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Computers, Environment and Urban Systems 102 (2023) 101957

Contents lists available at ScienceDirect

Computers, Environment and Urban Systems

journal homepage: www.elsevier.com/locate/ceus

Research paper

Causal effects of mobility intervention policies on intracity flows during the COVID-19 pandemic: The moderating role of zonal locations in the transportation networks

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ARTICLE INFO

Keywords:
Mobility intervention policies
Causality inference
Intracity flows
Transportation network
Interrupted time series (ITS)
COVID-19

ABSTRACT

Many studies have investigated the impact of mobility restriction policies on the change of intercity flows during the outbreak of COVID-19, whereas only a few have highlighted intracity flows. By using the mobile phone trajectory data of approximately three months, we develop an interrupted time series quasi-experimental design to estimate the abrupt and gradual effects of mobility intervention policies during the pandemic on intracity flows of 491 neighborhoods in Shenzhen, China, with a focus on the role of urban transport networks. The results show that the highest level of public health emergency response caused an abrupt decline by 4567 trips and a gradually increasing effect by 34 trips per day. The effectiveness of the second return-to-work order (RtW2) was found to be clearly larger than that of the first return-to-work order (RtW1) as a mobility restoration strategy. The causal effects of mobility intervention policies are heterogenous across zonal locations in varying urban transport networks. The declining effect of health emergency response and rebounding effect of RtW2 are considerably large in better-connected neighborhoods with metro transit, as well as in those close to the airport. These findings provide new insights into the identification of pandemic-vulnerable hotspots in the transport network inside the city, as well as of crucial neighborhoods with increased adaptability to mobility interventions during the onset and decline of COVID-19.

1. Introduction

At the early stage of the outbreak of COVID-19, many countries applied nonpharmacological interventions (NPIs), such as stay-at-home directives, lockdown measures, and travel bans, to reduce unnecessary mobility flows (Kraemer et al., 2020; Tian et al., 2020). Mobility flows, whether in the intercity or intracity context, are generated along varying transport networks (Lai et al., 2020; Millefiori et al., 2021; Kim, Lee, Ko, Jang, & Yeo, 2021). Many countries, therefore, proposed mobility interventions specific to important nodes or links in transport networks, such as in areas close to an airport, railway stations, metro transit stations, and routes close to specific airline or railway lines, and even locked down key city hubs of disease spread, such as the lockdown of Wuhan in China (Chinazzi et al., 2020; Huang & Li, 2022). People also tended to reduce the number of trips to areas close to transport hubs and avoid the potential risk of agglomeration of mobility flows during the outbreak of pandemic (Borkowski, Jażdżewska-Gutta, & Szmelter-Jarosz, 2021). Hence, it is important to examine the roles of varying transport networks and important hubs or nodes in the human mobility flows and to particularly understand whether transport hubs moderate the effectiveness of intervention policies in mobility flows.

However, most of the current studies on the mobility impact of COVID-19 focus only on the role of transport networks between cities, overlooking networks within cities and the role of zonal locations in such intracity networks. Compared to intercity mobility, studies on intracity flows should rather attract more attention, because most of the daily mobility occurs within cities, instead of between cities (Liang, Zhao, Dong, & Xu, 2013). In addition, intracity mobility seems to be rather complicated because it is associated not only with the networks' hubs, but also with the diverse routes and modes connecting such hubs, whereas intercity mobility flows are often affected only at key hubs and some fixed routes, such as along airlines or railway lines (Lu, Lin, Jiang, Zhang, & Yang, 2021; Zhang, Zhang, & Wang, 2020). It is also more difficult to moderate intracity flows than to moderate intercity long-distance flows by mobility interventions, because intracity flows are often highly frequent, necessary for daily life, and spatiotemporally

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https://doi.org/10.1016/j.compenvurbsys.2023.101957
Received 25 May 2022; Received in revised form 5 March 2023; Accepted 8 March 2023
Available online 14 March 2023
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heterogenous (Hong, Bonczak, Gupta, Thorpe, & Kontokosta, 2021; Mu, Yeh, & Zhang, 2021).

Therefore, to fill this research gap, we develop a quasi-experimental design by employing an interrupted time series (ITS) analysis to estimate the causal effects of travel restriction and restoration policies on *intracity* mobility flows in 491 neighborhoods (i.e., traffic analysis zones, TAZs) in Shenzhen, China, with a focus on the moderating role of urban transport networks on the effectiveness of these policies. We trace the changes in intracity flows before and after the outbreak of COVID-19 for a long time series from December 2019 to February 2020 in Shenzhen, China, on the basis of anonymized mobile phone trajectory data with fine-grained resolution in space and time. Specifically, we address two questions: (1) What are the causal impact levels and trends of mobility intervention policies on the number of intracity flows? (2) How do the positions of neighborhoods in varying intracity transport networks moderate the causal effects of mobility intervention policies on intracity flows?

Overall, this study makes two potential contributions. First, we are among the first to conduct an ITS quasi-experimental assessment of the abrupt and gradual effects of both travel restriction and restoration policies on intracity flows. In this study, we use a large set of anonymized mobile phone trajectory data with fine-grained resolution in space and time for three months. This dataset allows us to set an ITS design, which uses the trendline of daily flows extrapolated from the pre-existing trend in the preintervention period as the counterfactual and the postintervention outcomes as the treatment, by comparison, to infer both changes in level and trend of intracity flows in response to multiple interventions. Although the big data of mobile phone tracing have been widely used to estimate flows (Calabrese, Diao, Di Lorenzo, Ferreira Jr, & Ratti, 2013; Xu et al., 2017) and their associations with the spread of COVID-19 (Xiong, Hu, Yang, Luo, & Zhang, 2020), most of such data pertain to the mobility levels between cities or larger-scale regions (Nouvellet et al., 2021). Only a few have emphasized flows between neighborhoods or within cities, let alone the long-time-series tracking of daily mobility changes between smaller regions. This analysis should help us evaluate the effectiveness of mobility interventions as a strategy for changing intracity flows and provide new insights into spatial epidemiological models at finer scales.

Second, this study pays specific attention to the heterogeneity in the impact of policy interventions on intracity flows across zonal locations in urban transport networks. This is important for policymakers as it can help them identify pandemic-vulnerable hotspots in the transport network within a city, along with the crucial zones or locations that are more responsive and adaptive to mobility interventions during the onset and decline of COVID-19. Understanding the moderating effects of urban transport networks on travel restriction and restoration policies is valuable for informing public health interventions and surveillance and for building resilient places and transport systems.

The rest of this paper is organized as follows. Section 2 reviews the relevant literature. Section 3 describes the data, experimental design, and methods. Section 4 quantifies the effects of mobility intervention policies on the human mobility with a focus on the roles of varying urban transport networks. Section 5 discusses and concludes.

2. Literature review

To understand the spatial epidemiological process, many empirical or simulation studies have connected the outbreak of COVID-19 with human mobility flows between counties, cities, or larger regions (Chinazzi et al., 2020; Kim & Kwan, 2021; Nouvellet et al., 2021). Some early research has primarily focused on the changes in intercity or interstate human mobility before and after the outbreak of COVID-19 (Hadjidemetriou, 2020; Zhang et al., 2022). For instance, the before-and-after comparison reveals the threat of COVID-19 on mobility flows, although usually no causality is provided. For example, Lee, Baig, and Pervez (2021) reported changes in mobility flows based on multiple mobility metrics and found that a large number of people reduced their daily mobility levels and stayed more at home during the pandemic. Similarly, studies in the UK have also revealed that the population movement trend sharply decreased by 80% after the implementation of city lockdown (Hadjidemetriou, 2020). In addition, some of the large companies, such as Google, Apple, and Baidu, have shared their mobility reports and data at the aggregate level, often at the scales of counties, cities, or larger regions, which are widely used to explore changes in intercity flows (Li, Wang, Huang, Yang, & Chen, 2021; Nouvellet et al., 2021; Yilmazkuday, 2021). All of these empirical findings suggest that the outbreak of COVID-19 was associated with a significant reduction in daily mobility flows between cities, states, or larger regions.

Furthermore, many studies have opted to investigate which mobility intervention policies can affect human mobility behaviors during the pandemic. Most of these studies have focused on place- and flow-based mobility intervention policies, such as the effectiveness of place-based policies, including state/city-level social distancing, remote work for nonessential businesses, and closure of public schools. Although some of these studies have shown that noncompulsory measures were effective in reducing the travel distance by about 50% in Tokyo (Yabe et al., 2020), others have shown that the state-level stay-at-home directives in the US had a limited impact on reducing the frequency and distance of trips (Berry, Fowler, Glazer, Handel-Meyer, & MacMillen, 2021; Hu et al., 2021). This is because people had already spontaneously limited their travel before the implementation of such directives. However, another study has shown that statewide stay-at-home directives can substantially reduce out-of-home mobility beyond the effect of only voluntary measures (Abouk & Heydari, 2021). Flow-based NPIs include international and domestic travel bans, border closures, and lockdowns. Fang, Wang, and Yang (2020) quantified the causal effect of Wuhan's lockdown in China on mobility reduction by employing a difference-in-difference design. They found that the lockdown reduced the inflows to Wuhan by 77% and the outflows from Wuhan by 56%. At the beginning of the pandemic, some counties implemented international travel restrictions to prevent the spread of the virus. It is estimated that international airline closures or limitations reduced the traffic volumes by 40% and 90% to and from mainland China, respectively, at that time (Chinazzi et al., 2020).

