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Changxiu Cheng and Tianyuan Zhang contributed equally to this work.

Key Points:

- Population outflow from Wuhan had a long-term impact on the spread of COVID-19
- Areas with low population inflow lacked awareness of prevention, started emergency response later, and failed to prevent the COVID-19 caused by population mobility
- The degree to which population mobility and emergency measures affected the development of the epidemic exists spatial heterogeneity in China

Supporting Information:

Supporting Information S1

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The Coupled Impact of Emergency Responses and Population Flows on the COVID-19 Pandemic in China

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Abstract Coronavirus disease 2019 (COVID-19) has spread around the world and requires effective control measures. Like the human-to-human transmission of the severe acute respiratory syndrome-coronavirus 2 (SARS-CoV-2), the distribution of COVID-19 was driven by population flow and required emergency response measures to slow down its spread and degrade the epidemic risk. The local epidemic risk of COVID-19 is a combination of emergency response measures and population flow. Because of the spatial heterogeneity, the different impacts of coupled emergency responses and population flow on the COVID-19 epidemic during the outbreak period and a control period are unclear. We examined and compared the impact of emergency response measures and population flow on China's epidemic risk after the Wuhan lockdown during the outbreak period and a control period. We found that the population flow out of Wuhan had a long-term impact on the epidemic's spread. In the outbreak period, a large population flow out of Wuhan led to nationwide migration mobility, which directly increased the epidemic in each province. Meanwhile, quick emergency responses mitigated the spread. Although low population flow to provinces far from Hubei delayed the outbreak in those provinces, relatively delayed emergency response increased the epidemic in the control period. Consequently, due to the strong transmission ability of the SARS-CoV-2 virus, no region correctly estimated the epidemic, and the relaxed emergency response raised the epidemic risks in the context of the outbreak.

1. Introduction

Coronavirus disease 2019 (COVID-19) has continued to spread throughout most countries and regions since the World Health Organization (WHO) declared it a pandemic on 11 March (Cucinotta & Vanelli, 2020; Wu et al., 2020). As the Northern Hemisphere enters winter again, there has been a second outbreak of the worldwide epidemic. As of 12 November 2020, the death toll from COVID-19 had surpassed 1,200,000, and confirmed cases had topped 52 million (John Hopkins Univ Med, 2020). Meanwhile, COVID-19 has had an increasingly negative impact on the society and economy, including widespread unemployment (Blustein et al., 2020; Nicola et al., 2020), increasing social inequality (Bonaccorsi et al., 2020), and disruption in the global supply chain (Barrett, 2020; D. Guan, Wang, et al., 2020). At present, an urgent mission is to slow down the spread of COVID-19 and control it as soon as possible.

As the population flows are the main drivers of the spread of COVID-19 (Jia et al., 2020), emergency response measures have been employed to restrain its spread. Typical emergency response measures include social distancing, self-isolation, travel restrictions, and even regional lockdown (Hellewell et al., 2020; Jia et al., 2020; Kraemer et al., 2020; Lau et al., 2020; Wilder-Smith & Freedman, 2020). For instance, with the first outbreak in China in the early months of 2020, Wuhan municipal government issued a notice restricting travel leaving Wuhan City and temporally shut down the railway stations and airports on 23 January (called the Wuhan lockdown) (H. Chen, Chen, et al., 2020). Evidence has proven that emergency response measures can effectively mitigate the outbreak, slow down the spread, and limit the spread of COVID-19 (H. Chen, Chen, et al., 2020; Chinazzi et al., 2020; Kraemer et al., 2020; Lau et al., 2020; H. Tian, Liu, et al., 2020). Before the Wuhan lockdown, however, a large-scale population flow moved out



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Investigation: Tianyuan Zhang Methodology: Changxiu Cheng, Tianyuan Zhang, Changqing Song, Shi Shen, Yifan Jiang, Xiangxue Zhang Software: Tianyuan Zhang Supervision: Changxiu Cheng, Changqing Song Visualization: Tianyuan Zhang Writing – original draft: Tianyuan Zhang, Shi Shen Writing – review & editing: Changxiu Cheng, Changqing Song of Wuhan. People migrated across the country because of the Lunar New Year holiday (H. Chen, Chen, et al., 2020; Jia et al., 2020). The overlap of these two population mobilities increased the spread and influenced the epidemic's spatial distribution (Z. Chen, Zhang, et al., 2020; Jia et al., 2020; Jiang & Luo, 2020). Besides, after the Wuhan lockdown, the remaining provinces gradually issued the emergency responses at different times and levels according to increases in the number of confirmed cases (Figure 1).

