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Discovering the long-term effects of COVID-19 on jobs-housing relocation

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Jobs-housing relocation plays a crucial role in urban spatial restructuring and development. As the COVID-19 pandemic has dramatically altered the form of human mobility, it is likely to have affected individual relocation patterns. This study uses mobile phone signalling data from 2018 to 2022 in Beijing to examine and compare intra-urban jobs-housing relocation behaviours among commuters before and after the pandemic. This study captures the pandemic's long-term effects via an event study design. Despite prevalent negative impressions of the pandemic, this study found that it may have unexpected positive influences on our cities. The pandemic decelerated suburbanisation in young middle-income home relocators but encouraged suburbanisation in relatively older high-income home relocators, which may have helped to preserve inner city vitality. The pandemic accelerated the decentralisation of spatial distribution of employment, which may have helped to further break the monocentric city structure. The pandemic also accelerated inverse jobs-housing separation and improved jobs-housing balance, which may have made the city greener. It is suggested that policy makers seize this opportunity to guide cities towards structural improvement and sustainability.

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Introduction

The COVID-19 pandemic changed many aspects of human life. Although the world has moved on from the initial pandemic shock, the effects of COVID-19 on human behaviours may be lasting (Gkiotsalitis and Cats, 2020; Sharifi and Khavarian-Garmsir, 2020). Among these behaviours, work-place and residential mobility is particularly important because it is closely linked with fundamental urban issues such as employment, transportation and urban restructuring (Wu, 2004; Liu and Pei et al., 2021). Therefore, unveiling individuals' job and housing dynamics in the pandemic context, and indicating potential long-term changes in relocation patterns can offer an important understanding of the pandemic's impacts and provide useful guidance for future urban development (Liu and Pei et al., 2021).

The existing literature about human mobility has explored the changes in daily travel behaviours, urban activity intensities, and jobs-housing mobilities. On the topic of daily travel behaviours, the pandemic has highlighted the existence and importance of "essential" mobility (Salazar, 2021). For individual people, commuting trips (Angell and Potoglou, 2022) and leisure travel reduced, while shopping trips for daily necessities consisted of a large proportion of daily travels (Abdullah et al., 2021; Angell and Potoglou, 2022). Perceived risk of infection significantly influenced people's travel mode choice (Basnak et al., 2022). Due to people's increased desire to avoid crowding, private car travel (Abdullah et al., 2021; Bagdatli and Ipek, 2022; Hensher et al., 2022) became more popular, while public transit (Bucsky, 2020; Hu and Chen, 2021; Zhao and Gao, 2022) and shared transportation modes (ride-hailing, shared bicycle, shared scooter etc.) (Li et al., 2021; Zheng et al., 2021; Monahan and Lamb, 2022) experienced a sharp decrease in demand. Barbieri et al. (2020) provided a survey dataset on modal change during the pandemic in ten countries around the world. Daily mobility is the link between individuals' daily destinations including their residences and workplaces, and travel behaviour change can reflect people's perceptions about travelling during the pandemic, which can influence their jobs-housing choices.

On the topic of urban activities, there was also a decrease in "unessential" activities. At the peak of the pandemic, only necessary commercial or supportive activities maintained a certain level of activity intensity (Romanillos et al., 2021). Digital footprints show that activity intensity of workplaces decreased while that of residential areas increased (Liu and Pei et al., 2021; Guardabascio et al., 2023). On-site activities were replaced by tele-activities. In particular, the proportion of people working from home greatly increased during the pandemic (Jain et al., 2022; Mouratidis and Peters, 2022), and in the post-pandemic "new normality" after strict control policies are relieved, the level of teleworking is likely to remain higher than pre-pandemic level (Beck and Hensher, 2021; Jain et al., 2022). Besides teleworking, the importance of e-commerce and online shopping has also increased (Kawasaki et al., 2022). The internet made life easier especially for those under lockdown or home quarantine, but the lack of out-of-home activities may also reduce people's wellbeing (Arroyo et al., 2021; Nikolaeva et al., 2023). This drastic drop in activity level and growing dependence on online activities during the pandemic may affect the way people perceive urban space and travel, and thus may also influence their jobs-housing preferences.

On the topic of jobs-housing relocation, recent studies have presented many changes in people's work and/or home relocation choices. For workplace relocation, lockdowns and restrictions have jeopardised urban economies and resulted in job losses and reduced workforces worldwide (Barrero et al., 2020; Lenzen et al., 2020; Nicola et al., 2020; Raynor and Panza, 2021). Yet over time, COVID-19 may be regarded as a reallocation shock that has

caused deterioration in some industries but rapid growth in others (Barrero et al., 2020; Kramer and Kramer, 2020; Nicola et al., 2020), leading to job moves among workers. In addition, other triggers for job relocation may include positive experiences of working from home (Barrero et al., 2020; Kramer and Kramer, 2020), changes in occupational status perception (Kramer and Kramer, 2020) and rearrangements of work-related priorities (Lippens et al., 2021). Looking at residential relocation, besides commonly used explanations such as the life course approach (Rossi, 1955; Clark and Dieleman, 1996), the trade-off between housing and commuting costs (Alonso, 1964) and the structure of housing supply (Ball, 1986; Forrest and Murie, 1990; Teixeira and Murdie, 1997), COVID-19 has produced new motives for moving, including reduced income (Sharifi and Khavarian-Garmsir, 2020; Duque-Calvache et al., 2021), psychological needs (Duque-Calvache et al., 2021), the need to care for or to be cared for by family members (Duque-Calvache et al., 2021), the need for better living conditions during lockdown (Duque-Calvache et al., 2021), and the pursuit of a potentially more COVID-proof low-density living environment (Liu and Su, 2021). Lei and Liu (2022) provided a theoretical summary of the ways COVID-19 can influence residential mobility.

In post-pandemic mobility changes, socio-economic factors play an indispensable role. Gender, age, income and social status and connections can all affect mobility and cause inequalities. In the post-pandemic era, women and older people are in general more risk-averse (Basnak et al., 2022) and more immobile than men (Padilla-Pozo et al., 2023). The decrease in mobility among young people is also greater than that of others (Caselli et al., 2022), and they are also more economically vulnerable than their older counterparts due to their lack of career stability and wealth accumulation (Churchill, 2020). In the meantime, social gaps widened as low-income groups, minorities and vulnerable groups experienced more financial and health damage (Sharifi and Khavarian-Garmsir, 2020; Wade, 2020; Raynor and Panza, 2021), were often forced to move homes (Duque-Calvache et al., 2021) and had more difficulties in finding reemployment (Kramer and Kramer, 2020).

Besides the above topics, existing literature also studied changes in inter-city or inter-region mobility under COVID-19 (Gibbs et al., 2020; Saha and Chouhan, 2021; Perales and Bernard, 2022), the relationship between travel flow and COVID-19 transmission (Carteni et al., 2020; Kraemer et al., 2020; Xiong et al., 2020; Nouvellet et al., 2021) and the effects of travel restrictions and other control policies on the spread of COVID-19 (Kraemer et al., 2020; Lai et al., 2020; Tian et al., 2020; Askitas et al., 2021; Godøy et al., 2022).

Although these studies have provided a valuable background of the effects of COVID-19 on human mobility and an outline of individual jobs-housing relocation in the pandemic context, there are some deficiencies: (1) the existing literature has seldom considered job relocation, housing relocation and commuting choice as interacting or interdependent, and thus might not have presented the whole picture; (2) there are few long-term comparative studies to separate out the differences between pre-pandemic and post-pandemic jobs-housing mobility patterns; (3) many studies used survey data, which might contain potential bias and often makes it difficult to obtain large numbers of participants. One paper made important efforts to study the changes in dwelling and working intensity before, during and after COVID-19 using longitudinal mobile phone data (Liu and Pei et al., 2021); however, it focused on the trend of activity intensity over time, while individual-level workplace and residence location change within the case city and its relationship with commuting behaviour were not discussed.

Based on 10 months of citywide cellular signalling data spanning from 2018 to 2022, we examined the long-term effects of COVID-19 on intra-urban jobs-housing relocation behaviours among commuters in Beijing using an event study approach. The content of this paper is organised as follows. We first describe our research design and the empirical models used, then describe our data characteristics and sampling procedures. After this, we present our main results, and then discussed the implications of the main results and the contributions and limitations of this study. Finally, we conclude this study.

Research framework and empirical models

Research design. As an unanticipated major event, the COVID-19 outbreak was a natural experiment. Relocations in the pre-pandemic stage happened without its influence, while relocations in the post-pandemic stage are subject to its influence. Therefore, with an appropriate method, it is possible to single out its effects on jobs-housing relocation. We adopted an event study approach to compare relocation patterns of relocators from before the pandemic and at different stages after the pandemic. We divided the period between Apr. 2018 and Nov. 2022 into nine semi-annual phases (numbered $j = -3, \dots, 0, \dots, 5$) including three pre-pandemic phases (-3 to -1) and six post-pandemic phases (0 to 5). For each phase, we detected individuals' home and work locations and focused on relocators—those who had different home locations (home movers), work locations (work movers) or both (home-and-work movers) in the start month and end month. We calculated relocation patterns of relocators from each phase and examined the differences between post-pandemic relocation patterns and pre-pandemic relocation patterns while controlling for pre-relocation jobs-housing characteristics, sociodemographic attributes, and season fixed effects. A diagram of our research design is presented in Fig. 1.

Key relocation patterns of interest are home relocation patterns, work relocation patterns and jobs-housing relation patterns. Home and work features are represented by the locations of home and work relative to city centre, and more specifically the ring numbers of Beijing's ring road system in which home and work are positioned (r^h and r^w). The pre-post relocation changes (Δr^h and Δr^w) represent the changes in spatial distribution of home and work locations in the monocentric urban structure, which can reflect changed values of public

service facilities, living environment, working conditions etc. in relocation decisions. We also examine pre-post relocation changes of housing price (Δp), population density of home location ($\Delta dens$), and pre-post relocation changes of accessibility of public service facilities such as public transit stations (Δpt), schools ($\Delta kind$, Δpri and Δmid for kindergartens, primary schools and middle schools), healthcare facilities (Δmed) and green spaces ($\Delta green$). These relocation outcomes can shed some light on the motivations behind relocations. Note that we only study commuters whose places of residence and employment are within the sixth ring road, where data resolution is high. Jobs-housing relation is measured by commute length, and more specifically commute time (t). It is the link between home and work, and the way it is changed by relocation (Δt) can often reflect the changes in work and lifestyle of relocators.

