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Jobs-housing relationships before and amid COVID-19: An excess-commuting approach

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ABSTRACT

The outbreak of COVID-19 and subsequent pandemic containment measures have significantly affected our daily life, which has been extensively examined in the existing scholarship. However, the existing scholarship has done little on the jobs/housing relationship impacts of COVID-19. We attempted to fill this gap by using an excess-commuting approach. The approach allows us to analyse a series of jobs-housing matrices based on the location-based service big data of around fifty million individuals in the Pearl River Delta (PRD), China before and amid COVID-19. In the PRD, a zero-COVID policy was implemented, which presents a distinct and interesting context for our study. We found that after the COVID-19 outbreak: (1) residences and employment became more centrally located in downtowns, which is opposite to the suburbanization trend elsewhere; (2) in the whole PRD, the minimum and maximum commutes became smaller while the actual commute became larger, indicating the simultaneous presences of some paradoxical phenomena: a better spatial juxtaposition of jobs and housing, more compressed distribution of jobs and housing, and longer average actual commutes; (3) inter-city commutes between large cities were significantly refrained and decreased, while new inter-city commuters between smaller cities emerged; (4) it was more likely for the less-educated and female workers to see smaller minimum commutes amid COVID-19. This paper illustrates the potential of big data in the longitudinal study on jobs-housing relationships and excess commuting. It also produces new insights into such relationships in a unique context where stringent anti-COVID-19 policies have been continuously in place.

1. Introduction

Coronavirus disease 2019 (COVID-19) has significantly threatened the health of human beings and affected multiple dimensions of our daily life. To mitigate the spread of COVID-19, governments have introduced and implemented different non-pharmaceutical interventions (e.g., stay-at-home orders, travel restrictions, and lockdown), which are proved to be effective but costly (Dehning et al., 2020; Gostin and Wiley, 2020). Most of the interventions affect mobility patterns and then mitigate the infection risk on social contact networks (Eubank et al., 2004; Schlosser et al., 2020). Apart from the disease moderation effects, those measures have also brought impacts on transportation systems, e.g., a decreased transit ridership (Parker et al., 2021; Zhao and Gao, 2022), commuting trips (Currie et al., 2021), and non-essential trips (Abdullah et al., 2021). Thanks to the effective treatments and emerging vaccines, the world is gradually recovering from a mobility perspective (Dai et al., 2021; Dube et al., 2021). However, those interventions will bring attitudinal changes and long-lasting impacts on people's behavior of residence choice, daily visitation, and commutes.

Commutes are regular trips between residences and workplaces, which have a lot to do with urban spatial structure, transportation system performance, and social equity (Murphy and Killen, 2011; Shen, 2000; Zhang et al., 2019). Commuting patterns can directly represent the spatial relationships between jobs and housing, which in return have impacts on commuting choices (Yang, 2008). Because it is far more difficult and costly to relocate than to adapt daily travel behavior, the jobs-housing relationships are therefore more statable than daily mobility patterns. Mobility responses might happen in a few days (e.g., Kraemer et al., 2020; Parker et al., 2021; Zhou et al., 2021), but it can take decades for the jobs-housing relationship, especially the spatial distribution of jobs and housing, to change (e.g., Hu and Wang, 2016;

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Yang et al., 2012). Besides spatiality, social determinants of commuting patterns are worth attention (Shen, 2000). Specifically, the static and dynamic commuting patterns of subpopulations are a function of race, social status, education, and income level (Li et al., 2021; Yang, 2008). Knowing this function would enable us to better consider disparity in commuting and possible equity implications. Prior to the advent of big and/or open data that are passively and continuously produced and updated and that cover a large and even full set of the population, it has been challenging if not impossible for people to trace the evolution of the function and to see its time-sensitive variance across different subpopulations.

To fill this gap, we tried to characterize the jobs-housing relationship changes before and amid COVID-19 with a location-based service (LBS hereafter) dataset, which is acquirable in the market. We did not challenge existing knowledge concerning changes in daily mobility and travel behavior but added a new dimension: internal structural changes in the locational choice of residences and workplaces and their relative relationships before and amid COVID-19. Such changes can be resulted from pandemic mitigation policies, perceived health risks, and subsequent adaptations. We took the Pearl River Delta ("PRD" hereafter for shorthand) in southern China as our case, where the zero-COVID policy was implemented and the number of confirmed cases was relatively low (Chen and Chen, 2022). The case study, we hope, can provide findings from a populous country that carried out different measurements to deal with the pandemic from the west. These findings can supplement what we have known from the existing scholarship, the regional focuses of which were predominantly the west (e.g., Beck and Hensher, 2020; Irawan et al., 2021; Parker et al., 2021).

In this study, we investigated two research questions: (a) What were the overall trends of jobs-housing relationships in PRD after the outbreak of COVID-19, were they identical to the major findings in other contexts? (b) Were the changes in jobs-housing relationships comparable across different subpopulations? If not, how much was the divergence? We hypothesize that (a) residences and workplaces became more centrally located to avoid inter-region or inter-city travel, which was severely restricted during the pandemic, leading to a better juxtaposition of jobs and employment; (b) the jobs-housing changes varied across subpopulations with different socio-economic statuses and spatial characteristics.

To empirically examine the above hypotheses, we acquired a series of commuting trip matrices for the PRD, China, which were retrieved from the LBS big data. The matrices cover the three fourth quarters of 2019, 2020, and 2021, respectively. Approximately 50 million commuters were captured in each of the matrices.

In the remainder of the article, Section 2 reviews the relevant existing literature. Section 3 describes the empirical case and methods. Section 4 presents the results. Section 5 concludes.

2. Literature review

Jobs-housing relationships, i.e., the numbers and spatial distribution of employment and housing opportunities have been intensively studied in the existing scholarship. This is because many uphold the perspective that if there is a jobs-housing balance, i.e., a reasonable ratio of employment and housing opportunities across subdivisions of a city or region, most workers would enjoy a shorter commute and many negative consequences of long commutes such as traffic congestion, wasteful energy consumption, and air pollution can be decreased (Cervero, 1989). The excess commuting approach is frequently adopted for people to measure and compare jobs-housing relationships in a city across times or cross cities for a fixed time or across time. In the ensuing subsections, we first review existing scholarship on jobs-housing relationships based on the excess commuting approach. Then we focus on such scholarship in the Chinese context that is different significantly from that of the west, in which one can find the most literature on jobs-housing relationships based on the excess commuting approach.

2.1. Jobs-housing relationships and the excess-commuting approach

Commuting trips encapsulate a notable portion of daily travel demand and contribute to peak hours' congestion (Hu and Wang, 2016). The study of these trips, therefore, has been recurrent in fields such as urban planning, transportation, and geography (Ma and Banister, 2006a, 2006b). To mitigate commute-related issues such as traffic congestion and excessive travel time, the jobs-housing balance, i.e., the quantitative and/or qualitative match between jobs and housing opportunities, has been advocated (Cervero, 1989; Gordon et al., 1989; Kim, 2008). The efficacy of the jobs-housing balance in reducing commute-related issues, however, can be limited (Giuliano and Small, 1993; Wachs et al., 1993). Nevertheless, multiple frameworks and metrics for measuring the relationships between residences and workplaces have been proposed (Yang and Ferreira, 2005), e.g., the ratio of jobs to housing, which can be both measured at the local (Cervero, 1989) and regional levels (Levinson, 1998). From a systematic perspective, the excess-commuting approach can benchmark and evaluate the jobs-housing relationships with less bias (Yang and Ferreira, 2005). Such an approach is also more suitable for cross-city and longitudinal comparisons (Kanaroglou et al., 2015). Our study is a case in point.

The approach of benchmarking jobs-housing relationships using commuting costs was pioneered by Hamilton and Röell (1982). He used the optimum commute from the monocentric urban model to gauge the surplus (namely the wasteful commuting) of the actual commute (T_{act}). White (1988) improved the calculation of minimum commute (T_{min}, namely optimum commute in Hamilton's paper) by adopting the linear optimization method. This method has since then dominated the excess-commuting scholarship. T_{min} is achieved when (a) residences and jobs are considered homogeneous, (b) workers can exchange jobs and/or residences without losing any utilities, and (c) each worker is assigned to the nearest possible job from his/her residence given a fixed jobs/housing distribution in the study area. The differences between the T_{min} and T_{act} are considered "excess commuting". After Hamilton and Röell (1982) and White (1988), the scholarship on excess commuting has mushroomed, providing new lenses for us to examine issues such as commuting efficiency/economy (Horner, 2002; Murphy and Killen, 2011), jobs/housing balance (Giuliano and Small, 1993; Zhou et al., 2016), and urban spatial structure evolution (Schleith et al., 2016; Yang, 2008).

In a nutshell, the excess-commuting scholarship problematizes jobs-housing relationships into three sets of concepts and develops corresponding indicators: first, the (appropriate) lower or upper bounds for the average/total commute costs given known jobs-housing distribution— T_{min} (White, 1988), T_{max} (Horner, 2002), and random commute (T_{rand}) (Charron, 2007) are cases in point; second, various actual or predicted commutes, e.g., actual commute by distance (Frost et al., 1998), time (Giuliano and Small, 1993), or modes of travel (Murphy and Killen, 2011); third, the differences between the first two or some ratios based on them, e.g., commuting capacity used (C_u) (Horner and Murray, 2002), commuting economy (C_e) (Murphy and Killen, 2011), and commuting efficiency gains (Zhou et al., 2018). More details are as follows.

As the earliest commuting benchmark in the excess-commuting scholarship, T_{min} measures the absolute degree of the spatial juxtaposition of residences and employment, i.e., the existing or planned jobs/housing distribution. After this, more commuting benchmarks were developed. T_{max} was proposed by Horner (2002), which forms the duality of the same optimization problem together with T_{min}. It measures the maximum commute cost if workers prefer the furthest residence possible. Because T_{min} and T_{max} are extreme and seldom exist in the real world, Charron (2007) proposed T_{rand}. T_{rand} measures the average cost of many possible commuting trip matrices. Compared to T_{max}, T_{rand} is a more reasonable upper bound for us to gauge excess commuting. T_{rand} can be calculated using Yang (2005)'s approach of proportionally matched commute (T_{pro}), according to Kanaroglou et al. (2015).

T_{act} is relatively straightforward. It is the average commuting time or distance in the real world or simulation based on hypothetical data. The commuting time can be self-reported (Yang, 2008), predicted by travel demand models (Giuliano and Small, 1993), or from online map services (Zhang et al., 2021a, 2021b). The commuting distance can be the Euclidian distance (Zhou et al., 2014a, 2014b) or network distance (Zhou et al., 2020a, 2020b).

Commuting efficiency can be measured using metrics such as EC, C_u, and (normalized) C_e. As shown in Eq. (1), EC measures how much T_{act} deviates from T_{min} (Hamilton and Röell, 1982; White, 1988), which is the simplest and most long-standing measure of commuting efficiency. By introducing T_{max}, Horner (2002) proposed C_u and argued that C_u and EC together can paint a more accurate picture of commuting efficiency. The calculation of C_u is given in Eq. (2). Murphy and Killen (2011) proposed a commuting economy metric (C_e) and normalized commuting economy (NC_e) using T_{rand} instead of T_{max} as the upper bound. Eqs. (3) and (4) show how C_e and NC_e can be calculated, respectively.

$$EC = \left(\frac{T_{act} - T_{min}}{T_{act}}\right) * 100 \tag{1}$$

$$C_u = \left(\frac{T_{act} - T_{min}}{T_{max} - T_{min}}\right) * 100 \tag{2}$$

$$C_e = \left(\frac{T_{rand} - T_{act}}{T_{rand}}\right) * 100 \tag{3}$$

$$NC_e = \left(\frac{T_{rand} - T_{act}}{T_{rand} - T_{min}}\right) * 100 \tag{4}$$

Because the original excess-commuting approach oversimplifies the reality, more and more scholars have extended the framework by accounting for more influencing factors of commuting costs, for instance, congestion (Zhou et al., 2020a, 2020b), trip-chain (Hu and Li, 2021), and time of the day (Niedzielski et al., 2020) to improve its policy relevance. Meanwhile, the excess-commuting metric calculation inevitably faces the modifiable areal unit problem (MAUP) when workplaces or residences are aggregated into some unit of analysis. According to Horner and Murray (2002) and Niedzielski et al. (2013), the newly developed indicators (e.g., T_{max}, C_u) are less likely to be subject to MAUP than the traditional indicators (e.g., T_{min}, EC).

It is because of all the aforementioned efforts, the excess commuting approach has gradually become a widely accepted framework to evaluate and compare the jobs-housing relationships, commuting patterns, and urban structure across different subpopulations and times. Plus, consideration of mode choice, subpopulation, and time can greatly increase the approach's applicability and relevance. Last but not least, we need to look at several excess-commuting metrics (e.g., EC, T_{act}, and T_{min}) simultaneously to draw reliable conclusions concerning jobs-housing relationships.

An essential dimension of jobs-housing relationships is these relationships' changes over time. Despite its great significance, the literature on the temporal variation of jobs-housing relationships based on the excess commuting approach is rare (see the summary in Table A.1). The lack of comparable datasets across time is one of the reasons. In the case of the U.S., the Census Transportation Planning Package (CTPP) and Longitudinal Employer-Household Dynamics (LEHD) datasets generated more than half of the studies in Table A.1 (e.g., Horner and Schleith, 2012; Hu and Wang, 2016; Schleith et al., 2016; Yang, 2005). These studies have analyzed the temporal changes in the performance of commuting and corresponding jobs-housing relationships in multiple U. S. cities. Some developed cities in Asia and Europe, e.g., Dublin (Murphy and Killen, 2011), Seoul (Ma and Banister, 2006a, 2006b), and London (Frost et al., 1998) have also been the subjects of the existing scholarship. In these cities, scholars were able to access multi-year survey or simulation- or prediction-based datasets to examine the temporal changes of different excess-commuting metrics.