However, the spatial correlations between the COVID-19 epidemic and population flow and the emergency response efficiency (RE) lacked a quantitative evaluation. Additionally, the coupled association of population flow and emergency responses with the number of confirmed cases during the outbreak and the control periods remains unclear. The changes in the epidemic and the heterogeneous population flow and emergency response measures taken in China provide an opportunity to investigate and compare the spatial association between the epidemic and the population flow and the emergency RE. We collected the daily number of confirmed cases in China's provinces, the population mobility data in Baidu Migration Big Data, and the date on which the provinces launched the emergency response. Then we used geographically weighted regression (GWR) to evaluate the respective effects of population flows and emergency responses on the epidemic from a spatial perspective. We also evaluated the changes and the magnitude of these factors during the outbreak and control periods. By analyzing the quantitative results, we found that the population flow and the emergency RE had a coupled impact on the COVID-19 epidemic and quick emergency responses were more effective in slowing down the spread of COVID-19 during the outbreak period than in the control period.

2. Materials and Methods

2.1. Study Period and Its Division

As the Wuhan Health and Health Commission reported the number of existing confirmed cases, continuous diagnostic records began to appear from 16 January. On 23 January, Wuhan started to be locked down. Then the daily number of new cases accelerated and peaked on 3 February (Figure 2). After that, Wuhan significantly increased the hospitalization number until all incident cases were quarantined and treated, which lasted until 16 February (Pan et al., 2020). Since then, the daily number of new diagnoses in China has remained below 100, which means the epidemic has been under control. The above time nodes and the epidemic development are shown in Figure 2.

We divided the average daily new confirmed cases (DNC) to the outbreak period (from 24 January to 3 February) and the control period (from 4–16 February). We employed the average proportion of the population moving out of Wuhan (PPW) to denote Wuhan's population flow. The average migration scale index (MSI) represents the ordinary population migration of the whole of China. The time we selected for PPW and MSI data is the prelockdown period (from 16–23 January), which was part of the Spring Festival travel season. According to the emergency response start time of each province (Table S1 in the supporting information), we estimated the provincial emergency response efficiencies according to the RE value.

2.2. DNC Data

We obtained the number of new confirmed cases per day in each province from the spatiotemporal data set of the COVID-19 epidemic (https://github.com/Estelle0217/COVID-19-Epidemic-Dataset.git). We then averaged the data separately in two stages. The averaged data were processed logarithmically to make it obey the normal distribution, and we used the processed DNC data in our analysis operation.

2.3. PPW Data

The PPW is defined as the proportion of people moving from Wuhan to a destination province to the total population moving out of Wuhan on the same day. We obtained PPW data and MSI from the Baidu Migration Big Data platform (http://qianxi.baidu.com/). Baidu Migration Big Data reflects daily population movements through Location-Based Services (LBS) data of mobile phones. Baidu Map LBS open platform is the data and technical service platform with the broadest range of LBS data sources in China, providing free and high-quality location services for over 500,000 APPs and accepting over 120 billion location call requests each day from over 1.1 billion mobile devices (Gibbs et al., 2020). Baidu Map LBS open platform provides real-time location services by multiform positioning means, including GPS, WIFI, and base station. The positioning accuracy can be up to 3 m.



Response to major public health emergencies in the early stage of COVID-19 epidemic in China



Figure 1. The development of the COVID-19 epidemic in China. The *y* axis represents the date. Red boxes indicate the critical timing of COVID-19 confirmed cases, blue boxes show the emergency responses and their levels, and the purple box indicates the Wuhan lockdown's timing. The green box represents the beginning of a stable situation in most areas in China.

Baidu Migration Big Data have reached the individual level, covering people who use mobile positioning software (Baidu Map and third-party APPs). In 2019, the number of people using mobile phones reached 61.2% of China's population. With smart devices' popularity, Baidu Migration Big Data are considered to be widely represented by typical studies (Fang et al., 2020; Gibbs et al., 2020; Kraemer et al., 2019, 2020; Li et al., 2020; Wei & Wang, 2020).

Compared with traditional census data, Baidu Migration Big Data have some apparent advantages. It is a real-time, daily continuous source for analyzing the spatial pattern of national population flow (Wei & Wang, 2020). For the first time, it shows the pattern of population movement between cities dynamically and instantly through massive data. It also avoids the one-sidedness of obtaining migration data by a single transmission mode. However, due to the limitation of backstage computation, the time interval for Baidu Migration Big Data to record spatial displacement is 8 hr, which leads to the possibility that long-distance migration may be dismantled (Gibbs et al., 2020).



Figure 2. Division of temporal COVID-19 trend in China. The *y* axis represents the DNC, excluding Hubei province. The *x* axis indicates the date. The arrow indicates the Wuhan lockdown date. The shallow red region indicates the outbreak period of COVID-19 from 24 January to 3 February. The shallow green region indicates the control period of COVID-19 from 4–16 February.



We selected the time range of PPW data in this study from 16 January (continuous diagnosis records began to appear) to 23 January (Wuhan lockdown), considering that the uncontrolled population movement during this period was the main factor leading to the epidemic development (Pan et al., 2020). This study's PPW data were logarithmic processing results after the original ratio was expanded by 100 times.

