr. 2020 | New York | Metro | Cross-sectional analysis, generalized linear regression | The daily metro ridership decreases by 40.6% by the first week of March compared with the third week of January. The ridership of work-related stations decreases significantly than that of leisure-related stations. |
| Park (Park, 2020) | Jan.–Mar. 2020 | Seoul | Metro | Descriptive and statistical analysis | The number of bus trips and car trips decrease by 40% and 12% respectively compared with earlier weeks. The reductions of trips are more intensive during the daytime and weekends. Moreover, trips of people in wealthier areas decrease more than those in lower-priced areas, particularly bus trips. |
| Kwon et al. (Kwon et al., 2022) | 2019–2020 | Seoul, New York | Metro | K-means, Multiple regression | The daily metro ridership decreases by 40.6% by the first week of March compared with the third week of January. The ridership of work-related stations decreases significantly than that of leisure-related stations. |
| Teixeira and Lopes (Teixeira and Lopes, 2020) | Feb.–Mar. 2019 and 2020 | New York | Bike sharing, metro | Ordinary least square regression, descriptive statistics | Bike sharing is more resilient than the metro, with a lower ridership decrease (71% vs 90% decrease) and an increase on its average duration (13–19 min). It is a modal shift from metro to bike sharing. |
| Shang et al. (Shang et al., 2021) | 14 Jan.–10 Mar. 2020 | Beijing | Bike sharing | Estimate trip distance, complex network theory | The pandemic influences user behaviors of bike sharing significantly, a reduction of about 50%. |
| Hu et al. (Hu et al., 2021) | 11 Mar.–31 Jul. 2020 | Chicago | Bike sharing | Generalized additive (mixed) models | The proportion of commuting trips declines significantly. Bike sharing is more resilient than transit, driving, and walking. The usage follows an "increase–decrease–rebound" pattern. |
experienced a decrease in ridership and an increase in average travel time. Another study in Chicago observed that bike sharing was more resilient than transit, cars, and walking (Hu et al., 2021e). Furthermore, Wang and Noland (2021) observed that the use of bike sharing and metros decreased at the beginning of COVID-19. Subsequently, bike sharing use recovered to pre-pandemic levels, but metro use remained low after reopening. In addition, during a pandemic, e-scooters can be adopted to avoid public transport travel and private cars can be used instead (Dias et al., 2021). According to a survey conducted in Italy, Fistola et al. (2021) observed that college students were more likely to use e-scooters during the pandemic. In Istanbul, Bagdatli and Ipek (2022) analyzed the mode preferences of college students in the post-pandemic period and observed that they were more likely to use e-scooters and active modes. The impacts of the COVID-19 pandemic on urban mobility are summarized in Table 1.

Moreover, some studies have discussed the long-term effects of COVID-19. Gkiotsalitis and Cats (Gkiotsalitis et al., 2021) suggested that risk perceptions may have major implications for public transit ridership in the post-COVID-19 era. Salon et al. (2021) argued that people have experienced new ways of life passively and have the “stickiness” of pandemic-induced behavioral changes. For young adults, Delbosc and McCarthy (Delbosc and McCarthy, 2021) observed that the pandemic influenced travel behavior in the short term, long-term influences being more complex.

Although many studies have been devoted to analyzing the impact of COVID-19 on urban mobility, most have focused on ridership changes in the short term by comparing metro ridership differences before and during the COVID-19 pandemic. However, few studies have considered the new normal phase. Understanding the recovery pattern of metro usage after controlling the COVID-19 pandemic is crucial to provide insights for further operational management. Thus, this study compares the metro ridership of 2020–2021 and that of 2019 to show the ridership changes in two Chinese megacities, Beijing and Shanghai. In addition, a generalized linear model set is proposed to explore the impact of COVID-19 on metro ridership. The relative change in metro ridership is the dependent variable, and the explanatory variables consist of COVID-19, socio-economic, and weather variables. This study provides an in-depth understanding of metro ridership changes caused by the COVID-19 pandemic.

3. Study area and data

3.1. Study area

Two Chinese megacities, Beijing and Shanghai, are selected for the analyses. Beijing is the capital of China and is located in the northern part of the country. By the end of 2019, Beijing’s population was 21.7 million. In 2019, the average daily metro ridership was 10.82 million. In addition, the metro system, with a length of 637.6 km, included 20 lines and 359 stations. In normal periods, the metro system has an important role in urban passenger transport, with a percentage of 47.2% in 2019. Shanghai is the largest and most populous city in China, located in the eastern part of the country. At the end of 2019, Shanghai had a population of 24.2 million and the average daily metro ridership was 10.63 million. The metro system is complex, with 15 lines, 411 stations, and a length of 659.5 km. The metro system is a widely used commuting mode, accounting for 65% of the public transit ridership.