The studies mentioned above examined the temporal changes across years with traditional datasets, which might or might not cover the periods before and after some important mega events such as COVID-19. The only exception is Zhou and Murphy (2019), which calculated the day-to-day excess-commuting patterns with smartcard big data and found that the patterns were stable except on some special public holidays in Brisbane, Australia. Nevertheless, Zhou and Murphy (2019) did not consider abrupt events' impacts. To our best knowledge, there is still no research concerning the temporal changes in excess-commuting metrics in developing countries like China, especially given abrupt events such as COVID-19.

2.2. The literature in the Chinese context

Chinese cities have witnessed intensive spatial and institutional transformations in the past few decades (Yang, 2006; Zhou et al., 2014a, 2014b). As for the spatial transformation, the rapid urbanization and suburbanization processes significantly changed the supply and spatial configuration of land use and transportation. This has profoundly shaped and reshaped jobs-housing relationships and commuting patterns (e.g., Gao et al., 2019; Hu et al., 2018; Wang and Zhou, 2017). Institutional factors like *Danwei* (working units) and *Hukou* (household registration)[1] still had significant but weakening effects on jobs-housing relationships, because they shaped the preference of and imposed constraints on people's choices of residences and workplaces (e.g., Li et al., 2021). In the process of transition, both the government and market forces had important impacts on transportation and land use and thus jobs-housing relationships and commuting patterns (Hu et al., 2019).

The jobs-housing relationship literature using the excess-commuting approach in China is rather limited. Liu et al. (2008) were among the first cohorts in estimating the T_{min}, T_{act}, and EC for the city of Guangzhou, China. In 2016, they replicated a similar study by considering more time spans and more social groups (Liu and Hou, 2016). By integrating institutional factors, Zhou et al. (2016, 2014a, 2014b) uncovered the excess-commuting impacts of *Danwei* in Xi'an, China and the industry park in Suzhou, China. They found that *Danwei* had positive impacts on reducing excess commuting while industry park, which was also planned to be self-contained, did not. Using the excess-commuting indicators, Xu et al. (2019) evaluated the effects of different transportation policies on excess-commuting metrics in Xiamen, China. However, the aforementioned studies were all based on small samples of survey data (n - 1500 in Guangzhou, 3800 in Suzhou, 50,000 in Xi'an, and 96,000 in Xiamen). It is difficult to evaluate the representativeness of the samples. Plus, all the surveys were one-off and did not produce several waves of data for one to trace the changes in excess-commuting metrics.

The availability of big data has the potential to help us address some of these issues. Based on the smartcard and/or survey data, Zhou and Long (2014, 2015) studied the excess-commuting issue of 200,000+ transit riders in Beijing, China. They found that the excess-commuting patterns and internal modal differences were different from the western studies. With the smartcard data in Shanghai, Zhang et al. (2019) studied the efficiency and equity of commuting patterns simultaneously, whereas the large dataset enabled them to conduct complex simulations. To compare the commuting efficiency across cities, Zhang et al. (2021a, 2021b) proposed a framework using a publicly available point of interest dataset. They simulated the commuting flows based on the data

[1] *Danwei* is a self-contained and jobs-housing-integrated unit mainly set up in the centrally-planned economy era in China. *Hukou* is a household registration system in China that classifies people into agricultural and nonagricultural statuses, while a local *Hukou* can provide people with a few local rights such as access to education.

and compared the excess-commuting indicators across cities, but it was difficult to ascertain what contributed to the differences between the simulated commuting patterns and the actual ones.

Most excess-commuting studies in the Chinese context have adopted a cross-sectional perspective, even though some of them required a temporal examination to draw a robust conclusion (Hu et al., 2019). This is because it is challenging to obtain comparable datasets across time. Multi-year surveys are the common data source to conduct longitudinal analyses of commuting (e.g., Li et al., 2021; Liu and Hou, 2016). Data from these surveys, however, are subject to two disadvantages when compared to data from emerging sources such as smartcard swipes and mobile phone records: small sample sizes and discrete episodes. However, few studies have taken advantage of the data from emerging sources. One of the few exceptions is Yang (2020) work: he compared the basic commuting patterns in Shanghai between 2011 and 2014 with the mobile phone data, but he did not adopt the excess-commuting framework. To the best knowledge of the authors, analyzing (excess) commuting patterns across times and cities in China is still rare.

2.3. COVID-19 impacts on commuting and jobs-housing relationships

The impacts of COVID-19 on commuting and jobs-housing relationships can be temporary and permanent. The temporary impacts can be short-term adaptations resulting from anti-pandemic countermeasures. The permanent impacts are caused by people's changing attitudes toward and usage of the transportation-land use system—or more specifically, their choice of residences and workplaces and subsequent commuting patterns. The travel restriction measures could lead to decreasing commuting volume (Kissler et al., 2020; Shamshiripour et al., 2020), changing commuting mode choice (Abdullah et al., 2021; Harrington and Hadjiconstantinou, 2022), and increasing telecommuting population (Currie et al., 2021). These is people's instant responses to governments' measures, which help prevent them from being infected by the virus. These responses were short-lived and came and went quickly as the pandemic situation changed. In this paper, we focus on the impacts of COVID-19 on commuting and jobs-housing relationships in the longer term. In particular, we are interested in the numbers and spatial distribution of workplaces and residences before and amid COVID-19 and related excess-commuting metrics.

Fueled by the work-from-home requirement in many cities amid COVID-19, telecommuting is one of the major trends. This can challenge our existing notion of the jobs-housing relationships—for instance, more and more workers and employers might no longer be as sensitive to the physical separation of workplaces and homes as ever before and homes can be simultaneously workplaces (c.f., de Palma et al., 2022). Evidence in Australia showed that the work-from-home population significantly increased during the pandemic by >300% (Currie et al., 2021). Hensher et al. (2022) explored the determinants of telecommuting in Australia to provide more insights for policy making. In a developing country context, Irawan et al. (2021) found that high-income people were more likely to telecommute. In China, Pan and He (2022) hinted that there might be a new lifestyle concerning telecommuting though the evidence in early 2020 was not strong enough. Another significant issue is people's attitudes toward working from home. Irawan et al. (2021) found that attitudes toward telecommuting and COVID-19 directly affected the travel response of individuals. In the long run, Currie et al. (2021) and Beck et al. (2020) suggested that there might be an ongoing increase in working from home in the post-pandemic era, whose volume would be above the pre-COVID level because some people became accustomed to working from home and the corresponding attitudes changed. The evidence concerning working from home in China amid COVID-19 is still very limited, and our study attempts to provide some indirect evidence.

The discussion concerning whether the suburbanization trend will be boosted as people would leave downtowns with high infectious risk is also popular (Hamidi et al., 2020; Jasiński, 2022). Some surveys revealed the rationale of suburbanization by looking into the changing

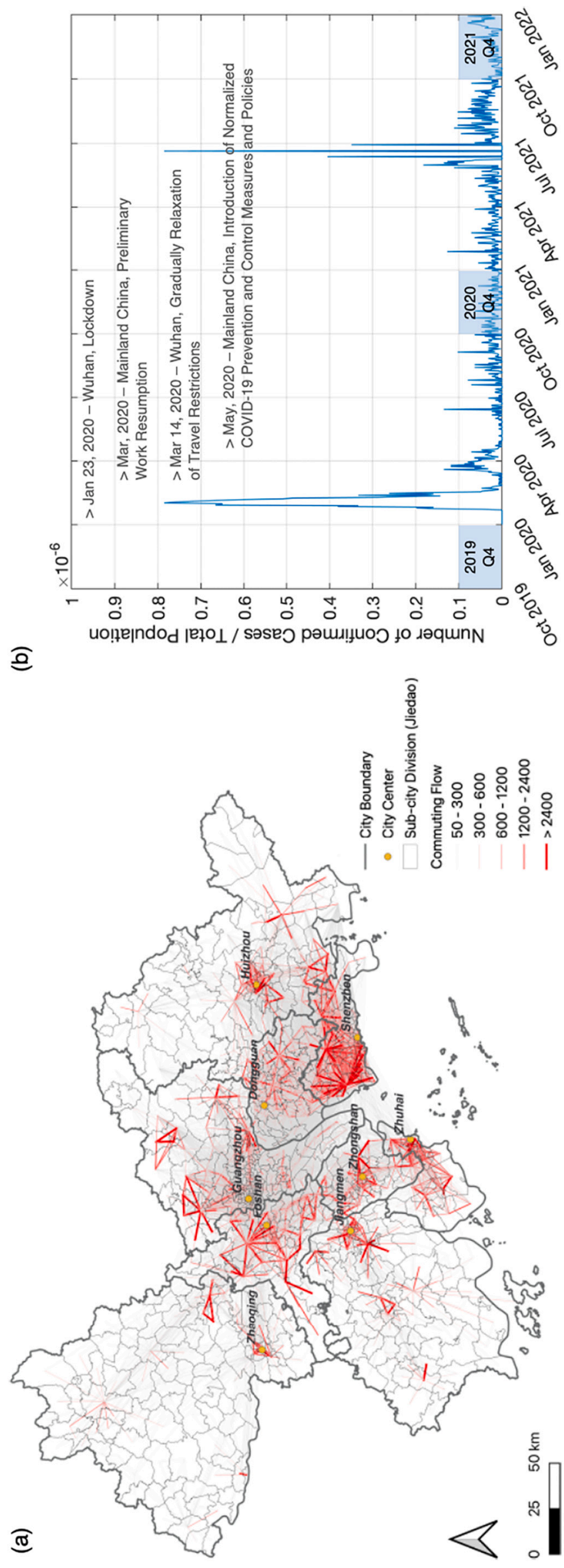

Fig. 1. Case description: (a) A map of the PRD and the spatial distribution of the jobs-housing linkage in 2019; (b) The COVID-19 trend in Guangdong and its corresponding policy.

preference of people's residential location choices: better open space accessibility and mental health benefits (Zarrabi et al., 2021), and home workability (Shamshiripour et al., 2020). Empirically, Liang et al. (2021) found that tourists preferred to rent places in suburbs during the pandemic, indirectly suggesting the potential trend of residential suburbanization. de Palma et al. (2022) summarized the potential popularity of a suburb lifestyle. Regarding the changes in the residence place, Stawarz et al. (2022) revealed a preliminary suburbanization process of jobs during the pandemic in Germany. Many scholars discussed the home as a workplace (e.g., Reuschke and Felstead, 2020), which could greatly blur the boundaries of homes and workplaces. But there is little empirical knowledge about the workplaces' quantity and spatial distribution changes after the outbreak of COVID-19. Concerning the jobs-housing relationships, we only found that Loo and Huang (2022) mentioned the potential impacts of working from home on the jobs-housing relationships based on empirical traffic data from Hong Kong.

Another issue related to the commuting impacts of COVID-19 is the different responses of inter-city and intra-city commuters. As long-distance and inter-city travel is regarded as a critical pathway of disease transmission (Kraemer et al., 2020; Schlosser et al., 2020), inter-city travel was at times restricted amid COVID-19 in most countries including China (An et al., 2021; Tian et al., 2020). The indirect evidence showed that inter-city travel probably decreased due to such restrictions compared to its intra-city counterpart (Huang et al., 2020). The year-to-year comparison of metro ridership showed that transfer stations for inter-city trips saw a declining ridership while other stations did not (Zhang and Yang, 2022), implying that the inter-city travel demand may decline amid COVID-19. Apart from the demand impacts, survey results from Pakistan suggested that the changes in modal split may be caused by the restrictions on inter-city travel (Abdullah et al., 2021). As a result, the COVID-19 impacts on commuting and jobs-housing relationships will probably be different between intra-city and inter-city commuters; however, little existing scholarship has examined this issue.

2.4. Summary

Given the above backdrop, we can conclude that studies simultaneously examining jobs-housing relationships and excess-commuting metrics amid abrupt events, e.g., COVID-19, are essentially non-existent. There are gaps to be filled because mega/abrupt events such as COVID-19 had brought many significant and unintended impacts to transportation-land use systems (Zhou et al., 2021). To best monitor and operate these systems, one cannot circumvent the topics such as the jobs-housing balance and (excess) commuting. Our empirical study below attempts to fill some of the gaps by (a) illustrating the potential of big data in the longitudinal and simultaneous study of jobs-housing relationships and excess commuting and (b) providing a novel method to evaluate the jobs-housing relationship and excess-commuting metric changes amid COVID-19, which can be transferable.

3. The case and methods

3.1. The site

Megaregions are a rising part of the global economy (Ross, 2009). There are many inter-city commutes in megaregions. Overlooking these commutes can produce misleading results (Zhang et al., 2020). In China, the PRD is one of megaregions envisioned by the central government (see Fig. 1-a). Its GDP and population are US$ 1300+ billion (similar to Australia) and 78+ million (similar to Germany), respectively in 2020. The PRD consists of 9 different cities, including Guangzhou and Shenzhen, i.e., two of the four most developed cities in China. We took the PRD and the corresponding jobs-housing relationships as our case.

To provide the analysis at a finer scale, we used *Jiedao* as our basic unit of analysis at the sub-city scale (see Fig. 1-a). *Jiedao* serves as the basic unit of social management in China, so it seldom separates spatial locations with similar and connected functions. It is also the basic unit of the population census dataset. From the perspective of function and scale, it plays a similar role as the census tract in the U.S. (Yang and Ferreira, 2008) or *Dong* in South Korea (Jun, 2020). Also, it has been widely used as a substitution for the traffic analysis zone in China (e.g., Hu et al., 2018; Wu and Hong, 2017; Zhao et al., 2011).