Research hypotheses. To conceptualize the COVID-19 pandemic's influence on relocation, we draw on migration theories including the stress-response model (Wolpert, 1966) and the dissatisfaction model (Speare, 1974). The stress-response model believes that relocation is triggered by environmental stress in the current location (Wolpert, 1966). The pandemic has introduced many stress factors. In residential areas, due to mobility restrictions, people stay at home longer, making residential areas more crowded, which may inflict neighbourhood tension and also increase infection risks. In workplaces, the most outstanding stress factor is infection risk. The dissatisfaction model believes that relocation is triggered by dissatisfaction with the current location. This theory entertains the thought that when new needs emerges, the current location, once satisfactory, may start to seem dissatisfactory (Speare, 1974). The pandemic has created new jobs-housing needs and preferences (Lei and Liu, 2022). For example, since the pandemic people have become more aware of health issues and may need more natural amenities near their homes; people who work from home may want to improve their living environment as they will be spending more time at home. In short, COVID-19 may have introduced stress factors in people's current jobs-housing locations, and may have created new jobs-housing requirement. This "push-pull" situation may lead to jobs-housing relocations.

On home relocation patterns, people may try to lower health risks or avoid immobility by moving to safer and less controlled

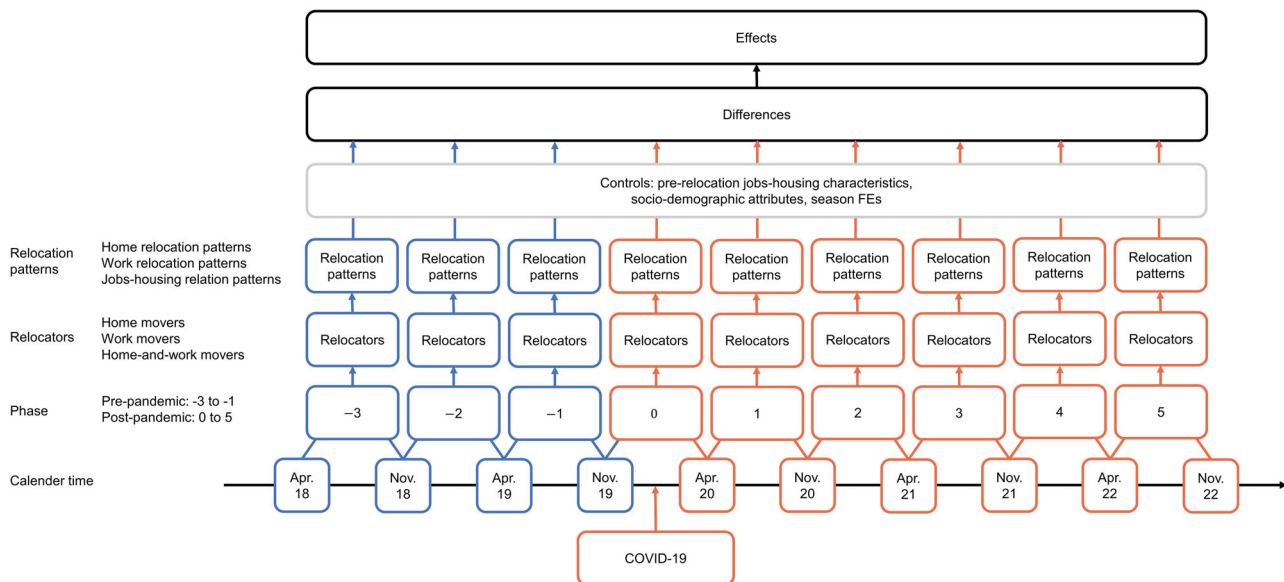


Fig. 1 Research design. This figure shows the event study research design.

environments in the short term (Dorsey, 2020; Liu and Su, 2021; Stawarz et al., 2022). Since the notion of viruses spreading quicker in densely populated areas is prevalent, the pandemic may have driven people out, making them relocate farther from the city centre for a better (presumably healthier and freer) living environment (Liu and Su, 2021; Lei and Liu, 2022). In the long term, people may keep suburbanizing. Another possibility is that during the pandemic, some groups of people made efforts to reduce the distance and frequency of their daily trips, and preferred active travel modes such as walking and biking to avoid infection (Shaw, 2020; Bohman et al., 2021; Bagdatli and Ipek, 2022); after strict control policies are lifted and the city centre is no longer highly contagious, these people may actually prefer a convenient “on-the-grid” life near the city center. Therefore, we propose Hypothesis H1a and H1b respectively for the kinds of two reactions. If H1a holds, we may have a more compact post-pandemic city, while if H1b holds, we may be looking at faster suburbanisation in the post-pandemic era.

H1a: After the pandemic, if relocators respond to increased public health risks by shortening their daily trips, then home locations will gather inwards relatively, i.e., conditional on all control variables, the pre-post-relocation change in home ring position of post-pandemic relocations will negatively deviate from that of pre-pandemic relocations.

H1b: After the pandemic, if relocators respond to increased public health risks by moving to low-risk areas, then home locations will spread outwards relatively, i.e., conditional on all control variables, the pre-post-relocation change in home ring position of post-pandemic relocations will positively deviate from that of pre-pandemic relocations.

On work relocation patterns, the adverse effects of the pandemic on the labour market imply that for many workers, employment changes may not result in ideal jobs. Since high-quality jobs are located mainly in business centres closer to the city centre (for example the central business district), their new work locations may be further away from the city centre, if they are able to find reemployment. There are also many workers who chose or were required to telework from home. As these workers stopped commuting, the workplace spatial distribution would be more dispersed. Therefore, we propose Hypothesis H2. If H2 holds, then employment will be more decentralised in the post-pandemic city.

H2: After the pandemic, relocators will be subject to adverse economic environment; thus, work locations will spread outwards relatively, i.e., conditional on all control variables, the pre-post-relocation change in work ring position of post-pandemic relocations will positively deviate from that of pre-pandemic relocations.

On jobs-housing relation patterns, the jobs-housing relationship depends on how both home locations and work locations are moved. The pandemic may accelerate or decelerate jobs-housing separation, thus we propose two opposite Hypotheses H3a and H3b. If H3a holds, there will probably be a better jobs-housing balance and fewer carbon emissions after the pandemic, while if H3b holds, the post-pandemic city may have more congestion problems and produce more carbon emissions.

H3a: After the pandemic, jobs-housing separation will decelerate relatively, i.e., conditional on all control variables, the pre-post-relocation change in commute time of post-pandemic relocations will negatively deviate from that of pre-pandemic relocations.

H3b: After the pandemic, jobs-housing separation will accelerate relatively, i.e., conditional on all control variables, the pre-post-relocation change in commute time of post-pandemic relocations will positively deviate from that of pre-pandemic relocations.

Empirical models. Empirical models estimated include velocity models and acceleration models, which are both based on the event study design (Dobkin et al., 2018).

The velocity models are as follows. Δy_{ij} is the dependent variable for commuter i in phase j , X_{ij} is a set of control variables and γ_j represents the seasonal fixed effect. The key coefficient M_j is the coefficient of dummy variable J which takes the value 1 for post-pandemic observations in and before phase J and 0 for pre-pandemic observations. M_j captures the post-pandemic deviance of Δy from its pre-pandemic state $\overline{\Delta y}_{pre-pandemic}$ during $J+1$ post-pandemic phases from 0 to J . The sum of M_j and the pre-pandemic mean of the dependent variable $\overline{\Delta y}_{pre-pandemic}$, Δy_j can be interpreted as the average velocity of change caused by relocation in y during $J+1$ post-pandemic phases from 0 to J ; hence, they are velocity models. For any given relocator group and dependent variable there were six velocity models estimated ($J=0, \dots, 5$).

For observations in and before phase J :

$$\Delta y_{ij} = M_j + \beta X_{ij} + \gamma_j + \varepsilon_{ij}, J = 0, \dots, 5 \quad (1)$$

The acceleration models are as follows. Δy_{ij} is the dependent variable for commuter i in phase j , X_{ij} is a set of control variables and μ_j represents the seasonal fixed effect. The key coefficients μ_j s are the coefficients of dummy variables js which take the value 1 for observations in phase j and 0 for observations in phases other than j . μ_j captures the post-pandemic deviance of Δy from its pre-pandemic state $\overline{\Delta y}_{pre-pandemic}$ in post-pandemic phase j . The sum of μ_j and the pre-pandemic mean of the dependent variable $\overline{\Delta y}_{pre-pandemic}$, Δy_j can be interpreted as the average velocity of change caused by relocation in y in phase j , or the rate of change in Δy_j in phase j ; hence, they are acceleration models. For any given relocator group and dependent variable one acceleration model was estimated.

For observations in all phases :

$$\Delta y_{ij} = \sum_{j=0}^5 \mu_j + \beta X_{ij} + \gamma_j + \varepsilon_{ij} \quad (2)$$

In the above models, the dependent variable is one of the relocation patterns of interest: Δt , Δr^h , Δr^w , Δp , $\Delta dens$, Δpt , $\Delta kind$, Δpri , Δmid , Δmed or $\Delta green$. For control variables, we include sociodemographic attributes and pre-relocation jobs-housing characteristics to remove potential differences in pre-relocation tendencies among relocators from each phase. Sociodemographic control variables available are gender *gender*, age *age* and affluence index *sp*. Based on previous research (Henderson and Ioannides, 1989; Gober and Reid, 1991; Deurloo et al., 1994; Huang and Dijst et al., 2018; Yang et al., 2019; Liu and Yu et al., 2021) we use pre-relocation commute time t^0 (representing commute lengths), pre-relocation home and work point positions in Beijing's ring road system r^{h0} and r^{w0} (representing commute direction and spatial distribution of workplaces and residences), pre-relocation housing price p^0 , population density of home location $dens^0$, accessibility of public transit pt^0 , schools $kind^0$, pri^0 and mid^0 , healthcare med^0 and green spaces $green^0$ of home location (representing neighbourhood features) to control for pre-relocation jobs-housing characteristics. To understand different income groups' reactions to the pandemic, we divided the sample by the median of affluence index 6 into middle income (affluence index < 6) and high income (affluence index ≥ 6).

Case city. This study used Beijing as a case city to examine the effects of COVID-19 on intra-urban jobs-housing relocation behaviours (Fig. 2).