Although there has been an increasing amount of research on neighborhood-level mobility (Dueñas, Campi, & Olmos, 2021; Huang & Li, 2022; Eom, Jang, & Ji, 2022), only a few studies have focused on the effect of policy interventions on intracity flows. Many cities implemented community mitigation policies, including physical-distancing measures, cancellation of mass gatherings, and community closures, to curb the spread of the virus. Lasry et al. (2020) confirmed that such community mitigation strategies were associated with a reduction in the percentage of people leaving their homes in four metropolitan areas in the US. Other researchers have also explored the spatial and group heterogeneity of the impact of the lockdown on neighborhood-level mobility trends over time, which vary across different categories of places, built environments, and socioeconomic characteristics (Eom et al., 2022; Hong et al., 2021). However, these studies did not estimate the causality. Moreover, rare research explores the changes in intracity flows between neighborhoods. One exception, however, is a study by Hao, Chen, Xu, and Li (2020), who built an epidemic simulator in downtown Beijing and found that place-based policy interventions in neighborhoods have a larger effect on reducing infectious cases than that of flow-based policies between neighborhoods.

Generally, transport networks play a crucial role in mobility flow changes (Guimera, Mossa, Turtschi, & Amaral, 2005), However, only a few studies have analyzed the role of intracity transport networks in the changes of mobility flows during the early stage of the COVID-19,

particularly the role of zonal locations in transport networks. It is reasonable to deduce that the mobility flow affected by the pandemic is highly associated with people's proximity and accessibility to important nodes in a transport network (Rodrigue, Luke, & Osterholm, 2020). The centrality or position of a city's airport in the global airline network largely affects the flow of mobility, particularly at the early stage of the COVID-19 pandemic (Kraemer et al., 2020; Tian et al., 2020). Moreover, railway networks between cities can also play similar important roles (Zhu & Guo, 2021). Cartenì, Di Francesco, and Martino (2021) found that rail transport accessibility, measured by the regional attractiveness (i.e., the number of opportunities) and average rail travel time, is an important factor that affects the number of COVID-19 infections in Italy. They suggested that the higher the flow-based rail transport accessibility, the tighter the mobility restriction policies adopted to effectively ensure social distancing should be. In China, some scholars found that the accessibility of road transport, aviation, and high-speed railway networks can significantly affect intercity mobility (Zhang et al., 2020). The aviation networks have been found to have the greatest impact on intercity travel, followed by railways and finally road accessibility (Li et al., 2021).

In summary, earlier studies have investigated the changes in intercity flows during the outbreak of COVID-19 and the imposed intervention policies between cities. However, several questions still require further investigation. First, compared to many studies of intercity flows, fewer have highlighted intracity flows between finer-grained spatial units during COVID-19. This is partly because it is difficult to access finer-grained mobility flow data that can reflect changes in intracity mobility patterns, such as between neighborhoods or subareas within a city (Hao et al., 2020; Jiang, Huang, & Li, 2021). Therefore, we surveyed the changes in the intracity flows of 491 neighborhoods in Shenzhen to enrich the debates on intracity mobility changes during the pandemic.

Second, although some studies have examined the associations between the change level of daily mobility and the outbreak of COVID-19 and/or the implementation of varying intervention policies, only a few of them have explored the causality between them. Hence, the questions of whether such interventions result in a reduction in flows, how large such intervention effects are, and how these effects change day by day remain ambiguous, with rarely enough empirical evidence. Moreover, only a few studies have examined the impact of recovery-related policies on the rebound of flows. All of these factors call for an innovative research design for causality inference. The current literature has recognized the importance of causality inference, and some studies have used quasi-experimental techniques, such as pretest–posttest, difference-in-difference, and ITS designs (Fang et al., 2020; Siedner et al., 2020; Vokó & Pitter, 2020). Compared to other quasi-experimental designs, the ITS design can estimate intervention effects separately for individual samples and analyze not only the change levels, but also the change trends of the interventions over time (Reichardt, 2019; Zhang & Ning, 2023). In the ITS design, the estimate of the intervention effects is derived by comparing the same participants at different time points, avoiding the bias of selection difference arising from between-group comparisons after controlling for time-varying confounders. In this study, using a large data set containing mobile phone trajectory data of approximately three months, we develop an ITS analysis to infer the abrupt and gradual effects of mobility interventions on intracity flows respectively, namely the change levels and trends (i.e., the change rate of policy effectiveness at both the impact and the recovery stages).

Third, although a few studies have examined the role of intercity transport networks in the changes of intercity flows and evaluated how the effectiveness of mobility intervention policies varies across city locations or positions in a transport network, few have focused on the role of urban transport networks in intracity flows. Such moderating effects of transport locations may be observed not only in public transport networks, but also in road networks and important regional transport hubs. In addition, the effects of COVID-19 and the related mobility intervention policies on intracity mobility flows should vary across neighborhoods of different locations in varying transport networks. Therefore, in this study, we investigate the moderating effects of varying transport networks, such as metro transit networks, road networks, and important regional transport hubs, to investigate the role of spatial heterogeneity in the impact of mobility interventions on intracity flows.

3. Data and method

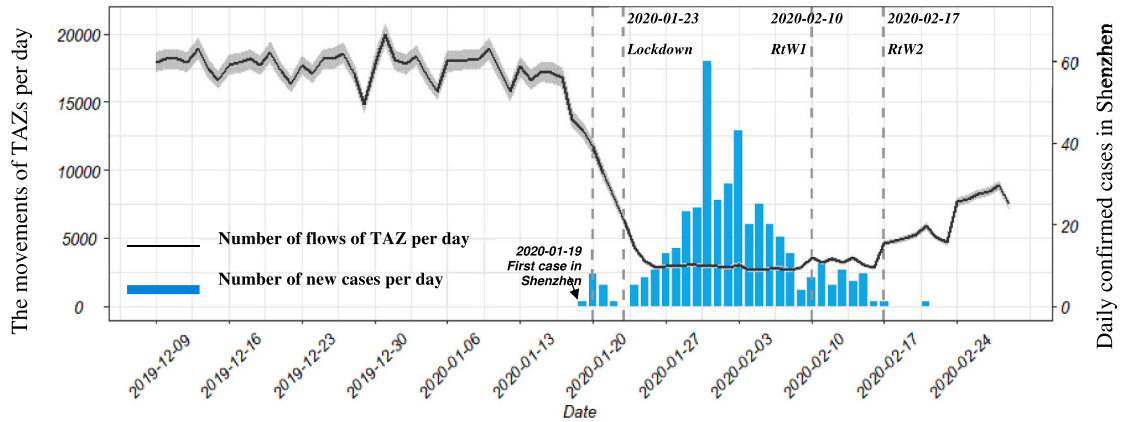
3.1. Research area and data

This study focuses on Shenzhen, one of the largest cities in China (Fig. 1) with a resident population of 17.56 million in 2020, according to the latest census data (Nation Bureau of Statistics of China, 2020). After the outbreak of COVID-19 in Wuhan, Hubei, in early January 2020, Shenzhen was the first city to report a COVID-19 case outside the province of Hubei on January 19, 2020.

