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Investigating the changes in residential location and commute patterns during the pandemic using smart card data

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ABSTRACT

Commute trips typically constitute a major share of weekday trips made in urban areas. Hence, commute distances and modes of travel usage are closely linked with the level of transport sustainability of a city. The COVID-19 pandemic has resulted in a significant change in commute patterns – the length and frequency of commute trips and the usage rate of public transport in particular. To ensure the long-term sustainability of transport in a world faced with the persistent threat of potential pandemics, it is crucial to understand these changes. This paper empirically examines how the residential locations and commute patterns of a segment of subway commuters in Beijing changed during the peak of the COVID-19 pandemic. Passively generated smart card data from 8,792,539 subway users were used to quantify the relative impact of different factors contributing to these changes. The results indicate a notable trend of residential relocation towards the city centre that is opposite to the trend of moving away from city centres observed in some other countries. Further, it is observed that the pandemic has acted as a catalyst for individuals with long commute times (over 45 min) to reconsider their locations, aiming to reduce commuting time. Consequently, such relocations lead to an average commute time reduction. The findings contribute to advancing existing knowledge related to the long-term mobility and sustainability implications of the pandemic, some of which are expected to be transferable to future pandemic contexts.

1. Introduction

Commute trips constitute a major share of the total Vehicle Miles Travelled (VMT), both in developed and developing countries (Choudhury & Bint Ayaz, 2015). Hence, the commute time and modes of travel are closely linked with the level of transport sustainability of a city. This has led to significant research efforts to understand the factors affecting residential and work locations and the choice of commute mode (e.g. Schwanen & Mokhtarian 2015, Lin et al. 2015). However, the COVID-19 pandemic has resulted in significant changes to individuals' patterns of travel and ways of living. In addition to shifts in travel behaviours in the short term like reduction in public transport usage and increase in the use of active travel (Hensher et al. 2021a, b; Moens et al., 2020; Marra et al., 2022), the pandemic also brought attitudinal changes and long-lasting impacts (de Palma et al., 2022; Aaditya & Rahul., 2023). These led to changes in the medium and long-term mobility behaviour of commuters: residential relocation, commute patterns change, etc. (Chen et al., 2023; de Palma et al. 2023). Understanding these changes and the factors affecting these changes is crucial for ensuring the long-term sustainability of transport in a world faced with the persistent threat of potential pandemics.

Thus far, most studies exploring the impact of COVID-19 in this regard have focused on short-term changes, such as travel mode change, travel frequency change, etc. (Wang et al., 2024; Currie et al., 2021; Shakibaei et al., 2021; Moens et al., 2020), while the lasting impact on commuting has received less attention. In particular, the pandemic will have long-term effects on commuters' residential relocation, thereby impacting commute patterns accordingly (de Palma et al., 2023). However, this topic remains a relatively under-explored area. Although it has been widely studied in normal contexts, the breakout of COVID-19 brings new trends in mobility (Chen et al., 2023). In addition, the trends vary across regions and countries (Chen et al., 2023; Wolday & Böcker, 2023; Stawarz et al., 2022). Studying the mechanism of factors influencing relocation behaviour in the context of COVID-19 and exploring

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the impact on commuting patterns helps policymakers adjust strategies for future urban development, public transportation, and behavioural intervention measures.

To fill this research gap, this study considers changes in public transport commuters' residential locations and commute patterns during and after a wave of the pandemic in Beijing, the capital of China, with a special focus on (1) what is the trend of relocation and commute pattern changes; (2) what are the factors that influence the change; (3) what are the heterogeneous impacts of the factors on commuters with different commuting times? To answer these questions, this study identifies the home and work stations of subway commuters with smart card trip records before, during and after the pandemic. Based on the identified stations, commuters' residential mobility and public transport usage patterns are analysed and the generalisability of the results is discussed. The findings contribute to advancing existing knowledge related to the understanding of the lasting impact of a pandemic on the changes in urban mobility. The methods and conclusions provided by this study can help the city authority capture the subsequent changes in public transport demand in the event of future pandemics and make quick planning decisions to respond to the changes.

The remainder of this paper is structured as follows: Section 2 provides an overview of the literature review. Section 3 describes the study design and methodology. Section 4 presents the results and discussion. Finally, section 5 summarises the paper and outlines limitations with possible directions for future research.

2. Literature review

2.1. Residential mobility and commute patterns

Residential mobility and commuting patterns play important roles in understanding the development of urban spatial structures and are interlinked (Ta et al., 2017). Changes in residential locations can alter commuting routes and modes, impacting commuting time and urban traffic flow. Conversely, commuting considerations often influence residential choices, shaping urban development and individual lifestyles (Zarabi et al., 2019; Tao et al. 2023a, b). In the study of residential mobility, many empirical studies utilise the life course framework to understand how individuals' relocation behaviour changes over time (Coulter & Scott, 2015; Rabe & Taylor, 2010). When the life cycle reaches some special stages, such as the beginning of parenthood, residents choose to relocate their residences and work due to its influence. Age, tenure, and housing space requirements are found to be significant predictors of residential relocation (Clark & Huang, 2003). In particular, Elliott & Howell (2017) find that experiences of natural hazards are important triggers to increase residential mobility and instability over the life course. Therefore, COVID-19 is likely to trigger changes in residents' relocation behaviour.

Many other factors are found to be influential, with previous studies finding that urban spatial structure, transportation system performance, and built environments have significant impacts (Zhang et al., 2019; Huang et al., 2019). On the one hand, daily commuting patterns and overall travel behaviour affect the relationship between work and housing, leading to relocation behaviours (Bloze & Skak, 2016). Further, relocation will in turn bring about changes in commute patterns (Van Ommeren, 2020). Huang et al (2018) found that at the 45-minute commuting mark, there is a notable shift in behavioural preference, with commuters whose travel time exceeds this inflexion point tending to relocate to shorten their commutes, while those with shorter commutes often opt for longer travel times in pursuit of better work and/or residences. On the other hand, the built environment is also an important factor influencing residential relocation, with residents always seeking better living conditions and a place in line with their travel preferences and needs (Ramezani et al., 2021; van Wee & Cao, 2022; Cao et al., 2006). Commuters who like their neighbourhood with better living conditions, such as public spaces, transport infrastructure, and shopping malls, are generally less likely to move (Molinsky & Forsyth, 2018).

From the perspective of capturing the changes in residential relocation and commute patterns, most studies use different kinds of follow-up survey data to study inner-city mobility (Lei & Liu, 2023; Wolday & Böcker, 2023; Kim et al., 2021). However, the survey data often lack precise locations of home and work, but only at the city level or district level (such as urban or suburb) (Lin et al., 2022). Another disadvantage is that survey data often lack long-term records of trajectories (Qin & Wang, 2019). To solve these issues, some studies use long-term panel "big data" of urban residents to capture residents' relocation, such as smart card data (Huang et al., 2018), mobile phone GPS data (Chen et al., 2023), etc. Compared with traditional data sources, urban big data has advantages in terms of accuracy, continuity, large-scale application, and cost efficiency (Wang et al., 2020; Chen et al., 2023). Huang et al. (2018) proposed a framework to capture consecutive trajectories of workplaces and residences over time to understand residents' relocation. Based on panel smart card data, the method identifies the most preferred station near each commuter's workplace and home according to individual commuting regularity. This paper adopts this method to capture commuters' residential/work relocation and commute patterns.