Note that new operational lines were added during the study period. The Yizhuang XinCheng Modern Tram T1 Line began to operate on December 31, 2020, in Beijing (with a length of 12.25 km and 14 stations). Moreover, two new lines in Shanghai were operational—Line 18 (14.5 km in length, 8 stations) on December 26, 2020, and Line 13 (58.8 km in length, 31 stations) on January 23, 2021. As new lines would attract more passengers to the metro system, we might underestimate the impact of COVID-19 on metro ridership.

Although we aimed to collect the daily gross domestic product (GDP) to investigate its impact on metro ridership, data were not available. Thus, we collected the quarterly GDP of Beijing and Shanghai to compute the average daily GDP for each quarter.

3.2. Data on metro ridership and weather

The numbers of daily metro ridership are collected from the official websites and Weibos of both metro systems in Beijing and Shanghai between January 1, 2019, and August 31, 2021, for an in-depth analysis. In addition, a three-day moving average ridership is calculated from the ridership in 2019 to be used as the baseline ridership for calculating the relative change in metro ridership, which is the average ridership of the same day of the week in three continuous weeks. It is carried out to avoid daily ridership variations resulting from unstable variables such as weather. Moreover, passengers’ travel patterns are significantly different between weekdays and weekends (including Saturdays, Sundays, and public holidays).

Weather is also an important variable that influences metro ridership. Singhal et al. (2014) confirmed that weather parameters, such as rain and snow, have significantly negative impacts on transit ridership on weekdays and more severe influences on weekends. Furthermore, Najafabadi et al. (2019) indicated that stations in residential areas are more sensitive to precipitation than stations in commercial areas. In addition, extreme weather events can severely affect recreational trips, diminish travel demand, and promote modal shifts (Jiang and Lin, 2022; Wu and Liao, 2020). Therefore, we collect daily meteorological records from the China Meteorological Administration to explore the effects of weather variables on metro ridership. Three basic weather parameters are collected: temperature, wind speed, and precipitation. In addition, the air quality index is attained for further analysis.

3.3. Data on COVID-19

COVID-19 first broke out in Wuhan and spread rapidly throughout China. Fig. 1 presents the timeline of the COVID-19 pandemic development. According to the development of COVID-19, emergency responses were launched in China. Public health emergencies are classified into four levels (I, II, III, and IV) according to the nature, severity, and scope of their impact, with the severity decreasing from level I to level IV. Information about COVID-19 is collected from various official websites of provincial and municipal health organizations. COVID-19 information is updated by the government and released to the public, which includes local COVID-19 cases, imported COVID-19 cases, asymptomatic cases, and suspected cases. In this study, we focus on three variables: the number of local COVID-19 cases, number of cumulative local COVID-19 cases within 14 days, and number of imported COVID-19 cases. In addition, an imported COVID-19 case refers to an individual entering a country and being confirmed as a COVID-19 patient. As all overseas travelers arriving in mainland China must complete at least 14 days of compulsory and centralized quarantine, the public is less likely to be infected by imported COVID-19 cases.

4. Methodology

The approach to exploring the impact of COVID-19 on metro ridership is to formulate a relationship between the COVID-19 pandemic and metro ridership by developing generalized linear models. The relative change in metro ridership is selected as the dependent variable (Spyropoulou, 2020; Pu et al., 2017), and the independent variables include COVID-19, weather, and socio-economic variables. The estimation equation is shown in Eq (1).

$$Y_i = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_l x_l + \epsilon_i$$  

(1)

where $Y_i$ is the dependent variable, $x_i$ is the independent variable, $\beta_0$ is the intercept of the regression model, $\beta_1$ to $\beta_l$ are beta parameters for...
estimation, and $\varepsilon_i$ is the error term. In addition, the assumptions, which include linearity, no or slight multicollinearity, and homoscedasticity, are tested with specific diagnostics, and the results are satisfactory.