The COVID-19 situation, policy making, and mobility outcomes in China and the PRD are quite different from the western world. As shown in Fig. 1-b, the relative number of confirmed cases is fairly low after March 2020. To sustain this situation, the government introduced the normalized COVID-19 prevention and control measures and policies under the background of the zero-COVID policy (Chen and Chen, 2022). This policy can provide most of the residents with a back-to-normal lifestyle by occasionally lifting swift and strict local lockdown. Without a threatening risk of being affected by COVID-19, working from home has not been strongly encouraged in China, and most people returned to their office after May 2020.[2]

3.2. Data

To measure the jobs-housing relationships before and amid COVID-19, we selected the dataset in the fourth quarter of 2019 as the control group before COVID-19 and the datasets in the fourth quarter of 2020 and 2021 as the short- and mid/long-term representation of the jobs-housing relationships amid COVID-19, respectively. The number of confirmed cases was very low during those periods (see Fig. 1-b). The LBS dataset provides the aggregated jobs-housing linkage of millions of mobile phone users in the format of origin-destination matrices at the scale of Geohash6 (-1.2 KM * 0.6 KM grids). Similar datasets like Safegraph in the U.S. (Benzell et al., 2020; Brough et al., 2020) have been widely used to study urban mobility. Datasets from the same company have been used to analyse the commuting patterns of the Greater Bay Area, China as well (Chen and Zhou, 2022). We aggregated the original data at the *Jiedao* scale and visualized the baseline commuting pattern in 2019 (Fig. 1-a).

The datasets use rules to single out workplaces and residences of millions of smartphone users. There were 50 million such users in the PRD as of 2019. The most frequently visited places of each mobile phone user during the day and night, respectively, are treated as the residence and workplace. The datasets were created based on the mobile phone users' high-resolution (-100 m) GPS records from 100+ smartphone apps. More details about the datasets are as follows. First, a server collected and stored all the GPS records because of mobile phone users' usage of the different smartphone apps. Second, using queries, the server administrator identified the places where mobile phone users visited most frequently during 9:00 p.m. - 6:00 a.m. and 10:00 a.m. - 5:00 p.m. on every weekday and regarded them as the probable daily residences and workplaces. Third, the administrator created a list for each mobile phone user's probable residences and workplaces on each weekday in three consecutive months. Fourth, an administrator counted each distinct residence and workplace by mobile phone user in the list. The probable residence and workplace that a mobile phone user frequented the most were treated as his/her final residence and workplace. Fifth, using the final residences and workplaces, the administrator created a series of origin-destination matrices concerning jobs-housing linkage and commuting trips.

The dataset is one of the few datasets that can cover all the 9 cities in the PRD with comparability, which has rarely been exploited in the existing studies. The quality and representativeness of the dataset were

[2] According to the Ministry of Industry and Information Technology of China (https://news.cctv.com/2020/05/20/ARTI7Kby06rLsqXVGts2dGEP200520.shtml, accessed on May 17, 2022), there are twenty provinces possessing a return to office ratio over 90% in May 2020.

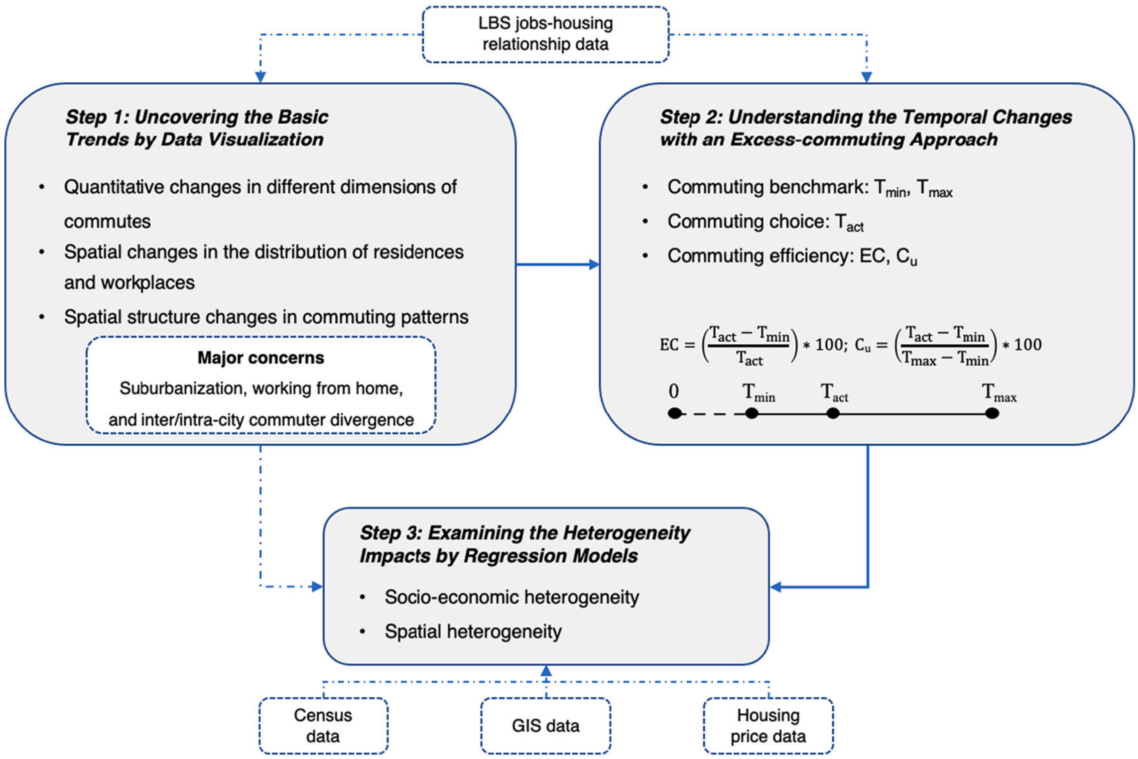

Fig. 2. Analytical framework of this paper.

validated. We checked the data quality by fitting a simple linear regression between the LBS- and census-based residential population density (see Fig. A.1). The result suggests that the LBS dataset can well represent the population ($R^2 > 0.85$) though systematical underestimation exists, which is understandable as not all the people used a smartphone or allowed their exact geolocation to be captured while using different smartphone apps. By comparing the relationships at the city scale, we can find that the proportion of the total residential population in most cities exceeds 50% (see Table A.2), indicating a much larger sample size than traditional survey data (normally <5%). Assuming that the smartphones' market penetration rate is high across all walks of life, a large sample size might also imply a good representation of the population.

Apart from the jobs-housing matrices, the 7th National Population Census data in 2020 was also used to provide evidence of socio-economic statuses, which covers all the cities mentioned above at the *Jiedao* scale with comparable formats. The price of second-hand housing from an online platform (fang.com) was also collected to enrich the profile of each *Jiedao*. We also used the GIS dataset from the Chinese Ministry of Natural Resources, which contains the shapefile of the local administrative boundaries and transportation networks.

3.3. Methodology

Fig. 2 describes the analytical framework. We considered three steps in the evaluation of jobs-housing relationship dynamics. Step 1: Uncovering the basic trends by data visualization. We explored the dataset by visualizing it spatially and quantitatively. We focused on three major issues identified in the literature review, namely the trends of suburbanization and working from home and the divergent response between inter-city and intra-city commutes. The results can uncover the basic patterns simply and obviously. Step 2: Understanding the temporal changes with an excess-commuting approach. The rationale underneath of the temporal changes is still unknown but important, thus we used the excess-commuting approach to examining it from the lens of commuting benchmark, commuting choice, and commuting efficiency, which imply the spatial distribution of jobs and housing, the preference/choice of commuters, and the overall performance/efficiency of transportation-land use system, respectively. Step 3: Examining the heterogenous impacts by regression models. As the profile of each *Jiedao* varies, we used the regression models to examine the heterogeneous impacts of socio-economic and spatial factors on the excess-commuting metrics. The results of Steps 1, 2, and 3 are detailed in 4.1, 4.2, and 4.3, respectively. As for the excess-commuting approach and regression models, more details are as follows.

3.3.1. The excess-commuting approach

The excess-commuting approach uses three categories of indicators: commuting benchmarks (e.g., T_{min}, T_{max}, and T_{rand}), actual commuting choice (e.g., T_{act}), and commuting efficiency (e.g., C_u), which can be used to fathom jobs-housing relationships. For the commuting benchmarks, we chose the two most widely used benchmarks: the T_{min} and T_{max}. T_{min} indicates the relative balance of jobs with respect to housing in a city or region (Small and Song, 1992). T_{max} reflects the amount of dispersion of jobs relative to residences, that is, the extreme quantitative imbalance of jobs relative to housing opportunities in a city or region (Horner, 2002). Following White (1988), T_{min} can be determined by solving a linear optimization problem:

$$\textit{Minimize}: T_{min} = \frac{1}{W}\sum_{i=1}^{n}\sum_{j=1}^{m} C_{ij}x_{ij} \tag{5}$$

$$\text{Subject to}: \sum_{i=1}^{n} x_{ij} = D_j, \forall j = 1, 2, \ldots, m \tag{6}$$

$$\sum_{j=1}^{m} x_{ij} = O_j, \forall i = 1, 2, \ldots, n \tag{7}$$

$$x_{ij} \geq 0, \forall i, j \tag{8}$$

where, n and m are the numbers of origin and destination unit of anal-

Table 1
Summary statistics of the variables in the regression analysis.

Dependent Variables	Description	Mean	S.D.	Median	Min	Max	Source
T_{min}_Change	Absolute changes in T_{min}, T_{act}, T_{max}, EC, and C_u from 2019Q4 to 2021Q4.	0.01	0.48	0.00	−3.20	4.11	The LBS dataset
T_{max}_Change		0.14	14.60	0.00	−98.91	123.09	
T_{act}_Change		0.10	1.51	0.00	−3.75	19.43	
EC_Change		0.13	7.06	0.35	−57.47	29.44	
C_u_Change		0.11	1.80	0.03	−4.52	19.34	
EC*C_u_Change		6.80	28.27	0.74	−8.09	387.97	
Independent Variables							
Socio-economic							
Year_Edu	Average year of education for residents over 15 years old.	11.00	1.39	10.89	8.25	15.03	The 7th national census of China
Ratio_Sex	Number of male/female residents * 100	115.45	16.17	113.59	86.25	271.63	
≤ 14%	Percentage of residents under 14 years old.	15.63	3.82	15.25	1.76	26.18	
≥ 60%	Percentage of residents over 60 years old.	11.86	6.18	10.27	2.00	28.28	
Price_Housing	Average price of the on-sale housing units in each *Jiedao* (CNY/m^2).	25,145.64	19,356.35	18,726.17	2984.00	106,632.90	Online platform (fang.com)
Inter_City%	Proportion of the inter-city commuters in *Jiedao.*	4.75	2.62	4.00	1.67	27.19	The LBS data
Spatial							
Dens_Worker	Density of residential/working population retrieved from the LBS data in the *Jiedao* (per km^2).	7313.48	11,516.29	2685.50	9.04	63,946.75	The LBS data
Dens_Resident		6750.71	9944.15	2594.93	7.89	83,062.13	
Dis_Center	Distance to the nearest city center from the *Jiedao* centroid (km).	20.44	17.35	17.02	0.55	106.80	The GIS dataset
Dens_Road	Density of the major road network length in the *Jiedao* (km/km^2).	0.72	0.60	0.57	0.00	4.17	
Dis_Metro	Distance to the nearest metro station from the *Jiedao* centroid (km).	24.54	17.35	17.02	0.03	168.77	
Dens_Bus	Density of the bus stations in the *Jiedao* (/km^2).	3.18	3.43	2.11	0.00	18.57	

$N = 414$

ysis respectively; O_i and D_j are the total number of residents living in unit i and employees working in unit j respectively; C_{ij} is the Euclidian distance between units i and j; x_{ij} is the number of commuting linkage from unit i to j; W is the total number of commuters.

Likewise, T_{max} can be calculated by maximizing the same objective function with identical constraints as Horner (2002) indicated, and the objective function is in Eq. (9):

$$Maximize : T_{max} = \frac{1}{W}\sum_{i=1}^{n}\sum_{j=1}^{m} C_{ij}x_{ij} \tag{9}$$

We used T_{act} as the commuting choice indicator. It is calculated based on the Euclidian distance between the centroids of *Jiedaos*. Even though it might oversimplify the real world travel cost, it is still proved to be effective enough (Frost et al., 1998; Murphy and Killen, 2011; Zhou et al., 2014a, 2014b). If a pair of residence and workplace were in the same unit, we used the radius of the circle with an identical area to the unit as the travel cost, following Zhou and Long (2014).

Combining the two types of indicators mentioned above, the two commuting efficiency indicators: EC and C_u by White (1988) and Horner (2002), respectively, can be calculated. EC and C_u jointly can allow us to measure the commuting efficiency of a given city or region (Horner, 2002). If there are EC and C_u across times, we can even see how the quantitative (im)balance between workplaces and residences evolves over time (Zhou et al., 2014a, 2014b). Together, T_{min}, T_{max}, T_{act}, EC, and C_u enable us to portray the jobs-housing relationships and their changes before and amid COVID-19 in the PRD based on the excess-commuting framework.