2.2. Commuters' behaviour change in the context of COVID-19

There are short and long-term impacts of COVID-19 on urban residents. Related to urban transportation, the short-term impacts include an overall reduction in daily travel, a reduction of out-of-home activities, and shift in travel modes, etc. These have been widely studied (Zhang et al. 2021a, b; Hensher et al. 2021a, b). The short-term impacts can be temporary adaptations because of multiple external factors, such as policy restrictions, lack of public transport, work-from-home policies, etc. (Tao et al. 2023a, b; Meredith-Karam et al., 2021; Hensher et al. 2021a, b). Long-term impacts, in a contrast, may be caused by internal factors such as resident's changing attitudes and their choice of house/work location and following changes in travelling (Chen et al., 2023; Zhang et al., 2020).

In the context of COVID-19, there have been numerous studies which have looked at modelling short-term behaviour changes in response to COVID-19 using smart card data (Almlöf et al., 2021; Long et al. 2023; Lizana et al. 2023, to name a few). Most of the previous research related to long-term relocation behaviours have relied on self-reported longitudinal revealed preference (RP) survey data, e.g. investigating changes in residential locations in the context of Norway (Wolday & Böcker, 2023), Australia (Perales & Bernard, 2022), etc. There have also been limited applications of passively generated data for investigating the changes in residential locations – utilising Google Query Trend Data (Lei & Liu, 2023) in the context of the USA, for example. Further, these studies have primarily focused on Western countries.

Meanwhile, the studies related to developing countries are also insufficient, despite these countries (such as China) also being hit hard by the pandemic. Chen et al. (2023) studied commuters' job-housing relationship in the Pearl River Delta, China, based on RP mobile phone data. Their findings indicate housing and workplaces have increasingly concentrated in city centres, which is opposite to the trend of suburbanisation elsewhere. This indicates that trends in different regions and countries are uncertain. Policymakers cannot simply adopt findings from other countries and overlook the uniqueness of their city. This is emphasised by results that contradict those of Chen et al. (2023), with Zhao and Gao (2023) using mobile phone signal data from Beijing to find a trend of suburbanisation in relatively older high–income home relocators. However, this paper focuses on analysing the relocation trends but lacks an analysis of influencing factors. In our work, we build upon that of Chen et al. (2023) and Zhao and Gao (2023) by additionally studying the various influencing factors that may have led to observed relocation behaviour, thus better identifying the reasons for these changes.

2.3. In summary

Given the above literature review, this study concludes that studying the new trends and influencing factors of the change of relocation and commute patterns during the pandemic is important for long-term urban planning, but it is also under-researched. In particular, few studies use RP big data, including long panels and comprehensive coverage of the population, to study the changes over time. To the best of the author's knowledge, this study is the first paper that uses subway smart card data to analyse commuters' residential mobility patterns in the context of the COVID-19 pandemic.

3. Study design and Methodology

To investigate the relocation trend, we first introduce the data set and explain how the home and work stations are identified. The trend of home and work relocation is shown visually. We then introduce the regression equations and the station-related variables used to explain changes in the home station.

3.1. Data

The automated fare collection (AFC) system was first operationalised in Beijing in 2006 and has been widely used in public transport systems. Travellers should swipe their smart cards when they check in and check out, giving two transaction records for each trip. Based on the unique card ID, we can track travellers' subway usage over time (Wang et al., 2020). Compared with traditional data sources, this passively generated data source has advantages in terms of accuracy, continuity, large-scale application, and cost efficiency (Zhao et al., 2018; Zhang et al., 2017). The primary information in the smart card transaction records used in this work is represented in Table 1.

This study uses smart card data from the entire Beijing subway network. The dataset covers the first two waves of the pandemic in Beijing. The following periods are selected to analyse the changes in subway commuters' behaviour in 2020. According to the classification of different periods of the pandemic by the Beijing government, this study treats January observations (06/01/2020–10/01/2020) as 'before the pandemic', February observations as 'during the pandemic' (03/02/2020–07/02/2020) and October observations (12/10/2020–16/10/2020) as 'after the pandemic' (as Beijing had no Covid infection cases between October and December 2020). The data selected for the analyses include data from normal working weekdays only, excluding weekends, holidays and dates with large-scale special events.

3.2. Identification of home and work station

This study employs the method by Huang et al. (2018) to identify workplaces (by corresponding 'work station') and residences ('home station') of regular commuters.

Shown in Fig. 1, The work station for each commuter is identified based on the following rules:

Table 1
An excerpt from smart card data.

Card ID	Check-in time	Origin station	Check-out time	Destination station
1000751085xxxxxx	20,200,130,085,200	9429	103,707	0103
1000751085xxxxxx	20,200,201,082,100	9429	100,826	0103
…	…	…	…	…
1,000,751,017 xxxxxx	20,200,130,081,100	9429	95,601	0104
…	…	…	…	…

- Filtering commuters: Given the focus of the research is regular commuters, only the records for travellers who travel at least 3 days/week are used for the analyses.
- Identifying the commuting trips: The trips whose boarding time is at least 6 h later than the alighting time of the previous trip are flagged as commuting trips.
- Identifying return trips: To acknowledge that the return segment of the commute trip could have been by a different mode of transport, the trips that do not occur on the same day as the previous trip are excluded. All remaining trips are classified as return commuting trips for this commuter.
- Identifying the 'work station': Among the origin stations of return commuting trips, the station where the commuter visited most frequently is regarded as the work station *W*.

Then, the home location of each commuter is identified based on the following rules:

- Access the individual dataset where the work station has been identified above.
- Among the destination stations of return commuting trips, the station where the commuter visited most frequently is regarded as the home station *H*.

Using this method at different periods reveals at most six stations for each commuter, as specified in Table 2.

Note that the locations may not change; change; or may not be possible to identify in all periods. The change of residential location and commuting patterns are then identified based on the status of home/work station locations in different periods. For example, for commuter 1, with status H1: place A, H2: place A and H3: place B, may move home; commuter 2 with status W1: place A, W2: cannot be identified, W3:place A again, may work from home during the pandemic; commuter 3 with status W1: place A, W2: cannot be identified, W3:place B may change job. This study focuses specifically on identifying the following four alternatives for relocation:

- Alternative 1: no change in home or work location
- Alternative 2: change work location, do not change home location
- Alternative 3: change home location, do not change work location
- Alternative 4: change both home and work location

To complete the above analysis, this study takes the commuters whose home/work location can still be identified in October as samples to analyse their behaviours before, during and after the pandemic. Commuters whose home/work locations are not trackable are omitted as there are many possibilities for why a commuter's locations may not be identified in October, such as working from home, losing their smart card, leaving Beijing, etc. However, it is impossible to directly infer what the reason is from the smart card data alone.

The final dataset included 82,720,872 trip records from 8,792,539 travellers. Following the above data cleaning process results in the identification of 425,439 commuters travelling to/from 340 distinct subway stations (out of 475 total stations). The research area and distribution of subway stations in this study are shown in Fig. 2.

