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Dynamic impacts of COVID-19 pandemic on the regional express logistics: Evidence from China

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ABSTRACT
The outbreak of the COVID-19 epidemic brings huge consequences on the global economy and health. Diverse restrictive policies have been enforced to prevent the novel Coronavirus from spreading. During the COVID-19 pandemic, the express logistics companies transport essential goods among different regions in China, supporting people’s normal lives. This study explores the dynamic impacts of COVID-19 epidemic on the intra-provincial and inter-provincial express parcel flows based on the statistical and econometric analysis considering the individual-specific effects of each province. The key results obtained from the unique long-run panel data analysis are: (1) the temporal fluctuation of inter-provincial express logistics flows affected by the epidemic is stronger than that of intra-provincial flows, both of which also show significant spatial heterogeneity; (2) the process of China’s fighting against the COVID-19 pandemic is divided into four stages according to the severity of pandemic and implications of restrictive policies, which have moderating effects for the impacts on the express logistics; (3) the dynamic effects of the pandemic on the express logistics are obviously heterogeneous in different stages, confirming the effectiveness of restrictive and support policies; (4) the delayed effects of COVID-19 epidemic on the regional express logistics vary with different setting of time lags. In the short term, the typical restrictive policies and Chinese Spring Festival holidays have significant negative effects on the express logistics. In the long term, the resumption of work and production stimulate the demands of express logistics, presenting significant positive effects in post-epidemic era. This study can provide the policy implications for the logistics planning and management under the public health intervention.

1. Introduction
The novel coronavirus 2019 (COVID-19) has spread rapidly since its outbreak, bringing detrimental consequences on the global economy and health (Briz-Redón and Serrano-Aroca, 2020). The World Health Organization (WHO) declared the outbreak of COVID-19 to be a Public Health Emergency of International Concern on January 30, 2020 (Sohrabi et al., 2020). The COVID-19 pandemic has led to more than 167 million confirmed cases and more than 3.4 million deaths globally by May 26, 2021 (WHO, 2021). The COVID-19 epidemic causes upheavals on all aspects of global economic and human life, such as the agriculture, manufacturing, education, trade, finance, healthcare, tourism, work mode (Boccaletti et al., 2020; Nicola et al., 2020).

The spatial spreading range of the COVID-19 pandemic is much wider than that of the severe acute respiratory syndrome (SARS) in 2003 (Wang et al., 2020a). Kang et al. (2020) verified significant spatial autocorrelation of the epidemic dynamics by utilizing the Moran’s I during the early stages of COVID-19 pandemic in the mainland of China. The evolution of COVID-19 epidemic is affected by diverse factors, such as the climate conditions, population mobility, restrictive policies, etc. Wang et al. (2020a) assessed the relationship between the transmissibility of COVID-19 and the temperature/humidity, considering the influence of lockdown measures in both China and the U.S. Yang et al. (2020) predicted the epidemics peaks and size of COVID-19 in the mainland of China. The evolution of COVID-19 epidemic is affected by diverse factors, such as the climate conditions, population mobility, restrictive policies, etc. Wang et al. (2020a) assessed the relationship between the transmissibility of COVID-19 and the temperature/humidity, considering the influence of lockdown measures in both China and the U.S. Yang et al. (2020) predicted the epidemics peaks and size of COVID-19 to assess the effects of the control measures based on population migration data in China. Jia et al. (2020) studied the spatial-temporal distribution of COVID-19 from the perspective of population flow drives. Hadjidemetriou et al. (2020) proposed that the COVID-19-related deaths could be...
directly reduced by enforcing the measures of human-mobility reduction in the UK.

Many restrictive measures have been enforced for the prevention and control of epidemic, such as wearing masks in public, prohibiting gatherings, lockdown, keeping social distances, etc., significantly affecting the global supply chains and transportation of goods, passengers and information (Ivanov, 2020a; Loske, 2020; Singhal, 2020). De Vos (2020) studied the effect of COVID-19 and social distancing on travel behaviors. Siewwuttanagul et al. (2020) investigated the physical distancing measures for the rail operation during the COVID-19. Wang et al. (2020b) studied the impact of stay-at-home policy on the control of COVID-19 epidemic based on the Baidu Mobility Index of 106 Chinese Cities, and demonstrated this policy could effectively decrease the new cases.

Chinese government has enforced a series of restrictive and support policies for the public health intervention, such as working or studying at home, the partial or full lockdowns, to make people minimize the outing activities, which promote the online consumption of daily necessities, medical and protective items. As a popular goods transportation mode, express logistics provide transportation services for the essential goods, the epidemic prevention and control materials among different regions, and support people’s normal lives and the recovery of economic development during the COVID-19 pandemic. Up to June 5, 2020, 703,300 tons of epidemic prevention and control materials and 388 million parcels have been delivered by the express logistics companies in China (State Post Bureau, China, 2020).

In the early stage of the COVID-19 pandemic, the increasing transportation requests of medical supplies and people’s daily necessities bring a tremendous pressure on the logistics systems. However, the shortage of labor and transport resources caused by Chinese spring festival holidays, as well as the intensive transportation restrictions make enormous disturbance for the operation of express logistics. Up to now, none of the existing research have studied the complex impacts of COVID-19 epidemic on the express logistics. It is of significant importance to explore whether the restrictive measures make effects on the resumption of production in the express logistics industry. In this study, we analyzed the dynamic impacts of COVID-19 pandemic on regional express logistics and the effectiveness of the related policies. The main scientific contributions of this study are as follows:

- The dynamic impacts of COVID-19 epidemic on the intra-provincial and inter-provincial express parcel flows are analyzed based on the statistical and econometric models considering the individual-specific effects of each province.
- Spatial and temporal characteristics of express logistics flows and COVID-19 epidemic are analyzed based on the huge real province-level express logistics flow dataset and COVID-19 dataset.
- The process of China’s fighting against the COVID-19 pandemic is divided into four stages according to the severity of pandemic and implications of restrictive policies, providing a novel modeling framework for the dynamic impact analysis of epidemic.
- The effectiveness of restrictive and support policies can be confirmed through adding the lag terms and cross terms to the basic regression models, which are utilized to study the delayed effects of COVID-19 on the express logistics in the short and long terms, and verify the moderating effects of stages on the impacts, respectively.
- This study can promote the reduction of the negative impact of COVID-19 on the express logistics and the rational allocation of logistics resources under the public health emergencies.