The relative change in ridership is the percentage difference between ridership during a pandemic and that in a normal scenario (Xin et al., 2021). This indicator is widely used to analyze the impacts of disasters, such as the COVID-19 pandemic, on metro ridership (Zhang et al., 2021; Chang et al., 2021), bus mobility (Dueñas et al., 2021), and stay-at-home time (Huang and Li, 2022). Dueñas et al. (Dueñas et al., 2021) explored the relationship between mobility changes and socio-economic conditions. In addition, this indicator has the advantage of avoiding seasonal trends in daily ridership. As the dependent variable, the relative change in daily ridership is calculated using Eq (2).

$$\text{Difference} = \frac{\text{ridership} - \text{ridership}_{\text{baseline}}}{\text{ridership}_{\text{baseline}}} \times 100\% \quad (2)$$

where ridership is the daily metro ridership during the COVID-19 pandemic and ridership_{baseline} is the daily metro ridership in 2019 (baseline). The data flow chart of this study is presented in Fig. 2 to provide a clear overview of this study.

Table 2 lists the descriptive statistics of dependent and explanatory variables. The relative change in metro ridership between 2020 and 2021 and 2019 is selected as the dependent variable. Five types of explanatory variables are considered in this study. The COVID-19 variables are calculated as the number of local COVID-19 cases per day, number of cumulative local COVID-19 cases within 14 days, and number of imported COVID-19 cases per day. To present the effect of economic activities on metro ridership, we calculated the average daily GDP of each city. In addition, we collect the weather information of the daily average temperature and total precipitation in a day to consider environmental impacts on travel behavior. As the travel behavior is different between weekday and weekends/holidays, we add a binary variable weekend to denote weekends and holidays. Moreover, the measures implemented by the government to fight against the COVID-19 also influence the travel behaviors. Therefore, we incorporate two binary variables to represent the first-level response to major public health emergency and second-level response to major public health emergency. Details of the variables are elaborated in Table 2.

5. Results and analysis

5.1. Descriptive statistics

To understand the changes in metro ridership influenced by COVID-19, Fig. 3 presents the number of metro rides and number of local COVID-19 cases per day in Beijing and Shanghai from January 2019 to August 2021. According to Fig. 3, metro ridership decreases steeply after the outbreak of COVID-19 in both cities. After controlling the COVID-19 pandemic, metro ridership increases steadily and the recovery speed is faster in Shanghai. Overall, Beijing and Shanghai experience similar scenarios in the first COVID-19 wave. In total, 415 and 338 local COVID-
19 cases were reported in Beijing and Shanghai, respectively. Over time, metro ridership in Shanghai gradually recovered to a stable status. However, a second COVID-19 wave occurred in June 2020 in Beijing, with 335 local confirmed COVID-19 cases. This also results in a significant decrease in ridership in Beijing, but it is less dramatic than the first wave. In addition, according to Fig. 3, small sporadic local confirmed COVID-19 waves occur in Beijing and Shanghai, and corresponding metro ridership decrease can be observed.

A comparison of the monthly metro ridership of the two metro systems is shown in Fig. 4. Visually, ridership is stable in 2019, and metro ridership is lower in February owing to the Spring Festival. After the COVID-19 outbreak, the number of metro rides decreases significantly. Metro ridership is the lowest in February 2020. Thereafter, metro usage recovers steadily and then reaches a stable phase in the latter part of 2020. In addition, compared with 2020, the metro ridership in 2021 is generally higher. However, the metro ridership in 2020 and 2021 has been consistently lower than the corresponding ridership in 2019. According to Table 3, the largest reduction in metro ridership occurs in February 2020, at 88.70% and 82.84% in Beijing and Shanghai, respectively. Generally, metro ridership recovers sooner and is higher in Shanghai. In particular, the metro ridership of Shanghai in June 2021 almost reach its pre-COVID-19 level.

5.2. Impacts of COVID-19 on metro ridership

The impact of COVID-19 and related prevention strategies on metro ridership are interesting and important problems to study. This study aims to explore the relationship between the COVID-19 pandemic and metro usage. Two specifications for local COVID-19 cases are compared using generalized linear models. In addition, we further investigate the effects of the imported risk of COVID-19 on metro usage, and the number of imported COVID-19 cases is adopted to reflect the imported risk. The models are then estimated with and without controlling for imported COVID-19 cases.