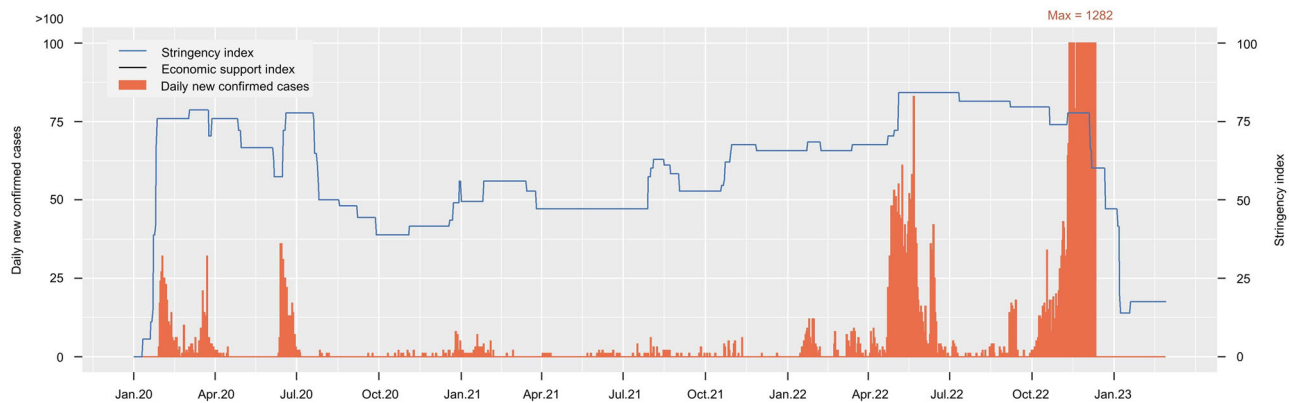


Fig. 2 Strictness of lockdown policies and the course of COVID-19 in Beijing. This figure shows the daily new confirmed cases and a policy stringency index for Beijing from Jan. 2020 to Jan. 2023.

At the start of the pandemic, Beijing initiated the first-level Public Health Emergency Response (PHER) on 24th January 2020 as a response to the nationwide outbreak. Many businesses, workplaces and public spaces were closed, residents were encouraged to quarantine at home and large portions of commuters worked from home; intra-urban travel was mainly limited to essential trips, masks were required in public spaces and a Beijing Health Code digital system was created and used for monitoring people's COVID-19 infection risk based on spatio-temporal trajectories; and infected individuals received treatment separately from other patients in several government-designated hospitals, while mandatory quarantine at designated quarantine sites or private residences was required for close contacts. The initial wave of COVID-19 was under control by April 2020.

Between the second half of 2020 and the second half of 2021, the course of the pandemic was relatively stable, with more new cases appearing in winter. Control policies during this period were similar to those in the initial period, but they were adjusted in accordance with the number of new cases and loosened in general: most public places resumed offline activities, intra-urban travel gradually resumed, and commuters worked on-site except for occasional interruptions when, for example, a colleague was infected.

Around the first half of 2022, pandemic control policies gradually tightened again. In May 2022, a large wave of infections occurred, and control measures were further tightened. Residents were further required to take nucleic acid tests regularly, and in addition to a green Beijing Health Code, a negative test result within 3 days was also required for permission to enter public places. This strict policy lasted till the end of 2022.

In Dec. 2022, nucleic acid tests and Beijing Health Code requirements, separate treatment for the infected and mandatory quarantine for close contacts were removed, and the Beijing Municipal Health Commission stopped reporting data on COVID-19 infection. On 26 December 2022, the National Health Commission downgraded COVID-19 to Class B-B, marking the end of government-level mass control of the COVID-19 pandemic in China. As of Jan. 2023, all COVID-related restrictions were removed. Due to the rapid loosening of preventive policies and the resulting rebound in travel, a large wave of infections broke out from Dec. 2022 to Jan. 2023 and gradually died down in Feb. 2023.

Methodology: data and sampling

Datasets

Cellular signalling data. We obtained 10 months (Apr. 2018, Nov. 2018, Apr. 2019, Nov. 2019, Apr. 2020, Nov. 2020, Apr. 2021, Nov. 2021, Apr. 2022, and Nov. 2022) of cellular signalling data

for Beijing from one of the three mobile networks operators in China. For each month, approximately 2 million users were recorded in the dataset. In addition to timestamped location data (location coordinates were calculated using cell tower triangulation by the operator) and basic sociodemographic attributes (starting from Sept. 2010, real-name registration became a mandatory requirement for mobile phone users in Beijing; thus, service providers are able to obtain these data), an affluence index dataset was also available (affluence indices were calculated based on users' online and offline activity information). The detailed data structure is shown in Supplementary Fig. S1.

Spatial data. The spatial data used in this study include a map of Beijing (within the sixth ring road) and the spatial distribution of population density, housing price, public transport stations, schools, medical facilities, and green spaces (Fig. 3).

We first divided the area within Beijing's sixth ring road into $1.5 \text{ km} \times 1.5 \text{ km}$ uniform grids. Then we intersected the grids with point of interest (POI) data for transport stations, schools and medical facilities to create 0–1 variables: grids that contain one or more certain type of facility points were assigned a value of 1, and grids that do not contain a certain type of facility were assigned a value of 0. We calculated population density based on the uniform grid using cellular signalling data of Nov. 2019 and district-level data from the 2020 Seventh National Population Census of China. We also intersected the grids with green space boundaries data and calculated the area percentage of green space in each grid. We took the average property resale price within each grid as the housing expenditure in each grid. The above process resulted in a grid attribute dataset.

The 2020 Seventh National Population Census of China dataset used to calculate population density was obtained from Office of the Leading Group of the State Council for the Seventh National Population Census (2020). Property resale prices used to calculate housing prices were gathered from Lianjia (2010) in Dec. 2021.

Other data. Commute length is of key interest in our study. We used commute time (t) to measure commute length between the centroids of each pair of grids. It was estimated with Baidu RouteMatrix API v2.0 (Baidu Maps Open Platform, 2012). The required inputs of this estimation method include longitudes and latitudes of origin and destination (OD) points, travel mode and tactics. We used the coordinates of grid centroid points for OD points, "driving" for travel mode, and "shortest route" for tactics. Computation was carried out in Mar. 2023 during Beijing's workday evening rush hours (between 17:00 and 19:00). The above process resulted in a dataset of shortest route distances and corresponding travel times during rush hours for each grid pair.

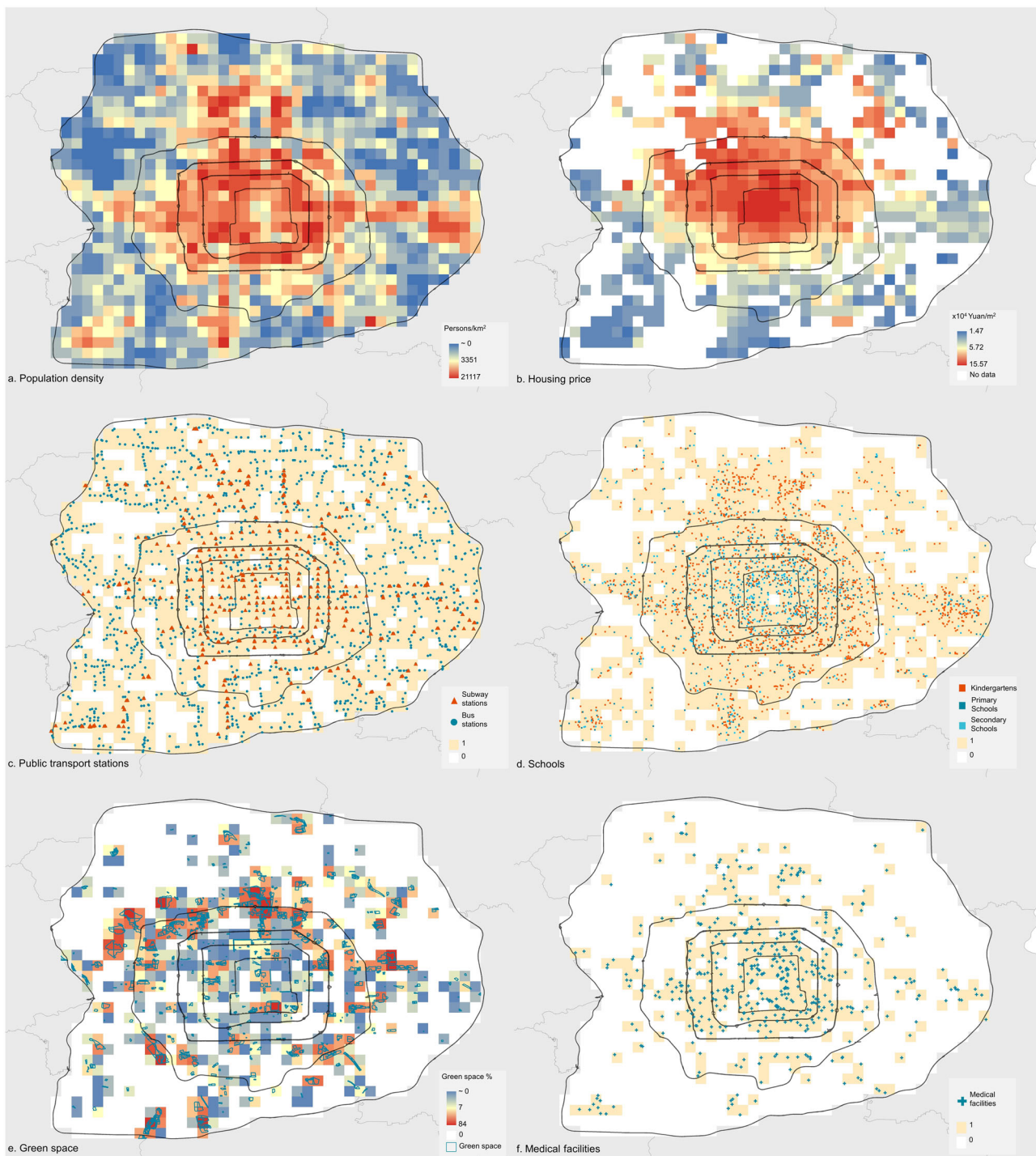


Fig. 3 Spatial data. This figure shows the spatial data used for analysis, including the spatial distribution of population density **a**, housing price **b**, public transport stations **c**, schools **d**, green spaces **e**, and medical facilities **f**.

To measure the dynamics of government response policies towards COVID-19, we used the Oxford Covid-19 Government Response Tracker. In particular, the stringency index that recorded “the strictness of ‘lockdown style’ policies that primarily restrict people’s behaviour” was used (Fig. 2) (Hale et al., 2021). This index ranges from 0 to 100, and the higher the index value, the stricter the control policies.

The COVID-19 infection data of Beijing from Jan. 2020 to Jan. 2023 was obtained from the Beijing Municipal Health Commission (2018) and supplemented by other online sources (Beijing Bendibao, 2004).

Sampling and data processing

Sampling. The sampling process of the current study is as follows. For each phase: (1) select continuous core users aged between 25 and 54 who are included in both the start and end months of the data; (2) identify home and work locations for users in the sample from Step (1), and select users whose home and work locations are successfully identified; (3) select users whose home and work locations are within the 6th ring road of Beijing from Step (2); (4) select regular commuters (home and work locations are not the same in both start and end months), used-to-commuters (home and work locations are not the same in the start month but are

the same in the end month, i.e. commuters who stop commuting) and about-to commuters (home and work locations are the same in the start month but are not the same in the end month, i.e. non-commuters who start commuting) from Step (3), and determine their jobs-housing relocation types: stayers, home movers, work movers, and home-and-work movers.