3.3. Modelling work

This study uses linear regression models (as shown in Eq. (1) to evaluate the relative impact of different influencing factors affecting residential mobility (Chen et al., 2023).

$$Y_s = \beta_0 + \sum_{i=1}^{n} \beta_i X_{s,i} + \varepsilon_s \tag{1}$$

***Y*:** Three different dependent variables related to home station *s* have

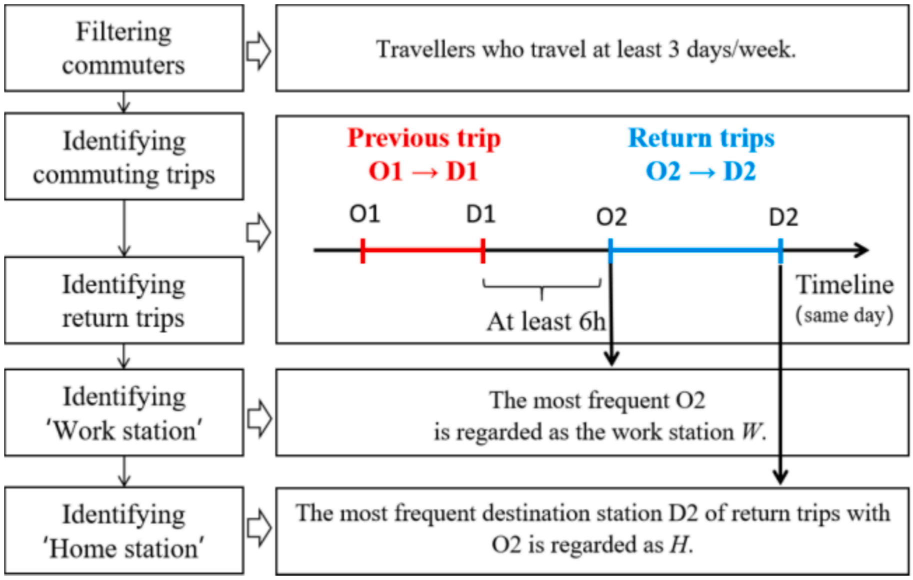

Fig. 1. Diagram of identifying the work/home station.

Table 2
The identification of home and work locations in different periods.

	Before the pandemic	During the pandemic	After the pandemic
Home station	H1	H2	H3
Work station	W1	W2	W3

been tested in this research: (1) $\delta_{\text{net move in}}$ is the net number of individuals that move into a location between January and October ($\delta_{\text{move in}} - \delta_{\text{move out}}$, the gap of move-in and move-out) (2) $\delta_{\text{move in}}$ is the number of individuals that move into a location between January and October and (3) $\delta_{\text{move out}}$ is the number of individuals that move out a location between January and October. Referring to Chen et al. (2023), these three dependent variables capture the changes in resident numbers before and after the pandemic, indicating that the model reflects the impact of the pandemic. Based on these three dependent variables, this study constructed a set of models labelled as Model 1, Model 2 and Model 3. As the choice of work location is affected by many complex factors that cannot be obtained only through subway data (e.g. work from home policy, job opportunity, type of job, etc), the modelling work does not focus on exploring what factors affect travellers' work relocation (Bick et al., 2023; Adeoti et al., 2021). In addition, due to most of the commuters' home or work locations not being captured in February (as shown in Fig. 2), we focus specifically on the changes observed before and after the pandemic (January and October, respectively).

***X*:** Based on the discussions in the literature review, this study used independent variables related to COVID-19, the built environment, and commuting-related variables. The variables are generated for the area within a 1 km radius of each station and are detailed in Table 3.

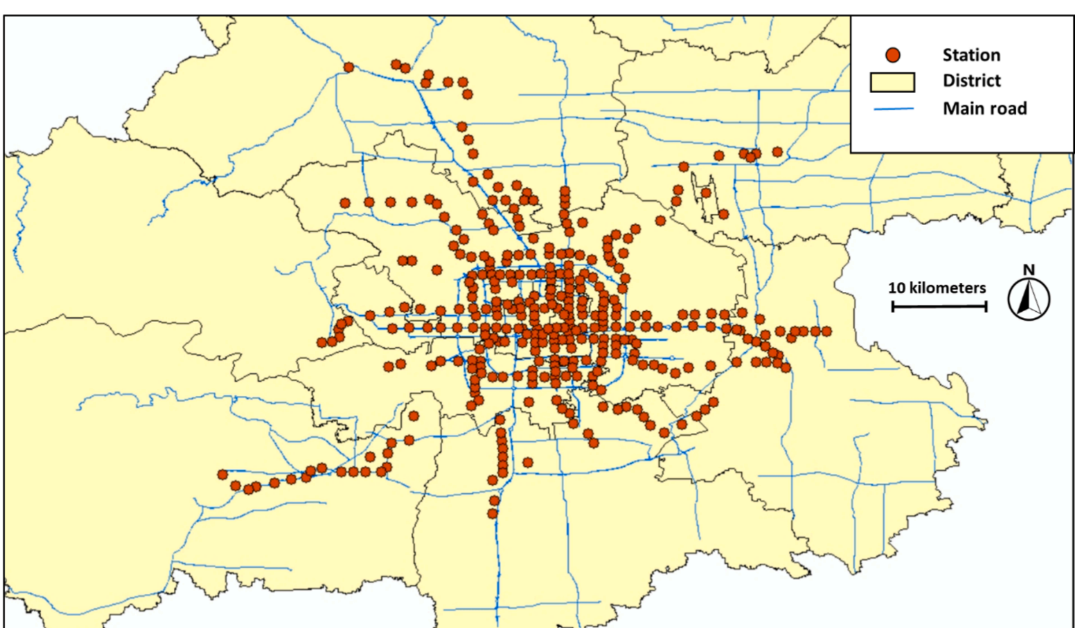

Fig. 2. Research area and distribution of subway stations.

In addition, β_0, β_i and ε_s are constant terms, regression coefficients and random errors.

4. Results and discussion

4.1. Descriptive statistics

4.1.1. Identification of relocations

The data in Table 4 represents the number of commuters who changed home and/or work locations in February and October compared with January which is the benchmark. Meanwhile, the Sankey diagram shown in Fig. 3 represents the change visually. For example, 95,165 commuters could not be captured during the pandemic and moved their home after the pandemic by October. The results show that the pandemic had a significant impact on commuters, and there are apparent differences in the choices made by commuters. Most commuters' home and work locations could not be identified during the pandemic (the brown part in Fig. 3). This is foreseeable since the majority of commuters suspended their use of public transportation during the pandemic, due to work from home, government restrictions, etc. This results in our inability to identify their work and residential locations in February.

After the pandemic, most commuters (43.4 %) did not relocate their home and work stations (the red part in Fig. 3). However, more than half of commuters changed either their home or work stations. 22.8 % of commuters relocated their home (the orange part in Fig. 3). 16.6 % of commuters relocate their work (the green part in Fig. 3). 17.2 % of commuters relocate both (the yellow part in Fig. 3). Beijing subway commuters are predominantly young travellers (Report of the 5th Beijing Comprehensive Transportation Survey, 2016), most of whom live in rented accommodations, making them more mobile in terms of relocation. For example, Huang et al. (2018) found that over a period of seven years, 83.62 % of the subway commuter sample had changed their residence, workplace, or both. Although we have not found official statistics for Beijing regarding the number of people who have moved during the pandemic, similar large cities worldwide have experienced significant impacts. For instance, the London Assembly Housing Committee reported that 'Half of Londoners wanting to move home want out of London.[1]

4.1.2. The trends of relocations

Based on the identification of the home station and work station, this study is interested in the change of numbers and spatial distribution of home and work locations. Fig. 4 shows the home location distribution of commuters during different periods of the pandemic. Although Fig. 4a and 4b show that the overall distribution of commuter home stations has not changed much before and after the pandemic, the mobility trend of home relocation can be seen in Fig. 4c. Fig. 4c reveals a decline in commuters departing from suburban subway stations, contrasted with increases around the majority of city centre stations and select suburban areas, indicating a post-COVID-19 trend of higher residential density in the city centre. This finding is different from previous results from studies based on Western countries' data and similar to the findings of Chen et al (2023), that residences became more centrally located in downtowns following the pandemic.