Table 4 presents the modeling results for Beijing according to Eq. (1) with a full sample. The results of the full model (controlling for imported COVID-19 cases) and restricted model (not controlling for imported COVID-19 cases) are provided in Panels I and II, respectively. In each model, two different specifications are adopted to measure the local COVID-19 cases. The first specification is the number of local COVID-19 cases and the second is the number of cumulative local COVID-19 cases within 14 days. According to Table 4, both specifications are significantly and negatively associated with the percentage difference in metro ridership. The number of cumulative local COVID-19 cases within 14 days performs better in the generalized linear models according to the Akaike information criterion (AIC) and Bayesian information criterion (BIC) in Table 4. The results reported in Panel I indicate that an additional local COVID-19 case result in a decrease in metro ridership of 0.627%. Furthermore, an additional cumulative local COVID-19 case within 14 days results in a 0.091% reduction in the metro ridership. For the restricted model, the results are similar to those in Panel II of Table 4.
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Note: ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Estimation results for the metro ridership in Beijing. Table 4

Month by month comparison of metro ridership. Table 4

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Fig. 4. Monthly metro ridership from 2019 to 2021.

Table 3

| Month | Beijing | Shanghai |
|-------|---------|----------|
|       | Change (%) | Change (%) | Change (%) | Change (%) |
|       | 2020 vs 2019 | 2021 vs 2019 | 2020 vs 2019 | 2021 vs 2019 |
| 1     | -26.91% | -38.41% | -24.71% | -15.76% |
| 2     | -88.70% | -32.42% | -82.84% | -12.74% |
| 3     | -80.81% | -20.37% | -59.75% | -5.24% |
| 4     | -66.16% | -15.21% | -40.28% | -4.79% |
| 5     | -47.65% | -17.49% | -32.37% | -7.16% |
| 6     | -47.44% | -13.15% | -21.24% | -0.84% |
| 7     | -49.24% | -16.84% | -18.01% | -9.44% |
| 8     | -38.12% | -34.53% | -16.34% | -14.27% |
| 9     | -16.79% | n. a. | -7.77% | n. a. |
| 10    | -20.22% | n. a. | -11.63% | n. a. |
| 11    | -16.14% | n. a. | -13.47% | n. a. |
| 12    | -16.57% | n. a. | -9.66% | n. a. |

Table 4

Panel I: Full model (control for imported COVID-19 cases)

Panel II: Restricted model (no control for imported COVID-19 cases)

Variable | Coef. | S.E. | Coef. | S.E. | Coef. | S.E. | Coef. | S.E. |
|---------|-------|------|-------|------|-------|------|-------|------|
| Constant | -36.988*** | 6.971 | -37.308*** | 7.311 | -38.125*** | 6.964 | -38.041*** | 7.295 |
| COVID19 | -0.091*** | 0.010 | n. a. | n. a. | -0.087*** | 0.010 | n. a. | n. a. |
| COVID19cum14 | -0.528** | 0.254 | -0.320 | 0.263 | n. a. | n. a. | n. a. | n. a. |
| Level1 | -48.157*** | 1.883 | -51.239*** | 1.911 | -49.021*** | 1.843 | -52.700*** | 1.876 |
| Level2 | -19.796*** | 1.797 | -23.834*** | 1.789 | -19.732*** | 1.803 | -23.701*** | 1.788 |
| GDPx | 0.208*** | 0.068 | 0.204*** | 0.071 | 0.218*** | 0.068 | 0.211*** | 0.071 |
| Temperature | -0.250*** | 0.051 | -0.209*** | 0.053 | -0.257*** | 0.051 | -0.215*** | 0.053 |
| Precipitation | -0.150** | 0.064 | -0.177*** | 0.066 | -0.151** | 0.064 | -0.177*** | 0.067 |
| Weekend | -10.967*** | 0.993 | -10.716*** | 1.037 | -10.977*** | 0.997 | -10.732*** | 1.038 |
| AIC | 4712 | 4761 | 4754 | 4799 |
| BIC | 4756 | 4809 | 4754 | 4799 |
| Observation | 609 | 609 | 609 | 609 |

Note: ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.
megacities such as Beijing and Shanghai, this study conducts a heterogeneity analysis to understand the different impacts of COVID-19 on metro usage between weekdays and weekends. In 2019, the average weekday and weekend ridership in Beijing were 12.29 million and 7.66 million, respectively. In Shanghai, the average weekday and weekend ridership reached 11.89 million and 7.93 million, respectively. Generally, weekday and weekend ridership in Beijing decrease by 32.37% and 22.86% on weekdays and weekends, respectively.