Note that in Step (4), if the straight-line distance between two points was less than 1.5 km, they were considered the same location. The threshold value of 1.5 km is derived from the notion of the 15-min life circle in urban planning practices. Planners are striving to create neighbourhoods that provide the most amenities within a 15-min walk. In this sense, two places more than 15 minutes (or 1.5 km if walking speed is assumed to be 1.6 m/s) apart may not belong to the same neighbourhood; therefore, we consider them to be different locations.

The home and work locations of users were detected based on stay times and a working-resting timeframe (Phithakkitnukoon et al., 2012; Kung et al., 2014; Yan et al., 2019). The working hours were from 9:00 to 17:00 on working days, and the resting hours were from 21:00 to 5:00 the next day¹. For each user month, we calculated every monthly stay POI's stay time during working hours and resting hours on workdays. We then identified the monthly stay POIs that had the largest total stay time during working and resting hours respectively. If the user's stay time at the place where he/she stayed the longest during workday working hours or resting hours was greater than half his/her total

stay time during workday working hours or resting hours, and his/her day and night combined online rate (user's total stay time/ total hours of the month) was greater than the median of the day and night combined online rate of the month, then this place was identified as the user's work or home location of the month.

Data processing. After selecting the appropriate sample, we joined the sample with the monthly user information table for each month and the affluence index table for Nov. 2019 from our cellular signalling data. Note that the farther away the month from Nov. 2019, the less the monthly user population overlaps with Nov. 19, and fewer users were matched with affluence index data in later phases. We used a Naive Bayesian algorithm to fill in missing affluence index based on gender, age, monthly fee, housing price, and ring positions of home and work places. We replaced users' work and home coordinates with the grid ID number to which they belonged, and we joined them with our grid attribute dataset and grid pair commute length dataset. On average 363546 users were selected for each phase in our final sample, and the pooled final sample contains 3271918 users. The variables in our final dataset used in the analysis are shown in Supplementary Table S1.

Sample composition and group traits. The size and composition of our final sample are shown in Fig. 4 and Table 1. The sample size for each phase is between 316119 and 450113. The average proportions

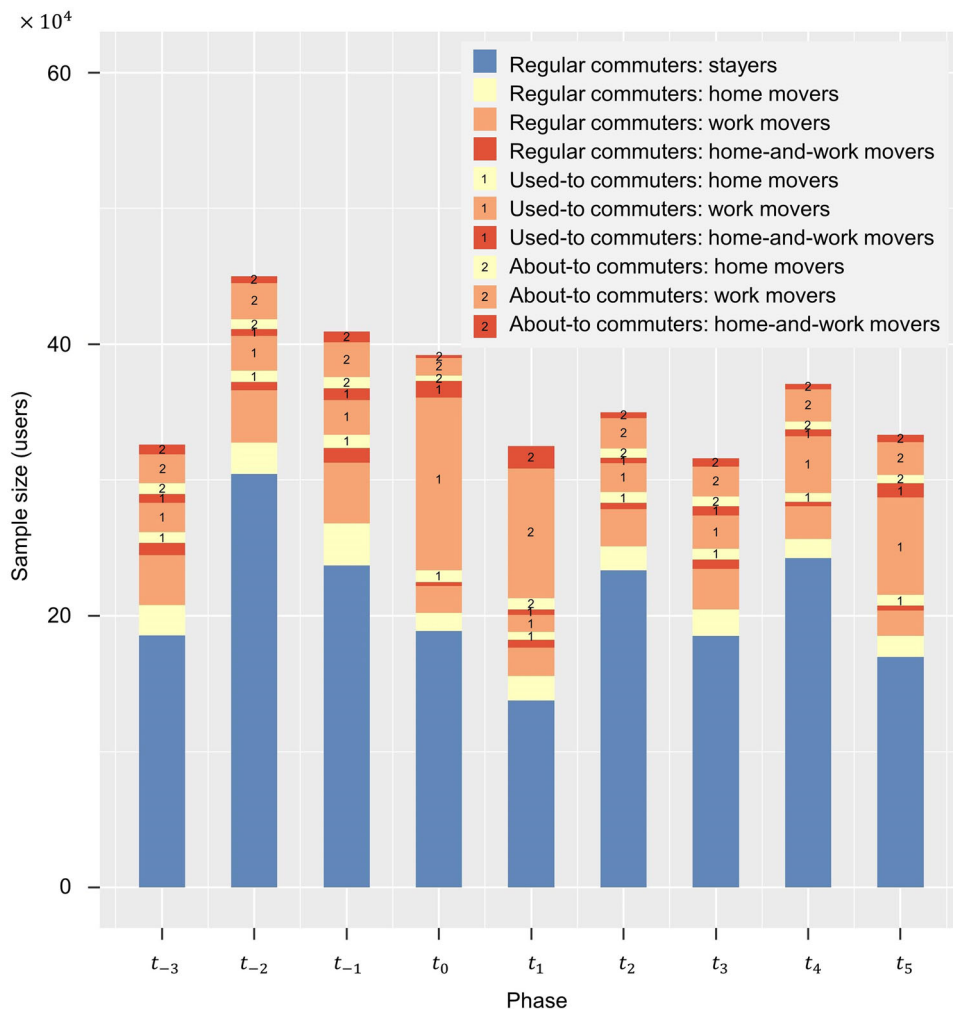


Fig. 4 Size and composition of the final sample. This figure shows the monthly sample size and the proportions of relocators (home movers, work movers, and home-and-work movers in regular commuters, used-to commuters and about-to commuters) in each month.

Table 1 Sample composition.

Phase	Commuter groups									Total sample size	
	Regular commuters			Used-to commuters			About-to commuters				
	Stayers	Home movers	Work movers	Home-and-work movers	Home movers	Work movers	Home-and-work movers	Home movers	Work movers		Home-and-work movers
t_{-3}	185666 (57%)	22380 (6.9%)	36686 (11.3%)	9045 (2.8%)	7782 (2.4%)	21584 (6.6%)	6584 (2%)	7784 (2.4%)	21502 (6.6%)	6919 (2.1%)	325932 (100%)
t_{-2}	304383 (67.6%)	23195 (5.2%)	38617 (8.6%)	6108 (1.4%)	8248 (1.8%)	25421 (5.6%)	4998 (1.1%)	7391 (1.6%)	26443 (5.9%)	5309 (1.2%)	450113 (100%)
t_{-1}	237007 (57.9%)	30986 (7.6%)	44810 (11%)	10779 (2.6%)	9589 (2.3%)	25784 (6.3%)	8384 (2%)	8301 (2%)	25584 (6.3%)	7896 (1.9%)	409120 (100%)
t_0	188664 (48.1%)	13446 (3.4%)	19879 (5.1%)	2768 (0.7%)	8669 (2.2%)	127319 (32.5%)	11995 (3.1%)	4243 (1.1%)	12862 (3.3%)	2087 (0.5%)	391932 (100%)
t_1	137826 (42.4%)	17897 (5.5%)	20784 (6.4%)	5671 (1.7%)	6001 (1.8%)	12665 (3.9%)	3724 (1.1%)	8378 (2.6%)	95384 (29.4%)	16574 (5.1%)	324904 (100%)
t_2	233459 (66.7%)	17807 (5.1%)	27358 (7.8%)	4616 (1.3%)	7945 (2.3%)	21056 (6%)	4269 (1.2%)	6732 (1.9%)	22163 (6.3%)	4489 (1.3%)	349894 (100%)
t_3	185333 (58.6%)	19419 (6.1%)	29697 (9.4%)	6995 (2.2%)	8090 (2.6%)	24356 (7.7%)	6739 (2.1%)	7159 (2.3%)	21910 (6.9%)	6421 (2%)	316119 (100%)
t_4	242461 (65.4%)	14110 (3.8%)	24262 (6.5%)	3185 (0.9%)	6429 (1.7%)	41687 (11.2%)	5279 (1.4%)	5516 (1.5%)	23878 (6.4%)	3857 (1%)	370664 (100%)
t_5	169701 (50.9%)	15489 (4.6%)	18839 (5.7%)	3525 (1.1%)	7772 (2.3%)	71848 (21.6%)	10452 (3.1%)	5977 (1.8%)	24429 (7.3%)	5208 (1.6%)	333240 (100%)

Table 2 Sample socioeconomic characteristics and jobs-housing features.

Group	Type	Male %	Average age, years	Average sp	Average t^0 , min
Regular commuters	Stayers	57.347	35.719	5.677	39.074
	Home movers	58.388	33.174	5.600	42.582
	Work movers	60.288	33.788	5.576	44.316
	Home-and-work movers	61.901	31.938	5.401	41.587
Used-to commuters	Home movers	59.546	35.166	5.468	32.654
	Work movers	53.211	35.706	5.619	38.441
	Home-and-work movers	56.067	34.494	5.459	37.370
About-to commuters	Home movers	59.318	35.098	5.495	—
	Work movers	53.592	35.807	5.590	—
	Home-and-work movers	58.017	33.946	5.401	—

of stayers, home movers, work movers, and home-and-work movers across phases are 57.2%, 9.4%, 28.0%, and 5.4% respectively. Note that the proportion of work movers is large because during the pandemic many people teleworked from home.

Socioeconomic characteristics and jobs-housing features of all commuter groups are shown in Table 2 and Fig. 5. In regular commuters, stayers are the oldest and the most affluent group, and they have the shortest commutes among regular commuter groups, indicating that they have probably established relatively stable quality residences and jobs in Beijing (Huang and Levinson et al., 2018). Therefore, they are likely to be middle-to-high income residents in stable stages of life. Home-and-work movers are the youngest and least affluent regular commuter group, and they have medium-length commutes, meaning that they are probably young workers or immigrants who are experiencing an unstable stage of life and still trying to improve their jobs-housing arrangements. Home movers and work movers are younger than stayers and older than home-and-work movers, and their average affluence indexes are lower than stayers and higher than job-housing relocators. Home movers have similar medium-length commutes to home-and-work movers. They are probably an upcoming group of young-to-middle-aged workers who have stable jobs and are seeking to optimise their housing conditions. Their reasons for relocation might include finding better education for children, improving living conditions, upgrading to ownership, etc. Work movers have the longest commutes among regular commuter groups. Unlike home-and-work movers, they might be an upcoming group

who have established stable residences in cheaper areas, which explains their long commutes and relatively low housing expenditures. Their relocation motives may be upward mobility in career, working environment improvement, etc.