2.4. MSI Data

Data sources and selected time ranges of MSI were the same as PPW. When each province is a destination, MSI expresses the population's size moving into the province from across the country. It is daily updated and can be used to indicate the intensity of population movement (Wei & Wang, 2020). As stated on the official website (http://qianxi.baidu.com/) by Baidu Inc., MSI scales the relative mobility magnitude of the total movement population and can be compared among provinces at the same level (Gibbs et al., 2020; Xiong et al., 2020; C. Zhang, Pei, et al., 2020).

2.5. RE Calculation

We set the date (21 January) before the start date of the response to major public health emergencies in Hubei province (22 January) as the initial date and then used the date on which a province begins its first-level response minus the initial date as the RE of the province (also known as RE_{basic}). China's major public health emergency response ranging from strict to lax is divided into four levels: Levels 1–4. If the initial response were *n* level in a province, the RE of the province would be calculated with the equation below, which was used to quantify relatively poor response measures:

$$RE = RE_{basic} + \frac{1}{4}(n-1). \tag{1}$$

For example, if the province started with a Level 2 response, 0.25 was added to the RE. The emergency response issued dates of the provinces is shown in Table S1. We collected the data from the news events in the "epidemic event" module of the National Earth System Science data sharing platform (http://www.geodata.cn/sari2020/web/yiqingdsj.html).

2.6. Spatial Analysis

In the case of considering geospatial differences, to explore the effect of population flows and emergency RE on the epidemic development, we used the GWR to assess the association between the DNC and PPW, MSI, and RE in each province during the outbreak period and control period.

GWR was a local spatial statistical model, which, as an extension of the ordinary linear regression model, embedded the spatial location of the data into the regression parameters and evaluated the change of the relationship between independent variables and dependent variables on the spatial scale by obtaining local parameters (Fotheringham et al., 2002). A specific form of the GWR model is as follows:

$$y_i = \beta_0(\mu_i, \nu_i) + \sum_{i=k}^n \beta_k(\mu_i, \nu_i) x_{ik} + \varepsilon_i,$$
(2)

where (μ_i, v_i) is the geographical center coordinate of the sample space unit *i* (a provincial administrative region in this study) and $\beta_k(\mu_i, v_i)$ is the value of the continuous function $\beta_k(\mu, v)$ in the sample space unit *i*. We established two GWR models corresponding to the outbreak period and control period according to the research questions. The dependent variables y_i were the daily average new confirmed cases in the outbreak period and control period. The independent variables were uniformly set to population flows out Wuhan indicated by PPW, ordinary population migration indicated by MSI, and emergency response efficiency represented by RE.

We estimated the coefficients of the GWR model by iterating n spatial weighted least squares regressions. Each regression had its distance-decay weighted matrix. For a space unit i, the coefficient estimation is described as follows:

$$\beta_i = \left(X^T W_i X\right)^{-1} X^T W_i y,\tag{3}$$

where β_i is the vector of estimated coefficients for the sample *i*, *y* is the dependent variable, *X* is the *n* × *k* matrix of the independent variables (i.e., the explanatory variables), and *W* is the distance-decay weighted





Figure 3. Spatial distribution of average DNC in China in outbreak and control periods. The red color represents the provincial average DNC during the outbreak period from 24 January to 3 February (a) and the provincial average DNC during the control period from 4–16 February (b). DNC change between two periods is shown in (c).

matrix around the sample i for the regression (Fotheringham et al., 2002). A Gaussian kernel function (Equation 3) is used as the weighted function.

$$W_{ij} = \begin{cases} -\frac{d_{ij}^2}{h^2}, d_{ij} \le h, \\ 0, d_{ii} > h \end{cases}$$
(4)

where W_{ij} is the distance-decay weighted of the effect of observation j on the observation, d_{ij} is the distance between *i* and *j*, and *h* is the predefined bandwidth. According to the Akaike Information Criteria, we assessed the GWR model's final performance (Aho et al., 2014).

3. Results

3.1. Changes in Temporal and Spatial Patterns of the COVID-19 Epidemic in China

We divided the development of COVID-19 in China into prelockdown, outbreak, control, and stable periods according to the number of DNCs, excluding the Hubei provinces (Figure 2). Starting on 17 January, the number of confirmed cases in other provinces rapidly increased (Z. Chen, Zhang, et al., 2020). After the Wuhan lockdown, the DNC surpassed 100 in 1 day and rapidly reached a peak on 3 February with 885 cases. We designated this period from 24 January to 3 February as the outbreak period in China. The DNC slowly began to decline on 16 February with 119 cases; hereafter, the DNC became stable as less than 100 cases and then decreased. We denoted this period from 4–16 February as the control period.