3.3.2. *The regression analysis*

We developed linear regression models to further evaluate the heterogeneous impacts of COVID-19 on different subpopulations' jobs-housing relationships, which we measured by different excess-commuting metrics. As for the dependent variables, we used the absolute changes of all the excess-commuting metrics (See Table 1). According to Horner (2002), EC and C_u should be examined simultaneously, therefore the product of changes in EC and C_u was developed as a combined variable. We used all the socio-economic characteristics available in the census data as the independent variables, i.e., the sex ratio, years of education, and proportions of juniors or seniors. Those variables can directly examine the impacts of the sex, educational level, and age composition on jobs-housing relationships. We collected the housing prices data by *Jiedao* averaged them to serve as a proxy of the average income level by *Jiedao*. Specifically, the average price per square meter of on-sale housing units in each *Jiedao* was calculated, and it can show the living cost of each *Jiedao* which is highly related to the corresponding income level of its residents. To examine the divergence among inter-city and intra-city commuters, we used the proportion of the inter-city commuters at the *Jiedao* level as an independent variable. As for spatial variables, we calculated the densities of residents and workers retrieved from the LBS dataset. Distance to the nearest city center was calculated to measure the degree of spatial centrality of each *Jiedao*. Besides, the density of the road, distance to the nearest metro station, and density of bus stations were calculated with the GIS dataset to measure the accessibility of different mode choices in the PRD.[3] Some *Jiedao*'s EC or C_u was negative, but this was not strange. According to Zhou et al. (2015), some units' T_{min} might be larger than T_{act} after the global optimization, then they would possess a negative EC or C_u.

Due to the data availability, 414 *Jiedaos* were included in the regression analysis, consisting of 93.75% and 93.69% of the residential population in the LBS and census datasets, respectively, indicating nice representativeness of the sample. All the cities in the PRD were covered.

[3] Without a regional-level travel survey, we took the travel survey data in Shenzhen, the second largest city in the study area, to draw a figure. In Shenzhen, the shares of bus, metro, taxi, and private cars among motorized modes are 18%, 20%, 5%, and 53% in 2020, respectively (https://mp.weixin.qq.com/s/Rk97owcnWv66B_mlOngTMQ, accessed on Sep 14, 2022, in Chinese).

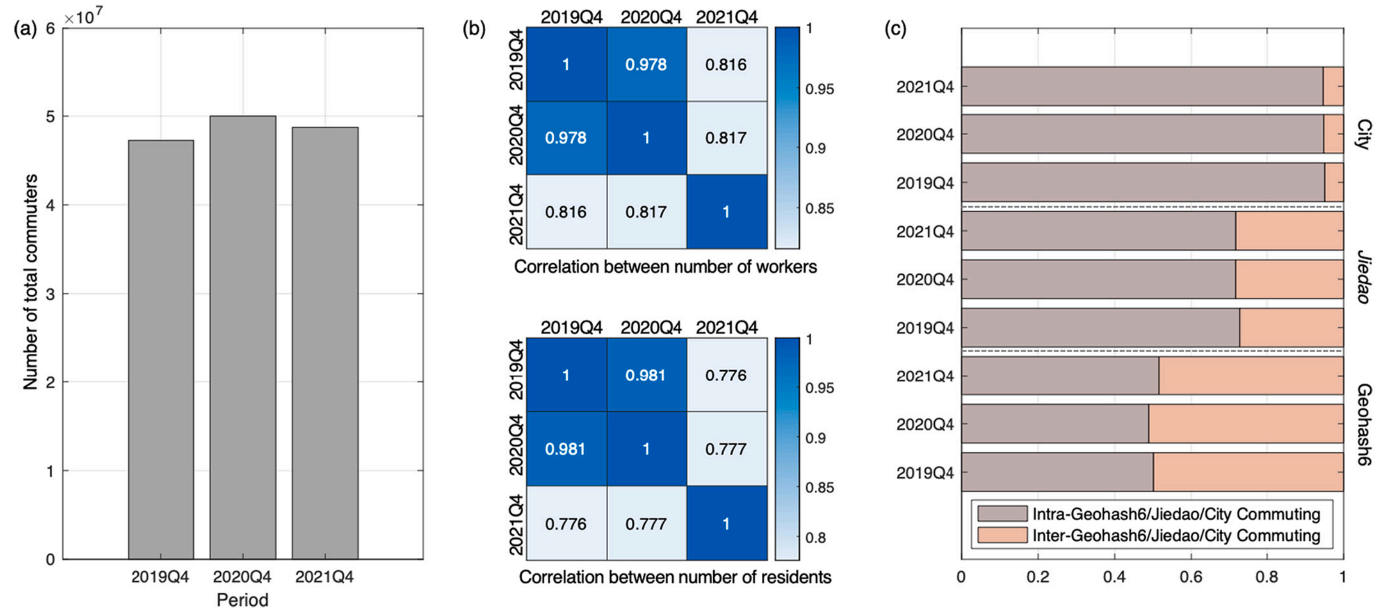

Fig. 3. Quantitative changes of jobs-housing characteristics: (a) Number of total commuters in each year; (b) Correlation coefficients at the Geohash6 level; (c) The proportional changes of inter/intra-Geohash6/Jiedao/city commuting trips.

4. Results

4.1. The overall trends in jobs and housing

We were interested in the numbers and spatial distribution of jobs and housing. As shown in Fig. 3-a, the total numbers of jobs and housing, i.e., the jobs-housing linkage, did not vary greatly across the years, implying that COVID-19 did not significantly reduce the numbers of active workers and occupied residences in the PRD. We further estimated the Pearson's correlation coefficient to see how the jobs or housing in different units of analysis varied across years. Specifically, the numbers of workers or residents at the Geohash6 level in two years were regarded as a pair of variables. As the correlation coefficient ranges between 0 and 1, the larger it is, the more two variables are correlated. The coefficients between the 2021Q4 and 2020/2019Q4 variables were the lowest (-0.8) whereas the coefficients between 2019Q4 and 2020Q4 were much higher (i.e., $>$ 0.97) (Fig. 3-b). This indicates that there existed notable differences in the numbers of workers and residents between 2021Q4 (amid COVID-19) and 2019Q4 (before COVID-19). Therefore, we focused on the changes in jobs and housing between 2019Q4 and 2021Q4 hereafter.

A dominant structural change in the jobs-housing linkage in the western world amid COVID-19 is the growing trend of working from home, where there could be fewer commuting trips as compared to the pre-COVID-19 time (e.g., Hensher et al., 2022; de Palma et al., 2022). In our datasets, we could not single out the telecommuters or those working from home. But comparing internal commuting trips within different units of analysis such as Geohash6, *Jiedao*, and city is helpful (see Fig. 3-c). It is highly likely that the percentage of internal commuting trips would increase if there existed a growing number of telecommuters. However, we did not find a higher percentage of internal commuting trips across three units of analysis: Geohash6, *Jiedao*, and city. It seemed that working from home had not become popular in China amid COVID-19.

The spatial distribution of residences and workplaces are worth mentioning (Fig. 4-a). *Jiedaos* near the city centers possessed more jobs than housing. In contrast, *Jiedaos* in suburbs owned more housing than jobs. These indicate a monocentric megaregion (e.g., Yang et al., 2012; Zhang et al., 2020). Further, we classified the *Jiedao* into four categories by looking at the signs of changes in the proportion of residences and workplaces compared with the total population. Fig. 4-b shows the spatial distribution of these four categories of *Jiedao*. The figure partially illustrates a suburbanization of workplaces, which has been observed in the west (e.g., Liang et al., 2021; Stawarz et al., 2022). Jobs and housing in most of the exurbs decreased simultaneously while increased in or around most city centers and some of the suburbs. In other words, city centers, their adjacencies, and some suburbs have a higher concentration of residences and workplaces after the outbreak of COVID-19. This could have significantly changed the jobs-housing relationships, which can be measured using various excess-commuting metrics.

Because inter-city and intra- city commuters possibly faced two different sets of policies and mobility restrictions amid COVID-19, we differentiated inter-city and intra-city commuters and consider their respective changes in jobs and housing. Following the symbology of Fig. 4-b, the patterns in Fig. 5 indicate that inter-city and intra-city commuters responded differently to the pandemic. The residences and workplaces of intra-city commuters were concentrated in most city centers and some of the suburbs following the major trend of the population in Fig. 4-b. In contrast, the numbers of inter-city residents and workers declined in the same place, especially in the suburbs of the two largest cities in PRD, i.e., Shenzhen and Guangzhou. Meanwhile, the numbers of inter-city workers and residents increased in the city centers and suburbs of smaller cities in PRD, respectively. This phenomenon implies that the inter-city commutes from and to larger cities were significantly confined while new inter-city commuters emerged in smaller cities amid COVID-19.

As a result of the spatial structure changes in jobs and housing distribution, the jobs-housing linkage changed accordingly. At the linkage level, we calculated the intensity of the weakened and enhanced jobs-housing linkage from 2019 to 2021 and visualized them separately in Fig. 6. The intensity was calculated based on the ratio of the number of commuters at the specific linkage from 2021 to 2019, where a value smaller than 1 implies more commuters on that linkage, and vice versa. As shown in Fig. 6-a, the weakened linkage was mainly long-distance and inter-city linkage, especially the cross-city linkage from and to larger cities like Guangzhou and Shenzhen. In contrast, the enhanced linkage was mainly short-distance and intra-city linkage, especially the intra-city linkage in Guangzhou.

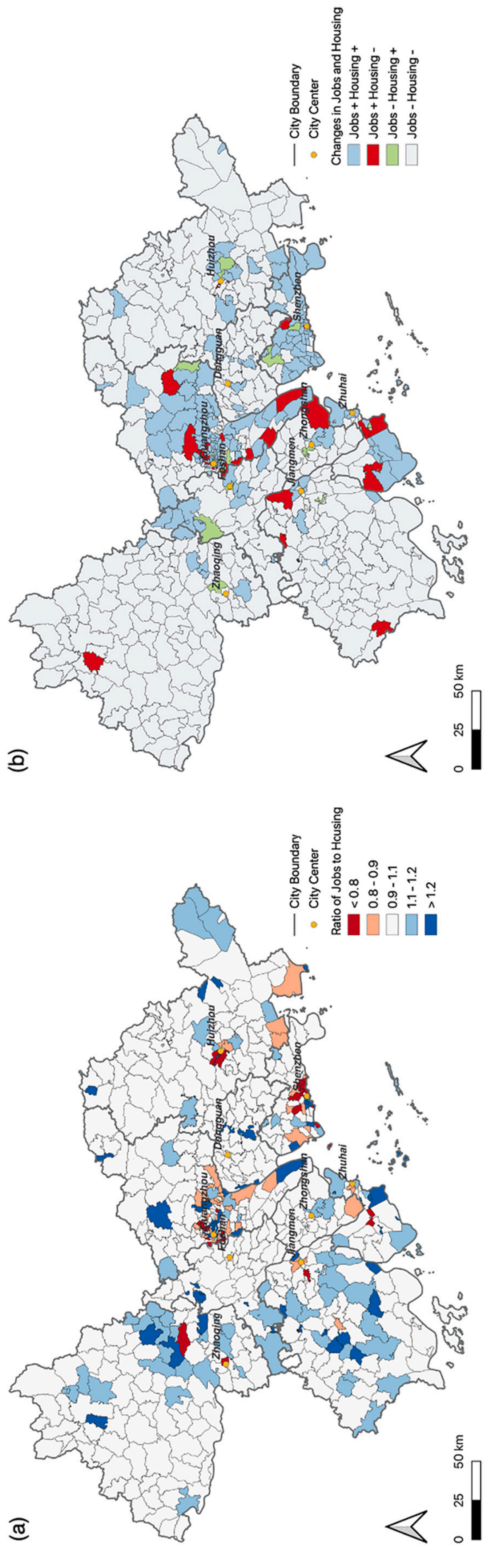

Fig. 4. Spatial changes in the distribution of residences and workplaces: (a) Spatial distribution of the ratio of jobs to housing (averaged from 2019 to 2021); (b) Changes in jobs and housing from 2019 to 2021.

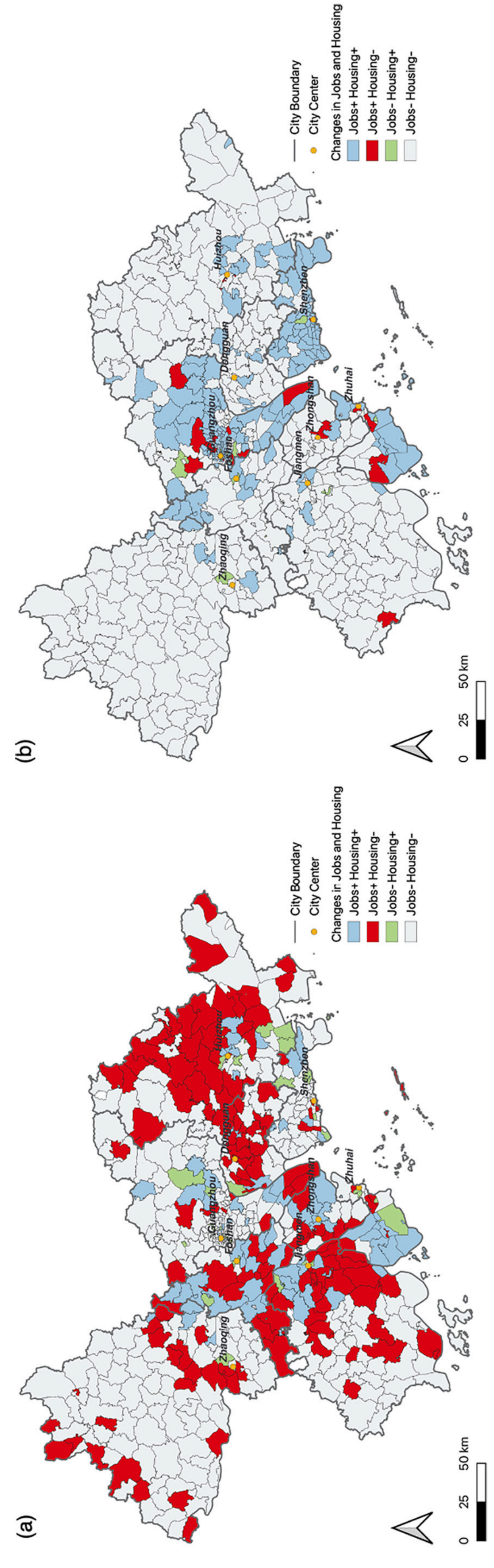

Fig. 5. Changes in jobs and housing of (a) inter-city commuters and (b) intra-city commuters from 2019 to 2021.