In Shanghai, metro ridership decreases by 57.49% and 11.64% in the two temporal phases to further analyze the effect of COVID-19 on metro ridership from a temporal perspective. The two phases are determined as follows:

1) The outbreak phase begins when the city records the first case and ends when the city shifts from a second-level response to a third-level response (Padmanabhan et al., 2021).
2) The new normal phase begins when the third-level response is adopted and ends at the end of the study period.

Table 6 provides the estimation results for the subsample for weekdays and weekends. As the number of cumulative local COVID-19 cases within 14 days performs better (Section 5.2), it is selected for the heterogeneity analysis. The estimation results show that the number of cumulative local COVID-19 cases within 14 days has a significantly negative effect on metro ridership on weekdays and weekends in both cities. In addition, the effect is greater on weekdays. For instance, one additional cumulative local COVID-19 case within 14 days would result in a decrease of 0.096% and 0.081% in Beijing’s metro ridership on weekdays and weekends, respectively. In addition, the number of imported COVID-19 cases is only significant for the weekend model in Beijing, and it is not significant for the models in Shanghai. In addition, the average daily GDP is only significant for weekday metro ridership in Beijing and Shanghai, respectively. In addition, temperature and precipitation would decrease metro ridership significantly on weekdays in both Beijing and Shanghai. However, for weekends, precipitation is significant only for Shanghai. Furthermore, one additional unit of precipitation results in a 0.395% reduction in metro ridership in Shanghai on weekends. Finally, an interesting observation is that the effect of the first-level response to major public health emergencies on metro ridership is larger on weekdays, whereas the effect of the second-level response on metro ridership is larger on weekends.

Table 7 provides the phases for the two cities.

Table 5
Estimation results for the metro ridership in Shanghai.

| Panel I: Full model (control for imported COVID-19 cases) | Panel II: Restricted model (no control for imported COVID-19 cases) |
|---------------------------------------------------------|---------------------------------------------------------------|
| **Variable** | **Coef.** | **S.E.** | **Coef.** | **S.E.** | **Coef.** | **S.E.** | **Coef.** | **S.E.** |
| **Constant** | –13.981*** | 5.355 | –13.580** | 5.504 | –12.857** | 5.302 | –12.912** | 5.534 |
| **COVID19** | –0.112** | 0.014 | n. a. | n. a. | –0.110*** | 0.014 | n. a. | n. a. |
| **COVID19** | n. a. | n. a. | –0.414** | 0.164 | n. a. | n. a. | –0.404** | 0.164 |
| **Level1** | –54.995*** | 2.101 | –61.27%*** | 2.044 | –55.038*** | 2.101 | –61.325*** | 2.044 |
| **Level2** | –31.330*** | 1.610 | –31.428*** | 1.681 | –31.744*** | 1.585 | –31.675*** | 1.654 |
| **GDPd** | 0.100** | 0.049 | 0.089** | 0.051 | 0.084* | 0.048 | 0.079* | 0.050 |
| **Temperature** | –0.182*** | 0.053 | –0.154*** | 0.055 | –0.175*** | 0.052 | –0.149*** | 0.055 |
| **Precipitation** | –0.261*** | 0.031 | –0.262*** | 0.032 | –0.261*** | 0.031 | –0.262*** | 0.032 |
| **Weekend** | –10.011*** | 0.849 | –9.817*** | 0.889 | –9.968*** | 0.850 | –9.795*** | 0.889 |
| **AIC** | 4519 | 4571 | 4563 | 4616 | 4559 | 4610 |
| **BIC** | 609 | 609 | 609 | 609 |

Note: ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.
These phases for Beijing and Shanghai are presented in Table 7.

Table 8 presents the estimation results with a subsample for the two phases of metro ridership in Beijing and Shanghai. According to Table 8, the number of cumulative local COVID-19 cases within 14 days is negatively correlated with metro ridership, and its marginal effect is larger in the new normal phase. Furthermore, the number of imported COVID-19 cases is significant only in the new normal-phase model for Beijing. Comparing Panels I and II, we observe that the first- and second-level responses have larger effects in Shanghai. This can be attributed to the duration of the emergency response being longer in Beijing. As a result, people might become acquainted to the emergency response and become less sensitive to it.

In addition, temperature and precipitation have a significantly negative effect on metro ridership in the new normal phase for both cities. However, temperature is significant only in the outbreak phase model for Beijing. Finally, the effects of weekends are similar in both phases for both cities, which result in a reduction in metro ridership by 10.162%–11.418%.