The spatial distribution patterns of COVID-19 confirmed cases were different in two periods (Figure 3). The DNC indicated the epidemic intensity in each province during the corresponding period. In the outbreak period, the epidemic showed a trend of a spreading circle with Hubei marking the center (Figure 3a). We classified the provincial epidemic intensities across mainland China into five groups: slightly infected $(n \le 11)$, moderately infected $(11 < n \le 28)$, heavily infected $(28 < n \le 51)$, severely infected $(51 < n \le 71)$, and more severely infected (n > 71) according to the DNC as summarized in Table 1. The epidemic intensities in Hubei and Zhejiang provinces were relatively more severe than in the other provinces,



Table 1

Provincial Administrative Regions Corresponding to Different Epidemic Degrees at Different Periods

	Provincial administrative region					
Epidemic degree	Outbreak	Control				
Slightly infected ($n \le 11$)	Xinjiang, Gansu, Inner Mongolia, Jilin, Liaoning, Ningxia, Shanxi, Tianjin, Qinghai, Tibet, Yunnan, Guizhou, Hainan, Hong Kong, Macao, Taiwan	Xinjiang, Gansu, Inner Mongolia, Jilin, Liaoning, Ningxia, Shanxi, Shaanxi, Tianjin, Shanghai, Qinghai, Tibet, Yunnan, Guizhou, Fujian, Guangxi, Hainan, Hong Kong, Macao, Taiwan				
Moderately infected ($11 < n \le 28$)	Sichuan, Shaanxi, Hebei, Beijing, Heilongjiang, Shandong, Jiangsu, Shanghai, Fujian, Guangxi	Sichuan, Chongqing, Hebei, Beijing, Heilongjiang, Shandong, Jiangsu, Zhejiang,				
Heavily infected $(28 < n \le 51)$ Severely infected $(51 < n \le 71)$ More severely infected $(n > 71)$ Moran's <i>I</i>	Chongqing, Anhui, Jiangxi Henan, Hunan, Guangdong Hubei, Zhejiang 0.436	Henan, Hunan, Guangdong, Anhui, Jiangxi — Hubei 0.317 ^{***}				

Statistically significant at p = 0.001 level.

with an average increase of more than 71 DNCs. Guangdong, Henan, and Hunan provinces had an average DNC of more than 50, belonging to the group of "severely infected." Moran's *I* of DNC in the outbreak period is 0.436 (Table 1).

In the control period, the epidemic situations in other parts of the country were restrained other than in Hubei and Heilongjiang provinces (Figure 3b). Hubei province remains the epicenter of the epidemic, and the epidemic intensity has remained severely infected with an average number of 3,522 DNCs. In contrast, the Heilongjiang province's epidemic situation has increased from DNC = 14 to DNC = 24, which appears to be relatively rare at the national level. In contrast, Zhejiang and Guangdong provinces degraded from more severely infected (DNC = 71) and severely infected (DNC = 68) to moderately infected (DNC = 27) and heavily infected (DNC = 40), respectively. This result demonstrated that quick emergency responses slowed down the development and controlled the spread of COVID-19 in most provinces in China. Moran's *I* of DNC in the control period is 0.317 (Table 1).

Throughout the entire research period, the spatial distribution of the overall epidemic situation in the country showed a pattern divided by the Hu Huanyong line, which was a demarcation line indicating a distribution rate of 4% of the population of China on the west of the line and 96% on the east (Hu, 1990). This result showed that the distribution of COVID-19 had a potential correlation with the population and population flow.

3.2. The Spatial Pattern of Population Flow and Emergency RE

We categorized population flows into two types: (1) population flow out of Wuhan and (2) regular population migration for the Lunar New Year holiday. Since the Wuhan lockdown and the nationwide first-level emergency response, population mobility was almost frozen in China (H. Chen, Chen, et al., 2020). Overall, the PPW to the remaining provinces (Figure 4a) and MSI (Figure 4b) before Wuhan lockdown, as well as the RE (Figure 4c), showed distinct spatial heterogeneity. Figure 4a illustrates the spatial distribution of the population flow out Wuhan before the lockdown, which was consistent with the distribution of the number of confirmed cases in both periods. Hubei province had the largest PPW, accounting for more than 70% of the total outflow. Most of Wuhan's population traveled to the surrounding counties and cities and then spread to the periphery of Hubei province. Henan, Anhui, Jiangxi, and Hunan provinces also had relatively high PPWs (>3%) and then spread to the surrounding provinces. The population flow out of Wuhan showed a unique circular and radiating pattern. Provinces far away from Wuhan, such as Xinjiang, Tibet, Qinghai, Tianjin, Inner Mongolia, and Jilin provinces, had lower PPWs (0.14, 0.09, 0.03, 0.12, 0.14, and 0.16, respectively). However, the PPWs in Heilongjiang and Liaoning were relatively high (PPW = 0.27 and 0.32, respectively). The Moran's I of PPW was 0.435, which meant that PPW had strong positive spatial autocorrelation across China. Table 2 shows a statistically (P < 0.01) significant relationship that existed between the population flow out of Wuhan and the DNC during the outbreak period (Pearson correlation coefficient of 0.946). This result indicated that PPW was the primary diver for the distribution of COVID-19 during the outbreak.