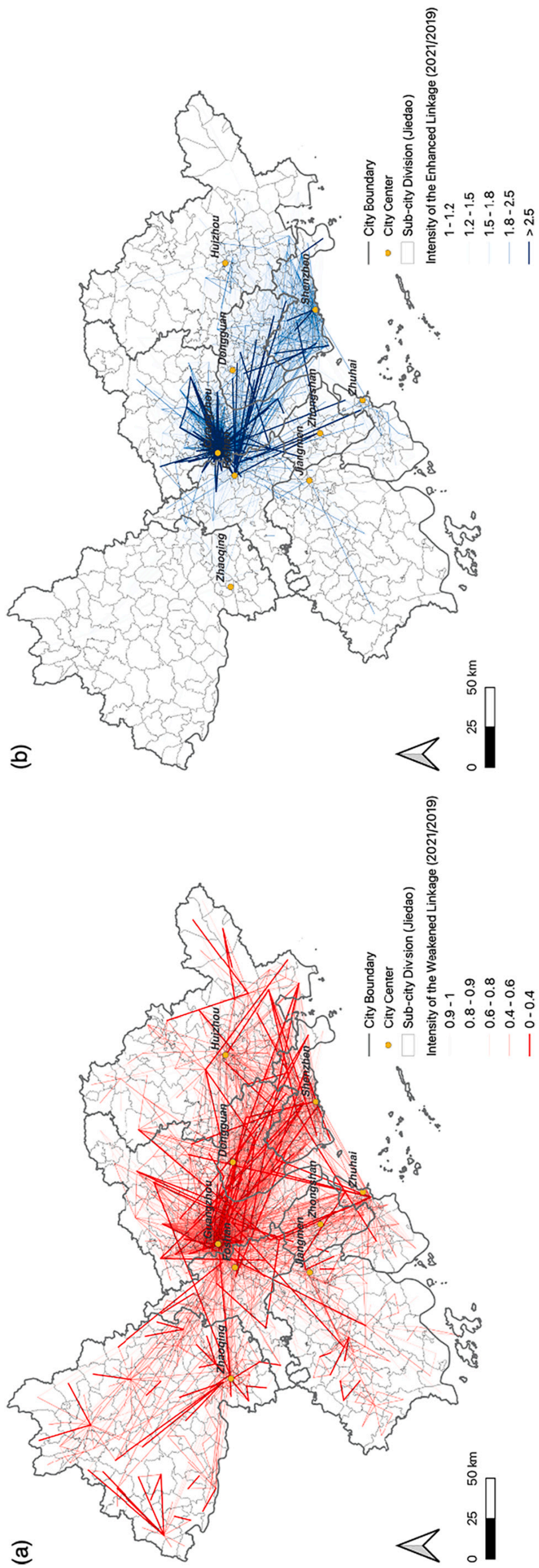

Fig. 6. Spatial distribution and intensity of (a) weakened and (b) enhanced jobs-housing linkage from 2019 to 2021.
Notes: Only the linkage with >50 commuters in 2019 is visualized.

4.2. Jobs-housing relationship changes from an excess-commuting perspective

After examining the overall trends in the numbers and spatial distribution of residences and workplaces, we calculated, visualized, and compared excess-commuting metrics such as T_{min}, T_{max}, T_{act}, EC, and C_u for the whole PRD region, each city, and every *Jiedao*. As mentioned above, these metrics allow us to better measure jobs and housing relationships. In all the calculations, we used *Jiedao* as the basic unit. This is because it is the most disaggregate unit that we can have statistics across all the datasets (i.e., commuting trip matrices, censuses, and GIS datasets) that we accumulated. Besides, a uniform unit is proved to be the best in terms of minimizing MAUP (Horner and Murray, 2002). Though MAUPs are unavoidable in any spatial analysis, Niedzielski et al. (2013) proved that those MAUP-related errors are systematical rather than random with the excess-commuting approach, thus comparing the indicators across time with the same spatial units is recommended.

Table 2 presents the region- and city-level excess-commuting metrics. Judged from the changes in T_{min} and T_{max} between 2019 and 2021, we can see that the PRD and most cities therein had seen a better spatial juxtaposition and a shrinking distribution of residences and employment. The decreasing trend of T_{min} and T_{max} also revealed an improved level of jobs-housing balance at the PRD level concerning the spatial distribution of residences and workplaces. However, such a configuration was not translated into a shorter average actual commute for workers. T_{act} for the whole region and most cities therein had become larger in the same period. Because of the above, it is not surprising that commuting efficiency in the whole region and most cities, which can be measured simultaneously by C_u and EC, worsened. Concerning the response of inter-city and intra-city commuters, their changes in the excess-commuting metrics were consistent with those of all the commuters. However, the inter-city commuters saw larger T_{min}, indicating that they possessed a better spatial juxtaposition of residences and employment and a more balanced jobs-housing relationship. This can be explained by the spatial pattern in Fig. 5-a that inter-city commuters declined in larger cities and concentrated in smaller cities thus leading to a more compact distribution. Given this, the commuting efficiency of the inter-city commuters declined more.

At the *Jiedao* scale, we used visuals to help us to better detect changes in the excess-commuting metrics and their spatial distribution given that there were 400+ *Jiedaos* in the PRD region. As shown in Fig. 7-a, the spatial distribution of *Jiedao*-level changes in T_{min} seemed random, implying that the jobs-housing distribution/juxtaposition might not follow a specific spatial pattern. In contrast, the changes in T_{max} displayed another pattern: it increased significantly in most suburbs. These results suggest that the relocation of residences and workplaces brought about a worsened jobs-housing balance in most suburbs. The changes in T_{act} also had a clear spatial pattern and had more clusters of comparable changes (see Fig. 7-c). The presence of the clusters indicated that it was more likely for residents from certain *Jiedaos* to change their commuting patterns, e.g., residents in suburbs might increase their actual commutes after the outbreak of COVID-19. From a *Jiedao* perspective, the EC significantly increased in suburbs and decreased in exurbs (see Fig. 7-d), indicating a more efficient combined pattern of jobs-housing relationships in exurbs but a less efficient one in suburbs. The pattern of C_u in Fig. 7-e was very similar, while the extent was smaller than that of EC. The results present very consistent spatial patterns with the changes in commuting choice above.

4.3. Heterogeneous jobs-housing relationship changes across social groups

We tried to explain the underlying mechanism of spatial heterogeneity with a set of linear regression models concerning socio-economic and spatial factors. Table 3 presents the results of the models. We found that T_{act} and EC were better predicted than the other indicators according to their larger R^2, this is consistent with their clearer spatial

Table 2
The temporal changes of the excess-commuting metrics.

Unit of Analysis	2019Q4					2020Q4					2021Q4				
	T_{min}	T_{max}	T_{act}	EC	C_u	T_{min}	T_{max}	T_{act}	EC	C_u	T_{min}	T_{max}	T_{act}	EC	C_u
PRD	4.69	108.60	8.95	47.63	4.10	4.68	108.55	9.14	48.77	4.29	4.61↓	106.91↓	9.22↑	50.03↑	4.51↑
PRD (Inter-city)	7.75	109.92	57.41	86.50	48.61	6.56	109.24	55.91	88.27	48.06	6.28↓	107.62↓	58.00↑	89.17↑	51.04↑
PRD (Intra-city)	4.60	108.51	6.44	28.57	1.77	4.63	108.50	6.58	29.64	1.88	4.57↓	106.80↓	6.47↑	29.37↑	1.86↑
Guangzhou	3.52	93.77	8.05	56.35	5.03	3.53	92.57	8.35	57.79	5.42	3.56↑	93.48↓	8.79↑	59.48↑	5.82↑
Shenzhen	3.96	107.83	8.42	52.92	4.29	3.95	109.32	8.64	54.32	4.46	3.93↓	106.56↓	8.31↓	52.65↓	4.26↓
Dongguan	5.27	90.83	8.01	34.18	3.20	5.28	88.00	8.20	35.54	3.52	5.26↓	88.57↓	8.14↑	35.33↑	3.45↑
Foshan	6.01	115.06	9.63	37.62	3.32	6.00	117.66	9.93	39.55	3.52	5.96↓	113.78↓	10.11↑	41.06↑	3.85↑
Huizhou	5.95	150.34	11.47	48.19	3.83	5.89	147.93	11.53	48.90	3.97	5.85↓	147.40↓	11.73↑	50.14↑	4.15↑
Zhongshan	4.91	80.38	8.12	39.53	4.25	4.92	81.87	8.40	41.45	4.52	4.91↑	80.74↑	8.69↑	43.52↑	4.99↑
Jiangmen	5.17	140.63	10.31	49.88	3.80	5.23	141.37	10.11	48.29	3.58	5.09↓	139.58↓	10.16↓	49.86↓	3.77↓
Zhaoqing	6.12	194.73	13.57	54.87	3.95	6.06	197.46	13.09	53.72	3.67	5.98↓	199.08↑	13.58↑	55.98↑	3.94↓
Zhuhai	5.00	117.73	10.64	53.01	5.00	5.01	116.09	10.96	54.26	5.35	5.06↑	116.03↓	11.73↑	56.90↑	6.01↑

Notes: All the city-level results are based on the residences of commuters.

patterns. The value of R^2 was satisfying for models explaining changes. The detailed result of the models is as follows.

Socio-economic factors proved to be effective and important in predicting and explaining commuting patterns (Shen, 2000) and particularly excess-commuting metrics (Yang, 2008). In the western context, race, sex, education, and income-related factors are usually included. Because there does not exist significant racial issues in the Chinese context, we included sex, education, and income-related factors in our socio-economic factors. Also, as inter-city and intra-city commuters faced different policies and mobility restrictions amid COVID-19, we included the proportion of inter-city commuters to consider this. As the results imply, at least one socio-economic factor significantly impacted the dependent variables in all models, indicating that the changes in jobs-housing relationships were not uniform among populations with different socio-economic statuses. Well-educated residents witnessed an increasing T_{min} and a decreasing EC. This means that corresponding jobs and housing opportunities became more spatially dispersed as compared to the pre-COVID-19 period; however, it was likely that more commuters chose to telecommute or chose workplaces closer to homes or vice versa. Female workers in general suffered from a larger T_{min} and enjoyed a smaller T_{max} after COVID-19. It was likely that for these workers, the number of jobs near their homes on average increased (or vice versa) after COVID-19; however, there were also probably slightly more jobs emerged further away from homes. As a result, female residents were less likely to possess an increased C_u. The above-mentioned trends suggested that the female residents, the subpopulations who possessed less mobility and capacity to adapt, were less likely to follow the flow under a spatial reconstruction. Besides, the impacts of the junior population proportion also suggested that they were more likely to possess a shortened T_{max}, indicating a smaller shed to search for residences and workplaces. There are similar findings in other studies (e.g., Liu et al., 2020; Shamshiripour et al., 2020; Zhang et al., 2021a, 2021b): the female, senior, and junior student had poorer access to media and information and thus were less likely to make optimal decisions, also, their mobility was more limited that they cannot easily adapted to the abrupt changes. As for the divergence between intra-city and inter-city commuters, the model suggested that inter-city commuters were more likely to witness a larger decrease in Tmin, indicating a better juxtaposition residences and workplaces therein. Also, they were more likely to see a larger T_{act}, implying that they were probably more capable to adapt their commuting patterns amid COVID-19. These results are consistent with the findings revealed by the visualization and estimation in the former sections.

Spatial factors were intuitively and empirically related to commuting patterns (Shen, 2000). As scholars suggested, locations (Alonso, 1964), jobs/housing densities (Cervero, 1996), and accessibility (Levinson, 1998) played an important role in determining commuting patterns. Given this, we chose the independent variables in response to those factors, respectively. In our results, spatial factors such as the density of workers and distance to city centers and the nearest metro station significantly predicted the changes in excess-commuting metrics, validating the spatial heterogeneity revealed by the geo-visualization above. Residents who lived in *Jiedaos* with higher job densities were more likely to possess a lengthened commute after the outbreak of COVID-19 compared to that before. The results are consistent with the increasing trend of T_{act} in the suburbs (see Fig. 7-c), where the jobs-housing ratio is relatively small. Concerning the distance to the city center, residents who lived closer to the city center were more likely to possess an increasing T_{act} and thus more excess commuting indicated by EC and C_u after the outbreak of COVID-19. Residents who lived closer to metro stations had a smaller chance to see larger EC.

5. Discussion and conclusions

COVID-19 has changed the daily life of every individual. In a world with the presence of the pandemic, it is vital to understand the pandemic's long-lasting impacts. Using millions of LBS records and based on the excess commuting approach, we empirically examined the probable impacts of COVID-19 on jobs-housing relationships in the PRD, China.