Fig. 5 shows the work station distribution of commuters. Similar to the results above, from Fig. 5a and b, the distribution of work stations does not change much. In addition, based on Fig. 5c, there is also no obvious trend of work relocation. A possible reason is that commuters have less flexibility in choosing where they work compared to choosing where they live.

4.1.3. The change in commuting time

Commuting time is one of the key elements of commuting patterns (Ma et al., 2017; Huang et al., 2018). Fig. 6 shows the comparison of commuting time distribution of four kinds of commuters before and after the pandemic. For commuters who moved home or moved both home and work, the commuting time was reduced. However, for those who just changed work stations or didn't move, the commuting time does not show significant changes.

Further, Table 5 shows the average commuting time of different categories of commuters in January and October. Commuters who did not move have the shortest average commuting time in January, while commuters who moved both have the longest commuting time in January. By moving, the commuting time of home movers and both movers dropped. When commuters only changed their home, their commuting times dropped the most. This is consistent with the findings above that commuters are more likely to move from the suburbs to the city centre, possibly because they intend to reduce their commuting time in the subway. This result is consistent with Huang et al. (2018) who also report that commuters prefer to use a house move to shorten commuting time.

4.2. Modelling

4.2.1. General model

This study considers the underlying drivers of commuters' residential relocation after the pandemic with three separate linear regression models. Table 6 presents the results of the models. The results of model 2 show the impact of factors on attracting commuters to move into the station area, while the results of model 3 explain the reasons for moving out of the station area. The results of model 1 show the overall (net) impact.

Variables related to the built environment are effective and significant in predicting and explaining the relocation behaviours of commuters (Sun et al., 2017; Zhou & Kockelman, 2008). Notably, if the station is in a city centre area, the number of move-ins is larger. This is remarkable as this is different from the trend in some of the other major cities and countries in the world, such as London,[2] Germany and Iran (Stawarz et al., 2022; Zarrabi et al., 2021). On the one hand, being close to the city centre helps to reduce the inconvenience of commuting to workplaces which are always located in the city centre area brought by public traffic control during a pandemic.[3] On the other hand, despite social distancing measures, urban areas provide better opportunities for social and professional networking (Qin & Wang, 2019). This is particularly important in times of economic uncertainty, as networks can play a crucial role in finding new job opportunities. In addition to the reasons mentioned above, in times of crisis, people tend to gravitate towards areas where they feel there are more opportunities and support systems (Yap, 1977). Urban centres, traditionally seen as hubs of activity and opportunity, could psychologically appear as safer or more promising during the uncertainty of a pandemic. City managers in the post-pandemic era need to pay attention to the differentiation of different areas within the city, for instance, economic recovery, changes in the attractiveness, job opportunities, etc. (Sharifi & Khavarian-Garmsir, 2020; Mouratidis, 2021).

Furthermore, similar to the results of previous studies, the good construction of transportation infrastructure is an important factor in positively attracting commuters to move in. During lockdowns and travel restrictions, areas with better transportation infrastructure provided more options for essential travel (Li & Ma, 2022). This includes

[1] https://www.london.gov.uk/press-releases/assembly/escaping-the-city-post-covid.

[2] Nearly a third of London renters plan to leave city center because of the pandemic: https://news.sina.com.cn/o/2020–12-17/doc-iiznezxs7421366.shtml.

[3] Work places in Beijing are mainly concentrated in the city center area: https://news.ifeng.com/a/20180320/56899358_0.shtml.

Table 3
Summary of the independent variables.

Variables[1]		Description	Source
Built environment variables	City centre	Whether the station is located in the city centre district. (dummy, 0/1)	Baidu POI[2]
	Transportation	The proportion of land used for transportation facilities, such as subway stations, roads, etc. (continuous)	
	Land use mix	Measure of the variety of different uses within an area, such as residential, commercial, and public spaces, etc.(continuous)[3]	
	Leisure facilities	The number of outdoor and leisure activity places such as park, gym, etc. (continuous)	
	Living facility	The number of living service facilities, such as laundry, post office, etc. (continuous)	
	Medical facility	The number of medical services facilities, such as hospital, pharmacy, etc. (continuous)	
	Educational facility	The number of schools educational facilities, such as school, training centres, university, etc. (continuous)	
	House price	Average house price. (continuous)	Lianjia[4]
Commuting related variables	Commuting time	Average commuting time in mins of commuters belonging to the station. (continuous)	Smart card data, Baidu POI
	Commuting cost	Average commuting fare cost in RMB of commuters belonging to the station. (continuous)	
	Commuting transfer	Average transfer times in mins of commuters belonging to the station. (continuous)	
	Station peak passenger volume	Average subway commuter flow in morning peak hours (7–9 am). (continuous)	
	Number of lines	The number of subway lines that pass through the station. (continuous)	
	Number of exits	The number of subway station exits. (continuous)	
	Mall	Whether the station is integrated as a transport hub with a mall. (dummy, 0/1)	
Covid-19 related variable	Risk duration	Number of days the station was in a zone deemed high or medium risk. (continuous)	Beijing Municipal Health Commission

[1] All variables are extracted for the area within 1 km radius of each station
[2] the POI data is based on Baidu Map:https://map.baidu.com/.
[3] http://www.thinkstreetsmart.org/land-use-mix.html.
[4] Lianjia is a real estate intermediary of China:https://bj.lianjia.com/.

Table 4
Home/work location change during/after the pandemic.

Number of commuters	Home move-during	Work move-during	All move-during	No move-during	Unknown-during
Home move-after	498	48	44	870	95,165
Work move-after	83	329	52	752	69,232
All move-after	205	157	193	506	72,435
No move-after	246	144	50	2,966	181,464
sum	1,032	678	339	5,094	418,296

not just public transportation, but also better road networks for cars or sharing travel modes. Similarly, areas with more living facilities also became more attractive. Areas with more living facilities offered commuters greater convenience and quality of life without the need to travel far, especially at a time when mobility was restricted and remote work became more common, which enhanced the work-life balance of commuters during uncertain times. However, under the context of the pandemic, some results are contrary to studies in normal contexts. Places of residence with better educational conditions are always attractive (Sun et al., 2017). However, for this data, the number of educational facilities has a negative impact on commuters' home relocation. A possible explanation is that Beijing implemented strict control measures in areas where students gather.[4] When cases occur in a school or university where there are lots of vulnerable students, nearby residential areas would also be affected and locked down. Therefore, commuters choose to live away from these places to reduce the risk of being affected. Additionally, the higher the average house prices in an area, the greater the number of commuters moving away. High housing prices in these areas became a significant burden, especially when commuters' incomes were unstable or reduced due to the economic impact of the pandemic.