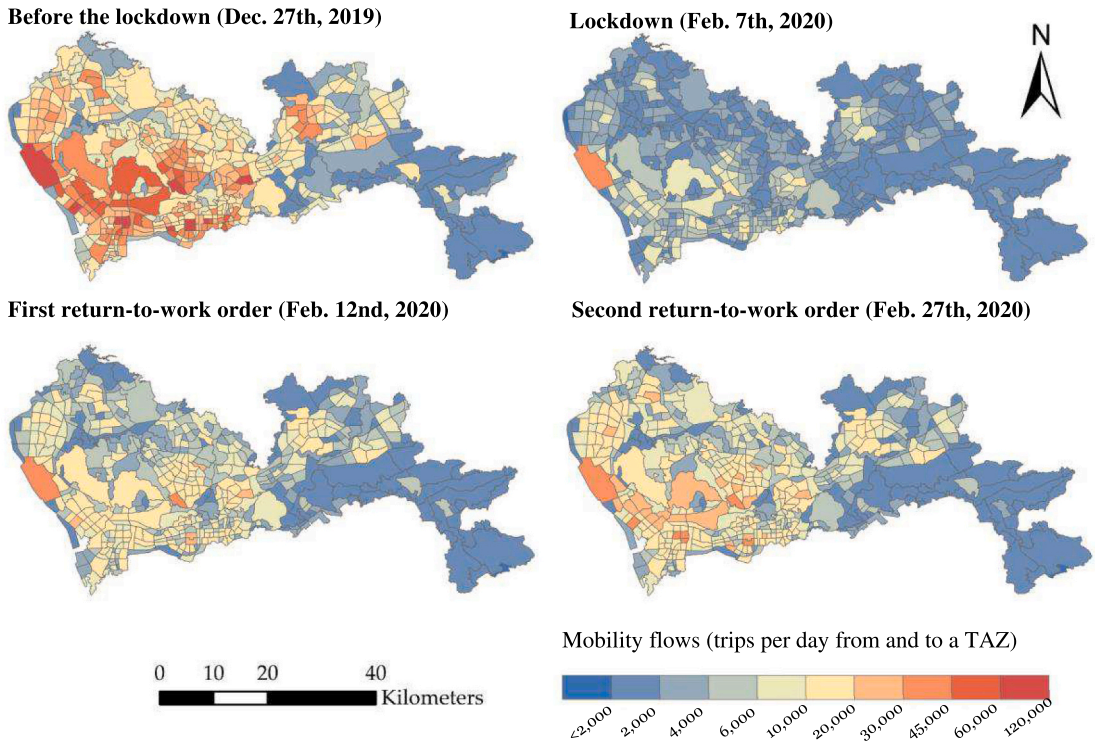
In this study, we investigate the changes in the intracity flows of 491 neighborhoods, delineated by TAZs covering the entire city of Shenzhen. We extracted mobility data from a large set of mobile phone data from the Smart Steps company, which collects anonymized mobile phone data from the devices of China Unicom, one of the three service providers in China. Before the pandemic, Shenzhen used to have more than four million regular users per day, accounting for about one-fourth of the total resident population. The mobile phone trajectory data used in this study were aggregated at the TAZ level in space and at the daily level in time, from December 9, 2019, to February 29, 2020, that is, 41 days before and after the first reported case on January 19, 2020, in Shenzhen. This mobile phone data set records the timing, duration, and location of each trip made by each individual when the device user uses their phone or when an activity lasts for more than half an hour. For data cleaning, we removed activity and trip records with significant errors resulting from data drifting, abnormal issues, and missing values, which are commonly found in most of such mobile phone data (Oksanen, Bergman, Sainio, & Westerholm, 2015).

Fig. 1 shows spatiotemporal heterogeneities in the total number of flows departing from and arriving at 491 TAZs for about three months. After the outbreak of COVID-19 on January 19, 2020, in Shenzhen, a highest-level public health emergency response (HLR, with a set of social distancing or soft lockdown policies) was imposed on January 23 to restrict intracity flows, including the prohibition of gatherings and activities, the closure of schools, and the testing of the body temperature of passengers at airports, railway stations, and subway stations. According to Fig. 1a, the average number of daily mobility flows (including inflows and outflows) passing TAZs significantly dropped from January 19 and remained stable at a low level from January 25, right after the implementation of the HLR, with the average flow amount shifting from 17,000 to 2800 trips per TAZ day. This abrupt change was linked to the daily number of infected cases (Fig. 1a), which reached 60 on January 31. As the number of cases decreased, some work resumption strategies were adopted in Shenzhen to promote the restoration of production and working activities. For example, phased reopening policies, including two return-to-work orders, were adopted. The first return-to-work order, issued on February 10, was specific to the industries involved in people's livelihood, such as public administration, transportation, agriculture, wholesale and retail trade, and environment and public facility management (Bai et al., 2021). At this stage, the number of flows increased only slightly from 2800 to 3500, remaining at a low level with a growth rate of 3.57% per day. The second return-to-work order, implemented on February 17, was specific to general manufacturing industries. At this stage, the number of flows increased from 3500 to 8800 by the end of February, with a relatively larger growth rate of 7.25% per day, indicating the gradual recovery of intracity flows.

This study emphasizes the above three mobility intervention policies. Our daily mobility data were divided into four periods: (1) before the lockdown: from December 9, 2019, before the pandemic, to January



(a) Temporal changes in TAZ-based daily mobility flows and the number of new COVID-19 cases from December 9, 2019, to February 29, 2020, in Shenzhen.



(b) Spatial distribution of mobility flow volumes in 491 TAZs over the four stages before and after the COVID-19 outbreak. (Note: One weekday from each of the four stages is selected for comparison.)

Fig. 1. Spatiotemporal distribution of mobility flows before and after the COVID-19 outbreak in Shenzhen.

Table 1
Description of variables.

Variables	Description	Mean	SD	Min	Max
Dependent variable					
Flows	Daily amount of mobility flows from and to a TAZ (person trips)	11,367	13,248	6	135,320
Mobility intervention policies (MIs)					
Lockdown	1: if the day is right after the issue of the highest-level response to public health emergency from Jan 23, 2020;0: other days.	0.458	0.498	0	1
RtW1	1: if the day is the date during the first return-to-work order from Feb 10, 2020 to Feb 16, 2020; 0: other days.	0.241	0.428	0	1
RtW2	1: if the day is the date during the second return-to-work order from Feb 17, 2020 to Feb 29, 2020; 0: other days.	0.157	0.363	0	1
Panic factors perceived by the COVID-19					
Risk	1: if the day is right after the first day of the declaration of person-to-person infection of the new coronavirus on Jan 20, 2020, when people start to perceive the risk of COVID-19; 0: else.	0.494	0.50	0	1
Case	Daily number of newly confirmed COVID-19 infection cases	5.02	11.14	0	62
Zonal locations in transportation networks					
MetroBC	Betweenness centrality of a TAZ's closest metro station in the metro transit network (hereinafter called "centrality of metro stations"). Here, betweenness represents the ratio of the shortest paths in the transit network between any two metro nodes passing through the metro station	0.054	0.098	0.000	0.962
RoadAcc	The average of road networked distance from a TAZ to all other TAZs (km) in Shenzhen	28.96	9.07	19.12	67.18
DisAirport	The road networked distance to the Baoan International Airport (km) in Shenzhen	35.33	18.24	0.01	98.39
DisRailSta	The road networked distance to the nearest rail station (km) in Shenzhen	9.04	6.71	0.57	43.46
Built environment variables of TAZs					
PopDen	The population density of TAZs (thousand/km^2)	17.47	18.04	0.00	93.6
LUmix	The land use mixture entropy of a TAZ (0–1), measuring a mixture of residential, public, commercial, industrial, and green space: $\frac{-\sum_{i=1}^{s}(p_i)ln(p_i)}{ln(s)}$, where s is the type of land use and $p_i$is the proportion of type-i land use.	0.637	0.195	0.025	0.937
DisCenter	The road networked distance to the nearest city center (km)	8.09	4.46	9.18	24.38
Socioeconomic variables of TAZs					
Male	The ratio of male population in a TAZ (%)	0.444	0.069	0.017	0.846
Age	The average age level in a TAZ	36.97	3.31	26.15	53.40
Edu	The ratio of the population with higher education (%) in a TAZ	0.132	0.142	0	0.846

23, 2020, when a highest-level HLR was declared (hereinafter referred to as the lockdown); (2) lockdown: from January 24 to February 9, 2020; (3) RtW1: from February 10, the first return-to-work order (hereinafter referred to as RtW1), to February 16; and (4) RtW2: from February 17, the second return-to-work order (hereinafter referred to as RtW2), to February 29, 2020.

Fig. 1b depicts the spatial variations in intracity flows across TAZs at the four abovementioned stages. Overall, we found that the number of flows declined rapidly from the first to the second stage and then gradually recovered in the third and fourth stages, with the maximum number of TAZ flows dropping from 120,000 to <33,000 trips per day, followed by a recovery stage to 45,000 trips per day. Before the lockdown in the first phase, the flows of most TAZs were >10,000, except for those in the districts of Yantian and Dapeng. However, during the lockdown, most of the TAZs had a flow of <10,000 trips. During the third phase, the flow of most TAZs recovered after RtW1, especially for TAZs that are considered important regional hubs in different transport networks, such as the TAZs surrounding the airport and two railway stations. After the issuance of RtW2, the flows of some TAZs increased to 20,000 trips. Moreover, some major residential and working areas in Nanshan, Futian, and Bao'an recovered faster, with the number of flows reaching up to approximately 30,000 trips during the fourth phase. The changes of spatial patterns of intracity flows across TAZs among four stages are shown in Fig. A1 in Appendix A.