In used-to commuters and about-to commuters, work movers are the oldest and the most affluent group, indicating that they are probably middle-to-high income stable residents similar to stayers in regular commuters, but started to work from home/were returning to the workplace after working from home, or were laid off/found suitable employment after being laid off. Home movers are also older but not affluent, and they have short pre-relocation commutes, meaning that they may be migrant workers who decided to live near or in their workplace to further shorten their commutes/who were forced to move away (evicted, for example) or chose to move to take care of family etc. Home-and-work movers are comparably young and are not affluent, meaning that they are probably middle-to-low income migrant workers who were laid off/who found reemployment.

Results

The effects of COVID-19 on home relocation. The differences in home relocation patterns between post-pandemic and pre-pandemic home relocations are presented in Figs. 6–8. The sample studied here consists of all home relocators, i.e. home movers and home-and-work movers in regular commuters, used-to commuters and about-to commuters ($n = 480,611$).

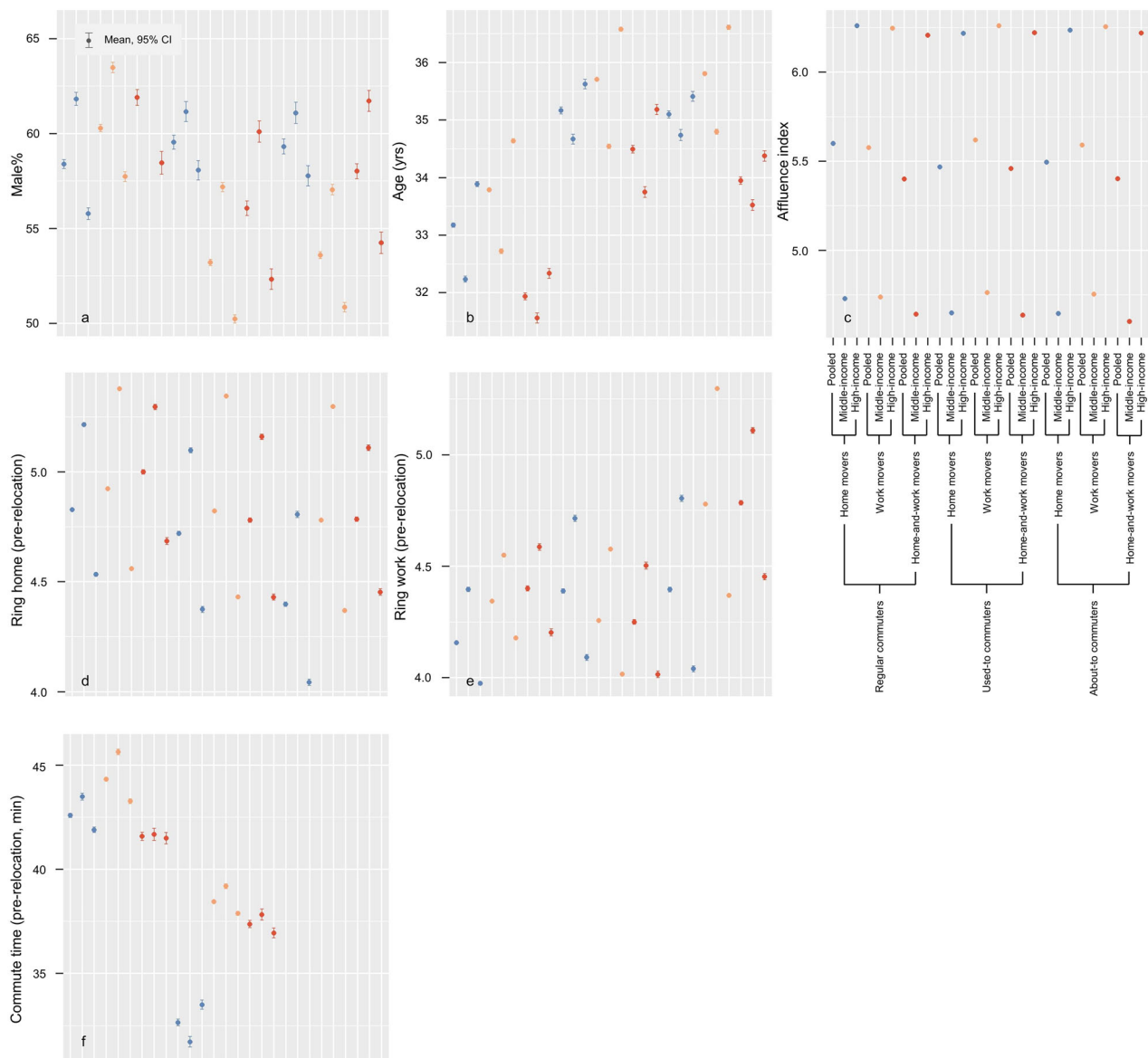


Fig. 5 Sociodemographic and jobs-housing differences between middle-income and high-income relocators. This figure shows the sociodemographic characteristics and the jobs-housing characteristics of home movers, work movers, home-and-work movers in regular commuters, used-to commuters and about-to commuters and their middle-income and high-income subgroups. **a** male percentage, **b** age, **c** affluence index, **d** home position in the ring road system of Beijing, **e** work position in the ring road system of Beijing, **f** commute time.

It seems that although there was an outward flight directly after the outbreak (Phase 0), the pandemic has slightly pushed residents inwards: in the post-pandemic era (Phases 1 to 5), Δr^h_j swiftly dropped below its pre-pandemic level, holding at approximately 0.05, reflecting a mild suburbanisation trend (Fig. 6a). The high $\Delta r^h_j = 0.22$ in Phase 0 captures people’s initial response to the pandemic, and it corresponds to people escaping to suburban temporary or second homes to avoid the spread of the virus in the inner city. As time passes, this wave of outward relocation is not persistent for the whole sample of home relocators.

However, there are structural changes hidden under this steady overall spatial pattern of home relocations. Although both middle-income ($n = 224,556$) and high-income ($n = 256,055$) home relocators Δr^h_j come to indicate a mild suburbanization at the end of the post-pandemic era (Phase 5), their pre-pandemic starting points are considerably different: middle-income home relocators display a strong suburbanisation trend pre-pandemic, and this trend is significantly decreased post-pandemic;

high-income home relocators do not have a visible suburbanization trend pre-pandemic, and after the pandemic they developed a mild suburbanisation trend (Fig. 6b, c). Empirical results show that the post-pandemic deviations of Δr^h_5 from the pre-pandemic mean of Δr^h , i.e., M_{5s} , are -0.11 and $+0.06$ for middle-income and high-income home relocators respectively, and these changes are persistent (Phases 1 to 5). This means that after the pandemic, high-income home relocators join the suburbanisation wave, and middle-income home relocators are no longer the major contributors to suburbanisation in this city.

To examine the changes in housing characteristics among different income groups, we analysed the pre-post-relocation changes in housing features. For middle-income home relocators (Fig. 7), empirical results show that their post-pandemic Δpri_j , Δmid_j and Δmed_j significantly positively deviated from pre-pandemic means ($p < 0.001$ for Phases 1 to 5), while the relative increase in change velocity for other service accessibilities (Δpt_j , $\Delta kind_j$, and $\Delta green_j$) are less obvious. For high-income

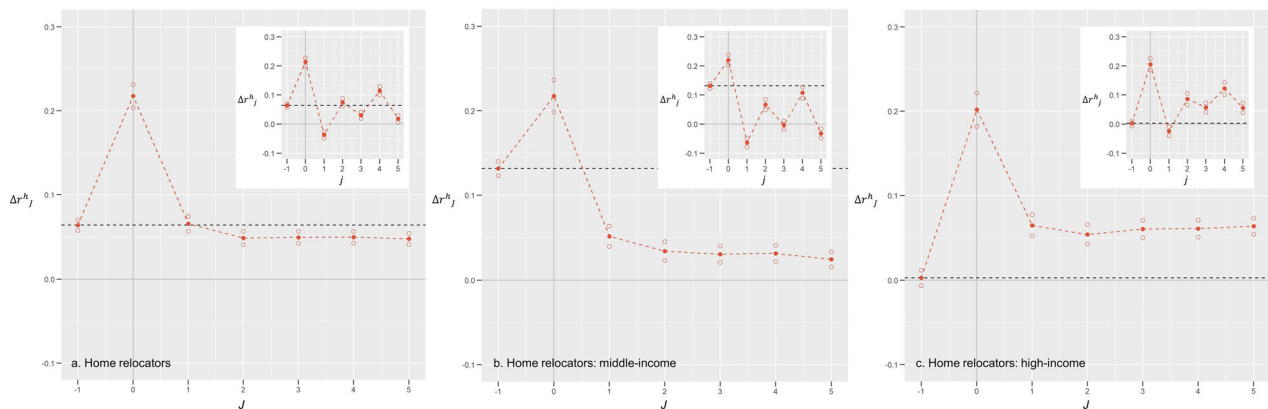


Fig. 6 The effects of COVID-19 on home relocation. This figure shows the post-pandemic change in pre-post-relocation home ring position change relative to pre-pandemic level for all home relocators (including home movers and home-and-work movers) **a**, middle-income home relocators **b** and high-income home relocators **c**. The main graphs show the results of “velocity” models ($\Delta y_j = M_j + \overline{\Delta y}_{pre-pandemic}$). The small graphs embedded in the main graphs show the results of “acceleration” models ($\Delta y_j = \mu_j + \overline{\Delta y}_{pre-pandemic}$). Dashed black lines show pre-pandemic means, dashed red lines and solid red dots show post-pandemic deviations, and hollow red dots show the 90% confidence intervals of post-pandemic deviations.