The remainder of the paper is organized as follows. Section 2 is the literature review. Section 3 presents the description of data sources and statistical analysis. Section 4 constructs the regression models, and makes stage division of the China’s fighting against COVID-19 epidemic. Section 5 analyzes the spatial and temporal characteristics of express logistics flows and epidemic. Section 6 discusses the regression results. Section 7 discusses the policy implications. Section 8 summarizes the conclusions of this study.

2. Literature review

Transport systems are the indispensable elements to ensure the normal operation of social and economic activities, which have been disrupted by the travel restrictions and quarantine measures during the COVID-19 pandemic. The COVID-19 epidemic has led to a significant reduction in travel activities by different transportation modes (Kim, 2021). Mogaji (2020) studied the effects of COVID-19 on transportation, and noted that the policies of lockdowns and restrictions are not effective for the emerging economies in Lagos, Nigeria. Zhang et al. (2020) studied the roles of different transport modes on the COVID-19 pandemic and investigated the related factors for the imported cases, spread speed and pattern of the pandemic in China. Oun and Kun (2020) proposed an economic model to determine the socially optimal lockdown and travel restrictions for COVID-19 pandemic considering the epidemic externality. Beck and Hensher (2020) analyzed the initial impacts of COVID-19 on travel activities under the strict social distancing measures in Australia. Nakamura and Managi (2020) calculated the risk of importation and exportation of the COVID-19 pandemic for the airports over the world and analyzed the related countermeasures. Zhang et al. (2021) conducted a world-wide expert survey and analyzed the related transport realities such as the lockdowns, restrictions for physical distancing, transport mode shifts etc.

The large-scale epidemic outbreak would have a significant impact on the logistics systems. Logistics operations and management undertake the transportation of essential medical and living supplies, playing important roles in controlling epidemic outbreaks (Dasaklis et al., 2012). Büyüktahatkin et al. (2018) developed a logistics mixed-integer programming model for resources allocation to control the Ebola outbreak. Liu et al. (2020) summarized the impacts of the COVID-19 pandemic on logistics industry, and proposed the driving factors from the perspective of demand, technology and policy for the development of logistics industry in China. Loske (2020) developed a linear regression model to analyze the relationship between the transport volume growth and food retail logistics capacity caused by the consumer behaviors of panic buying. Choi (2020) studied the “bring-service-near-your-home” operations and its related financial support policies during the COVID-19 pandemic. Cui et al. (2021) analyzed the impacts of COVID-19 pandemic on the disaggregated transport sectors, and found that the reduction of freight transport sectors is smaller than that of passenger transport sectors in China.

The COVID-19 outbreak has severely disturbed all the stages of global supply chain, including manufacture, transport, logistics, and demand shift etc. (Xu et al., 2020). Singh et al. (2020) developed a simulation model to explore the impacts of COVID-19 pandemic on the public distribution system disruptions for food supply chain. Ivanov (2020b) proposed a viable supply chain model in terms of the agility, resilience, and sustainability, providing decision support for restructuring the supply chains in the post-COVID-19 era. Moreover, the ripple effect caused by the COVID-19 pandemic has brought great challenge to supply chains (Queiroz et al., 2020). Ivanov (2020a) studied the short-term and long-term impacts of COVID-19 on the global supply chain risks through simulation analysis and analyzed the impacts of ripple effect on the performance of supply chain.

To clarify the contextual uniqueness of this study, we summarize the recent similar research on the impacts of COVID-19 epidemics and related restriction strategies, as shown in Table 1. Generally, these studies mainly focus on human travel activities, food logistics and supply chain, etc., through utilizing the method of simulation or case study based on sample survey data of different countries. However, there is no research on the express logistics. As an important logistics branch, express parcel logistics is closely related to social economy and people’s lives. This study first explores the dynamic impacts of COVID-19...
epidemic on the regional express logistics based on a large amount of express parcel flow data.

3. Data

3.1. Data sources

The data used in this study include the COVID-19 dataset, the intra-provincial and inter-provincial express parcel flow dataset, and the provincial statistics data.

(1) COVID-19 dataset

The COVID-19 dataset is obtained from an online open resources repository for COVID-19 Research published on the China Data Lab Dataverse of Harvard Dataverse (Hu et al., 2020). The Chinese COVID-19 data were gathered from an authorized COVID-19 Cases publishing platform (https://ncov.dxy.cn/ncovh5/view/pneumonia), presenting the real-time information of COVID-19 pandemic in China. The number of cumulative confirmed cases, cumulative recover cases, and cumulative death cases of 31 provinces are collected from January 1 to May 31, 2020.

(2) Express logistics flow dataset

To describe the logistics transportation demands since the outbreak of COVID-19 pandemic, the spatial-temporal express logistics data for the daily inter-provincial and intra-provincial flows of China Postal Express & Logistics for 31 provinces in the mainland of China are collected from January 1 to May 31, 2020 (152 days), representing the express delivery input and output flows for each day. China Postal Express & Logistics, as a representative direct-operated express logistics company in China, recovered faster than other franchised express delivery companies after the epidemic outbreak. The data information includes the original province, destination province, and origin-destination (O-D) flow of express packages, reflecting the logistics network structure and capabilities during the COVID-19 pandemic.

(3) Other provincial statistics data

The data of GDP, population, urban population, road mileage, area, and the number of health technicians for each province in 2018 are obtained from the website of China National Bureau of Statistics (National Bureau of Statistics, China, 2020).

3.2. Descriptive statistical analysis

Descriptive statistics analysis on the panel data for 31 provinces in China is summarized in Table 2.

4. Methodology

In this section, the multiple linear regression models based on long-run panel data are constructed to study the dynamic impact of COVID-19 on the express delivery flows. Since the epidemic shows a drastic change in the long-term dimension, we focus on the impact of different stages on the relationship according to the dynamic development of epidemic. Firstly, China’s fighting against the COVID-19 epidemic is divided into four stages. Then, the regression models are designed by introducing the dummy time variables for different stages. The delayed effects are explored through adding the lag terms and impulse response function. Finally, the regression models with cross terms are utilized to verify the moderating effects for the impacts of the COVID-19 epidemic on the express logistics in different stages.