Figure 4. Spatial distribution of population flows and emergency response efficiency in China. (a-c) The spatial distribution of PPW (the proportion of population moving out of Wuhan), MSI (migration scale index), and RE (response efficiency), respectively.

Population migration occurred mainly in eastern and central China, as shown in Figure 4b. Before the outbreak, the population of Hubei province spread to other provinces and could travel farther from these provinces to other regions. Taking this into account, we used the provincial MSI to represent the population volume moving into the province throughout the country. The MSIs of Beijing, Hebei, Henan, Anhui, and Jiangsu provinces were at a high level across the country with values greater than 7. This result indicated that these areas had large-scale population inflows from across the country and complex population mobility. The MSI level in central and southern China was moderately high, and there was also a risk of complex population inflows from other regions. The MSI in the western, northern, and southeastern China provinces and Hainan Province was relatively low (<2), which indicated that these provinces had few inflows from other regions. These results showed that the population migration was concentrated in eastern and central China, which have a high socioeconomic development level, better traffic conditions, and a dense population. Moran's *I* of MSI was 0.336, which meant a positive spatial aggregation of MSI. There was also a statistically (*P* < 0.01) significant relationship between MSI and DNC during the outbreak period (Pearson's correlation coefficient = 0.677) (Table 2).

The southern provinces and the Beijing-Tianjin-Hebei region had rapid emergency RE to the COVID-19 outbreak. Since 22 January, 31 provinces in China launched responses to major public health emergencies and finally reached the first-level response on 29 January. The spatial distribution of RE is shown in Figure 4c. Hubei province had the most efficient emergency response, and Hunan, Guangdong, and Zhejiang provinces also had a quick emergency response. The central and southern provinces and Beijing, Tianjin, Hebei, and Shandong provinces were also sensitive to the epidemic and had responded for 6 days by 29 January. The RE in most areas of the north, however, was relatively late. The Moran's *I* of RE was -0.018, which meant that RE was almost a discrete distribution. During the outbreak period, there was a negative statistically (*P* < 0.01) significant relationship between RE and DNC (Pearson's correlation coefficient = -0.740).

3.3. Spatial Associations Between Population Flows and Emergency RE

According to the development categories of COVID-19, we employed GWR to associate population flows and emergency RE to the new confirmed cases in both outbreak and control periods. We used the coefficient

 Table 2

 Pearson Correlation Coefficients Between DNC and Influencing Factors at Different Periods

	DNC in the outbreak period	DNC in the control period		
PPW MSI RE	0.946* 0.677* -0.740*	0.921* 0.619* -0.676*		
*Statistically significant at 0.01 level.				

of determination (pseudo- R^2) and adjusted pseudo- R^2 to evaluate the GWR model's aggregate explanatory power (Farber & Páez, 2007; Páez et al., 2002, 2011); see Table S2.

As shown in Figure 5, we found that the population flows have opposite influences in the outbreak period. The northeast, northern, and northwest China epidemic situation was positively affected by PPW (Figure 5a). In contrast, the nationwide MSI negatively influenced the DNC in the northeast and northern China (Figure 5b). The explanatory power of PPW in the whole country (0.846 to 0.871) was much higher than the MSI





Figure 5. Distribution map of GWR coefficients of factors affecting the epidemic development at different periods. (a–c) GWR coefficients of three respective factors during the outbreak period. (b–d) GWR coefficients of three respective factors during the control period. Warm colors (red and orange) indicate a positive effect, while cool colors (green and blue) indicate a negative effect. The darker the color, the greater the influence.

(-0.095 to -0.024) in the outbreak period (Table 3 and Figure 5). RE had a negative impact on the development of the epidemic, and the influence decreased gradually from east to west (Figures 5c and 5f).

In the control period, the PPW's positive influence became smaller (0.819–0.836) (Table 3), and the tendency to dominate the epidemic development grew weaker than before. This result indicated that the DNC would increase 0.827 on average when the level of PPW increased by one unit (Figure 5d).

3.4. Changes in the Impact of the Population Flows and RE on the New Confirmed Cases

The population flow out of Wuhan had less impact on the epidemic in the control period. Unlike the outbreak period, PPW in the control period had a higher influence coefficient on the epidemic in central and south China provinces, including Shanghai, Anhui, Hubei, Zhejiang, Chongqing, Sichuan, Jiangxi, Hunan, Fujian, Guizhou, Guangdong, Guangxi, Yunnan, and Hainan. The average a_2 of those provinces is 0.830. This parameter indicates that the DNC of the above regions would increase by 0.830 on average when the level of PPW increased by one unit. However, it had a relatively low influence coefficient on northeastern (Inner Mongolia, Heilongjiang, Jilin, and Liaoning) China. The average a_2 of those provinces is 0.821, which means that these areas' DNC would increase by 0.821 on average when the level of PPW increased by one unit.