5.3.3. Robustness check

In this study, the duration of cumulative local COVID-19 cases is set at 14 days according to the most widely used incubation period. The specification of the COVID-19 variable is the premise for the empirical analysis. To test whether our results are sensitive to the specification of cumulative local COVID-19 cases, we select Beijing to conduct a robustness check using the number of cumulative local COVID-19 cases within seven and 21 days. The estimation results are presented in Table 9, which shows that COVID19_cum7 and COVID19_cum21 are also negatively associated with the metro ridership. Except for temperature and precipitation, previous studies have observed that other weather variables also influence ridership (Jiang et al., 2021; Wu and Liao, 2020; Xue et al., 2020; Zhou et al., 2021). Thus, we explore alternative model variables, including the wind speed and air quality index (AQI). Table 9 shows the estimation results. We conclude that the wind speed and air quality index are not associated with metro ridership. These results are consistent with the findings presented in Table 4.

6. Discussion and recommendations

Using metro ridership in Beijing and Shanghai, this study uses generalized linear models to investigate the effects of COVID-19 on metro ridership. We summarized some interesting findings and discuss possible implications for planning and policy. First, we validate that COVID-19 has a significantly negative effect on metro ridership in both Beijing and Shanghai, which is consistent with the findings from New York City (Teixeira and Lopes, 2020), Hong Kong (Zhang et al., 2021), and Taipei (Chang et al., 2021). Comparing two specifications of COVID-19, namely, the number of local COVID-19 cases and number of cumulative local COVID-19 cases within 14 days, we observe that the latter performs better according to AIC and BIC. Thus, we suggest that the number of cumulative confirmed COVID-19 cases within 14 days is a more appropriate specification for evaluating the effect of COVID-19 on urban mobility in further studies. Additionally, one additional cumulative local COVID-19 case within 14 days results in a reduction in metro ridership by 0.091% in Beijing and 0.112% in Shanghai.

The influence of COVID-19 on metro ridership is largest in February 2020. Metro ridership decrease by 88.70% and 82.84% in Beijing and Shanghai, respectively, when compared to the pre-COVID level in 2019, which are slightly lower than those in New York (Teixeira and Lopes, 2020). New York’s metro ridership decrease by 90% in February and March 2020 (Teixeira and Lopes, 2020). In Seoul, metro ridership decrease by 40% (Park, 2020). Between January 1 and March 31, 2020, metro ridership in Hong Kong decrease by 43%, 49%, and 59% for weekdays, Saturdays, and Sundays, respectively (Zhang et al., 2021). At the same time, the ridership of the Taipei Metro system decrease by 25.2%, with a decline peak of 49% (Chang et al., 2021).

In addition, from April to July 2021, metro ridership reaches 80% and 90% of the pre-COVID-19 levels in 2019 in Beijing and Shanghai, respectively. In June 2021, Shanghai’s metro ridership reaches 99.2% of that in 2019. This means that the metro systems are crowded, particularly during peak hours, which might promote the spread of pandemics (Schlosser et al., 2020; Persson et al., 2021). Thus, it is important for cities to promote work-from-home and rotational working schedules to mitigate these peaks. In addition, metro systems should provide more capacity to transport passengers rapidly and avoid overcrowding at stations and in trains. Additionally, it is important to apply big data, artificial intelligence with communication technologies, such as Wi-Fi, Bluetooth, GPS, quick response codes, and the Internet of Things in contact tracing (Shahroz et al., 2021). Improving the accuracy of contact tracing can aid in implementing prevention strategies for specific communities and citizens. Understanding the relationship between the COVID-19 pandemic and metro ridership can be used to predict the travel demand in metro systems, which can be applied to adjust operational strategies and epidemic prevention policies. In addition, the impact of COVID-19 is important for the long-term planning of metro systems.

Second, emergency responses affect the usage of metro systems according to severity and duration. The first- and second-level responses have a significant and negative effect on metro ridership. As expected, the first-level response has a larger effect than the second-level one. In addition, the effects of the first- and second-level responses are larger in Shanghai than in Beijing. This is consistent with the fact that the duration of emergency responses are longer in Beijing, which is consistent with the findings of Xin et al. (2021). According to Tables 4 and 5, the first- and second-level responses result in a reduction in metro ridership.
Cluster infections related to them. Thus, people in Beijing perceive more contrast to the positive relationship between international arrivals and COVID-19 period, but the poor group does not have other options (Hu the pandemic (Kim et al., 2021). The rich group has more options for economic status tend to use public transit more than rich people during micro-mobility modes should be provided and promoted to serve vulnerable groups. In addition, infrastructure investments among different modes should be reconsidered if mobility and travel behavior, such as travel frequency and mode choice, would change in the post-COVID-19 era.