Our empirical work generates at least the following findings, some of which can be transferable to other contexts: (1) residence and employment became more centrally located in downtowns, which is opposite to the trend of suburbanization found elsewhere in the western context; (2) in the whole PRD, the overall T_{min} and T_{max} became smaller while the T_{act} became larger, indicating the co-presences of a better spatial juxtaposition of jobs and housing, more compressed distribution of jobs and housing, and longer average actual commutes, and those trends led to larger EC and C_u simultaneously; (3) compared with the centralization of intra-city commuters, the inter-city commutes from and to large cities were significantly confined and decreased, while new inter-city commuters who lived or worked in smaller cities emerged, leading to a larger decrease in T_{min}; (4) divergent changes in jobs-housing relationships among subpopulations, most notably, the less-educated and females were more likely to observe smaller T_{min} amid COVID-19.

These findings help advance existing knowledge related to the mobility implications of COVID-19. We found that the jobs and housing opportunities moved from suburbs to downtowns in the PRD, which conflicts with the existing knowledge from the survey in Germany and Iran (Stawarz et al., 2022; Zarrabi et al., 2021). We speculate that the differences can be due to these reasons. Firstly, a group of people may change their jobs proactively or become unfortunately unemployed. In this case, people would be more willing to work further away from homes. A similar phenomenon was witnessed after the Great Recession in the U.S. as well (Kim and Horner, 2021). Secondly, a group of people started moving to residences in city centers, because most people in China have suffered from the inconvenience of living in suburbs during

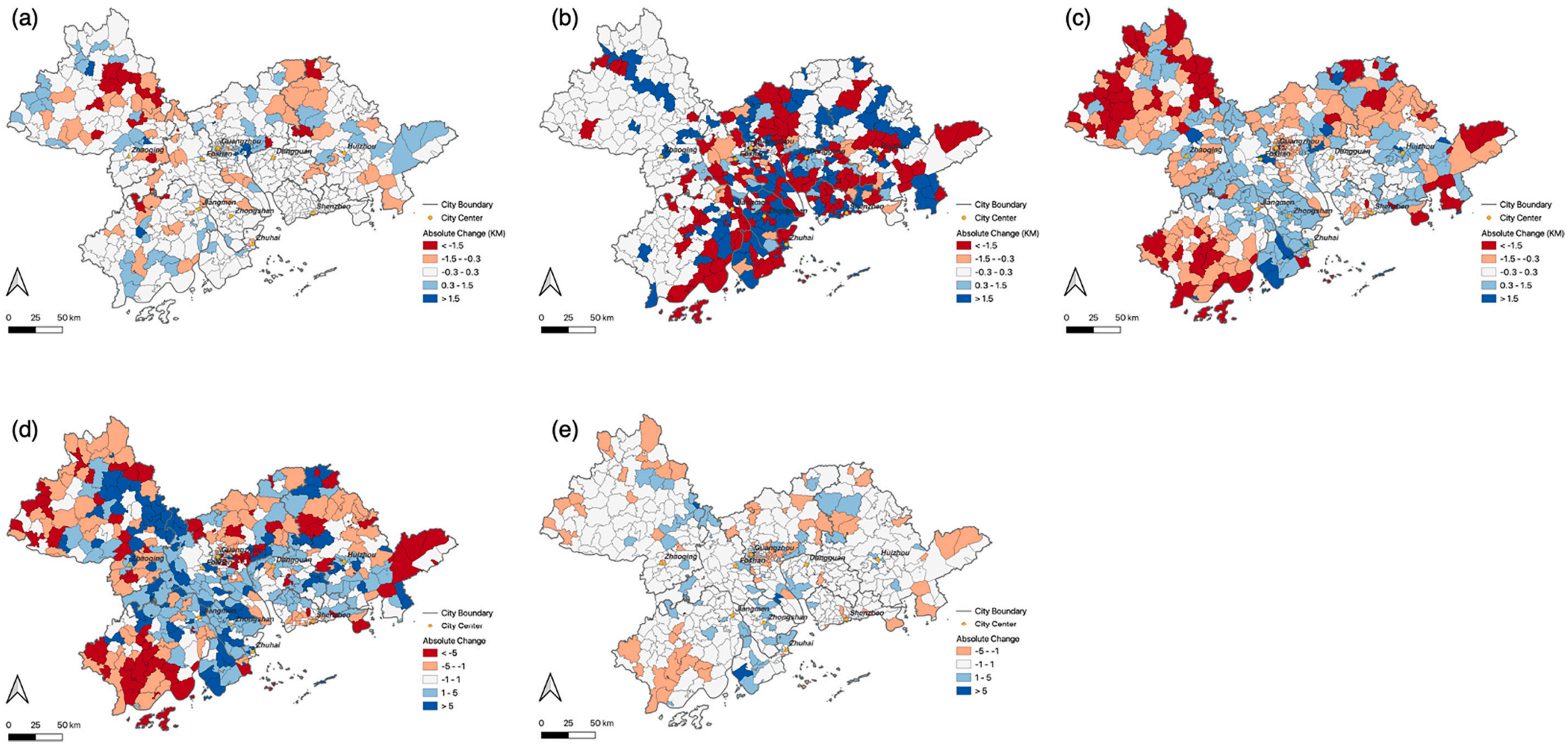

Fig. 7. Spatial distribution of changes in (a) T_{min}, (b) T_{max}, (c) T_{act}, (d) EC, and (e) C_u from 2019 to 2021.
Notes: All the *Jiedao*-level results are based on the residences of commuters.

Table 3
Linear regression results.

	Commuting benchmark				Commuting choice		Commuting efficiency					
	T_{min}_Change		T_{max}_Change		T_{act}_Change		EC_Change		C_u_Change		EC*C_u_Change	
	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
(Intercept)	(1.636)	0.007 **	48.170	0.009 **	(2.111)	0.262	0.145	0.095 #	(0.023)	0.312	(0.007)	0.064 #
Year_Edu	0.109	0.000 ***	(1.503)	0.113	0.092	0.343	(0.013)	0.004 **	(0.000)	0.727	0.000	0.053 #
Ratio_Sex	0.004	0.077 #	(0.175)	0.013 *	0.010	0.168	(0.000)	0.908	0.000	0.051 #	0.000	0.060 #
≤ 14%	0.005	0.538	(0.481)	0.053 #	0.034	0.185	0.001	0.611	0.000	0.152	0.000	0.949
≥ 60%	0.001	0.901	(0.280)	0.146	0.014	0.489	(0.000)	0.787	0.000	0.086 #	0.000	0.019 *
Price_Housing	(0.000)	0.025 *	0.000	0.668	(0.000)	0.254	0.000	0.430	0.000	0.916	0.000	0.972
Inter_City%	(0.017)	0.078 #	0.106	0.713	(0.054)	0.070 #	0.000	0.757	(0.000)	0.359	(0.000)	0.698
Dens_Worker	0.000	0.536	0.000	0.924	0.000	0.069 #	0.000	0.608	0.000	0.103	0.000	0.672
Dens_Resident	(0.000)	0.538	(0.000)	0.693	(0.000)	0.143	(0.000)	0.887	(0.000)	0.221	(0.000)	0.538
Dis_Center	0.002	0.217	(0.045)	0.435	(0.018)	0.003 **	(0.001)	0.000 ***	(0.000)	0.023 *	0.000	0.717
Dens_Road	(0.009)	0.842	0.107	0.935	(0.154)	0.255	(0.000)	0.941	(0.000)	0.897	(0.000)	0.838
Dis_Metro	0.000	0.870	0.026	0.512	0.005	0.172	0.000	0.084 #	0.000	0.490	(0.000)	0.347
Dens_Bus	0.015	0.166	(0.070)	0.833	0.010	0.760	(0.001)	0.381	(0.000)	0.663	(0.000)	0.167
R-square	0.048		0.026		0.052		0.078		0.040		0.036	

Notes: N = 414; '***' 0.001, '**' 0.01, '*' 0.05, '#' 0.1; values in the brackets are negative.

the multiple waves of the lockdown and the difficulties of inter-city commutes (An et al., 2021; Kraemer et al., 2020; Zhou et al., 2020a, 2020b). However, the costs of moving is too large that only a small group of people can afford it in the study period. As a combined effect, residences and workplaces concentrated in the city center simultaneously but a longer actual commute was observed.

Our study examined temporal changes in excess commuting metrics amid an abrupt change, i.e., COVID-19. By using passively collected big data, we illustrated the usefulness of big data in the longitudinal, cross-sectional, and continuous study of jobs-housing dynamics based on the excess commuting approach. The only comparable study is to examine the impacts of the Great Recession on commuting dynamics (Kim and Horner, 2021). The findings in our study in general echo to some of theirs. First, both their and our findings revealed that different subpopulations, for instance, public versus private workers and inter-city versus intra-city commuters responded differently amid an abrupt change. Second, an improved jobs-housing balance in the absolute manner (reflected by T_{min}) but a longer commute in reality were witnessed. It is likely that more were willing to commuter longer to earn a living in difficult times. Kim and Horner (2021) suggested that there was a temporal delay in response in certain subpopulations. As our input data were aggregated, we could not verify this in this PRD case.

Despite the above progress, this study does face some limitations. Firstly, as we mentioned before, the changes in jobs-housing relationships reflect variations in attitudes toward COVID-19 and various COVID-19-related policies. However, the relationships between COVID-19, attitudinal changes, and jobs-housing relationships cannot be uncovered without a combination of "big" LBS and "small" survey-based datasets containing detailed socio-economic attributes, e.g., job type and income level. Secondly, the excess-commuting matrices were aggregated by *Jiedao* in the current study, thus we cannot say much about what happened at scales smaller than *Jiedao*. To know more about those changes at smaller scales, personal-level data should be collected and analyzed. Thirdly, the excess-commuting matrices used in the study can only represent the population with smartphones and frequently using smartphone apps developed by specific companies. We could have overlooked many who did not own smartphones. Fourthly, there exist inevitable methodological shortcomings due to the nature of the geographical analysis. Besides the MAUP, the modifiable temporal unit problem and the uncertain geographic context problem can also exist. These issues will never be fully resolved but can be alleviated when datasets at finer scales are used and/or more sophisticated methods are employed.

Author statement

The views and any omissions in the paper are solely responsibilities of the authors.

Declaration of Competing Interest

None.

Data availability

The authors do not have permission to share data.

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Appendix A

Table A.1
Literature considering temporal variation in excess-commuting metrics.

Source	Objectives	Case	Data and time	Spatial unit	Benchmarks	Major findings
Frost et al., 1998	To calculate changes in excess commuting for two time periods.	Sample of British cities	Census worktravel data in 1981 and 1991	Census wards	T_{min}	The changing form of urban areas is exerting the strongest influence on the increasing length of work journeys.
Yang, 2005	To compare commuting and urban spatial structure across space and over time.	Boston and Atlanta, US	CTPP in 1980, 1990, and 2000	Census tracts	T_{min} and T_{pro}	Alternative decentralization pathways can result in very different transportation outcomes.
Ma and Banister, 2006a, 2006b	To measure the quantitative and qualitative imbalance of jobs and housing.	Seoul, Korea	Census of population and housing in 1995, 2000, and 2005	Zones	T_{min} and T_{max}	Measured in distance, T_{act} and T_{min} are relatively stable and T_{max} increases significantly. Measured in time, all indicators decrease.
Yang, 2008	To evaluate the impacts of a spatial decentralization process on excess commuting.	Boston and Atlanta, US	CTPP in 1980, 1990, and 2000	Census tracts	T_{min} and T_{pro}	The transport-land use connection appears weaker over the decades as the dispersion of jobs changes the dynamics of commuting and the selection of residential location varied.
Horner, 2008	To find the theoretical 'optimal' urban jobs–housing balance.	Tallahassee, US	CTPP in 1990 and 2000	TAZs	T_{min}	T_{min} of two years are not significantly different; but the actual commutes are.
Murphy, 2009	To investigate the divergence of excess commuting between different mode.	Dublin, Ireland	Traffic simulation model data in 1991 and 2001	Zonal sub-division	T_{min} and T_{max}	Excess commuting is considerably greater for users of private transport implying the greater inefficiency of commuting associated with that mode.
Murphy and Killen, 2011	To provide an alternative method of benchmarking commuting efficiency based on how individuals are economising commuting costs.	Dublin, Ireland	Traffic simulation model data in 1991 and 2001	Zonal sub-division	T_{min}, T_{rand}, and T_{max}	The T_{act} has moved further away from the T_{rand}, implying that greater intermixing of residential and employment functions has led to more efficient commuting behavior.
Horner and Schleith, 2012	To explore the relationships between land use and commuting outcomes over time.	Leon County, US	LEHD 2002– 2010	Census blocks	T_{min} and T_{max}	Estimation of several commuting and jobs-housing metrics lends insights into growth and decline that have occurred in the recent housing boom and bust.
Schleith et al., 2016	To measure how commuting travel has changed.	Sample of 26 US metro regions	LEHD 2003 and 2013	Block group	T_{min}, T_{rand}, and T_{max}	Commutes are generally increasing although Columbus, OH is the notable exception.
Hu and Wang, 2016	To analyse the temporal trends of commuting patterns in both time and distance.	Baton Rouge, US	CTPP in 1990, 2000, and 2006–2010	Census tracts	T_{min}	The percentage of excess commuting increased significantly between 1990 and 2000 and stabilized afterward.
Zhou and Murphy, 2019	To quantify the temporal variation in excess-commuting indicators over short time periods	Brisbane, Australia	Smartcard data Nov, 2012 - Apr, 2013	SA2s in Australia	T_{min}, T_{rand}, and T_{max}	Excess-commuting indicators vary considerably from one day to the next especially around public holidays.
Kim and Horner, 2021	To explore the impacts of major economic changes on commuting dynamics.	Atlanta, US	LEHD 2005– 2015	Census blocks	T_{min} and T_{max}	The Great Recession worsened the commuting situation, the effect was more significant for public workers in terms of increasing their travel burdens.
This study	To explore the impacts of COVID-19 on jobs-housing relationships	Pearl River Delta, China	LBS big data 2019–2021	*Jiedao*	T_{min} and T_{max}	The T_{min} and T_{max} became smaller while the T_{act} became larger, indicating the co-presences of better spatial juxtaposition of jobs and housing, more compressed distribution of jobs and housing, and longer average actual commutes.