The commuting-related variables demonstrate that station areas with better transport connections are more popular with commuters. Average commuting time has a significant positive impact on moving out. During the pandemic, travellers often want to reduce the time they spend in a subway carriage to reduce the possibility of infection. Meanwhile, the results reveal that more convenient travel conditions play an important role in attracting commuters, such as more subway lines, more exits of subway stations and connections with malls where there are convenient living facilities. The reasons have been discussed above.

In addition, in line with expectations, the longer an area has been designated as a risk area, the smaller the number of commuters choosing to move in.

4.2.2. *Considering heterogeneity*

As shown in the literature review, 45 min is a dividing point influencing residential relocation. Using 45 min as a split point to divide commuters into heterogeneous groups, this study conducted a heterogeneity analysis based on the commuting time of travellers before the pandemic. The 3 independent variables discussed are calculated separately based on the samples with a commuting time longer than 45 min and samples with a commuting time less than 45 min. The results are shown in Table 7.

The results show that in the case of the pandemic, commuters (over 45 min) are more likely to be influenced to move their home to the city centre stations. However, the 'city centre' is not significant for the commuters whose commuting time is less than 45 min. The commuting-related variables play more significant roles in explaining the changes in the samples with commuting time longer than 45 min. Stations with greater average commuting costs and more commuting transfer times have larger move-out flow and lower move-in flow. Those commuters prefer moving to places with convenient transportation, such as places with a higher proportion of land used for transportation facilities, more metro lines and stations with malls. Additionally, the risk duration has a more significant impact on the commuters (over 45 min). The policy implications we can obtain are that policymakers should pay particular attention to the long-duration commuters in future pandemic outbreaks. For example, providing subsidies to long-distance commuters, or

[4] https://baijiahao.baidu.com/s?id=1731414785094317009&wfr=spider&for=pc.

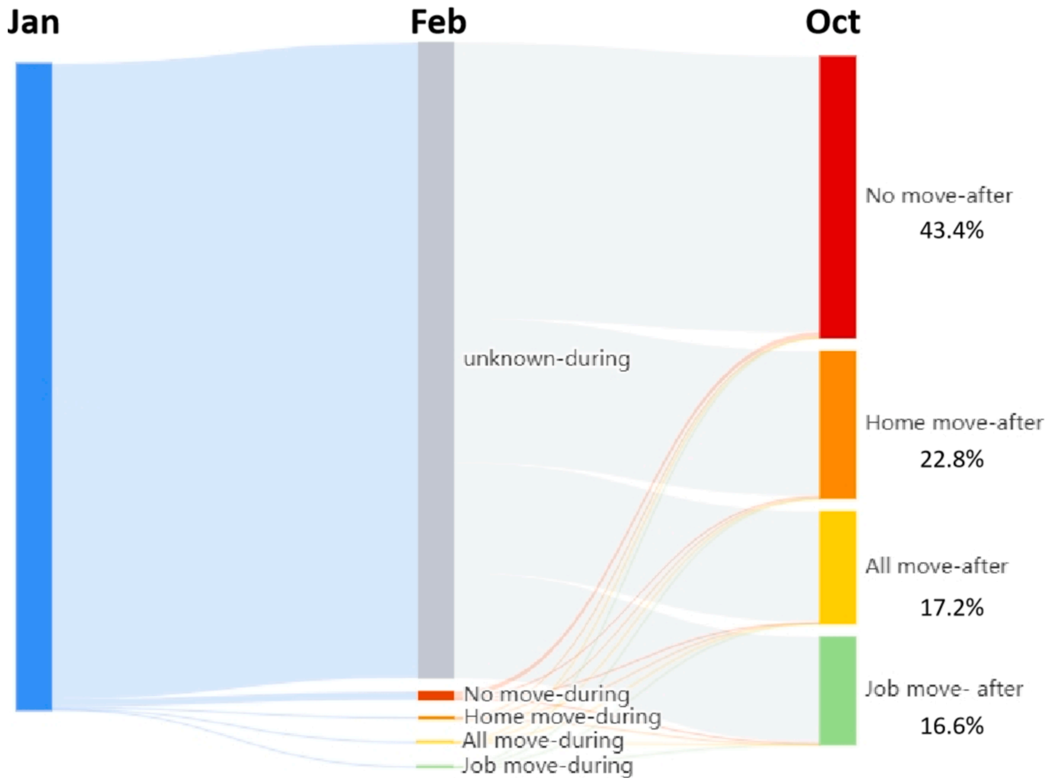

Fig. 3. Sankey diagram of home/work location change.

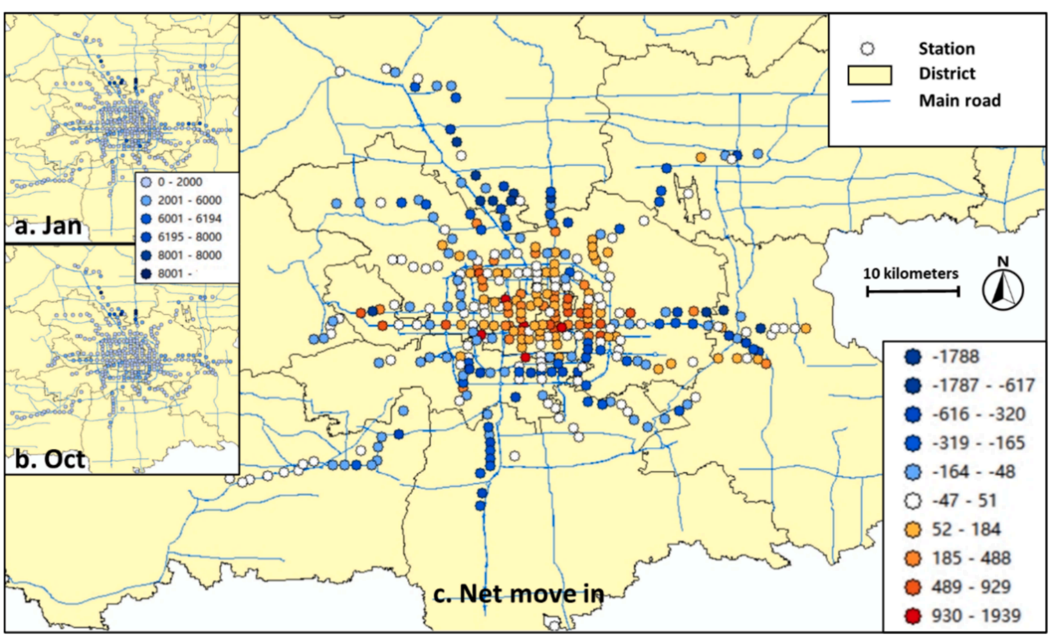

Fig. 4. The distribution change of home station. Note: Fig. 4a and b show the home location distribution of commuters in January and October. Each data point on the graph represents a specific subway station (Corresponding to Fig. 2). Fig. 4c shows the net change in the number of commuters living in each subway station between October and January. The colour varies based on the change of number of commuters at the respective subway station.

improving the quality of service for long-distance travel. Additionally, to reduce the commuting frequency of long-distance commuters, companies should be encouraged to offer greater flexibility for working from home. At the same time, the government should strive to enhance the supporting services for residential communities far from the city centre, such as better internet infrastructure and more efficient logistics services etc., to facilitate the choice of working from home for commuters.