The negative influence of population migration becomes weaker in the control period than in the outbreak period, as shown in Figure 5e. The MSI had a much higher negative coefficient ($b_2 = -0.025$ on average) on the DNC in northeastern (Inner Mongolia, Heilongjiang, Jilin, and Liaoning) China. In contrast, the negative



Table 3

GWR Models of Each Province at Different Periods

	GWR model								
		Out	break			Co	ntrol		
Provincial administrative	$DNC_1 = a_1 PPW - b_1 MSI - c_1 RE + e_1$			$DNC_2 = a_2 PPW - b_2 MSI - c_2 RE + e_2$					
region	<i>a</i> ₁	b_1	c_1	e_1	<i>a</i> ₂	<i>b</i> ₂	<i>c</i> ₂	<i>e</i> ₂	
Beijing	0.858	0.072	0.179	0.016	0.823	0.023	0.151	0.005	
Tianjin	0.857	0.070	0.179	0.016	0.823	0.023	0.150	0.005	
Hebei	0.857	0.070	0.179	0.015	0.823	0.023	0.151	0.005	
Shanxi	0.857	0.064	0.177	0.008	0.824	0.021	0.150	0.001	
Inner Mongolia	0.862	0.078	0.177	0.017	0.821	0.025	0.152	0.008	
Liaoning	0.857	0.077	0.181	0.025	0.822	0.025	0.151	0.009	
Jilin	0.859	0.085	0.182	0.032	0.821	0.028	0.151	0.013	
Heilongjiang	0.864	0.095	0.181	0.038	0.819	0.031	0.152	0.018	
Shanghai	0.848	0.055	0.183	0.011	0.827	0.019	0.147	-0.001	
Jiangsu	0.850	0.058	0.182	0.011	0.826	0.020	0.148	0.000	
Zhejiang	0.847	0.049	0.183	0.006	0.828	0.017	0.147	0.004	
Anhui	0.850	0.054	0.181	0.006	0.827	0.018	0.148	-0.002	
Fujian	0.846	0.042	0.183	-0.002	0.830	0.015	0.146	-0.008	
Jiangxi	0.848	0.044	0.181	-0.002	0.830	0.016	0.146	-0.007	
Shandong	0.854	0.064	0.180	0.013	0.825	0.021	0.149	0.003	
Henan	0.854	0.057	0.179	0.005	0.826	0.019	0.149	-0.002	
Hubei	0.852	0.051	0.178	-0.001	0.828	0.017	0.148	-0.006	
Hunan	0.851	0.044	0.179	-0.007	0.830	0.015	0.147	-0.009	
Guangdong	0.847	0.034	0.181	-0.012	0.833	0.013	0.145	-0.013	
Guangxi	0.851	0.035	0.177	-0.016	0.833	0.013	0.145	-0.014	
Hainan	0.848	0.024	0.179	-0.024	0.836	0.010	0.143	-0.019	
Chongqing	0.854	0.048	0.176	-0.008	0.829	0.016	0.148	-0.008	
Sichuan	0.858	0.047	0.172	-0.013	0.829	0.016	0.148	-0.010	
Guizhou	0.853	0.041	0.176	-0.014	0.831	0.014	0.147	-0.012	
Yunnan	0.856	0.036	0.172	-0.023	0.833	0.013	0.146	-0.016	
Shaanxi	0.857	0.058	0.176	0.000	0.826	0.019	0.150	-0.003	
Gansu	0.863	0.060	0.171	-0.006	0.825	0.020	0.151	-0.004	
Oinghai	0.864	0.054	0.168	-0.014	0.827	0.018	0.150	-0.007	
Ningxia	0.860	0.061	0.147	0.000	0.825	0.020	0.151	-0.002	
Xinjiang	0.871	0.058	0.163	-0.020	0.825	0.021	0.153	-0.006	
China Average	0.855	0.056	0.178	-0.002	0.827	0.019	0.149	-0.003	

impact was smaller ($b_2 = -0.015$ on average) in the south China provinces (Zhejiang, Hubei, Chongqing, Sichuan, Jiangxi, Hunan, Fujian, Guizhou, Guangdong, Yunnan, Guangxi, and Hainan). Compared with the outbreak period, the MSI affected the DNC in the south less than that in the north. This result demonstrated the impact of national population migration on the south, and the north was reversed.