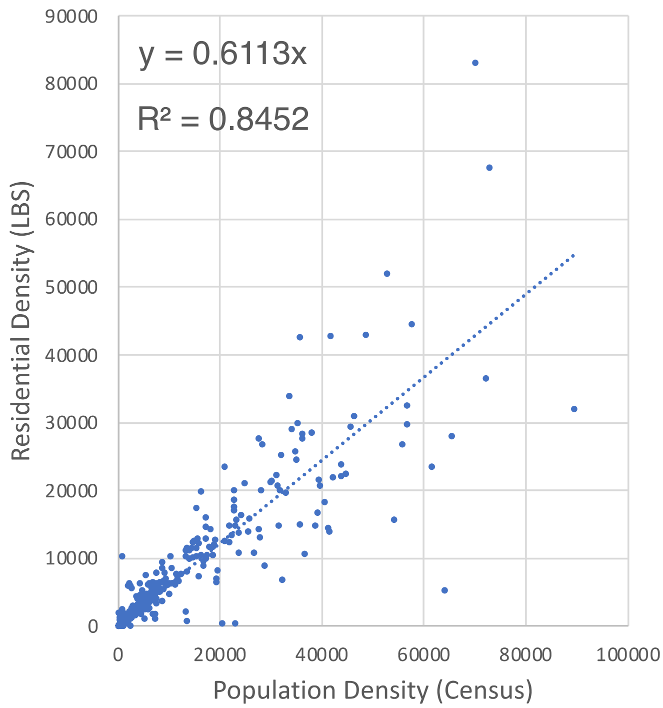

Fig. A.1. Relationship between the residential density derived from the LBS and census datasets in 2020.

Table A.2
Summary statistics of the LBS-based population and census-based population.

Unit of statistics	LBS data residential population			Census data	Ratio: LBS/census		
	2019Q4	2020Q4	2021Q4	2020	2019Q4	2020Q4	2021Q4
PRD	47,273,911	50,007,166	48,745,558	86,091,977	54.91%	58.09%	56.62%
Guangzhou	11,772,366	12,232,005	13,013,193	18,676,605	63.03%	65.49%	69.68%
Shenzhen	10,218,569	11,101,839	11,459,449	17,560,061	58.19%	63.22%	65.26%
Dongguan	7,861,322	8,293,806	7,474,515	10,466,625	75.11%	79.24%	71.41%
Foshan	5,665,886	6,085,205	5,675,712	9,498,863	59.65%	64.06%	59.75%
Huizhou	3,621,321	3,859,413	3,492,087	6,042,852	59.93%	63.87%	57.79%
Zhongshan	3,052,065	3,121,176	2,821,441	4,418,060	69.08%	70.65%	63.86%
Jiangmen	2,018,305	2,141,669	1,910,729	4,798,090	42.06%	44.64%	39.82%
Zhaoqing	1,661,182	1,707,679	1,451,590	4,113,594	40.38%	41.51%	35.29%
Zhuhai	1,402,895	1,464,374	1,446,842	2,439,585	57.51%	60.03%	59.31%

References

Abdullah, M., Ali, N., Hussain, S.A., Aslam, A.B., Javid, M.A., 2021. Measuring changes in travel behavior pattern due to COVID-19 in a developing country: a case study of Pakistan. Transp. Policy 108 (May), 21–33. https://doi.org/10.1016/j.tranpol.2021.04.023.

Alonso, W., 1964. Location and land use. Toward a general theory of land rent. In: Location and Land Use. Toward a General Theory of Land Rent.

An, Y., Lin, X., Li, M., He, F., 2021. Dynamic governance decisions on multi-modal inter-city travel during a large-scale epidemic spreading. Transp. Policy 104, 29–42.

Beck, M.J., Hensher, D.A., 2020. Insights into the impact of COVID-19 on household travel and activities in Australia – the early days under restrictions. Transp. Policy 96 (July), 76–93. https://doi.org/10.1016/j.tranpol.2020.07.001.

Beck, M.J., Hensher, D.A., Wei, E., 2020. Slowly coming out of COVID-19 restrictions in Australia: implications for working from home and commuting trips by car and public transport. J. Transp. Geogr. 88 (September), 102846 https://doi.org/10.1016/j.jtrangeo.2020.102846.

Benzell, S.G., Collis, A., Nicolaides, C., 2020. Rationing social contact during the COVID-19 pandemic: transmission risk and social benefits of US locations. Proc. Natl. Acad. Sci. 117 (26), 14642–14644. https://doi.org/10.1073/pnas.2008025117.

Brough, R., Freedman, M., Phillips, D., 2020. Understanding socioeconomic disparities in travel behavior during the COVID-19 pandemic. SSRN Electron. J. https://doi.org/10.2139/ssrn.3624920. December.

Cervero, R., 1989. Jobs-housing balancing and regional mobility. J. Am. Plan. Assoc. 55 (2), 136–150. https://doi.org/10.1080/01944368908976014.

Cervero, R., 1996. Jobs-housing balance revisited: trends and impacts in the San Francisco Bay Area. J. Am. Plan. Assoc. 62 (4), 492–511.

Charron, M., 2007. From excess commuting to commuting possibilities: more extension to the concept of excess commuting. Environ. Plan. A 39 (5), 1238–1254. https://doi.org/10.1068/a3897.

Chen, J.-M., Chen, Y.-Q., 2022. China can prepare to end its zero-COVID policy. Nat. Med. https://doi.org/10.1038/s41591-022-01794-3.

Chen, R., Zhou, J., 2022. Understanding the scaling patterns of commuting in the Guangdong-Hong Kong-Macao Greater Bay Area with location-based service big data (in Chinese: 基于位置服务大数据的粤港澳大湾区通勤标度特征分析). J. Tsinghua Univ. (Sci & Technol) 7. https://doi.org/10.16511/j.cnki.qhdxxb.2022.26.019.

Currie, G., Jain, T., Aston, L., 2021. Evidence of a post-COVID change in travel behaviour – self-reported expectations of commuting in Melbourne. Transp. Res. A Policy Pract. 153 (September), 218–234. https://doi.org/10.1016/j.tra.2021.09.009.

Dai, J., Liu, Z., Li, R., 2021. Improving the subway attraction for the post-COVID-19 era: the role of fare-free public transport policy. Transp. Policy 103 (December 2020), 21–30. https://doi.org/10.1016/j.tranpol.2021.01.007.

de Palma, A., Vosough, S., Liao, F., 2022. An overview of effects of COVID-19 on mobility and lifestyle: 18 months since the outbreak. Transp. Res. A Policy Pract. 159, 372–397. https://doi.org/10.1016/j.tra.2022.03.024.

Dehning, J., Zierenberg, J., Spitzner, F.P., Wibral, M., Neto, J.P., Wilczek, M., Priesemann, V., 2020. Inferring change points in the spread of COVID-19 reveals the effectiveness of interventions. Science 369 (6500), 0–10. https://doi.org/10.1126/science.abb9789.