5. Conclusion

This paper empirically examines the change in the residential location and commute patterns of subway commuters in Beijing during the COVID-19 pandemic using smart card data and explores the relative impact of different influencing factors affecting the changes. Analyses of the data show that 40.1 % of the commuters in our sample changed

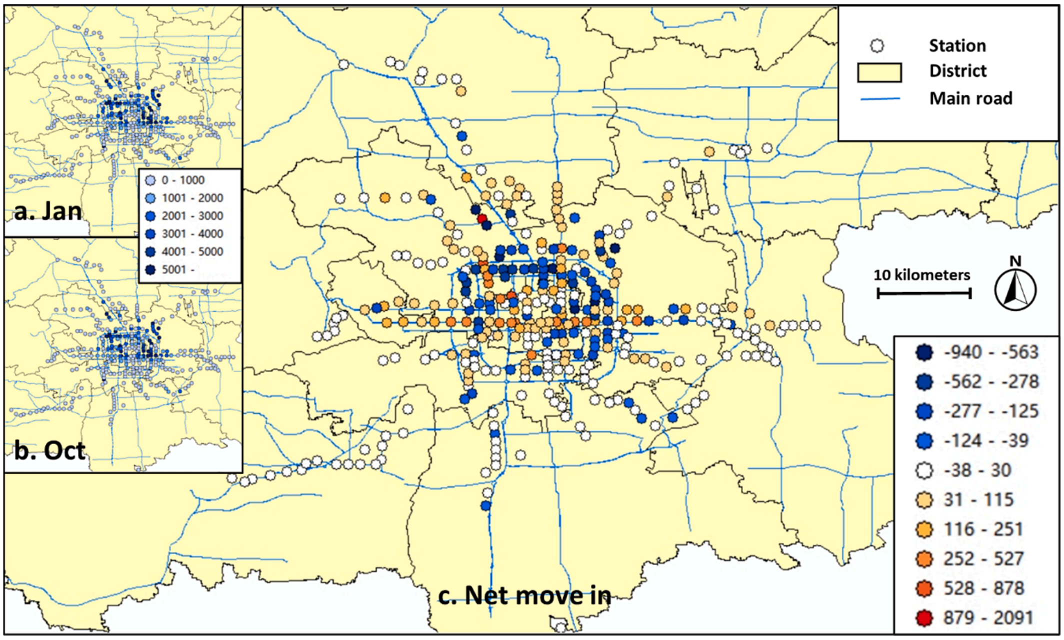

Fig. 5. The distribution change of work station. Note: Fig. 5a and b show the work location distribution of commuters in January and October. Each data point on the graph represents a specific subway station (Corresponding to Fig. 2). Fig. 5c shows the net change in the number of commuters working in each subway station between October and January. The colour varies based on the change of number of commuters at the respective e subway station.

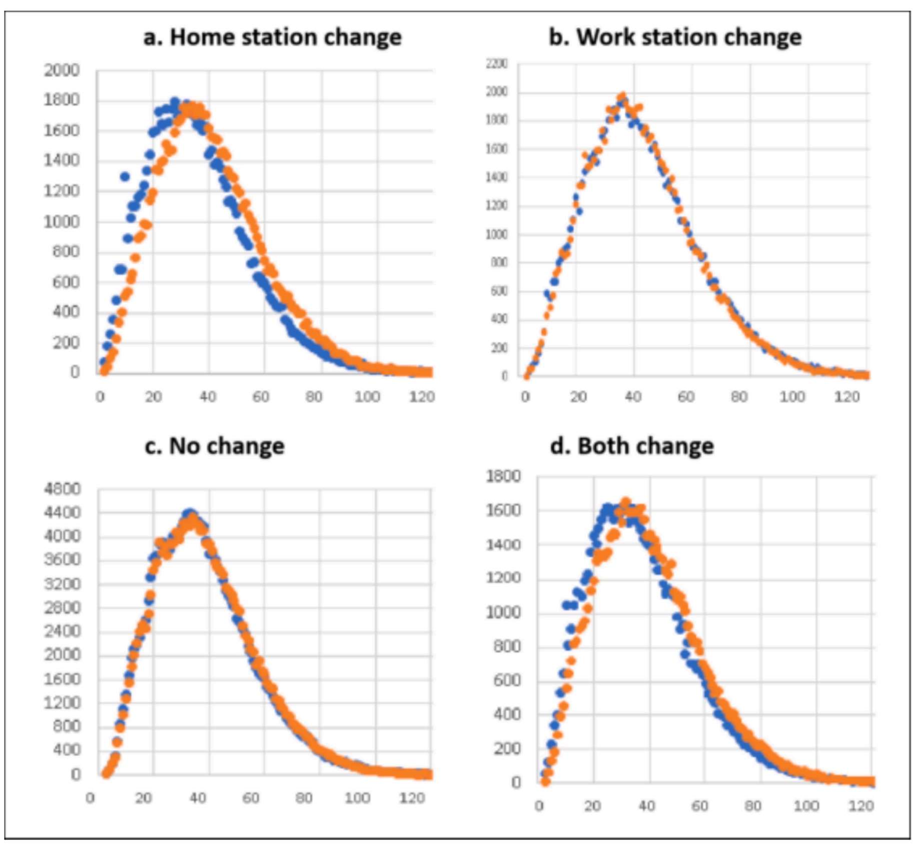

Fig. 6. The change in commuting time of heterogeneous commuters. Note: The vertical axis represents the number of people, and the horizontal axis represents commuting time in minutes.

either their home or work locations, while 16.6 % changed both. The net relocation numbers indicate that there is a propensity to move to residential locations closer to the city centre, which is different from the trend observed in some of the other big cities in the world. Among the influencing factors, the conditions of transportation infrastructure and the potential reduction in commuting time are found to have the most significant effect on the number of relocations. The relocation of home and work leads to on average a reduction in commuting time. The

Table 5
The change in average commuting time.

Average time (min)	Home move	Work move	No move	Both move
Jan	40.59	42.80	38.96	40.14
Oct	36.26	43.01	38.48	37.29
Change	−4.33	0.21	−0.48	2.85

pandemic prompts those with imbalanced job-housing relationships to consider relocation to achieve balance.

It should be noted that due to the anonymous nature of the data, this paper does not consider the demographic variables of individual commuters. Further, limited by the lack of job-related information from the data (e.g. type of job, salary and benefits, the extent of flexibility offered by the employer, etc.), this paper does not explore the factors influencing the work relocation behaviour. Though these limitations cannot be addressed by using passive smart card data only, there is scope to

Table 6
Linear regression results of analysis on home relocation.

Variables		Model 1	Model 2	Model 3
		net move-in	move-in	move out
Built environment variables	City centre	0.146**	0.090**	−0.004
		(2.40)	(2.55)	(−0.18)
	Transportation	0.320***	0.184***	−0.021
		(7.58)	(7.48)	(−1.32)
	Land use mix	0.026	−0.038	−0.044
		(0.51)	(−1.31)	(−2.39)
	Leisure facilities	0.054	0.043	0.011
		(0.68)	(0.94)	(0.37)
	Living facility	0.163*	0.135**	0.026
		(1.83)	(2.58)	(0.78)
	Medical facility	−0.036	−0.031	−0.011
		(−0.44)	(−0.67)	(−0.37)
	Educational facility	−0.119**	−0.094***	−0.018
		(−2.07)	(−2.83)	(−0.83)
	House price	0.076	−0.059	0.098***
		(0.96)	(−1.29)	(3.34)
Commuting related variables	Commuting time	0.046	−0.067	0.087**
		(0.42)	(−1.07)	(−2.19)
	Commuting cost	0.036	0.012	−0.006
		(0.36)	(0.21)	(−0.17)
	Commuting transfer	−0.006	−0.024	−0.023
		(−0.11)	(−0.84)	(−1.25)
	Station peak passenger volume	−0.347 ***	0.749 ***	0.917 ***
		(−7.29)	(7.13)	(5.56)
	Number of lines	0.143 ***	0.165 ***	0.072 ***
		(2.85)	(5.69)	(3.96)
	Number of exits	0.112 **	0.104 ***	0.027
		(2.19)	(3.48)	(1.42)
	Mall	0.196 ***	0.137 ***	0.002
		(4.35)	(5.23)	(0.11)
Covid-19 related variable	Risk duration	−0.087 **	−0.033	0.019
		(−2.02)	(−1.35)	(0.11)
R-squared		0.496	0.826	0.931

Note: t-values in parentheses; *** indicates |t|>=2.58, ** indicates 1.96<=|t|<2.58, and * indicates 1.64<=|t|<1.96.