4.1. Stage division of the COVID-19 epidemic

The existing confirmed cases for Hubei province and other 30 China’s provinces are shown in Fig. 1. As the outbreak site of COVID-19 epidemic, Hubei has the most cumulative confirmed cases, much more

| References | Research | Method | Data | Implication | Country |
|------------|----------|--------|------|-------------|---------|
| Mogaji (2020) | Impacts of COVID-19 pandemic on transportation | Correlation analysis | Questionnaire survey data | Lockdowns and restrictions may be not effective for large informal economy. | Lagos State, Nigeria |
| Oum and Kun (2020) | Socio-economically optimal lockdown and travel restrictions | Theoretical model | – | Optimal travel restriction polices are necessary. | – |
| Beck and Hember (2020) | Initial impacts of COVID-19 on travel activities | Statistical analysis | Questionnaire survey data | Disruption to travel is effective to combat COVID-19. | – |
| Liu et al. (2020) | Impacts of the COVID-19 pandemic on logistics industry | Qualitative analysis | – | China’s logistics is driven by the demand, technology and policy. | China |
| Lonke (2020) | Impacts of COVID-19 on food retail logistics | Linear regression | Transport volume data | Freight transport volume for dry products depends on new infections per day. | Germany |
| Ivanov (2020a) | Impacts of COVID-19 on global supply chain risks | Simulation model | – | Closing and opening time of facilities is the key factor for epidemic impact on supply chain performance. | Global |
| Singh et al. (2020) | Impacts of COVID-19 pandemic on food supply chain | Simulation model | – | Develop resilient food supply chain to match the varying demand. | India |
| This study | Impacts of COVID-19 pandemic on the regional express logistics | Linear regression | Express parcel flow data | Restriction or stimulus policies should be adjusted as the epidemic changes. | China |

Table 2

Data summary.

|                      | Mean     | Standard deviation | Minimum | Maximum |
|----------------------|----------|--------------------|---------|---------|
| Intra-provincial express flows (10k) | 8.349901 | 16.37594 | 0.0011 | 204.851 |
| Inter-provincial input express flows (10k) | 48.13574 | 36.76428 | 0.0023 | 210.4392 |
| Inter-provincial output express flows (10k) | 48.13574 | 69.99415 | 0.0019 | 457.7718 |
| Existing confirmed cases | 356.9648 | 3181.293 | 0 | 50.633 |
| Population density (k/km²) | 0.4609323 | 0.693335 | 0.0029 | 3.8229 |
| GDP per capita (RMB 10 k/person) | 6.525345 | 2.865107 | 3.1336 | 14.0211 |
| Road network density (km/km²) | 0.9670968 | 0.5372552 | 0.08 | 2.07 |
| Urbanization rate | 0.599871 | 0.1159251 | 0.3114 | 0.881 |
| Number of health technicians per 10k population | 69.349901 | 11.92754 | 0.0011 | 204.851 |
than those of other provinces. According to the COVID-19 severity of pandemic and implication of restrictive policies, we divide the research time horizon into four stages for other 30 China’s provinces and Hubei Province, respectively:

- **Stage division for other 30 China’s provinces**

  Stage I: the early swift response stage (January 1, 2020–January 19, 2020).
  
  Stage II: the COVID-19 pandemic stage (January 20, 2020–February 9, 2020).
  
  Stage III: the resumption stage for work and production (February 10, 2020–March 18, 2020).
  
  Stage IV: the COVID-19 ebbing stage (March 19, 2020–May 31, 2020).

- **Stage division for Hubei province**

  Stage I: the early swift response stage (January 1, 2020–January 19, 2020).
  
  Stage II: the COVID-19 pandemic stage (January 20, 2020–February 17, 2020).
  
  Stage III: the resumption stage for work and production (February 18, 2020–April 7, 2020).
  
  Stage IV: the COVID-19 ebbing stage (April 8, 2020–May 31, 2020).

As shown in Fig. 2, some importation events for fighting against the COVID-19 pandemic happened in different stages. Restrictive policies have been performed to prevent the spread of the virus and protect residents’ normal daily lives all over China, such as extending the Chinese Spring Festival holidays. Owing to the much higher severity of COVID-19 Pandemic in the outbreak site, the stage division for Hubei lags behind other provinces.

The related restrictive policies have been dynamically adjusted depending on the severity of COVID-19 pandemic, leading to significant disruption for the development of express logistics. This study sorts out some typical restrictive and support policies for COVID-19 pandemic according to the release time and purposes, mainly focusing on public health intervention, extensive traffic and transportation control, and tax and fee reduction, as shown in Table 3.

| Public health intervention | Extensive traffic and transportation control | Tax and fee reduction |
|---------------------------|---------------------------------------------|-----------------------|
| Stage I                   | Implement China CDC emergency response Level 1 | ——                   |
| Stage II                  | Maintain safe social distance                | Lockdown of Wuhan and other 12 cities in Hubei | Exempt value added tax |
|                           | Temporary closure of community               | Contactless delivery  |
|                           | Extend Chinese Spring Festival holidays      |                       |
| Stage III                 | Reopening of Hubei (except Wuhan)            | Exempt vehicle tolls |
| Stage IV                  | Reopening of Wuhan                           | Restore vehicle tolls |

The implications of typical policies in Table 3 are explained in detail as:

![Fig. 2. Stage division of the COVID-19 epidemic.](image-url)
was upgraded to Level 1 (the highest level) on January 15, 2020 (Li et al., 2020).

- Maintain safe social distance in the public places: It can effectively reduce the public gatherings activities of people and cut off the virus transmission. After the extended Chinese Spring Festival holidays, telecommuting is encouraged for the work resumption to avoid unnecessary contacts during the COVID-19 pandemic.

- Temporary closure of community: During the peak of the pandemic, many provinces enforced the rigorous access control for residential communities (State Council Information Office, China, 2020). Non-residents are not allowed to access the community area, and residents could go out to buy essentials only for limited times for every day.

- Extend Chinese Spring Festival holidays: Chinese Spring Festival affected the prevention and control of the epidemic due to the large-scale population mobility. The original Spring Festival holiday is January 24-January 30, 2020, which was later extended to February 2, 2020 to reduce the public gatherings. Some cities even postponed resumption of work until February 9, such as Shanghai, Suzhou, Fuzhou, etc.

- Lockdown of Wuhan and other 12 cities in Hubei at Jan 23, 2020: Hubei Province suffered the worst outbreak, and full lockdown measures were taken for Wuhan to restrict population movement to other regions, which highly depended on the delivery of goods from outside regions. Differentiated policies have been implemented in accordance with the local epidemic risk in different provinces to reduce non-essential travel activities. Some provinces prohibited the vehicles from all the other provinces passing, and some provinces restricted the vehicles from the provinces with severe epidemics. In the early stage, the expressway imports and exports were frequently controlled, or temporarily closed, etc., and then disturbed the road freight transportation. Each province set up health and quarantine stations on highway borders, service areas, entrances and exits, national and provincial highways. Drivers needed to stop and check the temperature, leading to vehicles idling at highways and reducing the efficiency of freight logistics transportation.