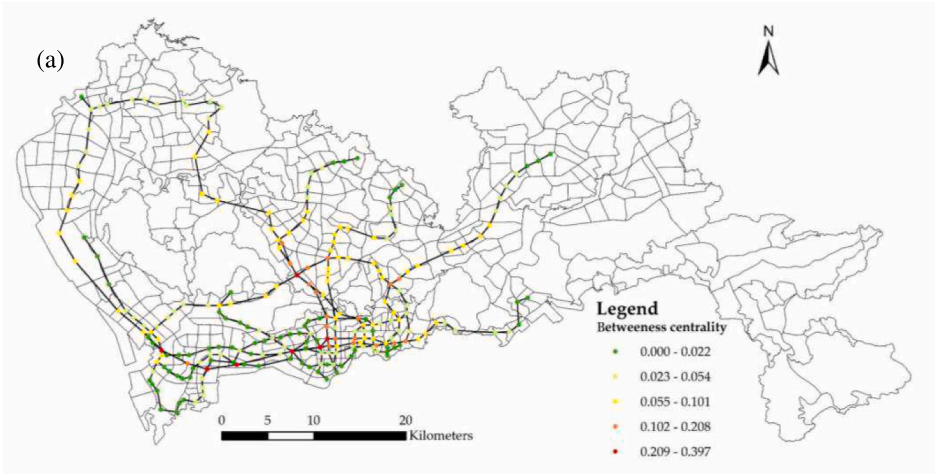
3.2. Interrupted time series analysis and variables

In this study, we developed an ITS design to infer the causal effects of mobility intervention policies in Shenzhen on the changes in daily mobility flows of a TAZ before and after the COVID-19 outbreak. ITS is often considered as one of the most powerful quasi-experimental designs for causality inference that uses long time-series observations of behavioral trends (Reichardt, 2019; Zhang & Li, 2023). Particularly, ITS estimates the treatment effect of an intervention by projecting forward the trend of the observations in the preintervention period as the counterfactual and comparing the projected trend with the actual trend of observations after the treatment. Overall, ITS has some advantages compared to other quasi-experimental designs, such as difference-in-difference and regression discontinuity designs. First, ITS infers the treatment effect through one-group long-time-series behavioral observations, and therefore it can avoid the bias of selection difference in between-group designs. Second, ITS designs can assess how the effect of a treatment changes over time, including any changes in the level and/or trend.

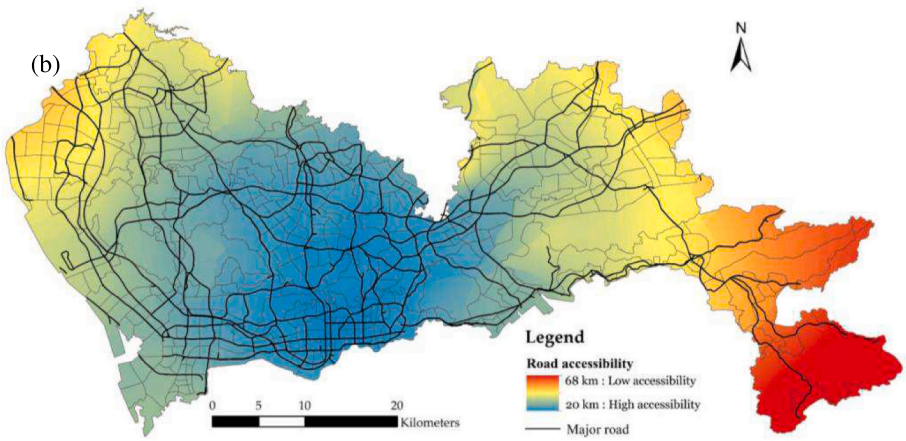
Although ITS analyses have been widely used in the fields of public health and clinical and guideline implementation (Reichardt, 2019), they are less adopted in the fields of transportation and geography. One critical issue in the application of ITS is that it requires a sufficiently long period of time for mobility flow data of research units. This long time series of mobility flow data within cities is difficult to obtain, especially for the long-time-series tracking of daily mobility flow changes between neighborhoods. Thus, few studies have employed an ITS design to explore the causality between human mobility and intervention policies.

Table 1 shows a list of dependent and independent variables for an ITS analysis, as the modeling specification detailed below. For the dependent variable, we focus on the daily number of intracity flows from or to each TAZ. During the research period, the average number of flows per TAZ was around 11,400 trips per day, with the maximum reaching up to 135,000 trips per day.

For an ITS model, independent variables often include both time-varying and time-invariant variables (Table 1). Among these, the time-varying variables involve the mobility intervention variables and time-varying confounders, including newly confirmed cases on each day (i.e., the variable of '*Case*') and the timing slots during which people perceive the risk of COVID-19 in person after the authoritative announcement that was made to the public on January 20, 2020 (i.e., the variable of '*Risk*'), the cycling effects of weekdays, and holidays of the Spring Festival in China. Many studies have reported that besides the intervention effects due to NPIs, there are significant voluntary changes in mobility induced by the announcement of confirmed cases per day and some authoritative announcements of the risk of the virus to the public, particularly at the early stage of the outbreak (e.g, Brodeur, Grigoryeva, & Kattan, 2021; Yan et al., 2021). In China, as found in many studies (e.g., Fang et al., 2020; Zhang et al., 2020), people started



(a) Distribution of the betweenness centrality scores of 327 stations in Shenzhen. Higher scores represent more important positions in the metro transit network.



(b) Accessibility to other TAZs through the primary road network. Accessibility represents the average of the distance to other TAZs' centroids. The larger the distance is, the lower the accessibility level is.

Fig. 2. Spatial distribution of a TAZ's zonal location in both the metro transit network and road network in Shenzhen.

to perceive the definite risk of COVID-19 in person after the official declaration of person-to-person infection on January 20 and begun to voluntarily alter their mobility behaviors. It is thus important to control for the panic effects by these two variables (i.e., *Case* and *Risk*).

The time-invariant variables include variables of zonal location in varying transport networks, the built environment, and the socioeconomic variables of each TAZ (Table 1). Among these, we measured the position of each TAZ in the metro transit, road transport, intercity train, and airport networks by assessing centrality, proximity, and accessibility, as defined in Table 1. Using these zonal location or position measures, we were able to estimate their moderating effects on intracity flows and to also compare their roles in different transport networks. In 2020, the transit system of Shenzhen had 237 stations alongside 10 metro lines. We calculated the betweenness centrality of these 237 stations on the basis of a complex network analysis (Fig. 2a). Betweenness centrality is an important index measuring the roles of transit stations in the metro network, representing the ratio of shortest paths passing through a station between any pairs of stations in the entire network. Compared to degree centrality and closeness centrality, betweenness centrality can more indicate the transfer role of a station in the public transport system. In general, the higher the betweenness centrality is, the more convenient the station is for transfer. According to the spatial distribution of stations, we aggregated the betweenness centrality scores of these stations within each TAZ on average to represent the TAZ's centrality level in the transit network. By contrast, we measured the position of a TAZ in the road network by averaging the network-based distance from the TAZ to all other TAZs, which represents the level of accessibility to other areas in the city, as visualized in Fig. 2b. In this context, the measure of the road network mainly includes national highways, provincial highways, county highways, expressways, and urban expressways. In addition, we considered the role of a TAZ in connection with outward transportation through its proximity to the nearest rail stations and airport.

For ITS analysis, multilevel models are widely adopted for estimation when there are multiple time points of observations nested within individual samples (Reichardt, 2019). In this study, we observed 83 days of daily flow numbers for 491 TAZs. This data structure allows us to construct two-level models: Level 1 involves day-varying variables within each TAZ, while Level 2 consists of time-invariant TAZ-level covariates that vary across TAZs. With this multilevel model, we can estimate individual models for each TAZ as well as regression parameters, such as.

Level-1: Time-varying model

Table 2
Estimated results of core variables in the ITS model (Dependent variable: Daily amount of mobility flows from and to a TAZ (person trips)).

Variables		Coef.		St.Err.	*P*-value
Before the lockdown	Intercept	18,059.03	***	505.84	0
	Day	−45.16	***	1.52	0
Mobility intervention policies	Lockdown	−4567.31	***	433.32	0
	Lockdown*Day1	−34.17	***	7.72	0
	RtW1	138.91		113.90	0.223
	RtW1*Day2	166.10	***	24.75	0
	RtW2	1449.72	***	172.47	0
	RtW2*Day3	478.45	***	11.70	0
Time-varying confounders	Risk	−7086.22	***	81.64	0
	Cases	−24.09	***	2.22	0
	SFH	−246.69	***	69.63	0
	Monday	1376.34	***	54.20	0
	Tuesday	1512.21	***	53.78	0
	Wednesday	1428.84	***	52.85	0
	Thursday	1622.95	***	53.22	0
	Friday	1919.80	***	52.83	0
	Saturday	541.96	***	51.65	0
The moderating of effects of urban transport networks for intracity flows					
Before the lockdown	MetroBC	6082.70	***	556.05	0
	RoadAcc	1259.18		829.68	0.129
	DisAirport	−4110.63	***	651.18	0
	DisRailSta	−697.38		954.48	0.465
Lockdown	MetroBC	−5144.45	***	461.81	0
	RoadAcc	−970.72		689.06	0.159
	DisAirport	3658.23	***	540.81	0
	DisRailSta	498.05		792.71	0.53
RtW1	MetroBC	−129.12	**	61.16	0.035
	RoadAcc	−53.84		91.26	0.555
	DisAirport	1.01		71.63	0.989
	DisRailSta	−13.42		104.99	0.898
RtW2	MetroBC	768.46	***	113.84	0
	RoadAcc	254.43		169.86	0.134
	DisAirport	−1029.58	***	133.32	0
	DisRailSta	−60.45		195.41	0.757