Table 7
Linear regression results of models considering heterogeneity.

Variables		>=45 min			<45 min		
		Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Built environment variables	City centre	0.043	0.071*	0.013	0.061	0.059	0.003
	Transportation	0.100 ***	0.072**	−0.025	0.078	0.010	−0.032
	Land use mix	−0.061	0.036	0.076***	0.088	−0.027	−0.089
	Leisure facilities	0.103	0.044	−0.041	0.140	0.081	−0.012
	Living facility	0.029	0.033	0.006	−0.098	0.093	0.080
	Medical facility	−0.016	0.018	0.026	−0.022	−0.069	−0.068
	Educational facility	−0.023	−0.037	−0.010	−0.040	−0.034	−0.018
	House price	−0.072	−0.070	0.001	0.168	−0.093*	0.115**
Commuting related variables	Commuting cost	−0.167 **	0.053	0.092*	−0.179	0.082	0.081
	Commuting transfer	0.040	−0.065*	0.072**	0.019	0.010	0.040
	Station peak passenger volume	−0.436 ***	0.728 ***	0.839 ***	0.019	0.650 ***	0.768 ***
	Number of lines	0.260 ***	0.274***	−0.008	−0.066	0.370***	0.265***
	Number of exits	0.116 ***	0.066*	−0.040	0.274 ***	0.087**	0.015
	Mall	0.094**	0.123 ***	0.003	0.062	0.025	−0.044
Covid-19 related variable	Risk duration	−0.101 ***	−0.001	0.077***	−0.093	−0.029	−0.002
R-squared		0.512	0.863	0.756	0.431	0.652	0.672

Note: *** indicates |t|>=2.58, ** indicates 1.96<=|t|<2.58, and * indicates 1.64<=|t|<1.96.

address some of the problems by fusing multiple sources of datasets (e.g. survey SP choice experiment data and smart card data) or constructing choice models with latent demographics (e.g. Bwambale et al. 2019). In addition, this study only focuses on subway commuters and does not study commuters in other travel modes. Moreover, due to the nature of our dataset, the sample size is relatively small compared to the entire population of Beijing (400,000 vs 22 million). In the future, the relocation and commute patterns trend of multiple different modes of commuters should be considered. Meanwhile, new datasets and data methods should be used to get a larger range of samples.

However, even in its current form, the paper provides useful insights into the long-term impacts of the pandemic. Understanding urban residents' mobility during an outbreak is important for controlling the spread of the pandemic. The findings and methods of this paper can help city planners to better predict the change in residential mobility and transport demands in the event of future similar pandemic outbreaks, which will lead to a more sustainable urban transport system in the long run. City planners could additionally use urban traffic big data to mine the trends of commuters and analyse the heterogeneity of different groups. This has implications for designing more targeted policies or subsidies to reduce the impact of the pandemic on residents.

CRediT authorship contribution statement

Yu Wang: Writing – review & editing, Supervision, Project administration, Funding acquisition, Data curation, Conceptualization. **Charisma Choudhury:** Writing – review & editing, Supervision, Investigation. **Thomas O. Hancock:** Writing – review & editing, Supervision, Investigation. **Yacan Wang:** Writing – review & editing, Supervision, Project administration, Funding acquisition, Data curation, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