Third, although the overall reduction in metro ridership is larger on weekends, it is interesting to note that the marginal effects of COVID-19 and the first-level response are larger on weekdays than on weekends. The COVID-19 pandemic not only decreases non-essential travel, but also results in a dramatic reduction in commuting trips. In the outbreak phase, schools, offices, cinemas, restaurants, and other places are closed or limited in capacity, particularly with the first-level response. In addition, inter-province travelers are required to complete a 14-day home quarantine. In the new normal phase, prevention strategies are implemented for specific communities according to the local pandemics. For example, a community with local COVID-19 cases might be locked down, and all citizens follow the stay-at-home order for 14 days. In addition, close contact with COVID-19 cases might require centralized quarantine. This finding is inconsistent with a previous study (Chang et al., 2021), which indicated that the marginal effect of COVID-19 is larger on weekends than on weekdays, as schools and offices remain open and work-online is not generally feasible.

Fourth, the number of imported COVID-19 cases, which can represent border controls, has a significantly negative effect on metro ridership in the weekend and new normal phase models for Beijing, in addition, the transportation sector is required to prepare different operation strategies for different levels of pandemics to ensure normal operation and safety in the field. Third, life has been dramatically

### Table 9
Results of robustness check in Beijing.

| Variable | Coef. | S.E. | Coef. | S.E. | Coef. | S.E. | Coef. | S.E. |
|----------|-------|------|-------|------|-------|------|-------|------|
| Constant | –37.532*** | 7.120 | –37.535*** | 7.120 | –37.185*** | 6.970 | –35.351*** | 7.243 |
| COVID19sm14 | n. a. | n. a. | n. a. | n. a. | n. a. | 0.010 | –0.090*** | 0.010 |
| COVID19sm7 | –0.134*** | 0.018 | n. a. | n. a. | n. a. | n. a. | n. a. | n. a. |
| COVID19sm21 | n. a. | n. a. | –0.077*** | 0.007 | n. a. | n. a. | n. a. | n. a. |
| COVID19sm30 | –0.429* | 0.259 | –0.602** | 0.251 | –0.531** | 0.254 | –0.543** | 0.255 |
| Level1 | –49.628*** | 1.900 | –46.559*** | 1.886 | –48.330*** | 1.914 | –48.355*** | 1.898 |
| Level2 | –21.596*** | 1.800 | –18.096*** | 1.809 | –19.929*** | 1.816 | –19.893*** | 1.800 |
| GDPx | 0.210*** | 0.069 | 0.215*** | 0.066 | 0.204*** | 0.068 | 0.197*** | 0.069 |
| Temperature | –0.233*** | 0.052 | –0.263*** | 0.051 | –0.248*** | 0.051 | –0.241*** | 0.052 |
| Precipitation | –0.170*** | 0.065 | –0.135** | 0.063 | –0.151** | 0.064 | –0.155** | 0.064 |
| Wind speed | n. a. | n. a. | n. a. | n. a. | n. a. | 0.198 | 0.396 | n. a. |
| AQI | n. a. | n. a. | n. a. | n. a. | n. a. | n. a. | –0.008 | 0.010 |
| Weekend | –10.868 | 1.015 | –11.194*** | 0.978 | –10.961*** | 0.993 | –10.919*** | 0.995 |
| AIC | 4737 | 4694 | 4714 | 4713 | 4762 | 4762 |
| BIC | 4781 | 4738 | 4762 | 4762 |
| Observation | 609 | 609 | 609 | 609 |

Note: ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

by 48%-61% and 20%-32%, respectively. Thus, the government must implement an emergency response and end it in a timely manner according to the current COVID-19 pandemic. Note that people with lower economic status tend to use public transit more than rich people during the pandemic (Kim et al., 2021). The rich group has more options for traveling, and they are more likely to shift to private cars during the COVID-19 period, but the poor group does not have other options (Hu and Chen, 2021; Hook et al., 2021). Thus, customized bus and traveling, and they are more likely to shift to private cars during the pandemic significantly influence metro ridership. Thus, the inflow risk from the imported cases, even if strict quarantine and testing policies have been applied to incoming passengers. However, the number of imported COVID-19 cases in Shanghai is not significant. Thus, we can infer that more attention should be given to airports with incoming travelers. Additionally, as some confirmed cases exhibit a considerable long incubation period, incoming travelers should be tracked closer and longer.