- Contactless delivery: The service mode of contactless delivery is encouraged, and customers are advocated to pick up the parcels at the distribution sites by themselves, which can reduce the distribution costs of the last-mile delivery. In addition, the smart terminal facilities and public service stations play an important role in the work and production resumption. For example, smart distribution stations and distribution robots are utilized to serve the communities in Wuhan and Changsha, which can reduce the risk of infection in the distribution process, and bring significant benefits to the terminal cost reduction and efficiency increase.

- Exempt value added tax: The income obtained by providing essential living materials express delivery services has been exempted from value added tax after February 7, 2020 (Ministry of Finance, China, 2020).

- Reopening of Hubei: The restrictions on all the expressways leaving Hubei Province (except Wuhan City) were removed, and Hubei reopened to the outside world after March 25, 2020.

- Exempt vehicle tolls nationwide: In the transportation industry, all the toll roads were exempted from vehicle tolls after February 17, 2020 (Ministry of Transport, China, 2020a).

- Reopening of Wuhan: The restrictions on all the expressways leaving Wuhan City were removed, and Wuhan reopened to the outside world after April 8, 2020.

- Restore vehicle tolls nationwide: In the transportation industry, all the toll roads restored vehicle tolls after May 6, 2020 (Ministry of Transport, China, 2020b).

Generally, the restrictive policies in the early stage tend to restrict people’s travel activities, and then more people start to select online shopping, promoting the development of express parcel logistics in the long term. In the post-epidemic stage, on one hand, the support policies of tax and fee reduction could effectively reduce the operation cost, and promote the resumption of production as soon as possible; on the other hand, people would gradually change the traditional habits of offline shopping, and be accustomed to online shopping by using the e-commerce platforms, which can increase the penetration rate of online shopping, and accelerate the development of express logistics.

4.2. Model specification

To study the impact of COVID-19 on the intra-provincial and inter-provincial express service condition in details, the basic four-stage multiple linear regression models for the intra-provincial express parcel flows (Model 1), inter-provincial express parcel input flows (Model 2), and inter-provincial express parcel output flows (Model 3) are as shown in Eqs. (1)-(3) with the hypothesis of H1, respectively. Non-epidemic factors are also considered in the regression models, including the road network density, urbanization rate, GDP per capita, population density, healthcare level, etc. The effect of COVID-19 on the daily express parcel flows is analyzed by using the following individual-specific effects regression models.

H1. The intra-provincial/inter-provincial input/inter-provincial output parcel flows are significantly related to the existing cases. The impacts of the pandemic on the express logistics are obviously heterogeneous in different stages.

Model 1

\[ \ln \text{Intraflows}_i = \alpha \ln \text{Existcases}_i + \beta_1 \ln \text{Road}, \beta_2 \ln \text{Urbanization}, \beta_3 \ln \text{GDP} + \beta_4 \ln \text{Population}, \beta_5 \ln \text{Healthcare}, \beta_6 \ln \text{D}, \beta_7 \ln \text{D}, u_i + \epsilon_1 (i=1, \ldots, n; t=1, \ldots, T) \]  

Model 2

\[ \ln \text{Inputflows}_i = \alpha \ln \text{Existcases}_i + \beta_1 \ln \text{Road}, \beta_2 \ln \text{Urbanization}, \beta_3 \ln \text{GDP} + \beta_4 \ln \text{Population}, \beta_5 \ln \text{Healthcare}, \beta_6 \ln \text{D}, \beta_7 \ln \text{D}, u_i + \epsilon_2 (i=1, \ldots, n; t=1, \ldots, T) \]  

Model 3

\[ \ln \text{Outputflows}_i = \alpha \ln \text{Existcases}_i + \beta_1 \ln \text{Road}, \beta_2 \ln \text{Urbanization}, \beta_3 \ln \text{GDP} + \beta_4 \ln \text{Population}, \beta_5 \ln \text{Healthcare}, \beta_6 \ln \text{D}, \beta_7 \ln \text{D}, u_i + \epsilon_3 (i=1, \ldots, n; t=1, \ldots, T) \]  

in which \( \alpha, \beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6, \beta_7, \) and \( \beta_8 \) are the parameters to be estimated. \( u_i + \epsilon_k \) is the composite error term, of which the unobservable random variable \( u_i \) is the intercept term representing individual heterogeneity, and \( \epsilon_k \) is the perturbation term varying with time and individuals. All the variables are explained as follows:

(1) Explanatory variables \( \text{Intraflows}_i, \text{Inputflows}_i, \) and \( \text{Outputflows}_i \) represent the daily intra-provincial express parcel flows, inter-provincial express parcel input flows, and inter-provincial express parcel output flows (10k) of province \( i \) at day \( t \).

(2) Explanatory variable \( \text{Existcases}_i \) represents the severity of COVID-19 epidemic, depicted by the existing confirmed cases of COVID-19 of province \( i \) at day \( t \). We propose a simple measurement index \( \text{Existcases}_i \), denoting the number of existing confirmed cases to assess the severity of the epidemic for each province \( i \). The calculation formula is:

\[ \text{Existcases}_i = \text{Confirmedcases}_i - \text{Recovercases}_i - \text{Deathcases}_i \]  

where \( \text{Confirmedcases}_i \) denotes the number of cumulative confirmed cases, \( \text{Recovercases}_i \) denotes the number of cumulative recovery
cases, and Deathcases denotes the number of cumulative death cases.

(3) Control variables includes:
- Infrastructure level: Road\( (\text{km} / \text{km}^2) \), Road network density of province \( i \), measured by the road mileage per unit area.
- Urbanization level: Urbanization\(_i\), Urbanization rate of province \( i \), measured by the proportion of urban population to total population.
- Socio-economic statuses: GDP\(_i\) (RMB 10 k/person), GDP per capita of province \( i \).
- Demographics: Population\(_i\) (\text{k/km}^2), Population density of province \( i \).
- Healthcare level: Healthcare\(_i\) (person/10k persons), measured by the number of health technicians per 10,000 population of province \( i \).