Robust standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

$$\text{Flow}_{it} = \beta_{0i} + \beta_{1i}Day_{it} + \boldsymbol{\beta_{2i}MIs_{it}} + \boldsymbol{\beta_{3i}MIs_{it}}*\boldsymbol{Day^{*}_{it}} + \beta_{4i}Risk_{it} + \beta_{5i}Case_{it} + \beta_{6i}Festival_{it} + \beta_{7i}Day\ of\ week + \varepsilon_{it} \quad (1)$$

where subscript i represents the TAZs (i varies from 1 to 491) and subscript t represents time (t varies from 1 to 83, referring to the dates from December 9, 2019, to February 29, 2020). The dependent variable, $Flow_{it}$, is the number of the population flows of TAZ i on day t. *Day* is a variable representing time (1, 2, …, 83). $\boldsymbol{MIs_{it}}$ is a vector of dummy variables, including *Lockdown, RtW1*, and *RtW2*. $\boldsymbol{Day^{*}_{it}}$ is (Day_{it} *minus* $\boldsymbol{Day_I}$) where $\boldsymbol{Day_I}$ is the *time* of $\boldsymbol{MIs_{it}}$. *Risk* is a dummy variable that is equal to 0 before the declaration of person-to-person infection with COVID-19 on January 20, 2020, and 1 afterward, when people started to perceive the risk of COVID-19. *Case* is the daily number of one-day-lagged newly confirmed COVID-19 cases in Shenzhen, used to control for the impact of people's reaction to the pandemic. In addition, we added the Spring Festival holiday dummies (*Festival*) and weekly dummies (***Day of Week***), in order to control for the possible holiday and weekly changes in zonal mobility common to TAZs over the research period. Notably, due to the COVID-19, the Spring Festival holiday in 2020 was extended from regular seven days to ten days (i.e., from Jan. 24 to Feb. 2, 2020).

According to the estimated coefficients, we can analyze the changes in the levels and trends of intracity flows before and after a policy intervention. In detail, β_{0i} represents the baseline level on day 0, given that all other impact factors are controlled for. β_{1i} is the average changing rate of daily travel distance over time. $\boldsymbol{\beta_{2i}}$ reflects the abrupt effects in levels due to three intervention policies, whereas $\boldsymbol{\beta_{3i}}$ reflects the gradual change trends per day of intracity flows after three interventions. β_{4i}, β_{5i}, and β_{6i} represent the average effects of risk perception, newly confirmed cases, and the Spring Festival holiday, respectively. The standard error ε_{it} is clustered at the daily level.

In the Level 2 model, we added time-invariant variables, including the zonal location in varying transport networks, built environment, and socioeconomic variables of each TAZ, to explore the moderating effects of intracity transport networks on time-varying effects, as estimated in Level 1. We used four main covariates (*MetroBC*, *RoadAcc*, *DisAirport*, and *DisRailSta*) to examine the changes in the levels or slopes for different zonal transport locations. These variables were simply assumed to be constant during the study period:

Level-2: TAZ-level effects (the moderating of transport networks):

$$\beta_{0i} = \gamma_{00} + \gamma_{01}*MetroBC + \gamma_{02}*RoadAcc + \gamma_{03}*DisAirport + \gamma_{04}*DisRailSta + r_{0i} \quad (2)$$

$$\boldsymbol{\beta_{2i}} = \boldsymbol{\gamma_{20}} + \boldsymbol{\gamma_{21}}*MetroBC + \boldsymbol{\gamma_{22}}*RoadAcc + \boldsymbol{\gamma_{23}}*DisAirport + \boldsymbol{\gamma_{24}}*DisRailSta + \boldsymbol{r_{2i}} \quad (3)$$

where γ_{j0} is the mean of the β_{ji} parameters across TAZs. The value of γ_{01} is the difference in the means of the β_{0i} parameters between higher *MetroBC* and lower *MetroBC*. The value of $\boldsymbol{\gamma_{20}}$ is the estimate of the average change in level for TAZs due to the mobility intervention policies. The value of $\boldsymbol{\gamma_{21}}$ reflects how much higher *MetroBC* and lower *MetroBC* differ on average in the change in level due to the mobility intervention policies. The r_{0i} and $\boldsymbol{r_{2i}}$ terms are residuals. We considered the built environment and socioeconomic covariates of TAZs as the control variables of the models (Detailed in Table 1). These covariates are all standardized in the estimation, and the mean level of a standardized variable is thus indicated as zero in the model. We first conducted a null model to see if there is a necessary need for multilevel modeling. We found that 50.56% of the total variance is attributed to

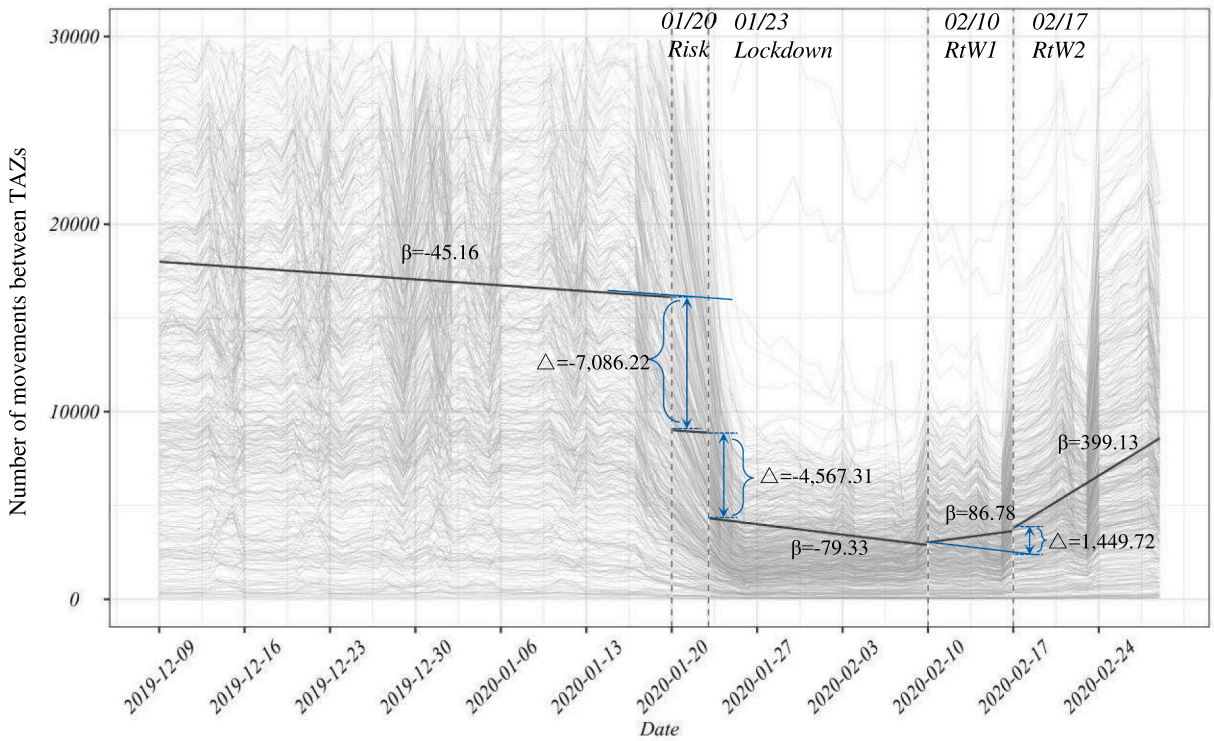


Fig. 3. Estimated causal effects (abrupt and gradual effects) of the three mobility intervention policies over time on the number of TAZ-based flows. The background curves depict the average number of flows from and to most TAZs.

variance of Level 2 at the 0.001 probability level, and this suggests multilevel structure is needed. Estimates of the full model and the robustness tests are shown in Table B1 in Appendix B, including all of the independent variables.

4. Results

Table 2 presents the estimated core coefficients of the ITS model. We estimated both the abrupt effects (changes in level) and the gradual effects (changes in trend) of the three mobility intervention policies on neighborhood-level mobility changes, after controlling for the panic effects perceived from the official declaration of person-to-person infection and daily updated confirmed cases. Moreover, we compared how the abrupt and gradual effects of these policies varied across TAZs with different zonal locations, after controlling for the confounding effects of zonal built environment and socioeconomic variations.

4.1. Abrupt and gradual effects of the three mobility intervention policies

According to Table 2, the intervention impacts of the highest-level emergency response (i.e., soft lockdown) and the two return-to-work orders (i.e., part of RtW1 and RtW2) on the intracity flows of Shenzhen are significant, as visualized in Fig. 3. The estimate of the intercept shows that the average intracity flow was around 18,059 trips ($p < 0.01$) on the day right before the study time series (i.e., *day* 0), given that all other impact factors are controlled for. The estimated coefficient of *Day* shows that there is a slight downward trend in intracity flows, with a decrease of 45 trips ($p < 0.01$) per day before the outbreak of COVID-19.