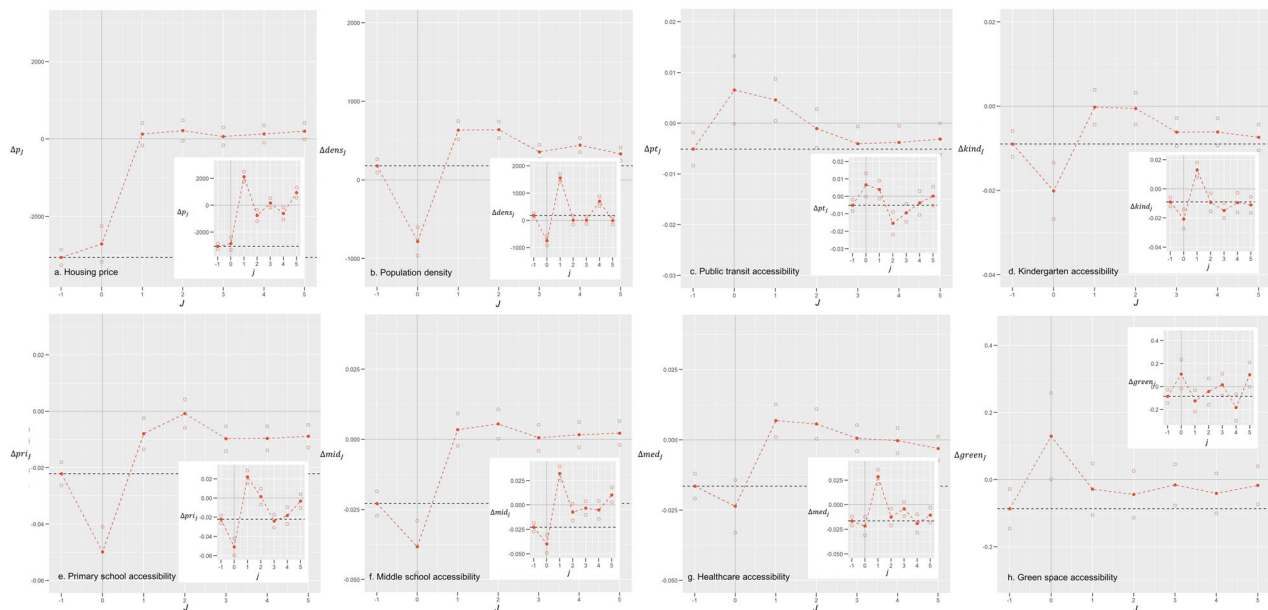


Fig. 7 Motives for home relocation in middle-income home relocators. This figure shows the post-pandemic change in pre-post-relocation housing price change **a**, home location population density change **b**, public transit accessibility change **c**, kindergarten accessibility change **d**, primary school accessibility change **e**, middle school accessibility change **f**, healthcare accessibility change **g** and green space accessibility change **h** relative to pre-pandemic level for middle-income home relocators. The main graphs show the results of “velocity” models ($\Delta y_j = M_j + \overline{\Delta y}_{pre-pandemic}$). The small graphs embedded in the main graphs show the results of “acceleration” models ($\Delta y_j = \mu_j + \overline{\Delta y}_{pre-pandemic}$). Dashed black lines show pre-pandemic means, dashed red lines and solid red dots show post-pandemic deviations, and hollow red dots show the 90% confidence intervals of post-pandemic deviations.

home relocators (Fig. 8), empirical results show that for all kinds of public service facilities studied, the post-pandemic change velocities of accessibility (Δpt_j , $\Delta kind_j$, Δpt_j , Δpri_j , Δpt_j , Δmid_j , Δmed_j , $\Delta green_j$) negatively deviated from pre-pandemic means, which may be a direct result of the relative increase in Δr^h_j . In short, H1a holds for middle-income home relocators, while H1b holds for high-income home relocators.

The effects of COVID-19 on work relocation. The differences in work relocation patterns between post-pandemic and pre-pandemic work relocations are presented in Fig. 9. The sample studied here consists of all work relocators, i.e., work movers and home-and-work movers in regular commuters, used-to-commuters and about-to-commuters ($n = 1,080,683$).

As expected, there is a significant outward scatter directly after the pandemic outbreak (Phase 0, $\Delta r^w_0 = 0.42$, $p < 0.001$), and although Δr^w_j dropped to near pre-pandemic level in phase 2, it started to climb again after phase 2 (Fig. 9a). Before the pandemic $\overline{\Delta r^w}_{pre-pandemic} = 0.08$, reflecting a mild trend of employment decentralisation due to increasing job offerings provided by high-tech employment subcentres in the suburbs. In Phase 0, Δr^w_j reached 0.42 probably because many employees in the inner-city business centres teleworked during the pandemic, or were laid off and had to seek (often less ideal and lower paid) employment elsewhere. The outward scatter of jobs is more persistent than the outward flight of residents: as of Phase 5, $\Delta r^w_j = 0.15$ is still significantly higher than the pre-pandemic value ($p < 0.001$). In short, H2 holds for work relocators, and group-

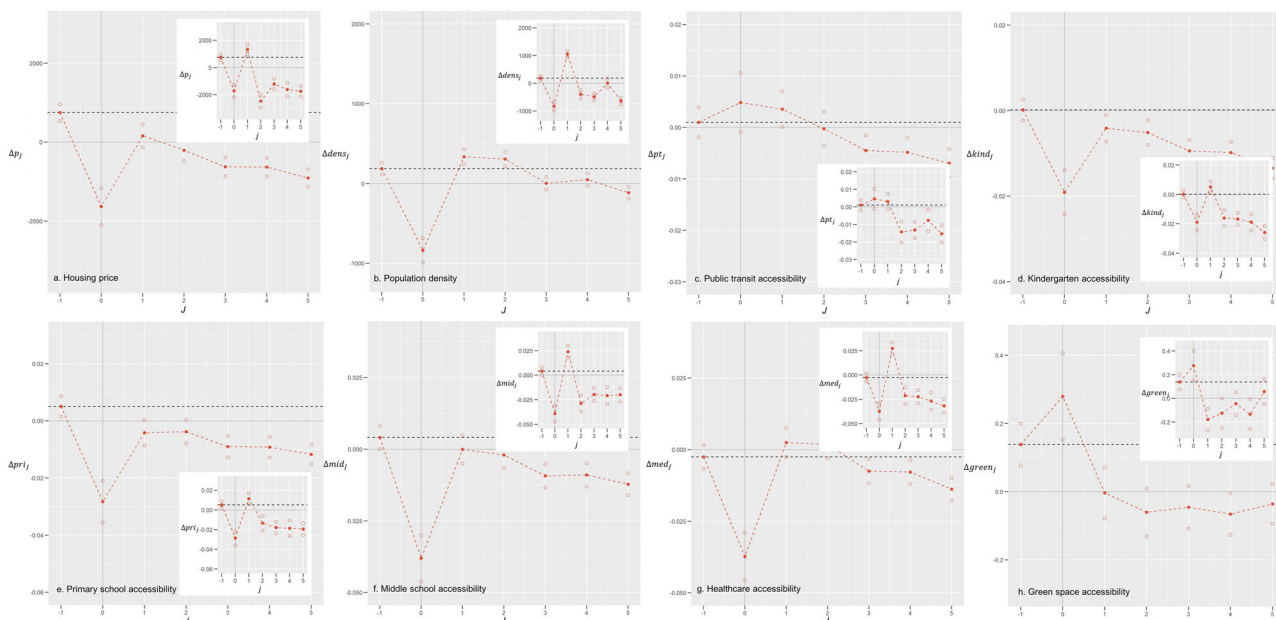


Fig. 8 Motives for home relocation in high-income home relocators. This figure shows the post-pandemic change in pre-post- relocation housing price change **a**, home location population density change **b**, public transit accessibility change **c**, kindergarten accessibility change **d**, primary school accessibility change **e**, middle school accessibility change **f**, healthcare accessibility change **g**, and green space accessibility change **h** relative to pre-pandemic level for high-income home relocators. The main graphs show the results of “velocity” models ($\Delta y_j = M_j + \overline{\Delta y}_{pre-pandemic}$). The small graphs embedded in the main graphs show the results of “acceleration” models ($\Delta y_j = \mu_j + \overline{\Delta y}_{pre-pandemic}$). Dashed black lines show pre-pandemic means, dashed red lines and solid red dots show post-pandemic deviations, and hollow red dots show the 90% confidence intervals of post-pandemic deviations.

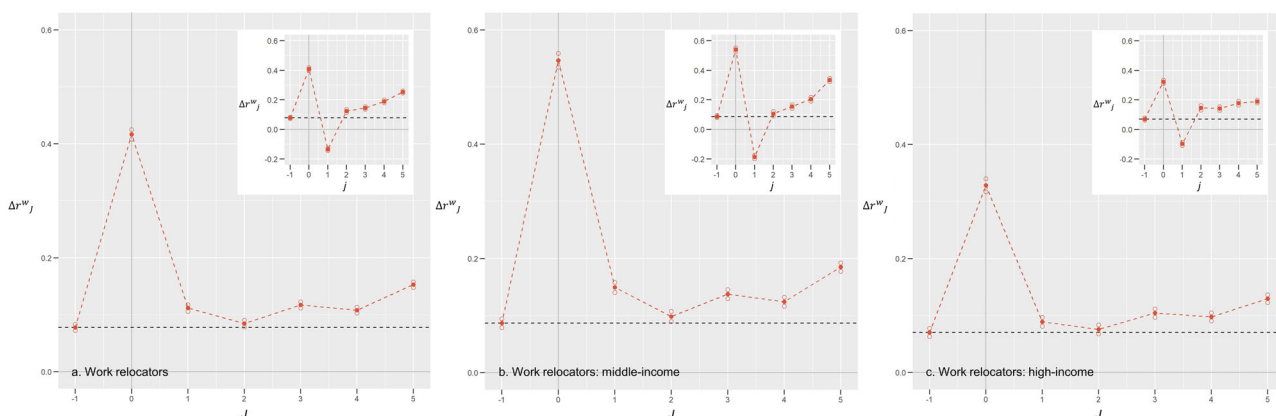


Fig. 9 The effects of COVID-19 on work relocation. This figure shows the post-pandemic change in pre-post- relocation work ring position change relative to pre-pandemic level for all work relocators (including work movers and home-and-work movers) **a**, middle-income work relocators **b**, and high-income work relocators **c**. The main graphs show the results of “velocity” models ($\Delta y_j = M_j + \overline{\Delta y}_{pre-pandemic}$). The small graphs embedded in the main graphs show the results of “acceleration” models ($\Delta y_j = \mu_j + \overline{\Delta y}_{pre-pandemic}$). Dashed black lines show pre-pandemic means, dashed red lines and solid red dots show post-pandemic deviations, and hollow red dots show the 90% confidence intervals of post-pandemic deviations.

wise analysis finds that the changes in work relocation spatial pattern of middle-income ($n = 483,281$) and high-income ($n = 597,402$) work relocators are quite similar (Fig. 9b, c).

The effects of COVID-19 on jobs-housing relation. The differences in jobs-housing relation outcome between post-pandemic and pre-pandemic work relocations are presented in Figs. 10 and 11. The sample studied here consists of all relocators, i.e., home movers, work movers, and home-and-work movers in regular commuters, used-to commuters and about-to commuters ($n = 1,387,418$).

Empirical results show that all relocators groups’ Δt_j s are negatively deviated from pre-pandemic values, meaning that the overall jobs-housing separation trend is decelerated (Fig. 11).

Consequently, all relocators appears to follow H3a (Fig. 10). Before the pandemic, all relocators’ jobs-housing on average have a slight reverse separation trend of $\Delta t_{pre-pandemic} = -27$ s; in the post-pandemic era (Phases 1 to 5) their Δt_j reached -424 s or 7 min (phase 5, $p < 0.001$). Group-wise analysis finds that home movers have a considerable reverse jobs-housing separation trend before the pandemic, while other groups do not have visible trends pre-pandemic; the groups most affected in the long term are middle-income home movers and high-income work movers.