(4) Dummy variables \( D_1, D_2, D_3 \) are introduced for the four-stage regression models, as shown in Eq. (5).

\[
D_1 = \begin{cases} 
1, & t \in \text{Stage II} \\
0, & \text{others} 
\end{cases} 
\]

\[
D_2 = \begin{cases} 
1, & t \in \text{Stage III} \\
0, & \text{others} 
\end{cases} 
\]

\[
D_3 = \begin{cases} 
1, & t \in \text{Stage IV} \\
0, & \text{others} 
\end{cases} 
\]

\[
D_1 = 0, 
D_2 = 0, 
D_3 = 0, 
\text{t \in \text{Stage I}} 
\]

(5) Considering the delayed effects of the COVID-19 epidemic on logistics, the temporally-lagged variates \( \ln \text{Existcases}_{i,t-Lag} \) is introduced for Model 1, 2 and 3, as shown in Eqs (6)–(8) with the hypothesis of H2.

H2. The COVID-19 epidemic has delayed and dynamic effects on the express logistics. The express logistics demands at the day \( t \) are affected by the existing confirmed cases at the day \( t - \text{Lag} \).

Model 1

\[
\ln \text{Inputflow}_{i,t} = \alpha \ln \text{Existcases}_{i,t-Lag} + \beta_1 \ln \text{Road}, + \beta_2 \ln \text{Urbanization}, + \beta_3 \ln \text{GDP}, \\
\beta_4 \ln \text{Population}, + \beta_5 \ln \text{Healthcare}, + \beta_6 \text{D}_1 + \beta_7 \text{D}_2 + \beta_8 \text{D}_3 + u, \\
+ \epsilon_{it}(i = 1, \ldots, n; t = 1, \ldots, T) \]  

(6)

Model 2

\[
\ln \text{Inputflow}_{i,t} = \alpha \ln \text{Existcases}_{i,t-Lag} + \beta_1 \ln \text{Road}, + \beta_2 \ln \text{Urbanization}, + \beta_3 \ln \text{GDP}, \\
\beta_4 \ln \text{Population}, + \beta_5 \ln \text{Healthcare}, + \beta_6 \text{D}_1 + \beta_7 \text{D}_2 + \beta_8 \text{D}_3 + u, \\
+ \epsilon_{it}(i = 1, \ldots, n; t = 1, \ldots, T) \]  

(7)

Model 3

\[
\ln \text{Outputflow}_{i,t} = \alpha \ln \text{Existcases}_{i,t-Lag} + \beta_1 \ln \text{Road}, + \beta_2 \ln \text{Urbanization}, + \beta_3 \ln \text{GDP}, \\
\beta_4 \ln \text{Population}, + \beta_5 \ln \text{Healthcare}, + \beta_6 \text{D}_1 + \beta_7 \text{D}_2 + \beta_8 \text{D}_3 + u, \\
+ \epsilon_{it}(i = 1, \ldots, n; t = 1, \ldots, T) \]  

(8)

To study the moderating effects of different stages, the cross terms \( D_1 \ln \text{Existcases}_{i,t-1}, D_2 \ln \text{Existcases}_{i,t-1} \) and \( D_3 \ln \text{Existcases}_{i,t-1} \) are added for Model 1, Model 2, and Model 3 with Lag = 1, as shown in Eqs (9)–(11) with the hypothesis of H3.

H3. The COVID-19 development stages have moderating effects for the impacts of the COVID-19 epidemic on the express logistics.

Model 1

\[
\ln \text{Inputflow}_{i,t} = \alpha \ln \text{Existcases}_{i,t-Lag} + \beta_1 \ln \text{Road}, + \beta_2 \ln \text{Urbanization}, + \beta_3 \ln \text{GDP}, \\
\beta_4 \ln \text{Population}, + \beta_5 \ln \text{Healthcare}, + \beta_6 \text{D}_1 + \beta_7 \text{D}_2 + \beta_8 \text{D}_3 \\
+ \beta_9 D_1 \ln \text{Existcases}_{i,t-1} + \beta_{10} D_2 \ln \text{Existcases}_{i,t-1} + \beta_{11} D_3 \ln \text{Existcases}_{i,t-1} + u, \\
+ \epsilon_{it}(i = 1, \ldots, n; t = 1, \ldots, T) \]  

(9)

Model 2

(10) Model 3

\[
\ln \text{Outputflow}_{i,t} = \alpha \ln \text{Existcases}_{i,t-Lag} + \beta_1 \ln \text{Road}, + \beta_2 \ln \text{Urbanization}, + \beta_3 \ln \text{GDP}, + \beta_4 \ln \text{Population}, + \beta_5 \ln \text{Healthcare}, + \beta_6 \text{D}_1 + \beta_7 \text{D}_2 + \beta_8 \text{D}_3 \\
+ \beta_9 D_1 \ln \text{Existcases}_{i,t-1} + \beta_{10} D_2 \ln \text{Existcases}_{i,t-1} + \beta_{11} D_3 \ln \text{Existcases}_{i,t-1} + u, \\
+ \epsilon_{it}(i = 1, \ldots, n; t = 1, \ldots, T) \]  

(11)

5. Spatial and temporal characteristics of express logistics flows and epidemic

The intra-provincial and inter-provincial express parcel flows are highly related to the severity of the COVID-19 pandemic. During the COVID-19 epidemic, both supply and demand sides of the delivery industry have been affected to some extent in the short term. As shown in Fig. 3, the fluctuation of inter-provincial express logistics flows affected by the epidemic is stronger than intra-provincial express logistics flows. Chinese Spring Festival is a critical turning point in trend change of the intra-provincial and inter-provincial express logistics demands. Both the intra-provincial and inter-provincial flows began to reduce in January 15, 2020, because Chinese Spring Festival (January 24, 2020) was approaching, and the inherent logistics demand reduced. Generally, the stability of intra-provincial express logistics demand was better than the inter-provincial express delivery flows, for the reason that many highways were temporarily closed, blocking the inter-provincial delivery transportation.

5.1. Intra-provincial flows of express parcels

Due to the imbalance of e-commerce development, the inherent demands of express delivery vary greatly corresponding to different regions. For example, the express delivery volumes of Zhejiang and Guangdong are larger than other provinces in China. To demonstrate the spatial distribution characteristics of the express parcel flows during the pandemic, we take 4 days as examples, including January 29, February 12, March 4, and April 8. As shown in Fig. 4, the spatial and temporal distribution characteristics of express delivery demands are related with the severity of COVID-19 epidemic. The darker the color, the more cumulative confirmed cases. In spite of Hubei, the provinces with the most cumulative confirmed cases are: Guangdong, Henan, Zhejiang, Hunan, Anhui, and Jiangxi because of the higher degree of population mobility. They are either geographically close to Hubei such as Henan, Hunan, Jiangxi, or may be where many Hubei people work, such as Guangdong and Zhejiang.