The RE still negatively affected the DNC (China average $c_2 = 0.149$, which means if the RE increased by one unit, China's average DNC would decrease by 0.149) in the control period. The influence coefficient of RE decreased prominently, and the negative influence of this period decreased gradually from southwest to northeast (Figure 5f). Combined with Figure 4c, we found that areas with a short RE, such as in the southwest, had a more vital ability to restrain the epidemic. The ability to restrain the epidemic situation was weak in areas with a long RE, such as in the northeast. This result indicated that a late response to the epidemic might have increased the number of confirmed cases of COVID-19.

4. Discussion

Based on these results and analyses, we found the impact of the population flow and emergency RE on China's COVID-19 outbreak. Overall, the influence of PPW, RE, and MSI on the epidemic development was weakened in turn. Consistent with the previous researches (Chinazzi et al., 2020; Jia et al., 2020; H. Tian, Liu, et al., 2020), the population flow out of Wuhan was confirmed as the main driver of the spread of COVID-19. Population migration also had an impact on the spread of the epidemic. Nevertheless, a quick

emergency response could restrain the spread and be more crucial in the control period (Hellewell et al., 2020; Jiang & Luo, 2020). The potential mechanisms of the population flow and emergency RE on the COVID-19 are discussed in the following.

4.1. Direct Impact of Population Mobility on the Epidemic

Due to the transmission mechanism of infectious diseases, the regional and global spread and distribution of the human-human epidemics, including COVID-19, are the result of a combination of population mobility factors (W. Guan, Ni, et al., 2020; Rothan & Byrareddy, 2020; Yang et al., 2020). Considering the two different population flows (1) migration out of the place where the epidemic was found, and (2) population migration across the country. We confirmed that both types of population flow impacted the spread of COVID-19, which is consistent with previous studies (H. Chen, Chen, et al., 2020; H. Tian, Liu, et al., 2020).

The population flow out of Wuhan, however, was primarily responsible for the spread. Evidence shows that people who moved out of Wuhan before the lockdown were the first confirmed cases in the remaining provinces (Bai et al., 2020; W. Guan, Ni, et al., 2020; S. Tian, Hu, et al., 2020). The SARS-CoV-2 virus, which induces COVID-19, can be living in carriers, including humans. After the people from Wuhan arrived at their destinations, it likely introduced the secondary transmission due to the lack of knowledge about COVID-19 and the relatively weak emergency response at the start of the outbreak (Bai et al., 2020).

Similarly, when people migrated and used public transportation because of the national holiday, passengers were vulnerable and sensitive to the SARS-CoV-2. They may have come into close contact with its carriers (i.e., the population flow out of Wuhan), which may have introduced COVID-19. Because the majority of the PPW spread to Hubei, Guangdong, and Zhejiang provinces (Jia et al., 2020), and also due to the low probability of contact and reasonable protection measures taken by transportation systems (Y. Zhang, Zhang, et al., 2020), the impact of population migration was relatively lower than the population moving out of Wuhan.

Thus, we can explain the spatial heterogeneity in the impact of the population flows. In central China, the proportion of PPW and the number of migrating people were more extensive than in other areas. The overlap of the population flow increased their significant impact on the spread of COVID-19 in central China. Accordingly, remote regions, such as Tibet, Xinjiang, and Qinghai, had a low population flow out of Wuhan and small-scale population migration (H. Chen, Chen, et al., 2020; Du et al., 2020), which directly reduced the probability of COVID-19 infection. Hence, the number of cases in the Wuhan population became a more specific factor in determining the outbreak's spread than the population migration in the remote provinces.

4.2. Time Lag of Emergency Response

The local epidemic response's efficiency had a significant effect on restraining and controlling the epidemic situation's development (Sun et al., 2020). Conversely, the number of confirmed cases determined the efficiency and level of the emergency response. The emergency response of prevention and control in central China started earlier than that in other areas. However, it still failed to control the spread of the epidemic rapidly, indicating that the central area of the epidemic led by Hubei province should have begun prevention and control measures earlier (Sun et al., 2020). Although the number of confirmed cases was high in the eastern coastal areas, such as Zhejiang, Guangdong, and Fujian, their high RE (e.g., fire-level emergency responses even earlier than the Hubei province) still achieved remarkable results in the second phase.

4.3. Coupled Impact of Population Mobility and Emergency Response

We further discovered the coupled impact of emergency responses and population flows on the COVID-19 pandemic in China (Figure 6). A massive population inflow in the areas was close to the center of the epidemic in the outbreak period, resulting in a severe epidemic outbreak. However, the massive population inflow made these areas more vigilant and started the emergency response earlier. Due to timely emergency measures, the epidemic situation gradually stabilized.

Because staying away from the epidemic center, the population inflows of remote areas were less, which led to a weak sense of prevention. The slow and weak emergency response could not prevent epidemic spread caused by population mobility. According to the correlation characteristics and attribution analysis





Figure 6. Coupled impact of population mobility and emergency response in different regions. (a) The coupled impact in the area close to the epidemic center and (b) the coupled impact in the area far from the epidemic center. Green represents a safety incident, while red represents a dangerous incident.