Before the implementation of the three policies, the panic and infection risk made the residents voluntarily alter their mobility behaviors. The results show that the risk effect resulting from informing the public of the risk of person-to-person transmission of COVID-19 resulted in a drop of 7086 trips, 43.97% lower than the counterfactual outcome on January 20, which was estimated at 16,117 trips. This finding is similar to that of Badr et al. (2020), who found that people altered their travel behaviors voluntarily to avoid the risk of infection before the issuance of the intervention policies.

With the highest-level emergency response issued by the local government after the outbreak, the lockdown intervention caused an abrupt drop of 4567 trips ($p < 0.01$) and a gradually enlarging effect, with a downward change rate of 34 trips per day ($p < 0.01$, Fig. 3). This negative gradual effect suggests a temporal heterogeneity in the mobility-reduction effectiveness of the lockdown policy, which grows on a daily basis. Specifically, compared to the preintervention level under the effect of panic, the number of intracity trips dropped by 51.34% (i.e., 4567/8895) on the first day after imposing the city lockdown, followed by another drop by 66.44% (i.e., [4567 + 79*17]/8895) on day 17 after the issuance of the lockdown order. Overall, the lockdown intervention led to a 28.56%–34.17% (i.e., [4567 + 79*(day-46)]/(18,059–45*day), 46 ≤ day ≤63) decrease in flows within Shenzhen, which is lower than the 55.91% decrease within Wuhan found by Fang et al. (2020). This is because Wuhan implemented stricter lockdown measures that prohibited people from leaving their homes, whereas Shenzhen's soft-lockdown measures were aimed at reducing the residents' unessential trips to curb the spread of the virus. This is, however, in contrast to some studies in the US (Berry et al., 2021; Hu et al., 2021), which revealed that the effect of state-level stay-at-home orders on mobility flow decrease is limited, ranging from only <1% to 7.9%.

The first return-to-work order (RtW1) insignificantly affected the level of mobility trips in the level (Table 2), while it resulted in an upward rate of 139 trips ($p < 0.01$) per day compared to the former lockdown phase. This is probably because people were still afraid of the pandemic and were still adapted to the lockdown policy, except for a small number of employees in essential industries, who needed to leave their homes to work. By contrast, the second order (RtW2) generated a significant abrupt growth of 1450 trips and an upward rate of 478 trips per day, compared to the counterfactual outcome under the lockdown ($p < 0.01$). Overall, the effectiveness of RtW2 is clearly larger than that

of RtW1 as a mobility recovery strategy, and RtW1 is still an important signal to recover commute for citizens working in essential industries involved in people's livelihood. In summary, the causal effect of mobility intervention policy is not fixed, it could have a lasting influence over time. Thus, there is a need for policy maker to capture the gradual effect of policies to determine whether supplemental or mitigation policies are needed.

4.2. Moderating roles of zonal locations in varying transport networks

In this section, we explore the heterogeneity in the impact of mobility interventions on intracity flows across zonal locations in varying urban transport networks. Overall, the modeling results show the moderation effects of four variables of zonal transport location on the treatment effects of mobility intervention policies on TAZ-based flows (Table 2), after controlling for the contextual effects of zone-based social and built environment features (as reported in Appendix B). Based on the modeling estimations, spatial heterogeneities in the intervention effects on intracity mobility across TAZs are further shown in Appendix C.

Before the pandemic, neighborhoods located at more accessible locations in varying types of transport networks, such as those with higher metro network centrality and those closer to the airport, had higher levels of daily flows. For example, as shown in Table 2, a one-standard-deviation increase in the betweenness centrality of metro stations is associated with an increase of 6083 trips in neighborhoods, respectively ($p < 0.01$), whereas a one-standard-deviation increase in the distance to the international airport is associated with a decrease of 4111 trips in neighborhoods ($p < 0.01$).

After the declaration of the highest-level response to emergency (i.e., lockdown phase), the zonal locations of a neighborhood in public transport networks can significantly moderate the treatment effects of mobility intervention policies. For instance, the lockdown effects on reducing flows are larger in neighborhoods close to a transfer station (versus terminals) in the metro network (i.e., with higher betweenness), as well as in those close to the airport. This suggests that the effectiveness of mobility restriction intervention is also considerably larger in neighborhoods that are better connected with public transport network. For instance, the better-connected neighborhoods with high-betweenness areas have reduced 5.53% more flows, implying that these areas are more adaptive to lockdown interventions. Many researchers have shown that proximity to transport networks is associated with high levels of risk and panic from infection (Cartenì et al., 2021; Rodrigue et al., 2020), leading to a sharp decline in mobility due to the pandemic or lockdown policies. Another possible explanation is that better-connected areas could have more unnecessary trips (e.g., transit, recreational and touristic trips), which should be reduced in priority in lockdown. However, better-connected neighborhoods retain a larger flow level than that of worse-connected areas (e.g., 1876 more flows in high-betweenness versus low-betweenness areas), probably because of the denser population.

Compared to the moderation effects on the impacts of the lockdown policy, these moderation effects on the impacts of RtW1 are much smaller and mostly insignificant. Only the metro network had a negative moderating effect at the 0.05 significance level, suggesting that the mobility recovery effect of the first work resumption order was rather ineffective in neighborhoods with a better centralized location in the metro network. Although the first relaxing order has been issued, the fear of infection still lasting among people discouraged the use of public transport systems (Lee et al., 2021). Thus, it is necessary to pay attention to people who do not own private cars and rely on public transport for commuting in the early stage of work resumption. On the contrary, the moderating effects of zonal locations on the second work resumption order (i.e., RtW2) were the most significant. The rebounding effects of RtW2 were significantly larger in TAZs with better-connected locations, such as those with a higher level of betweenness in the metro network, as well as those close to the airport. It is worth noting that accessibility of major road network has no significant moderating effect on policy intervention. Overall, better-connected neighborhoods with public transport networks need more surveillance during the stage of extensive work resumption, in order to prevent the rebound of COVID-19.

5. Conclusions

Earlier studies have investigated the changes in intercity mobility flows during the outbreak of COVID-19 and their association with disease transmission and imposed mobility intervention policies between cities (Tian et al., 2020), with a focus on the role of intercity transport networks (Lai et al., 2020). However, only a few studies have highlighted intracity flows during COVID-19, and even fewer studies have explored the causality between the change level of daily mobility and the implementation of varying mobility interventions. In addition, most of the current studies on COVID-19 transmission have overlooked the transport networks within cities and the role of zonal locations in such intracity networks. Therefore, to fill this research gap, we performed an ITS analysis to infer the abrupt and gradual effects of travel restriction and restoration policies on the intracity flows of 491 neighborhoods in Shenzhen on the basis of anonymized mobile phone trajectory data of approximately three months with fine-grained resolution in space and time, with a focus on the moderating role of zonal locations in the urban transport networks.

Our results show that the highest-level emergency response and the two relaxing mobility orders implemented were effective in reducing and resuming daily intracity flows in Shenzhen. The lockdown intervention caused an abrupt drop of 4567 trips and a gradually enlarging effect, with a downward change trend of 34 trips per day. In addition, a temporal heterogeneity was observed in the mobility-reduction effectiveness of the lockdown policy, which grows on a daily basis. The first return-to-work order had insignificantly immediate effects on mobility flows but a significant upward rate of 139 trips per day, suggesting the slow recovery of intercity mobility. The second return-to-work order played a more important role in mobility flow recovery. Overall, the mobility intervention policies significantly changed intracity flows in terms of levels and trends in Shenzhen.

To our knowledge, this research is among the first to investigate the heterogeneity in the impact of mobility intervention policies across zonal locations in varying urban transport networks. The results suggest that neighborhoods with convenient transport locations were able to achieve higher reductions in flows, indicating that these areas were more adaptive to the lockdown interventions (Borkowski et al., 2021). Such higher reductions may be due to the stricter control and management measures and the greater prevention consciousness among people (Kraemer et al., 2020; Rodrigue et al., 2020). Moreover, better-connected neighborhoods may witness more nonessential trips, such as touristic, recreational, and transit trips, which are primarily reduced by the residents. In addition, the moderating effect of transport networks was found to be more significant and crucial for the second mobility relaxing order (i.e., RtW2) than for the first one. The metro transit network had a negative moderating effect on the first relaxing order, implying that the people were still worried about the risk of infection through close physical contact with others in the public transport system during the early mobility relaxation phase (Lee et al., 2021; Gkiotsalitis & Cats, 2021).

These findings provide some policy implications. The significant abrupt and gradual effects over time suggest that it is crucial for policymakers to capture the dynamics effect of intervention policies over time and decide whether to supplement or mitigate the target policy (Kim & Kwan, 2021). Second, it is necessary to pay attention to the mobility management and living security measures of neighborhoods with relatively poor transport connections, which may have been less adaptive to the travel restrictions during the lockdown. The weak-connected neighborhoods are more likely to have difficulty in

reducing trips for out-of-home activity demand because most of their travel demand are necessary, such as commuting (Chen, Guo, Yang, Ding, & Yuan, 2021). For the mobility relaxing orders, policymakers should care for people who do not own cars and rely on public transport, especially those engaged in livelihood industries, during the early period of work resumption (Basu & Ferreira, 2021). During the second mobility relaxing order stage, it is vital to pay more attention to neighborhoods that are better connected with urban transport networks to avoid the resurgence of COVID-19 due to the increase in intracity trips.