Robustness. We estimated alternative specifications of the event study model, including models without seasonal fixed effect,

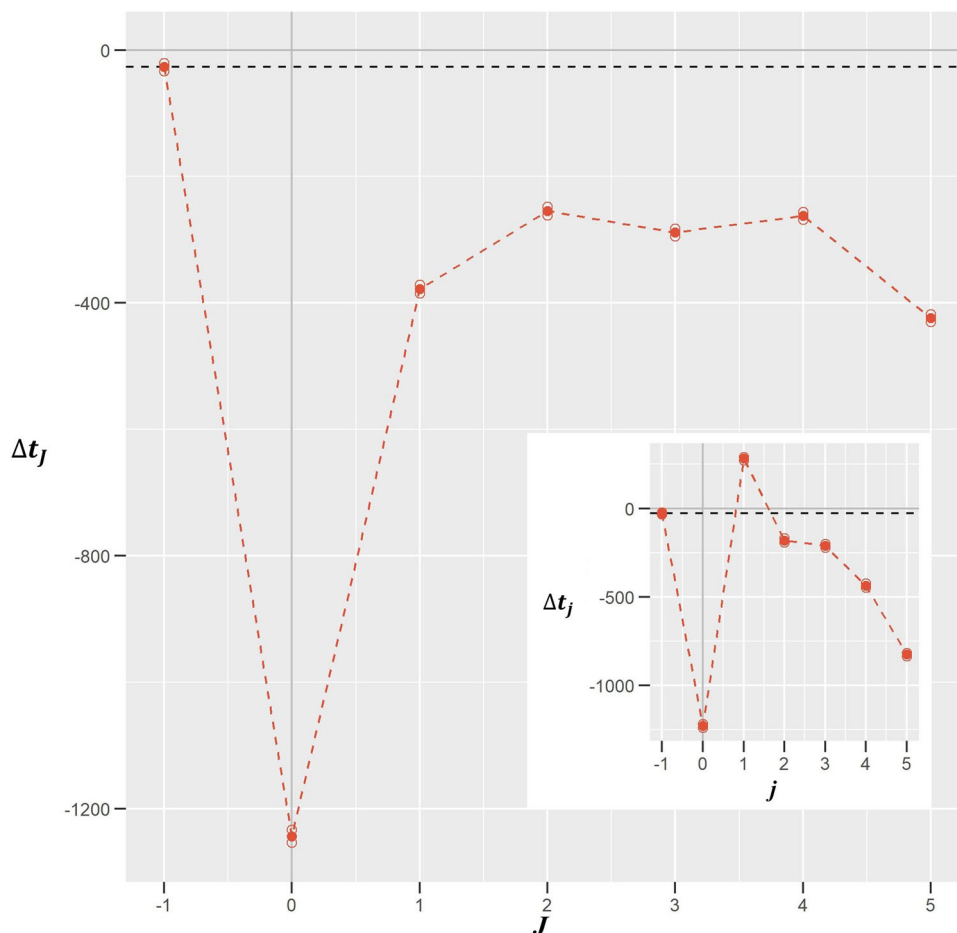


Fig. 10 The effects of COVID-19 on jobs-housing relation: whole sample. This figure shows the post-pandemic change in pre-post-relocation commute time change relative to pre-pandemic level for all relocators (including home movers, work movers, and home-and-work movers). The main graphs show the results of “velocity” models ($\Delta y_j = M_j + \Delta y_{pre-pandemic}$). The small graphs embedded in the main graphs show the results of “acceleration” models ($\Delta y_j = \mu_j + \Delta y_{pre-pandemic}$). Dashed black lines show pre-pandemic means, dashed red lines and solid red dots show post-pandemic deviations, and hollow red dots show the 90% confidence intervals of post-pandemic deviations.

models with individual weights applied, and Poisson regression models. The results are shown in Supplementary Table S2, which suggests that the results of the baseline models are generally robust.

Discussion

The present study examined the effects of the COVID-19 pandemic on intra-urban jobs-housing relocation behaviours using an event study approach covering a 4.5-year period and 3 million relocators over time. This section discusses the effects of the pandemic discovered by our analysis and the long-term implications for future urbanism, summarises the main contributions of this study, and discusses the limitations of this study.

The effects of COVID-19 on jobs-housing relocation and the Implications for future urbanism. Regarding home relocation, the pandemic slowed down the suburbanisation of middle-income residents but encouraged the suburbanisation of high-income residents. Before the pandemic, middle-income home relocators lived far from the city centre and tended to suburbanise: their pre-relocation residences are positioned within an average of 4.93 rings, and on average they move 0.13 rings/half-year away from the city centre ($\overline{\Delta r^h}_{pre-pandemic} = 0.13$). After the pandemic, their suburbanisation trend significantly decreased: on average they moved

0.02 rings/half-year away from the city centre ($\Delta r^h_5 = 0.02$, $p < 0.001$). This is probably related to more middle-income home relocators choose to move in for better public service accessibility (for example school and healthcare accessibility) to reduce infection risks during daily travel (for example for their children or elderly family members). However, the household composition of relocators are unknown to us, and although there is evidence that parents have concerns about their children getting infected in school (Godøy et al., 2022), we cannot say that they have the same concerns about infection risks during their children’s trips to and from school. Another possibility is that they moved in for better walkability. The pandemic has changed people’s travel mode choices (Bucsky, 2020), and increased active travel is found during the pandemic (Shaw, 2020; Bohman et al., 2021; Bagdatli and Ipek, 2022). Before the pandemic, high-income home relocators lived closer to the city centre than middle-income home relocators and did not have suburbanisation trends: their pre-relocation residences are positioned within an average of 4.51 rings, and on average they did not have notable movement trends towards or away from the city centre ($\overline{\Delta r^h}_{pre-pandemic} = 0.003$). After the pandemic, high-income home relocators took on a tendency of suburbanisation: on average they moved 0.06 rings/half-year away from the city centre ($\Delta r^h_5 = 0.06$, $p < 0.001$). This may also due to the intention to avoid infection. Scholars have found evidence of people renouncing the convenient live in the inner city in exchange for a low-density living

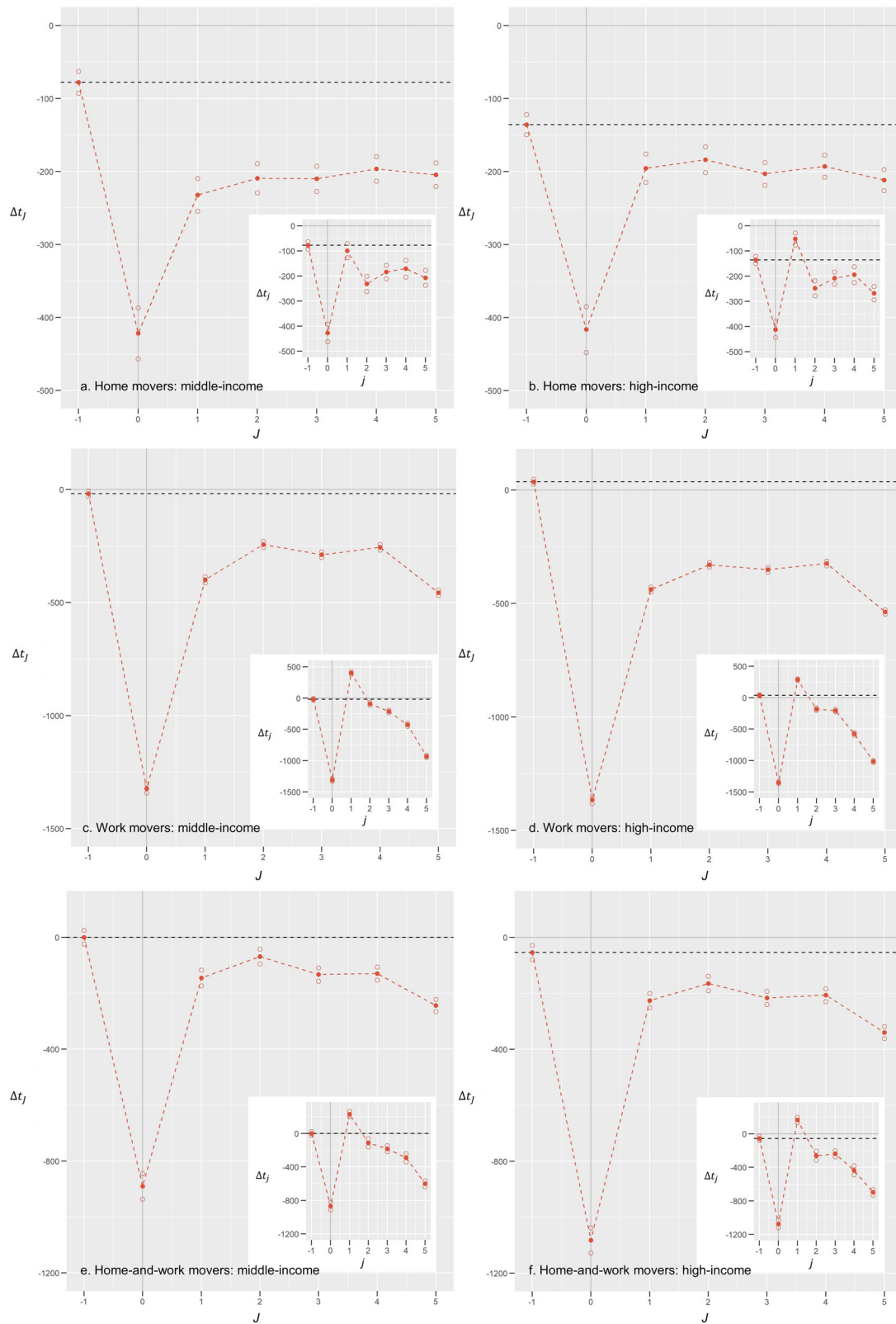


Fig. 11 The effects of COVID-19 on jobs-housing relation: group analysis. This figure shows the post-pandemic change in pre-post-relocation commute time change relative to pre-pandemic level for middle-income home movers **a**, high-income home movers **b**, middle-income work movers **c**, high-income work movers **d**, middle-income home-and-work movers **e**, and high-income home-and-work movers **f**. The main graphs show the results of “velocity” models ($\Delta y_j = M_j + \overline{\Delta y}_{pre-pandemic}$). The small graphs embedded in the main graphs show the results of “acceleration” models ($\Delta t_j = \mu_j + \overline{\Delta y}_{pre-pandemic}$). Dashed black lines show pre-pandemic means, dashed red lines and solid red dots show post-pandemic deviations, and hollow red dots show the 90% confidence intervals of post-pandemic deviations.

environment (Liu and Su, 2021). However, other reasons are also possible. For example, people undergone economic difficulties may move out for cheaper housing.