The larger the icon, the larger express parcel flows. In January 29, owning to the Chinese Spring Festival holidays and the COVID-19 pandemic, the intra-provincial O-D flows of express parcels are much smaller than other days. As for Hubei Province, due to the worst outbreak and the lockdown of many cities, the intra-provincial O-D flows recovered slowly, of which at April 8 is larger than other days. Due to the earlier work resumption, the intra-provincial delivery demands of Zhejiang, Jiangsu, Shanghai, Guangdong, etc., raised more rapidly.

5.2. Inter-provincial flows of express parcels

Similarly, the inter-provincial input flows of express parcels are shown in Fig. 5. The node size represents the total number of the input
parcels from other 30 provinces, and the line thickness represents the number of the input parcels from each province to the specific destination province. The inter-provincial output flows of express parcels are shown in Fig. 6. The node size represents the total number of the output parcels to other 30 provinces, and the line thickness represents the number of the output parcels from the specific original province to each province. Both the input and output flows of Hubei are much lower than those of its provinces nearby, for the reason of the severity of the epidemic. As a whole, the inter-provincial flows of Southeast China are larger, of which the recovery efficiency is higher than other regions.

6. Empirical results

6.1. Statistical tests

To ensure the stability of data and avoid spurious regression, given that the dimension of the cross section $N$ is smaller than the dimension of time $T$, the Levin-Lin-Chu (LLC) unit root test with null hypotheses of...
panels’ containing unit roots is performed for the express parcel flow and the existing confirmed cases, as shown in Table 4. The values of adjusted $t^*$ is significant negative at the level of significance at 5 %, strongly rejecting the null hypothesis that the panel contains unit roots. Therefore, this long-run panel data is stationary.

Hausman test is utilized to select the random-effects or fixed-effects (within) regression models. As shown in Table 5, all the $P$ values are smaller than 0.05, which means that it rejects the null hypotheses at the level of significance at 5 %. Hence, we select the fixed-effects (within) regression models.

The results of the modified Wald test for the heteroskedasticity between groups in fixed effect regression models are shown in Table 6. All the $P$ values are 0, indicating that they significantly reject the null hypothesis, and there exists heteroscedasticity between groups.

To test the autocorrelation test within groups, the Wooldridge test results strongly reject the null hypothesis of no first order autocorrelation, as shown in Table 7.

To test the synchronous correlation between groups, the Breusch-Pagan LM test of independence is performed based on 152 complete observations over panel units for each model. The results in Table 8 strongly reject the null hypothesis of no synchronous correlation.

### 6.2. Regression analysis

#### 6.2.1. Main results

Based on the above statistic tests, there exists heteroscedasticity between groups, autocorrelation within groups, and synchronous correlation between groups for this long-run panel data. Therefore, the feasible generalized least square method (FGLS) is selected to estimate these regional-level regression models. The cross-sectional time-series FGLS regression results of three models are shown in Table 9, which further confirm the hypothesis H1. The coefficients of existing confirmed cases are negative, denoting the negative effects of the severity of the epidemic on the express flows.

As mentioned above, various restrictive and support policies have been enforced during different stages, of which the effects can be demonstrated by the regression results of dummy variables. The inter-provincial and intra-provincial express flows for all the three models are significantly affected by the dummy variable $D_1$ with negative coefficients, which can further verify the effectiveness of restrictive policies in stage II. The intra-provincial express parcel flows are not significantly influenced by the dummy variables $D_2$ and $D_3$ in Model 1. Hence, the intra-provincial express logistics is not significantly affected by the policies in the Stage III and Stage IV. The significance of $D_2$ and $D_3$ in Model 2 and Model 3 indicates the restrictive and support policies enforced in post-epidemic eras make effects on the resumption of inter-provincial express logistics.

#### 6.2.2. Delayed effects analysis

In this study, the parameter Lag is set as 0–5 days, respectively, and the regression results for Model 1, Model 2 and Model 3 are in Table 10, which can verify the hypothesis H2. It can be concluded that the relationship between the express logistics and the epidemic status vary with different setting of time lags.

For Model 1, the coefficients of $\ln \text{Exist cases}_{it-Lag}$ are negative when $\text{Lag} \leq 3$. With the increasing of $\text{Lag}$, the negative impact of the epidemic

![Fig. 5. Spatial distribution of the cumulative confirmed cases and inter-provincial input flows of express parcels.](image-url)
on the intra-provincial express parcel flows is reduced. On one hand, the epidemic obstructs the normal operation for the express logistics in the short term, owning to the restrictive policies. On the other hand, the online shopping demands would be suppressed owning to poor immediacy. For example, during the early two days after the outbreak of epidemic, the restrictive policies and the panic caused by the COVID-19 promote the residents buying the daily necessities in offline physical stores. However, when $\text{Lag} > 3$, the coefficients of $\ln \text{Existcases}_{it-Lag}$ are positive, and thus the epidemic can boost the express logistics demands in the long term. People may buy some daily necessities online, such as protection and disinfection materials, leading to an increase in logistics demand. When $\text{Lag} = 5, 6, 7, 8$, the coefficients of $\ln \text{Existcases}_{it-Lag}$ are

![Fig. 6. Spatial distribution of the cumulative confirmed cases and inter-provincial output flows of express parcels.](image-url)
The main results of regression models are shown in Table 9. The regression models are used to analyze the impact of various factors on the number of confirmed cases, including urbanization rate, GDP per capita, and population density. The models are estimated using the panel vector autoregression (PVAR) model.

Moreover, the impulse response function (IRF) is used to describe the dynamic responses of the existing confirmed cases to the shocks. The IRF for Model 3 is shown in Fig. 7(a), where a standard deviation shock is implemented on the lagged confirmed cases. The impulse responses show that the confirmed cases respond positively to the shock, and the response is significant at the 1% level.