This study has several limitations that require further research. First, although this study is among the first to investigate the causal effects and heterogeneity of mobility intervention policies on intracity flows, further studies should focus on the changes in flow pairs between neighborhoods. For comparison, more similar empirical studies on other cities are also needed in order to draw more generalized conclusions in our future work. Second, although ITS is often considered as one of the most powerful quasi-experimental designs (Reichardt, 2019), it is difficult to rule out all time-varying confounders. Future studies could adopt a comparative time series (e.g., identified data in 2019) to conduct a comparative ITS design (CITS) to control for the mobility trends in the absence of pandemic interventions. Third, mobility intervention policies might have advanced or delayed effects on mobility behavior (Bian et al., 2021; Brodeur et al., 2021). While ITS analysis has the capacities to estimate immediate or lagged effects (based on the statistical estimation of the change pattern in trend) (Bernal, Soumerai, & Gasparrini, 2018), it is not sensitive to the advanced effects of interventions. Finally, although we have investigated the daily intracity mobility changes for the long-time-series mobile phone trajectory data of approximately three months, future studies should explore a longer time series that includes the full impact and recovery phases since the unprecedented lasting effect of COVID-19 (Vickerman, 2021).

CRediT authorship contribution statement

Caicheng Niu: Data curation, Software, Visualization, Writing - original draft, Writing - review & editing. **Wenjia Zhang:** Resources, Supervision, Conceptualization, Funding acquisition, Writing - review & editing.

Data availability

Data will be made available on request.

Acknowledgements

This work was supported by the National Natural Science Foundation of China (42171201), the Shenzhen Municipal Natural Science Foundation (Key Project) (GXWD20201231165807007-20200810223326001), and the Shenzhen Municipal Natural Science Foundation (JCYJ20190808173611341).

Appendix A. Spatial distribution of changing intracity flows across TAZs in Shenzhen

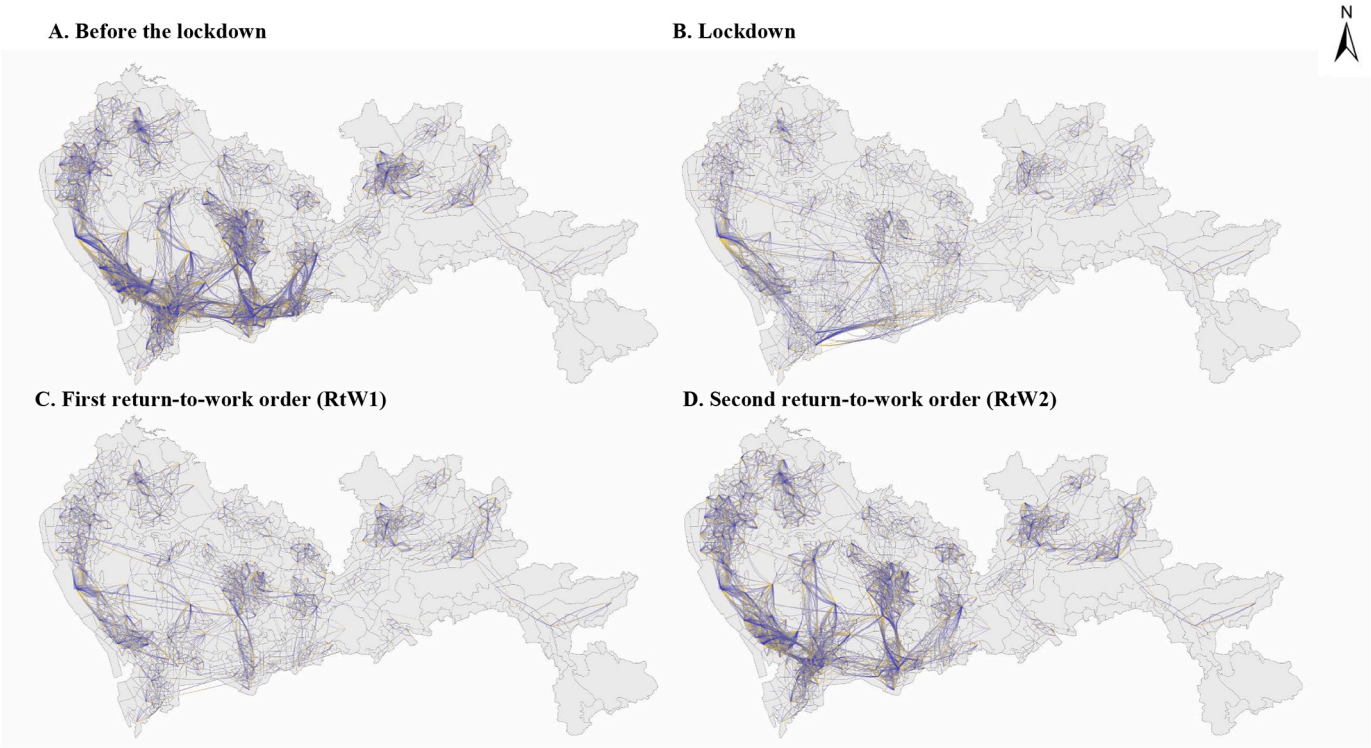


Fig. A1. Spatial distribution of intracity mobility flows across 491 TAZs in Shenzhen over the four stages before and after the COVID-19 outbreak. (Notes: Only the node dyads with the top 2% strength of linkages are shown. The width and color of the line represent the magnitude of connections and directions of links. The top intracity linkages are concentrated in core districts and traffic-developed districts of Shenzhen, such as Futian, Nanshan, Bao'an (where the international airport is located) and Longhua (where the biggest high-speed railway station is located) (A). During the lockdown, it is obvious that the pattern has changed and the strength of linkages is weaker than before, especially the linkages across districts reduced more (B). At the first work resumption stage, there is no significant recovery of the patterns of intracity flows (C). The intracity flows across districts have been restored at the second work resumption stage, but the strength of flows has not recovered to the level before the lockdown (D).

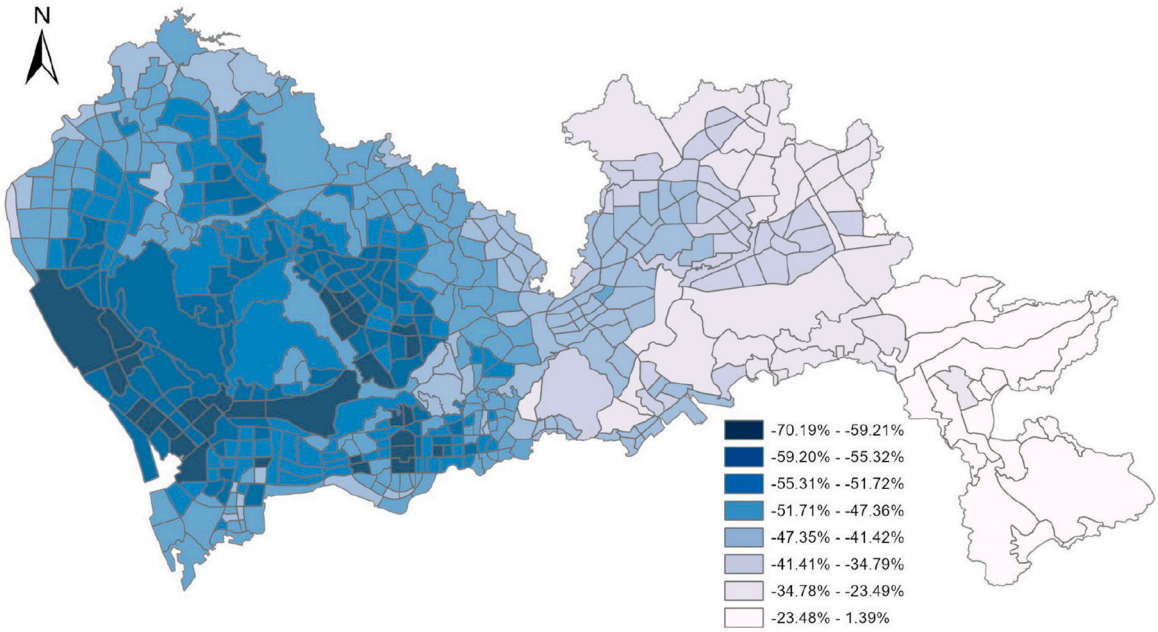
Appendix B. Results of robustness tests

Table B1
Estimated results of the ITS models.