(Table 2 and Figure 5), the PPW played a positive role in developing the epidemic situation in Heilongjiang due to the advanced transportation system (Y. Zhang, Zhang, et al., 2020). The above is closely related to the following fact: Heilongjiang province showed a rising trend when the epidemic situation was generally stable throughout the country.

4.4. Policy Implications

This study's findings emphasized the significance of quick emergency response and spatial heterogeneity when setting COVID-19 control policies. The experience of Zhejiang and Guangdong showed that quickly initiating an emergency response can effectively control the spread of COVID-19, such as restricting population movement, reducing human-to-human contact, and cutting off the route of virus transmission (Galbadage et al., 2020; Lotfi et al., 2020; Wilder-Smith & Freedman, 2020). Also, while the epidemic strictly guarded against population export, the remote areas in Heilongjiang experienced a higher number of confirmed cases, due to the relatively relaxed emergency response and a large volume of population flow from areas where the epidemic had spread. Because of its timely containment and intervention policy, China took only 3 months to transition the COVID-19 epidemic in China from the first appearance to outbreak to stabilization. The temporary emergency response measures are the key to control the spread of COVID-19.

Meanwhile, before an effective vaccine is released, maintaining social distance and wearing a universal mask is vital to reducing the transmission of the severe acute respiratory syndrome-coronavirus 2 (SARS-CoV-2) virus (Prather et al., 2020). We suggest that the government of COVID-19-spreading regions should take quick emergency responses to restrain the epidemic. Low-spreading areas also need to be prepared to make quick and strict responses according to the population flow from an epidemic center.



4.5. Notification and Limitations

This study's method can discuss the comprehensive impact of multifactors on the COVID-19 spread and explore the spatial heterogeneity of the influence mechanism. GWR method's study area is not limited to a single country but can be applied to larger study areas. However, for a larger area, the coupled impact found in this paper might not maintain. Each country's national conditions and policies are different, which may lead to substantial spatial heterogeneity of the research results. Hence, more large-scale research is required in the future.

In addition, the conclusions of this study are not necessarily applicable to a broader time range. This study's time background is from the outbreak to the decline of the epidemic, which was in the early stage (January to February) of the China epidemic. In April and May, the number of cases was much lower, which came from two sources: (1) overseas imported cases (L. Chen, Cai, et al., 2020) and (2) small-scale outbreaks in port cities caused by improper management of imported cases (such as the Suifenhe City epidemic in April). Under such circumstances, people had adapted to epidemic prevention and responded quickly to each possible outbreak.

5. Conclusions

This study investigated the coupled relationship between the spatiotemporal pattern and the leading factors of the epidemic degree of COVID-19 in China. Based on an analysis of the evolution of the spatiotemporal distribution pattern of the epidemic in different stages and across different regions, a quantitative analysis of the evolution of the epidemic situation's influence mechanism in various places in China was made. The coupled relationship between the epidemic situation and the influencing factors analyzed. The conclusions of this study are the following.

- 1. During the outbreak period (24 January to 3 February), the epidemic situation showed a trend of spreading from Hubei province to the outer circle, with a higher degree in Hubei, Zhejiang, Guangdong, Henan, and Hunan provinces. Additionally, in the control stage (4–16 February), the epidemic control effect in Zhejiang province was noticeable. However, the epidemic situation in Hubei and Heilongjiang provinces had not been controlled.
- 2. The influence of the factors on the development of the epidemic situation in China is PPW > RE > MSI. PPW was the most significant positive factor, and it had a greater influence on the epidemic situation in the control period; that is, PPW had a long-term effect. The negative influence of MSI and RE weakened in the control stage.
- 3. The influx of population led to a rapid epidemic outbreak in Wuhan's adjacent areas, while the timely emergency response brought the epidemic under control; less population inflow in remote areas reduced local vigilance, resulting in a large-scale outbreak at a later stage.
- 4. The high-risk epidemic level in the adjacent areas of the Hubei province was affected by various population mobility factors. Early long-distance population inflow and low RE led to the rising trend of the Heilongjiang province. For areas like Heilongjiang in China, which were far from the center of the epidemic but did not avoid widespread outbreaks, the causes of the outbreaks should be given special attention.

Conflict of Interest

The authors declare no conflict of interest relevant to this study.

Data Availability Statement

Data sets for this research are publicly available. COVID-19 epidemic cases' data are visible via the spatiotemporal data set of the COVID-19 epidemic (https://github.com/Estelle0217/COVID-19-Epidemic-Dataset.git), and population mobility data are visible via Baidu Migration data (http://qianxi.baidu.com/). The emergency response issued dates data are from the news events in the "epidemic events" module of the National Earth System Science data sharing platform (http://www.geodata.cn/sari2020/web/yiqingdsj.html).



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