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# Tracing long-term commute mode choice shifts in Beijing: four years after the COVID-19 pandemic

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The COVID-19 pandemic has brought urban mobility into a new era. This study traces post-pandemic shifts in commute mode switch behaviors and their environmental effects based on an event study design and a mobile phone signaling dataset for Beijing from April 2018 to November 2023. The results show that in the outbreak stage, public transit mode share nosedived, with transit riders 5.11 and 3.75 times more likely to switch to private car and active modes, respectively; in the post-pandemic stage, public transit recovered rapidly and to a large extent, but the increase of private mode dependency persisted, as transit riders were 1.88 times more likely to switch to private cars, and transit riders and car drivers were 1.37 and 1.32 times more likely to adopt active modes, respectively; in the pandemic-free stage, signs of private car dominance began to emerge, as driving habits strengthened and more active travelers resorted to driving, indicating the closing of the window of opportunity to promote low-carbon private transport. This study presents the longest longitudinal tracking of post-pandemic travel mode choice so far. The challenges and opportunities faced by the transportation system are discussed, and policy implications and future research directions are provided.

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## Introduction

**Background**. The COVID-19 pandemic induced numerous changes in human mobility, which brought both challenges and opportunities to the transportation system (Basu and Ferreira, 2021). Environmentalists worry that with higher private car dependency and lower public transit ridership, urban mobility has taken a turn for the unsustainable (Ceccato et al. 2022; Lyons, 2021). Meanwhile, behaviorists point out that the drastic disruption in daily mobility during the pandemic may serve as an opportunity to break old habits and to promote unshared but sustainable active modes (Schmidt et al. 2021; Sunio and Mateo-Babiano, 2022). In the long run, there are three main hypothetical scenarios regarding the trend of transport mode split: the optimistic view believes in a full and fast recovery of public transit, the pessimistic view predicts a permanent downfall of public transit, and the neutral perspective assumes the coexistence of a partial recovery of public transit and increased private car use and active travel (Abdullah et al. 2021). Four years after the outbreak, as the world begins to rise from the ashes of this unprecedented crisis, it is high time to retrospect on the course of travel mode change, to determine how far urban mobility has deviated from its pre-pandemic norms, and to decide what countermeasures should be taken to restore or even enhance sustainability in daily travels.

**Literature overview**. The existing literature has depicted short-term paradigm shifts in travel mode choice with striking consistency. In the early phases of the pandemic, travel demand dropped first for non-essential trips and then for all trips (Shakibaei et al. 2021), resulting in significant reductions in the usage of all travel modes (Barbieri et al. 2021; Bucsky, 2020). Public transit underwent the most serious disruption (Bucsky, 2020; Parker et al. 2021), with reductions in related activity levels of between 50% and 85% in many countries worldwide (Zhao and Gao, 2022). In contrast, high levels of driving, cycling, and walking trips were observed (Marra et al. 2022; Molloy et al. 2021; Shakibaei et al. 2021). Daily mobility changes during this time were mostly due to lockdowns, virus spread, and pandemic fear (Borkowski et al. 2021; Jiang et al. 2020). After mobility restrictions were lifted, shifts from public transit to private car driving became more evident, as shown in a large number of studies conducted in 2020 (Abdullah et al. 2021; Das et al. 2021; Hensher et al. 2022; Thombre and Agarwal, 2021). During this phase, individual transport mode shift was mainly correlated with the interaction between infection concerns manifested as crowd aversion and the perceived safety brought by social distancing and sanitizing measures (Abdullah et al. 2021; Ceccato et al. 2022; Iglesias and Raveau, 2024; Przybylowski et al. 2021).

Heterogeneities in pandemic reactions and inequities have also been explored by previous works. Among various socio-demographic groups, low-income individuals and those without access to private vehicles were more likely to be captive riders and depended more on public transit for their daily mobility during and after the pandemic (Das et al. 2021; He et al. 2022; Parker et al. 2021). In addition, gender, age, marital status, employment status, and personality influenced travel mode choice (Das et al. 2021; Hamad et al. 2024; Liu and Lee, 2023; Mussone and Changizi, 2023). Trip characteristics such as length and frequency also played a part in post-pandemic travel mode choice (Das et al. 2021; Dingil and Esztergár-Kiss, 2021).