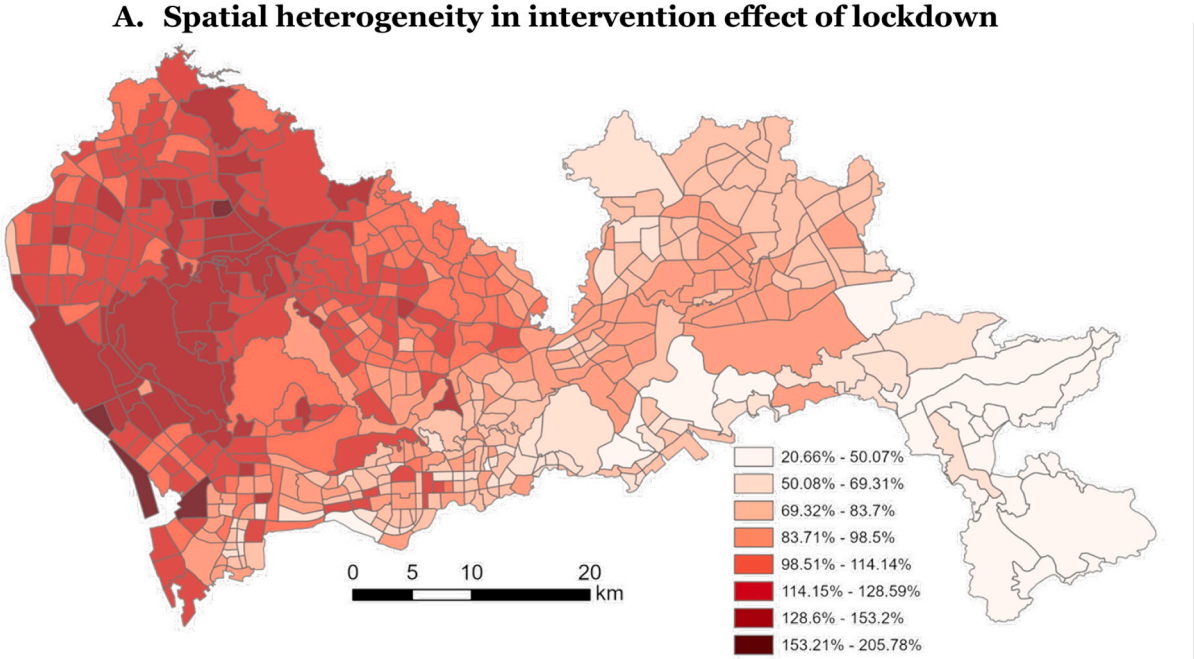
Coefficients		model1			model2			model3			model4 (full model)		
		Coef.		**St.Err.**	**Coef.**		**St.Err.**	**Coef.**		**St.Err.**	**Coef.**		**St.Err.**
Before the lockdown	Intercept	18,234.54	***	654.48	18,234.54	***	654.48	18,037.79	***	507.28	18,059.03	***	505.84
	Day	−43.26	***	1.46	−43.26	***	1.46	−45.13	***	1.52	−45.16	***	1.52
Mobility intervention policies	Lockdown	−5201.82	***	556.94	−5201.83	***	384.00	−4586.38	***	402.81	−4567.31	***	433.32
	Lockdown*Day1	−33.76	***	7.40	−33.76	***	7.40	−34.46	***	7.69	−34.17	***	7.72
	RtW1	160.15		108.13	160.15		108.12	156.14		113.33	138.91	***	113.90
	RtW1*Day2	156.28	***	23.73	156.28	***	23.72	164.49	***	24.64	166.10	***	24.75
	RtW2	1596.42	***	181.81	1596.42	***	164.87	1476.53	***	173.38	1449.72	***	172.47
	RtW2*Day3	456.90	***	11.22	456.90	***	11.22	476.93	***	11.65	478.45	***	11.70
Time-varying confounders	Risk	−6742.26	***	78.27	−6742.26	***	78.26	−7049.67	***	81.28	−7086.22	***	81.64
	Cases	−23.04	***	2.13	−23.04	***	2.13	−24.03	***	2.21	−24.09	***	2.22
	SFH	−226.98	***	66.76	−226.98	***	66.75	−241.47	***	69.33	−246.69	***	69.63
	Monday	1294.10	***	51.96	1294.10	***	51.96	1361.93	***	53.96	1376.34	***	54.20
	Tuesday	1425.63	***	51.56	1425.63	***	51.56	1498.10	***	53.55	1512.21	***	53.78
	Wednesday	1350.44	***	50.67	1350.44	***	50.67	1417.32	***	52.62	1428.84	***	52.85
	Thursday	1531.26	***	51.02	1531.26	***	51.02	1608.50	***	52.99	1622.95	***	53.22
	Friday	1816.74	***	50.65	1816.74	***	50.65	1905.01	***	52.60	1919.80	***	52.83
	Saturday	517.38	***	49.52	517.38	***	49.51	539.79	***	51.42	541.96	***	51.65
The moderating of effects of urban transport networks for intracity flows													
Before the lockdown	MetroBC				6700.77	***	548.78	5828.56	***	503.07	6082.70	***	556.05
	RoadAcc				1131.10		863.19	1189.33		763.26	1259.18		829.68
	DisAirport				−4286.16	***	568.34	−4271.22	***	588.51	−4110.63	***	651.18
	DisRailSta				−2082.54	**	825.06	−611.51		788.35	−697.38		954.48
Lockdown	MetroBC				−5656.52	***	455.62	−4902.36	***	409.75	−5144.45	***	461.81
	RoadAcc				−884.99		716.66	−932.63		621.67	−970.72		689.06
	DisAirport				3659.34	***	471.86	3774.33	***	479.34	3658.23	***	540.81
	DisRailSta				1659.61	**	685.00	415.73		642.10	498.05		792.71
RtW1	MetroBC				−166.44	***	54.72	−169.21	***	58.17	−129.12	**	61.16
	RoadAcc				2.85		86.06	−12.82		88.26	−53.84		91.26
	DisAirport				−33.38		56.67	9.35		68.05	1.01		71.63
	DisRailSta				−46.79		82.26	11.95		91.16	−13.42		104.99
RtW2	MetroBC				818.59	***	111.84	665.66	***	109.34	768.46	***	113.84
	RoadAcc				323.29	*	175.92	318.66	*	165.89	254.43		169.86
	DisAirport				−1097.92	***	115.83	−1061.26	***	127.91	−1029.58	***	133.32
	DisRailSta				−360.55	**	168.15	−3.08		171.34	−60.45		195.41
Controlling the effects of built environmental factors for intracity flows													
Before the lockdown	PopDen							2938.45	***	751.32	2776.40	***	574.99
	LUmix							3015.73	***	549.71	2615.79	***	604.77
	DisCenter							−1500.52	**	576.81	−1498.94	**	617.88
Lockdown	PopDen							−2391.17	***	611.94	−2258.30	***	477.54
	LUmix							−2475.71	***	447.73	−2147.97	***	502.27
	DisCenter							1443.37	***	469.81	1451.16	***	513.16
RtW1	PopDen							−59.12		86.88	−59.21		63.25
	LUmix							150.37	**	63.56	156.35	**	66.52
	DisCenter							12.68		66.70	5.07		67.96
RtW2	PopDen							400.57	***	163.29	391.28	***	117.72
	LUmix							699.29	***	119.47	654.42	***	123.82
	DisCenter							−299.87	**	125.36	−302.58	**	126.50
Controlling the effects of socioeconomic factors for intracity flows													
Before the lockdown	Male										236.87		555.41
	Age										−1561.42	***	572.79
	Edu										921.82		635.28
Lockdown	Male										−119.41		461.28
	Age										1280.78	***	475.71
	Edu										−698.32		527.61
RtW1	Male										−151.07	**	61.09
	Age										−132.24	**	63.00
	Edu										−23.50		69.88
RtW2	Male										−295.14	***	113.71
	Age										−544.02	***	117.27
	Edu										176.89		130.06
Random effects													
Chi-square		18,897.32					21,490.83	21,870.41			22,121.40		
Akaike crit. (AIC)				762,595.73			761,637.25			726,988.72			722,391.28
Prob > chi2				0			0			0			0

Notes: The dependent variable is the daily number of intracity flows of each TAZ. Coefficients in three models are derived from multilevel model regressions. In model 1, we include a set of time-varying variables. In model 2, we sequentially add a set of variables of zonal location in varying transport networks. Model 3 includes the confounding variables of built environment and socioeconomic indicators of TAZs.
Robust standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix C. Spatial heterogeneity of intervention effects of policies in Shenzhen



A. Spatial heterogeneity in intervention effect of lockdown



B. Spatial heterogeneity in intervention effect of the RtW2

Fig. C1. Spatial heterogeneities in the intervention effects of lockdown and the second work resumption order (RtW2) across 491 TAZs in Shenzhen. (Notes: The intervention effects of lockdown on intracity flows vary from-70.19% to 1.39%. Such effects are considerably larger in neighborhoods with a better level of transport connectivity and in compacter areas near city centers (A). The abrupted effect of the first return-to-work order is insignificant; its heterogeneous effect is thus not visualized here. The recovery effect of the second work resumption order ranges from 20.66% to 205.78%, compared to the counterfactual outcome under the lockdown. The rebounding effects are more effective in neighborhoods with a more centralized location in Shenzhen (B).)

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