Dube, K., Nhamo, G., Chikodzi, D., 2021. COVID-19 pandemic and prospects for recovery of the global aviation industry. J. Air Transp. Manag. 92 (January), 102022 https://doi.org/10.1016/j.jairtraman.2021.102022.
Eubank, S., Guclu, H., Kumar, V.S.A., Marathe, M.V., Srinivasan, A., Toroczkai, Z., Wang, N., 2004. Modelling disease outbreaks in realistic urban social networks. Nature 429 (6988), 180–184. https://doi.org/10.1038/nature02541.
Frost, M., Linneker, B., Spence, N., 1998. Excess or wasteful commuting in a selection of British cities. Transp. Res. A Policy Pract. 32A (7), 529–538. https://doi.org/10.1016/s0965-8564(98)00016-0.
Gao, Q., Li, Q., Zhuang, Y., Yue, Y., Liu, Z., Li, Q., Sui, D., 2019. Urban commuting dynamics in response to public transit upgrades: a big data approach. PLoS One 14 (10), 1–18.
Giuliano, G., Small, K.A., 1993. Is the journey to work explained by urban structure? Urban Stud. 30 (9), 1485–1500. https://doi.org/10.1080/00420989320081461.
Gordon, P., Kumar, A., Richardson, H.W., 1989. The influence of metropolitan spatial structure on commuting time. J. Urban Econ. 26 (2), 138–151. https://doi.org/10.1016/0094-1190(89)90013-2.
Gostin, L.O., Wiley, L.F., 2020. Governmental public health powers during the COVID-19 pandemic: stay-at-home orders, business closures, and travel restrictions. J. Am. Med. Assoc. 323 (21), 2137–2138. https://doi.org/10.1001/jama.2020.5460.
Hamidi, S., Sabouri, S., Ewing, R., 2020. Does density aggravate the COVID-19 pandemic?: early findings and lessons for planners. J. Am. Plan. Assoc. 86 (4), 495–509. https://doi.org/10.1080/01944363.2020.1777891.
Hamilton, B.W., Röell, A., 1982. Wasteful commuting. J. Polit. Econ. 90 (5), 1035–1053.
Harrington, D.M., Hadjiconstantinou, M., 2022. Changes in commuting behaviours in response to the COVID-19 pandemic in the UK. J. Transp. Health 24 (December 2021), 101313. https://doi.org/10.1016/j.jth.2021.101313.
Hensher, D.A., Balbontin, C., Beck, M.J., Wei, E., 2022. The impact of working from home on modal commuting choice response during COVID-19: implications for two metropolitan areas in Australia. Transp. Res. A Policy Pract. 155 (December 2020), 179–201. https://doi.org/10.1016/j.tra.2021.11.011.
Horner, M.W., 2002. Extensions to the concept of excess commuting. Environ. Plan. A 34 (3), 543–566. https://doi.org/10.1068/a34126.
Horner, M.W., 2008. "Optimal" accessibility landscapes? Development of a new methodology for simulating and assessing jobs-housing relationships in urban regions. Urban Stud. 45 (8), 1583–1602. https://doi.org/10.1177/0042098008091492.
Horner, M.W., Murray, A.T., 2002. Excess commuting and the modifiable areal unit problem. Urban Stud. 39 (1), 131–139. https://doi.org/10.1080/00420980220099113.
Horner, M.W., Schleith, D., 2012. Analyzing temporal changes in land-use–transportation relationships: a LEHD-based approach. Appl. Geogr. 35 (1–2), 491–498.
Hu, Y., Li, X., 2021. Modeling and analysis of excess commuting with trip chains. Ann. Am. Assoc. Geogr. 111 (6), 1851–1867. https://doi.org/10.1080/24694452.2020.1835461.
Hu, Y., Wang, F., 2016. Temporal trends of intraurban commuting in Baton Rouge, 1990–2010. Ann. Am. Assoc. Geogr. 106 (2), 470–479. https://doi.org/10.1080/00045608.2015.1113117.
Hu, L., Sun, T., Wang, L., 2018. Evolving urban spatial structure and commuting patterns: a case study of Beijing, China. Transp. Res. Part D: Transp. Environ. 59 (January), 11–22. https://doi.org/10.1016/j.trd.2017.12.007.
Hu, L., Yang, J., Yang, T., Tu, Y., Zhu, J., 2019. Urban spatial structure and travel in China. J. Plan. Lit. https://doi.org/10.1177/0885412219853259.
Huang, J., Wang, H., Fan, M., Zhuo, A., Sun, Y., Li, Y., 2020. Understanding the impact of the COVID-19 pandemic on transportation-related behaviors with human mobility data. In: Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 3443–3450. https://doi.org/10.1145/3394486.3412856.
Irawan, M.Z., Belgiawan, P.F., Joewono, T.B., Bastarianto, F.F., Rizki, M., Ilahi, A., 2021. Exploring activity-travel behavior changes during the beginning of COVID-19 pandemic in Indonesia. Transportation 0123456789. https://doi.org/10.1007/s11116-021-10185-5.
Jasiński, A., 2022. COVID-19 pandemic is challenging some dogmas of modern urbanism. Cities 121. https://doi.org/10.1016/j.cities.2021.103498.
Jun, M.J., 2020. The effects of polycentric evolution on commute times in a polycentric compact city: a case of the Seoul metropolitan area. Cities 98 (December 2019), 102587. https://doi.org/10.1016/j.cities.2019.102587.
Kanaroglou, P.S., Higgins, C.D., Chowdhury, T.A., 2015. Excess commuting: a critical review and comparative analysis of concepts, indices, and policy implications. J. Transp. Geogr. 44, 13–23.
Kim, C., 2008. Commuting time stability: a test of a co-location hypothesis. Transp. Res. A Policy Pract. 42 (3), 524–544. https://doi.org/10.1016/j.tra.2008.01.001.
Kim, K., Horner, M.W., 2021. Examining the impacts of the great recession on the commuting dynamics and jobs-housing balance of public and private sector workers. J. Transp. Geogr. 90 (July 2020), 102933 https://doi.org/10.1016/j.jtrangeo.2020.102933.
Kissler, S.M., Kishore, N., Prabhu, M., Goffman, D., Beilin, Y., Landau, R., Gyamfi-Bannerman, C., Bateman, B.T., Snyder, J., Razavi, A.S., Katz, D., Gal, J., Bianco, A., Stone, J., Larremore, D., Buckee, C.O., Grad, Y.H., 2020. Reductions in commuting mobility correlate with geographic differences in SARS-CoV-2 prevalence in New York City. Nat. Commun. 11 (1), 8–13. https://doi.org/10.1038/s41467-020-18271-5.
Kraemer, M.U.G., Yang, C.H., Gutierrez, B., Wu, C.H., Klein, B., Pigott, D.M., du Plessis, L., Faria, N.R., Li, R., Hanage, W.P., Brownstein, J.S., Layan, M., Vespignani, A., Tian, H., Dye, C., Pybus, O.G., Scarpino, S.V., 2020. The effect of human mobility and control measures on the COVID-19 epidemic in China. Science 368 (6490), 493–497. https://doi.org/10.1126/science.abb4218.
Levinson, D.M., 1998. Accessibility and the journey to work. J. Transp. Geogr. 6 (1), 11–21. https://doi.org/10.1016/s0966-6923(97)00036-7.
Li, C., Zhang, Y., Chai, Y., 2021. Do spatial factors outweigh institutional factors? Changes in influencing factors of home-work separation from 2007 to 2017 in Beijing. J. Transp. Geogr. 96 (November 2020) https://doi.org/10.1016/j.jtrangeo.2021.103201.
Liang, S., Leng, H., Yuan, Q., Yuan, C., 2021. Impact of the COVID-19 pandemic: insights from vacation rentals in twelve mega cities. Sustain. Cities Soc. 74 (July), 103121 https://doi.org/10.1016/j.scs.2021.103121.
Liu, W., Hou, Q., 2016. Excess commuting in transitional urban China: a case study of Guangzhou. Chin. Geogr. Sci. 26 (5), 599–608. https://doi.org/10.1007/s11769-015-0793-7.
Liu, W., Yan, X., Fang, Y., Cao, X., 2008. Related characteristics and mechanisms for excess commuting in Guangzhou (in Chinese: 广州市过剩通勤的相关特征及其形成机制). Acta Geograph. Sin. 63 (10), 1085–1096.
Liu, L., Miller, H.J., Scheff, J., 2020. The impacts of COVID-19 pandemic on public transit demand in the United States. PLoS One 15 (11 November), 1–22. https://doi.org/10.1371/journal.pone.0242476.
Loo, B.P.Y., Huang, Z., 2022. Spatio-temporal variations of traffic congestion under work from home (WFH) arrangements: lessons learned from COVID-19. Cities 124 (January), 103610. https://doi.org/10.1016/j.cities.2022.103610.
Ma, K., Banister, D., 2006a. Excess commuting: a critical review. Transp. Rev. 26 (6), 749–767.
Ma, K.R., Banister, D., 2006b. Extended excess commuting: a measure of the jobs-housing imbalance in Seoul. Urban Stud. 43 (11), 2099–2113. https://doi.org/10.1080/00420980600945245.
Murphy, E., 2009. Excess commuting and modal choice. Transp. Res. A Policy Pract. 43 (8), 735–743.
Murphy, E., Killen, J.E., 2011. Commuting economy: An alternative approach for assessing regional commuting efficiency. Urban Stud. 48 (6), 1255–1272. https://doi.org/10.1177/0042098010370627.
Niedzielski, Michael A., Horner, M.W., Xiao, N., 2013. Analyzing scale independence in jobs-housing and commute efficiency metrics. Transp. Res. A Policy Pract. 58, 129–143. https://doi.org/10.1016/j.tra.2013.10.018.
Niedzielski, Michał A., Hu, Y., Stępniak, M., 2020. Temporal dynamics of the impact of land use on modal disparity in commuting efficiency. Comput. Environ. Urban. Syst. 83 (July), 101523 https://doi.org/10.1016/j.compenvurbsys.2020.101523.
Pan, Y., He, S.Y., 2022. Analyzing COVID-19's impact on the travel mobility of various social groups in China's Greater Bay Area via mobile phone big data. Transp. Res. A Policy Pract. 159 (March), 263–281. https://doi.org/10.1016/j.tra.2022.03.015.
Parker, M.E.G., Li, M., Bouzaghrane, M.A., Obeid, H., Hayes, D., Frick, K.T., Rodríguez, D.A., Sengupta, R., Walker, J., Chatman, D.G., 2021. Public transit use in the United States in the era of COVID-19: transit riders' travel behavior in the COVID-19 impact and recovery period. Transp. Policy 111, 53–62. https://doi.org/10.1016/j.tranpol.2021.07.005.
Reuschke, D., Felstead, A., 2020. Changing workplace geographies in the COVID-19 crisis. Dialogues Human Geogr. 10 (2), 208–212. https://doi.org/10.1177/2043820620934249.
Ross, C., 2009. Megaregions: Planning for Global Competitiveness. Island Press.
Schleith, D., Widener, M., Kim, C., 2016. An examination of the jobs-housing balance of different categories of workers across 26 metropolitan regions. J. Transp. Geogr. 57, 145–160. https://doi.org/10.1016/j.jtrangeo.2016.10.008.
Schlosser, F., Maier, B.F., Jack, O., Hinrichs, D., Zachariae, A., Brockmann, D., 2020. COVID-19 lockdown induces disease-mitigating structural changes in mobility networks. Proc. Natl. Acad. Sci. U. S. A. 117 (52), 32883–32890. https://doi.org/10.1073/PNAS.2012326117.
Shamshiripour, A., Rahimi, E., Shabanpour, R., Mohammadian, A., (Kouros)., 2020. How is COVID-19 reshaping activity-travel behavior? Evidence from a comprehensive survey in Chicago. Transp. Res. Interdiscip. Perspect. 7, 100216 https://doi.org/10.1016/j.trip.2020.100216.
Shen, Q., 2000. Spatial and social dimensions of commuting. J. Am. Plan. Assoc. 66 (1), 68–82. https://doi.org/10.1080/01944360008976085.
Small, K.A., Song, S., 1992. Comment " wasteful " commuting: a resolution. J. Polit. Econ. 100 (4), 888–898.
Stawarz, N., Rosenbaum-Feldbrügge, M., Sander, N., Sulak, H., Knobloch, V., 2022. The impact of the COVID-19 pandemic on internal migration in Germany: a descriptive analysis. Populat. Space Place 1–11. https://doi.org/10.1002/psp.2566. December 2021.
Tian, H., Liu, Y., Li, Y., Wu, C.-H., Chen, B., Kraemer, M.U.G., Li, B., Cai, J., Xu, B., Yang, Q., 2020. An investigation of transmission control measures during the first 50 days of the COVID-19 epidemic in China. Science 368 (6491), 638–642.
Wachs, M., Taylor, B.D., Levine, N., Ong, P., 1993. The changing commute: a case-study of the jobs-housing relationship over time. Urban Stud. 30 (10), 1711–1729.
Wang, D., Zhou, M., 2017. The built environment and travel behavior in urban China: a literature review. Transp. Res. Part D: Transp. Environ. 52, 574–585. https://doi.org/10.1016/j.trd.2016.10.031.
White, M.J., 1988. Urban commuting journeys are not "Wasteful.". J. Polit. Econ. 96 (5), 1097–1110. https://doi.org/10.1086/261579.
Wu, W., Hong, J., 2017. Does public transit improvement affect commuting behavior in Beijing, China? A spatial multilevel approach. Transp. Res. Part D: Transp. Environ. 52, 471–479. https://doi.org/10.1016/j.trd.2016.08.032.
Xu, W., Yang, L., Zhang, W., 2019. Evaluation of transport policy packages in the excess commuting framework: the case of Xiamen, China. Cities 87 (July 2018), 39–47. https://doi.org/10.1016/j.cities.2018.12.009.

Yang, J., 2005. Commuting impacts of spatial decentralization: a comparison of Atlanta and Boston. J. Regional Anal. Policy 35 (1), 69–78.
Yang, J., 2006. Transportation implications of land development in a transitional economy: evidence from housing relocation in Beijing. Transp. Res. Rec. 1954, 7–14. https://doi.org/10.3141/1954-02.
Yang, J., 2008. Policy implications of excess commuting: examining the impacts of changes in US metropolitan spatial structure. Urban Stud. 45 (2), 391–405. https://doi.org/10.1177/0042098007085969.
Yang, T., 2020. Understanding commuting patterns and changes: counterfactual analysis in a planning support framework. Environ. Plan. B: Urban Anal. City Sci. 47 (8), 1440–1455. https://doi.org/10.1177/2399808320924433.
Yang, J., Ferreira, J., 2005. Evaluating measures of job-housing proximity: Boston and Atlanta, 1980–2000. In: Access to Destinations, pp. 171–192. https://doi.org/10.1108/9780080460550-009.
Yang, J., Ferreira, J., 2008. Choices versus choice sets: a commuting spectrum method for representing job - housing possibilities. Environ. Plan. B: Plan. Design 35 (2), 364–378. https://doi.org/10.1068/b3326.
Yang, J., French, S., Holt, J., Zhang, X., 2012. Measuring the structure of U.S. metropolitan areas, 1970-2000. J. Am. Plan. Assoc. 78 (2), 197–209. https://doi.org/10.1080/01944363.2012.677382.
Zarrabi, M., Yazdanfar, S.A., Hosseini, S.B., 2021. COVID-19 and healthy home preferences: the case of apartment residents in Tehran. J. Build. Eng. 35 (May 2020) https://doi.org/10.1016/j.jobe.2020.102021.
Zhang, Q., Yang, H., 2022. Geovisualizing the changes in metro passenger flows of Kunming under the impact of COVID-19. J. Transp. Geogr. 104 (March), 103420 https://doi.org/10.1016/j.jtrangeo.2022.103420.
Zhang, Y., Zhang, Y., Zhou, J., 2019. A novel excess commuting framework: considering commuting efficiency and equity simultaneously. Environ. Plan. B: Urban Anal. City Sci. 0 (0), 1–18. https://doi.org/10.1177/2399808319851517.
Zhang, W., Fang, C., Zhou, L., Zhu, J., 2020. Measuring megaregional structure in the Pearl River Delta by mobile phone signaling data: a complex network approach. Cities 104 (April), 102809. https://doi.org/10.1016/j.cities.2020.102809.
Zhang, N., Jia, W., Wang, P., Dung, C.-H., Zhao, P., Leung, K., Su, B., Cheng, R., Li, Y., 2021a. Changes in local travel behaviour before and during the COVID-19 pandemic in Hong Kong. Cities 112 (September 2020), 103139. https://doi.org/10.1016/j.cities.2021.103139.
Zhang, H., Xu, S., Liu, X., Liu, C., 2021b. Near "real-time" estimation of excess commuting from open-source data: evidence from China's megacities. J. Transp. Geogr. 91 (August 2020), 102929 https://doi.org/10.1016/j.jtrangeo.2020.102929.
Zhao, P., Gao, Y., 2022. Public transit travel choice in the post COVID-19 pandemic era: An application of the extended theory of planned behavior. Travel Behav. Soc. 28 (April 2021), 181–195. https://doi.org/10.1016/j.tbs.2022.04.002.
Zhao, P., Lü, B., de Roo, G., 2011. Impact of the jobs-housing balance on urban commuting in Beijing in the transformation era. J. Transp. Geogr. 19 (1), 59–69. https://doi.org/10.1016/j.jtrangeo.2009.09.008.
Zhou, J., Long, Y., 2014. Jobs-housing balance of bus commuters in Beijing: exploration with large-scale synthesized smart card data. Transp. Res. Rec. 2418, 1–10. https://doi.org/10.3141/2418-01.
Zhou, J., Long, Y., 2015. Losers and Pareto optimality in optimising commuting patterns. Urban Stud. 53 (12), 2511–2529. https://doi.org/10.1177/0042098015594072.
Zhou, J., Murphy, E., 2019. Day-to-day variation in excess commuting: An exploratory study of Brisbane, Australia. J. Transp. Geogr. 74 (August 2018), 223–232. https://doi.org/10.1016/j.jtrangeo.2018.11.014.
Zhou, J., Murphy, E., Long, Y., 2014a. Commuting efficiency in the Beijing metropolitan area: An exploration combining smartcard and travel survey data. J. Transp. Geogr. 41, 175–183. https://doi.org/10.1016/j.jtrangeo.2014.09.006.
Zhou, J., Zhang, C., Chen, X., Huang, W., Yu, P., 2014b. Has the legacy of Danwei persisted in transformations? The jobs-housing balance and commuting efficiency in Xi'an. J. Transp. Geogr. 40, 64–76. https://doi.org/10.1016/j.jtrangeo.2014.04.008.
Zhou, J., Wang, Y., Cao, G., Wang, S., 2016. Jobs-housing balance and development zones in China: a case study of Suzhou Industry Park. Urban Geogr. 38 (3), 363–380. https://doi.org/10.1080/02723638.2016.1152845.
Zhou, J., Murphy, E., Long, Y., 2018. Commuting efficiency gains: assessing different transport policies with new indicators. Int. J. Sustain. Transp. 13 (10), 710–721. https://doi.org/10.1080/15568318.2018.1510562.
Zhou, J., Murphy, E., Corcoran, J., 2020a. Integrating road carrying capacity and traffic congestion into the excess commuting framework: the case of Los Angeles. Environ. Plan. B: Urban Anal. City Sci. 47 (1), 119–137. https://doi.org/10.1177/2399808318773762.
Zhou, T., Nguyen, T.V.T., Zhong, J., Liu, J., 2020b. A COVID-19 descriptive study of life after lockdown in Wuhan, China: descriptive study of life after lockdown. R. Soc. Open Sci. 7 (9) https://doi.org/10.1098/rsos.200705.
Zhou, J., Wu, J., Ma, H., 2021. Abrupt changes, institutional reactions, and adaptive behaviors: An exploratory study of COVID-19 and related events' impacts on Hong Kong's metro riders. Appl. Geogr. 134 (December 2020), 102504 https://doi.org/10.1016/j.apgeog.2021.102504.