Table 9: Main results of regression models.

| Models             | Model 1          | Model 2          | Model 3          |
|--------------------|------------------|------------------|------------------|
| Existing confirmed |                  |                  |                  |
| cases              | -0.0376203***    | -0.0191933***    | -0.0202333***    |
| (0.0071972)        | (0.0016157)      | (0.0048401)      |
| Population density | 0.2230678*       | 1.18359**        | 0.0202539        |
| (0.1217557)        | (0.0463073)      | (0.1209845)      |
| GDP per capita     | 0.519294***      | 2.328622***      | 5.262272***      |
| (0.410085)         | (0.2516694)      | (0.4542279)      |
| Road network density | 0.3095234       | -0.551626***     | 1.647531***      |
| (0.1916109)        | (0.0828314)      | (0.2017455)      |
| Urbanization rate  | -11.8743***      | -9.142463***     | -11.37407***     |
| (0.8414066)        | (0.4752922)      | (0.8431017)      |
| Number of health technicians per 10k population | -3.329558** | -0.827176*** | -2.792177*** |
| (0.2539653) | (0.160055) | (0.2786098)      |

The Table 10 shows the lagged effects of the epidemic for the intra-provincial and inter-provincial express logistics. The impulse response function (IRF) is used to describe the response of the endogenous variables to the standard deviation shocks based on the panel vector autoregression model (PVAR). The optimal orders with asterisks are selected for each model with the smallest values based on the panel vector autoregression model (PVAR). The optimal orders are Order1 = 3 for Model 1, Order2 = 3 for Model 2 and Order3 = 4 for Model 3.

The dynamic impulse-responses of the existing confirmed cases to the intra-provincial flows, inter-provincial input flows and inter-provincial output flows with the corresponding optimal orders are shown in Fig. 7. The horizontal axis of the coordinate represents the time lags. The vertical axis represents the values of the response function, and the dash lines represent the deviation bands of 5% errors on each side generated by Monte-Carlo with 200 reps.

The IRF of the existing confirmed cases to the intra-provincial express flows is different from the inter-provincial express flows. As shown in Fig. 7(a), when a standard deviation shock is implemented on the lagged confirmed cases, the impulse responses show that the confirmed cases respond positively to the shock, and the response is significant at the 1% level.

Table 10: Regression results with different setting of lags.

| Lag  | Model 1 | Model 2 | Model 3 |
|------|---------|---------|---------|
|      | ln Existcases_{t-Lag} | ln Existcases_{t-Lag} | ln Existcases_{t-Lag} |
|      | -0.0347881*** | -0.0128988* | -0.0015484 |
|      | (0.0070946) | (0.0070108) | (0.0069566) |
| D1   | -0.354285** | -0.594334*** | -0.5994531*** |
|      | (0.0869694) | (0.0899169) | (0.0901905) |
| D2   | 0.0680525 | -0.0259753 | -0.0532020 |
|      | (0.1078609) | (0.1105108) | (0.1117379) |
| D3   | 0.0178916 | 0.0860490 | -0.127624 |
|      | (0.1467405) | (0.1489957) | (0.1501317) |
|      | -0.0048146*** | 0.0603676** | 0.0160455** |
|      | (0.0014714) | (0.0013429) | (0.0015131) |
| D1   | -0.7456807*** | -0.7411535** | -0.795464** |
|      | (0.0751975) | (0.0742015) | (0.0749856) |
| D2   | -0.3273491** | -0.3305016** | -0.3982356*** |
|      | (0.0951787) | (0.0935574) | (0.0939385) |
| D3   | -0.3588641** | -0.389957** | -0.4617638** |
|      | (0.1350392) | (0.1325952) | (0.1275754) |

Table 11: Criteria for the selection of optimal orders

| Orders | AIC | BIC | HQIC |
|--------|-----|-----|------|
| 1      | 0.30541 | 0.42203 | 0.362719 |
| 2      | 0.218911 | 0.316477 | 0.253244 |
| Model 1 | 0.198849* | 0.305278* | 0.235363* |
| 4      | 0.202787 | 0.312744 | 0.241502 |
| 5      | 0.206051 | 0.323223 | 0.247099 |
| 1      | 0.129532 | 0.221004 | 0.16171 |
| 2      | 0.01244 | 0.085125 | 0.021893 |
| Model 2 | 0.059436* | 0.050528* | -0.02014 * |
| 4      | 0.059062 | 0.075209 | -0.018104 |
| 5      | 0.049067 | 0.067204 | 0.001609 |

Orders AIC BIC HQIC
1 0.30541 0.42203 0.362719
2 0.218911 0.316477 0.253244
Model 1 3 0.198849* 0.305278* 0.235363*
4 0.202787 0.312744 0.241502
5 0.206051 0.323223 0.247099
1 0.129532 0.221004 0.16171
2 0.01244 0.085125 0.021893
Model 2 3 0.049336 0.060393 0.000464
4 0.058864* 0.05188* 0.019361*
5 0.049067 0.067204 0.001609

Significant at 10%.
** Significant at 5%.
*** Significant at 1%.
the number of the existing confirmed cases, the IRF value gradually decreases with the increasing of time lags, showing a stable negative effect on the intra-provincial express flows. However, the IRF of the existing confirmed cases to inter-provincial express input or output flows is not monotone decreasing. With the increasing of time lags, the responses show that the negative impacts are enhanced gradually when the time lags \( s \leq 3 \), and then decreases when \( s \geq 4 \). Later, the negative effects are weakened and finally turn into the positive response. Therefore, with the nationwide resumption of work and production, the negative impact of the epidemic on the inter-provincial express logistics has gradually decreased, and the effects are positive in the long term.

6.2.3. Models with cross terms

To study the influence of epidemic on logistics in different stages, the cross terms \( D_1 \ln \text{Existcases}_{it-1} \), \( D_2 \ln \text{Existcases}_{it-1} \) and \( D_3 \ln \text{Existcases}_{it-1} \) are added for Model 1 with \( \text{Lag}=1 \). The regression result can confirm the hypothesis \( \text{H3} \), as shown in Table 12. The strong significance of the three cross terms indicate that the stages of epidemic progress have moderating effects for the impacts of the COVID-19 epidemic on the intra-provincial or inter-provincial express logistics. The coefficient of \( D_1 \ln \text{Existcases}_{it-1} \) is smaller than that of \( D_2 \ln \text{Existcases}_{it-1} \) at 1% significance level. Therefore, the negative effects of COVID-19 pandemic on express logistics in Stage II is greater than that in Stage III, as China began to resume work and production nationwide in Stage III.