#### 7. Conclusions

This study investigates the influence of the COVID-19 pandemic on metro ridership in Beijing and Shanghai, using generalized linear models. Overall, the results reveal that the COVID-19 pandemic has a significant impact on metro ridership. Two specifications have been adopted to reflect the local COVID-19 pandemic, including the number of local COVID-19 cases and number of cumulative local COVID-19 cases within 14 days. The results show that the latter performs generally better according to AIC and BIC, and it has a significantly negative effect on metro ridership. In addition, the number of imported cases is significant only in the weekend and new normal phase models for Beijing. Moreover, emergency responses have had significantly negative effects on metro ridership, according to severity and duration.

To comprehensively analyze the influence of COVID-19 on metro ridership, we conduct a heterogeneity analysis. The results show that the reduction in metro ridership is greater on weekends than on weekdays. However, an interesting observation is that the marginal effects of COVID-19 and first-level response are larger on weekdays than on weekends. In the two phases, the marginal effect of the number of cumulative local COVID-19 cases within 14 days is larger in the new normal phase. For example, one more cumulative local COVID-19 case in Shanghai result in a reduction in metro ridership by 0.102% and 0.540% in the two phases, respectively. In addition, we demonstrate that the average daily GDP is significantly and positively associated with metro ridership on weekdays but not significantly on weekends. Generally, both temperature and precipitation have significant negative effects on metro ridership, but they are not significant in specific models. This study provides a reference for cities with metro systems to estimate the effect of COVID-19 on the use of metro systems. The findings of this study help understand the use of metro systems in different phases. Metro ridership trends can help manage operations in the new normal phase.

Based on the results, three policy implications are proposed for other cities and countries. First, we confirmed that the local COVID-19 pandemic significantly influence metro ridership. Thus, the inflow risk pressure should be controlled from the epicenter, which requires immediate governance responses, as well as the support of citizens. Second, we observed that the response to major public health emergencies has a large impact on metro ridership. To implement anti-epidemic measures and minimize the influence on the entire city, we should implement specific strategies for different regions based on their current pandemic scenarios, such as work from home and regular nucleic acid testing. In addition, the transportation sector is required to prepare different operation strategies for different levels of pandemics to ensure normal operation and safety in the field. Third, life has been dramatically
altered by COVID-19, and it is essential to identify new mobility trends and promote “new normality” in metro systems. After the COVID-19 pandemic outbreak, metro ridership gradually recover to a stable level. Although ridership has not reached the pre-pandemic level, it is a crowded and closed space in the metro system, which poses a high risk of viral transmission. In the long term, the COVID-19 pandemic would decrease the demand for metro systems and promote the demand for active mobility. Thus, government officers and transport engineers should rethink investment in infrastructure in different transportation modes in cities. Transport engineers should measure travel demand in different transportation modes for intracity and intercity travel after the outbreak of the COVID-19 pandemic. Finally, transport engineers can use the results of this study to predict the travel demand in the metro system after the outbreak of the COVID-19 pandemic and propose a corresponding operation plan.

However, this study had several limitations. This study used daily metro ridership data; however, detailed transaction data were not available. As a result, it was impossible to conduct further analyses at the station level or at different periods. Additionally, several modes of transportation exist in cities. It is more valuable to analyze the ridership changes of different modes related to COVID-19. If surveys are conducted to learn about travel demand changes and the inter-modal shift, we can further identify the disappeared and transferred ridership to provide a more comprehensive understanding of the changes. Moreover, with more information on travel behavior changes, we can understand the mechanism of ridership changes. Despite these limitations, this study aids in understanding the effect of COVID-19 on metro ridership.

CRediT authorship contribution statement

Shixiong Jiang: Conceptualization, Methodology, Software, Data curation, Writing – original draft, Investigation, Writing – review & editing, Project administration. Canhuang Cai: Software, Data curation, Writing – original draft.

Declaration of competing interest

None.

Data availability

Data will be made available on request.

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None.

Appendix A

Fig. A.1. Distribution of all metro stations in Beijing. Note: By the end of 2019, 359 stations were operated in the Beijing Metro system. The figure was derived from the website of Beijing Metro.
Fig. A.2. Distribution of all metro stations in Shanghai. Note: By the end of 2019, 411 stations were operated in the Beijing Metro system. The figure was derived from the website of Shanghai Metro.

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