Aaditya, B., Rahul, T.M., 2023. Long-term impacts of COVID-19 pandemic on travel behaviour. Travel Behav. Soc. 30, 262–270.
Adeoti, M.O., Shamsudin, F.M., Mohammad, A.M., 2021. Opportunity, job pressure and deviant workplace behaviour: does neutralisation mediate the relationship? A study of faculty members in public universities in Nigeria. Eur. J. Manag. Bus. Econ. 30 (2), 170–190.
Bick, A., Blandin, A., Mertens, K., 2023. Work from home before and after the COVID-19 outbreak. Am. Econ. J. Macroecon. 15 (4), 1–39.
Bloze, G., Skak, M., 2016. Housing equity, residential mobility and commuting. J. Urban Econ. 96, 156–165.
Bwambale, A., Choudhury, C.F., Hess, S., 2019. Modelling trip generation using mobile phone data: A latent demographics approach. J. Transp. Geogr. 76, 276–286.
Cao, X., Handy, S.L., Mokhtarian, P.L., 2006. The influences of the built environment and residential self-selection on pedestrian behavior: evidence from Austin, TX. Transportation 33, 1–20.
Chen, R., Zhang, M., Zhou, J., 2023. Jobs-housing relationships before and amid COVID-19: An excess-commuting approach. J. Transp. Geogr. 106, 103507.
Choudhury, C.F., Bint Ayaz, S., 2015. Why live far?—Insights from modeling residential location choice in Bangladesh. J. Transp. Geogr. 48, 1–9.
Clark, W.A., Huang, Y., 2003. The life course and residential mobility in British housing markets. Environ Plan A 35 (2), 323–339.
Coulter, R., Scott, J., 2015. What motivates residential mobility? Re-examining self-reported reasons for desiring and making residential moves. Popul. Space Place 21 (4), 354–371.
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, 218–234.
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.
Elliott, J.R., Howell, J., 2017. Beyond disasters: A longitudinal analysis of natural hazards' unequal impacts on residential instability. Soc. Forces 95 (3), 1181–1207.
Hensher, D.A., Beck, M.J., Wei, E., 2021a. Working from home and its implications for strategic transport modelling based on the early days of the COVID-19 pandemic. Transp. Res. A Policy Pract. 148, 64–78.
Hensher, D.A., Wei, E., Beck, M., Balbontin, C., 2021b. The impact of COVID-19 on cost outlays for car and public transport commuting-the case of the Greater Sydney Metropolitan Area after three months of restrictions. Transp. Policy 101, 71–80.
Huang, J., Levinson, D., Wang, J., Zhou, J., Wang, Z.J., 2018. Tracking job and housing dynamics with smartcard data. Proc. Natl. Acad. Sci. 115 (50), 12710–12715.
Huang, J., Levinson, D., Wang, J., Jin, H., 2019. Job-worker spatial dynamics in Beijing: Insights from smart card data. Cities 86, 83–93.
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, 102933.
Lei, L., Liu, X., 2022. The COVID-19 pandemic and residential mobility intentions in the United States: Evidence from Google Trends data. Popul. Space Place 28 (6), e2581.
Li, B., Ma, L., 2022. JUE insight: Migration, transportation infrastructure, and the spatial transmission of COVID-19 in China. J. Urban Econ. 127, 103351.
Lin, D., Allan, A., Cui, J., 2015. The impacts of urban spatial structure and socio-economic factors on patterns of commuting: a review. Int. J. Urban Sci. 19 (2), 238–255.
Lin, X., Zhong, J., Ren, T., Zhu, G., 2022. Spatial-temporal effects of urban housing prices on job location choice of college graduates: Evidence from urban China. Cities 126, 103690.
Lizana, M., Choudhury, C., Watling, D., 2023. Using smart card data to model public transport user profiles in light of the COVID-19 pandemic. Travel Behav. Soc. 33, 100620.
Long, A., Carney, F., Kandt, J., 2023. Who is returning to public transport for non-work trips after COVID-19? Evidence from older citizens' smart cards in the UK's second largest city region. J. Transp. Geogr. 107, 103529.
Ma, X., Liu, C., Wen, H., Wang, Y., Wu, Y.J., 2017. Understanding commuting patterns using transit smart card data. J. Transp. Geogr. 58, 135–145.
Marra, A.D., Sun, L., Corman, F., 2022. The impact of COVID-19 pandemic on public transport usage and route choice: Evidences from a long-term tracking study in urban area. Transp. Policy 116, 258–268.
Meredith-Karam, P., Kong, H., Wang, S., Zhao, J., 2021. The relationship between ridehailing and public transit in Chicago: A comparison before and after COVID-19. J. Transp. Geogr. 97, 103219.
Moens, E., Lippens, L., Sterkens, P., Weytjens, J., Baert, S., 2022. The COVID-19 crisis and telework: a research survey on experiences, expectations and hopes. Eur. J. Health Econ. 23 (4), 729–753.
Molinsky, J., Forsyth, A., 2018. Housing, the built environment, and the good life. Hastings Cent. Rep. 48, S50–S56.
Mouratidis, K., 2021. How COVID-19 reshaped quality of life in cities: A synthesis and implications for urban planning. Land Use Policy 111, 105772.
Perales, F., Bernard, A., 2023. Continuity or change? How the onset of COVID-19 affected internal migration in Australia. Popul. Space Place 29 (2), e2626.
Qin, P., Wang, L., 2019. Job opportunities, institutions, and the jobs-housing spatial relationship: Case study of Beijing. Transp. Policy 81, 331–339.
Rabe, B., Taylor, M., 2010. Residential mobility, quality of neighbourhood and life course events. J. R. Stat. Soc. Ser. A Stat. Soc. 173 (3), 531–555.
Ramezani, S., Hasanzadeh, K., Rinne, T., Kajosaari, A., Kyttä, M., 2021. Residential relocation and travel behavior change: Investigating the effects of changes in the built environment, activity space dispersion, car and bike ownership, and travel attitudes. Transp. Res. A Policy Pract. 147, 28–48.
Schwanen, T., Mokhtarian, P.L., 2005. What affects commute mode choice: neighborhood physical structure or preferences toward neighborhoods? J. Transp. Geogr. 13 (1), 83–99.
Shakibaei, S., De Jong, G.C., Alpkökin, P., Rashidi, T.H., 2021. Impact of the COVID-19 pandemic on travel behavior in Istanbul: A panel data analysis. Sustain. Cities Soc. 65, 102619.
Sharifi, A., Khavarian-Garmsir, A.R., 2020. The COVID-19 pandemic: Impacts on cities and major lessons for urban planning, design, and management. Sci. Total Environ. 749, 142391.
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. Popul. Space Place 28 (6), e2566.
Sun, B., Ermagun, A., Dan, B., 2017. Built environmental impacts on commuting mode choice and distance: Evidence from Shanghai. Transp. Res. Part D: Transp. Environ. 52, 441–453.
Ta, N., Chai, Y., Zhang, Y., Sun, D., 2017. Understanding job-housing relationship and commuting pattern in Chinese cities: Past, present and future. Transp. Res. Part D: Transp. Environ. 52, 562–573.
Tao, Y., Petrović, A., van Ham, M., 2023a. Working from home and subjective wellbeing during the COVID-19 pandemic: The role of pre-COVID-19 commuting distance and mode choices. J. Transp. Geogr. 112, 103690.
Tao, Y., Petrović, A., van Ham, M., Fu, X., 2023b. Residential relocation as a key event in commuting mode shift. Transp. Res. Part D: Transp. Environ. 119, 103772.

Van Ommeren, J., Rietveld, P., Nijkamp, P., 2000. Job mobility, residential mobility and commuting: A theoretical analysis using search theory. Ann. Reg. Sci. 34, 213–232.
van Wee, B., Cao, X.J., 2022. Residential self-selection in the relationship between the built environment and travel behavior: A literature review and research agenda. Advances in Transport Policy and Planning 9, 75–94.
Wang, Y., Wang, Y., Choudhury, C., 2020. Modelling heterogeneity in behavioral response to peak-avoidance policy utilizing naturalistic data of Beijing subway travelers. Transport. Res. F: Traffic Psychol. Behav. 73, 92–106.
Wang, Y., Choudhury, C., Hancock, T.O., Wang, Y., de Dios Ortúzar, J., 2024. Influence of perceived risk on travel mode choice during Covid-19. Transp. Policy 148, 181–191.
Wolday, F., Böcker, L., 2023. Exploring changes in residential preference during COVID-19: Implications to contemporary urban planning. Environ. Plann. B: Urban Anal. City Sci. 50 (5), 1280–1297.
Yap, L.Y., 1977. The attraction of cities: a review of the migration literature. J. Dev. Econ. 4 (3), 239–264.
Zarabi, Z., Manaugh, K., Lord, S., 2019. The impacts of residential relocation on commute habits: A qualitative perspective on households' mobility behaviors and strategies. Travel Behav. Soc. 16, 131–142.
Zarrabi, M., Yazdanfar, S.A., Hosseini, S.B., 2021. COVID-19 and healthy home preferences: The case of apartment residents in Tehran. Journal of Building Engineering 35, 102021.
Zhang, J., Lu, H., Zeng, H., Zhang, S., Du, Q., Jiang, T., Du, B., 2020. The differential psychological distress of populations affected by the COVID-19 pandemic. Brain, Behaviour, and Immunity 87, 49–50.
Zhang, J., Hayashi, Y., Frank, L.D., 2021a. COVID-19 and transport: Findings from a world-wide expert survey. Transp. Policy 103, 68–85.
Zhang, Y., Martens, K., Ying, L., 2017. Revealing group travel behavior patterns with public transit smart card data. Travel Behav. Soc. 10, 42–52.
Zhang, Y., Zhang, Y., Zhou, J., 2021b. A novel excess commuting framework: Considering commuting efficiency and equity simultaneously. Environ. Plann. B: Urban Anal. City Sci. 48 (1), 151–168.
Zhao, P., Gao, Y., 2023. Discovering the long-term effects of COVID-19 on jobs–housing relocation. Humanities and Social Sciences Communications 10 (1), 1–17.
Zhao, Z., Koutsopoulos, H.N., Zhao, J., 2018. Individual mobility prediction using transit smart card data. Transp. Res. Part C Emerging Technol. 89, 19–34.
Zhou, B., Kockelman, K.M., 2008. Self-selection in home choice: Use of treatment effects in evaluating relationship between built environment and travel behavior. Transp. Res. Rec. 2077 (1), 54–61.