6.3. Robustness check

The robustness check is performed for Model 1, Model 2 and Model 3 over two situations that consider the influence of different regions and explanatory variables.
(1) Regions excluding Hubei Province

The COVID-19 epidemic broke out in Hubei Province, which was much more serious than other provinces in China, especially during Stage I and Stage II. As shown in Fig. 1, the number of existing confirmed cases was much larger than that of other 30 China’s provinces. Hence, we remove Hubei Province to check the robustness of the proposed regression models. The results of the robustness analysis for the three models are shown in Table 13, revealing that the existing confirmed cases have a strong negative influence on the intra-provincial and inter-provincial output with strong statistical significance. Therefore, the results for this situation demonstrate that the basic regression models are relatively robust after excluding the data of Hubei Province.

(2) Replacing explanatory variable

Some research utilized the daily new confirmed cases to depict the severity of epidemic. In this situation, the original explanatory variable Existing cases is replaced by the new confirmed cases New cases for the robustness check. The regression results are shown in Table 14, showing that the new confirmed cases make negative effects on both the intra-provincial and inter-provincial express logistics with strong statistical significance. Then, the results of the regression models after replacing explanatory variable demonstrate the robustness of basic regression models.

7. Policy implications

The express parcel flow data analysis and modeling in this study could provide valuable policy implications in both the short term and long term to reduce the negative impacts of the epidemic on express logistics and economics. These lessons can also be considered for promoting the resumption of work and production in other similar countries.

7.1. Short-term policy implications

In the early stage, the lockdown and travel restrictions are implemented in key and high-risk regions to slow down the spread of the epidemic. People stay at home with increasing consumption of daily necessities, causing the panic buying behaviors. The shift from offline consumption to online shopping increase the demands of express logistics. Therefore, the emergency response capability of express logistics industry needs to be strengthened in the short term.

Moreover, limited express logistics resources need to be reasonably allocated during the COVID-19 epidemic. After the outbreak, China’s express logistics industry faces the problems such as labor shortage, transportation restrictions, difficulties in resuming work, and high service costs. In response to the special period, logistics companies can take temporary management measures to mitigate resource shortages. For example, during Chinese Spring Festival holidays of 2020, express employees returned home, and express logistics industry faced serious problems of labor shortage and activity restrictions owing to the postponed resumption of work, which affected the efficiency and quality of logistics services and suppressed the online shopping demands in the short term. Suning Logistics, a Logistics company in China, implements the distributed collaboration employment mode through shared employees to mitigate the labor shortage and unemployment during the COVID-19 epidemic (Liu et al., 2020).

7.2. Long-term policy implications

With the epidemic had been further controlled, some restrictions started to be relaxed or abrogated, promoting the rapid release of delayed online shopping demand. Supporting policies such as tax reduction and fee reduction can also promote the development of China’s express logistics. As shown in Fig. 3, in the early days of work and production resumption, a large backlog of e-commerce delivery orders give rise to a surge of inter-provincial express demands. In the long term, with e-commerce booming and changes of consumer purchase behaviors, more and more online shopping demands are stimulated with the resumption of work and production, leading to an increase trend of express logistics demand.

In order to ensure the safety of express employees and customers, express logistics companies need to disinfect work places, express parcels and vehicles regularly. Therefore, it is necessary to optimize the

Table 14

Regression results after replacing explanatory variable.

|                          | Model 1 | Model 2 | Model 3 |
|--------------------------|---------|---------|---------|
| New confirmed cases      | -0.0202505*** | -0.006197*** | -0.014608*** |
| Population density       | 1.470503***  | 2.358615***  | 2.619077***  |
| GDP per capita           | -2.49056***  | -4.96407***  | -10.99942*** |
| Road network density     | 1.52348***   | 0.56103358  | 2.710608***  |
| Urbanization rate        | -1.83843***  | -2.507364*** | -2.697808*** |
| Number of health         | 17.6501**    | 18.19358**   | 41.0423**    |
| technicians per 10k      | (3.758576)   | (0.9720358)  | (5.482027)   |
| population               |          |          |          |
| D1                       | -0.5962309** | -0.7210212*** | -0.9191411*** |
| D2                       | -0.0142372*** | -0.3356561*** | -0.5044853*** |
| D3                       | (0.1012475)  | (0.1032068)  | (0.0790007)  |
| Number of obs            | 4712      | 4712      | 4712      |
| Number of groups         | 31        | 31        | 31        |
| Time periods             | 152       | 152       | 152       |
| Wald test                | 11401.16  | 58410.59  | 30498.06  |
| P value                  | 0.0000    | 0.0000    | 0.0000    |

* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.
The severity of the COVID-19 pandemic makes significant effects on the express logistics at the regional level, which vary with different time lags. The related restrictive and support policies discussed in this study make positive or negative effects on the express industry in different stages. The short-term and long-term impacts of COVID-19 pandemic have been revealed by adding the lag terms, providing the policy supports for the recovery of express logistics and social activities in the post-epidemic. From the perspective of the short-term impacts, the restrictive policies and Chinese Spring Festival holidays suppressed the low capacity of express logistics in the early stage. From the perspective of the long-term impacts, more online shopping demands are stimulated with the resumption of work and production. The rapid recovery of China’s logistics industry benefit from effective control of the epidemic. China has accumulated rich experience in fighting against the COVID-19 pandemic. A series of prevention measures have been widely adopted such as lockdown, isolation, wearing masks, social distance, contactless delivery, which gradually changed the travel and consumption behaviors of Chinese people in the post-COVID-19 era. These empirical evidences from China could provide valuable learning lessons to other countries across the world. For example, Chinese medical experts went to Italy to assist in the fight against the epidemic and shared a lot of China’s experience in fighting the epidemic (World Economic Forum, 2020). Italy adopted the similar measures, such as building shelter hospitals, wearing masks, lockdown and restricting population movement after the COVID-19 outbreak in March 2020, and the epidemic was effectively controlled after May 2020.

This study provides the evidence for the dynamic impacts of the epidemic and restrictive policies on the express logistics demands, which can contribute to optimizing the spatial and temporal distribution of express logistics capabilities and adjusting the restrictive and support measures under public health emergencies. It is critical to reduce the negative impacts of COVID-19 on the transportation systems in the post-COVID-19 era. In the future, we will construct the spatial economic models to further study the spatial-temporal correlation of the express logistics flows and the severity of the epidemic, which can explicate the spatial effects of the spread of the epidemic.

Declarations of competing interest
None.

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