In the long run, the difference in home location preferences between middle-income residents and high-income residents may change the spatial structure of population distribution in the city. In the future, there will be relatively more middle-income home relocators and their families moving towards the city centre, while high-income home relocators and their families will be moving away from the city centre. Therefore, in contrast to the pre-pandemic situation where younger and less wealthy families moved out and older and wealthier families moved in, in the post-pandemic future, younger and less wealthy families will be swapping in while older and wealthier families will be swapping out. Consequently, the vibrance and energy of the inner city may be preserved as young parents and their children stop moving out.

Regarding work relocation, the pandemic accelerated the decentralisation of employment spatial distribution. Before the pandemic, employment had a mild decentralising tendency: on average work relocators moved their jobs 0.08 rings/half-year away from the city centre ($\overline{\Delta r^w}_{pre-pandemic} = 0.08$). This is because a few employment centres in the outer city are emerging, and some companies and enterprises located in the city centre are beginning to move out as well. After the pandemic, work relocators' work locations experienced a sudden outwards scatter: between Nov. 19 and Apr. 20 on average work relocators moved their jobs 0.42 rings/half-year away from the city centre ($\Delta r^w_0 = 0.42$, $p < 0.001$). This may be caused by the wave of commuters who stopped commuting and worked from home during the pandemic (Hensher et al., 2022). Another reason may be the adverse economic effects of the pandemic: the densely built inner city with more confirmed cases took a bigger hit than suburban employment centres, many businesses reduced staff or closed and workers had to find employment elsewhere. As of Nov. 22, the post-pandemic decentralising tendency of workplaces was still significantly stronger than before the pandemic ($\Delta r^w_5 = 0.15$, $p < 0.001$) and increasing. Compared with the outward flight of homes directly after the outbreak, the outward scatter of jobs is more persistent. This might be the reflection of a long-term increase in teleworking predicted by many scholars (Beck and Hensher, 2021; Jain et al., 2022). It could also be because job changes are generally more difficult than home moves, so workspace spatial distribution is stickier than home spatial distribution.

In the long run, the rate of workspace decentralisation may return to pre-pandemic level as the economy gradually recovers, or remain at an accelerated level due to increased teleworking. Either way, the outward scatter of work activities and accompanying demand for infrastructure may help small or temporary commercial centres to develop into larger or more permanent ones. Thus, there is a possibility of improving employment spatial distribution and accelerating the decline of the monocentric city structure.

Regarding the jobs-housing relation, surprisingly, the pandemic has improved jobs-housing balance in general. Before the pandemic, there was a mild trend of inverse jobs-housing separation: on average relocators' home and work locations moved 26.89 s/half-year together ($\overline{\Delta t}_{pre-pandemic} = -26.89$ s). After the pandemic, the combination of home relocation pattern changes and work relocation pattern changes has reinforced this trend: on average relocators' home and work locations moved 423.99 s/half-year together ($\Delta t_3 = -423.99$ s, $p < 0.001$), meaning that inverse jobs-housing separation is in general accelerating by 397.10 s/half-year.

In the long run, the general improvement in the jobs-housing balance will help to reduce urban traffic and transport carbon

emissions. A 397.10 s/half-year post-pandemic acceleration in inverse jobs-housing separation means that if there had been no pandemic, urban carbon emission caused by commuting would have included an extra 5055.08 t/half-year and urban carbon emissions caused by commuting in the past 3 years (from Nov. 19 to Nov. 22) would have been 3.03×10^4 t more, which is over a month's total transport carbon emission (Beijing's 2019 total carbon emission was 88×10^4 t, of which about 30% came from transportation; data sources: Carbon Emission Accounts & Datasets, 2016; Shan et al., 2017; Shan et al., 2018; Shan et al., 2019; Shan et al., 2022; Guan and Tian, 2019). This estimation is based on the assumption that there are approximately 20% of relocators among the city's working population (1273×10^4 persons in 2019; data source: Liu, 2022) every half-year, and that the average carbon emission per minute of motor vehicles is approximately 150 g. Therefore, if the rate of inverse jobs-housing separation can remain high, the post-pandemic future city may be greener and less congested.

Contributions and limitations. The contributions of this study are as follows. First, the present study is one of the first to examine the COVID-19 pandemic's effects on intra-city jobs-housing relocation reaching 3 years into the post-pandemic era. Research on similar topics often focused on the period directly after the pandemic outbreak, seldom reaching beyond 2020 (Liu and Pei et al., 2021). By estimating and comparing post-pandemic jobs-housing relocation pattern changes from Nov. 2019 to Nov. 2022, we are able not only to identify the pandemic's immediate effects, but also to discover its long-term effects and to demonstrate that these effects are persistent in the scale of years.

Second, the present study provides useful information regarding the post-pandemic urban jobs-housing spatial distribution and jobs-housing relationship for planners and policy makers. We found that the pandemic may have changed the course of urban restructuring (the development of population spatial distribution), and may have accelerated workspace decentralisation. We also found that the post-pandemic city may be greener and less congested due to an improvement in jobs-housing balance. In a word, although the pandemic has brought a widespread economic downturn, it may also have brought some favourable results regarding urban spatial structure through its effects on relocation. It is not the first time that a negative exogenous shock is found to have positive influence on human population. In economic epidemiology, scholars have found that economic depressions may reduce death rate (Ogburn and Thomas, 1923; Granados et al., 2014; Granados, 2015). Thereby, planners and policy makers should take the pandemic as an opportunity to improve the jobs-housing distribution and relationship in the city, rather than a setback in urban economy and development.

Third, the long-term changes in relocation patterns discovered in the present study can serve as a basis for parameter recalibration of post-pandemic urban simulation models. For example, simulations should probably take into consideration the need to shorten school trips for young parents in their home relocation decisions.

There are some limitations to this study. First, there may be other long-term influencing factors besides the pandemic in the study area and the study period. One long-term influencing factor is the welfare housing policies in Beijing. In 2018 and 2019, Beijing launched a limited competition housing policy, aiming to help middle and low-income families to purchase low-price housing. This policy led many low-to-middle-income families away from the city centre towards the near suburbs where the

limited competition housing is located. This low-price housing generally sold out around 2021. Therefore, we may have overestimated the pandemic's role in decelerating the suburbanisation of middle-income home relocators. Another long-term influencing factor is the Russia-Ukraine conflict, which started in Feb. 2022. The Russia-Ukraine conflict had large-scale adverse effects on the global economy and has added further layoffs and job shifts on top of the economic downturn caused by the pandemic. Therefore, we may have overestimated the pandemic's influence on work relocations.

Second, the sample used for analysis is different from the population of Beijing. Users whose socioeconomic data are available tend to be comparatively younger, better educated and more active online, and thus they may not represent the whole regular commuter group. Also, our strict filtering process for regular commuters excluded workers with lower socioeconomic status and urban temporary populations. To derive a more representative sample, we applied sample weights based on the joint distribution of gender and age from the Seventh National Population Census of China (Supplementary Table S2), but our weighted sample is still wealthier than the general population. Therefore, our results should be interpreted as the pandemic's effects on middle-to-high-income workers' relocation behaviour. A considerable proportion of low-income workers and other temporary populations fled big cities during the pandemic due to financial and social difficulties; those who stayed were less resilient and might have undergone more drastic changes in jobs-housing arrangements: one possibility is that they may have moved further away from the city centre to low-price housing areas and found local employment under the aid of the government or residential neighbourhoods or temporary work. One study discussed the role of temporary populations in cities against the pandemic backdrop (Brollo and Celata, 2022). Future attempts are suggested to explore the long-term impact of the pandemic among these groups.

Third, Beijing may not be enough to represent all cities around the world. China's approach to control the pandemic was among the strictest in the world, and Beijing's pandemic control policy was one of the strictest in China. In Beijing, mobility restrictions and personal protection requirements were persistently and strictly implemented for three years (Jan.20 – Dec.22), which is unusual. This means that in the post-pandemic era which we studied to find long-term effects of the pandemic, people were still under the influence of government pandemic control and were still quite aware of the pandemic situation; however, in the post-pandemic era in other countries or cities, the pandemic may have already ceased to be a public focus. Future studies are suggested to find out whether the relocation pattern changes found in this study will still apply in other parts of the world.

Fourthly, the discussions about possible factors influencing jobs-housing mobility patterns should be interpreted with caution, since we do not know for sure relocators' motives but only inferred them through pre-post-relocation jobs-housing characteristics, socio-demographic characteristics and social contexts based on existing evidences.

Last but not least, this study did not take into consideration the travel mode changes throughout the study period. Commute time for all commuters is calculated based on private car mode, which may not accurately reflect their real commute time if other travel modes are taken. In recent literature, many scholars have studied post-pandemic modal changes in urban daily mobility, but mainly using survey data. Examining this subject based on big data with large spatiotemporal span could shed more light on post-pandemic human mobility and could provide useful guidance for planners and policy makers in the future.

Conclusion

The present study examined the COVID-19 pandemic's long-term effects on intra-urban jobs-housing relocation behaviours with 10 months of cellular signalling data over a 4.5-year period. Surprisingly, we found that despite adverse economic effects, the pandemic may have brought positive changes to the jobs-housing spatial distribution and jobs-housing relationships in the city. Compared with the hypothetical situation where there had been no pandemic, the post-pandemic city may have developed a more vibrant centre residentially speaking due to the swapping in of young families for accessibility and the swapping out of older families for low-density living environment. Its employment spatial structure may have become more dispersed due to the decentralising effects of the reemployment of pandemic laid-off workers. And it may have become greener and less congested due to improved overall jobs-housing balance. Planners and city officials should seize this opportunity to improve the structure of the city.

Data availability

The cellular signalling dataset analysed during the current study is not publicly available due to confidentiality agreement with the cellular network operator, but a processed final dataset used for estimating event study models in this study is available for the replication of results only by contacting the corresponding author (if permission of the cellular network operator is granted). The spatial datasets, the commute time (between grids) dataset, and the COVID-19 infection dataset analysed during the current study are available from the corresponding author on reasonable request. The stringency index dataset analysed during the current study is available from the Oxford COVID-19 Government Response Tracker, <https://www.bsg.ox.ac.uk/research/covid-19-government-response-tracker>.

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Note

1 According to Beijing Municipal Bureau of Statistics (2009), in 2019, there were 13.7×10^4 people working evening/night shifts, which is approximately 1.1% of the working population in Beijing.

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PZ: Conceptualization, supervision, writing–reviewing and editing, revision. Yukun Gao: Data analysis, methodology, writing–draft preparation.

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The authors declare no competing interests.

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Additional information

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