Findings on daily mobility changes have triggered intense discussions over the environmental effects of the pandemic, although consensus has not been reached. Increased driving behavior and decreased public transit use have led many researchers to assume a high-carbon future for urban transportation. Consequently, to boost environmentally friendly travel after the pandemic, policy suggestions have been put forward such as improving public transit services by implementing sufficient infection control measures (He et al. 2023), adopting crowd management and contactless service (Das et al. 2021), disclosing real-time crowding level information (Myftiu et al. 2024), expanding service coverage and frequency (Chen et al. 2024; He et al. 2022; Myftiu et al. 2024), and providing customized public transportation (He et al. 2023; Thombre and Agarwal, 2021). Moreover, providing supportive infrastructure for active mobility has also been advocated (Hamad et al. 2024; Thombre and Agarwal, 2021). Besides transport mode split, travel volume is also vital in determining daily mobility (Javadinasr et al. 2022). Research has shown that in the post-pandemic era, the level of working from home may be significantly higher than before (Hensher et al. 2022), and that individual daily trip length and frequency may have dropped (Kellermann et al. 2022). Whether the greenhouse gas and air pollution emissions reductions from reduced in-person travel can offset the negative effects of mode split change is still in debate. Several studies have found significant lockdown-related reductions in emissions (Cicala et al. 2021; Crowley et al. 2021), yet this positive change may be nonexistent when controlling for meteorological factors (Briz-Redón et al. 2021). One study has combined trip frequency, mode, length, and vehicle type to simulate future pollutant emissions of commuting behaviors, suggesting that the influence of unsustainable travel mode adoption may override any emission conservations due to telework (Ceccato et al. 2022).

Even though it has been widely researched, there are still unanswered questions concerning the effects of the COVID-19 pandemic on travel mode choice and the environment. One of the most relevant questions for today's academics and decision makers is to what extent and by what course has travel mode choice shifted after 4 years, during which time waves of pandemic spread, non-pharmaceutical interventions, and persistent efforts to restore green travel modes took place. Existing research has seldom reached into the long-term shifts of daily mobility, with a large proportion of studies focusing on 2020. Among works that have discussed long-term changes, the most commonly used method is inferring future changes based on self-reported behavioral intentions (Ceccato et al. 2022; Currie et al. 2021; He et al. 2023; Myftiu et al. 2024) and model predictions (Ceccato et al. 2022; Luan et al. 2021), which is susceptible to the risk of mispresenting reality. Several studies have focused on 2021 and 2022, but they have only analyzed mode choice behaviors at a single time point (Aaditya and Rahul, 2023) or have compared two to four time points using recalled travel behavior data for earlier time points (Hamad et al. 2024; Ishibashi et al. 2024; Zheng et al. 2023); thus, they are not sufficient to trace the change process of travel mode choice over time. One study has effectively examined the dynamics of travel behavior using a longitudinal dataset of individual GPS trajectories from January 2019 to September 2021 (Kellermann et al. 2022), yet it does not cover periods after 2021, which reflect important stages of mobility recovery.

**Research questions and study aim**. The current study addresses the research gap of post-pandemic long-term shifts in travel mode choice by analyzing changes in commute mode switch behaviors based on an event study design and 12 months of mobile phone signaling data for Beijing between April 2018 and November 2023. The existing literature has shown that regular commuting trips constitute a major proportion of urban transportation, and their patterns shape the rhythm of daily mobility

(Huang et al. 2018). Thus, examining changes in commuting behavior is an effective way to understand the transformation of urban daily mobility in the long run. Beijing is a suitable case city to study pandemic influences because it has been considerably affected by the pandemic in terms of commuting behaviors (Zhao and Gao, 2023). Also, as the capital city of China, Beijing's post-pandemic situation is quite representative of the post-pandemic Chinese context in general, and the city has a large and diverse urban population, which translates into large samples and enables group analyses.

Given the above justifications, this study addresses three research questions within the scope of the long-term effects of COVID-19 on commute mode choice:

***RQ1: How has commute mode choice shifted in the long run?***

This study uncovers the patterns of commute mode choice change, evaluates the level of recovery, and assesses which of the three scenarios presented above (Abdullah et al. 2021) best reflects the reality 4 years after the pandemic.

***RQ2: What are the differences in long-term commute mode choice shifts between different income and commute distance groups?***

Research has suggested that income level and travel distance were two most essential influencers of travel choice during the pandemic (Dingil and Esztergár-Kiss, 2021). This study looks into the inequities between different commuter groups in the post-pandemic context.

***RQ3: How have commute mode choice shifts impacted per-capita unit distance commute carbon emissions?***

Long-term per-capita emissions changes are further investigated to provide individual-level real-world evidence instead of intention-based inferences (Ceccato et al. 2022) on the environmental effects of travel mode changes. The answers to this question can help to identify the current position of the transportation system on the sustainability spectrum, and thus hold valuable implications for future transportation policy making.

The remaining parts of this paper are organized as follows. Section "Methodology" provides methodological details, including the event study research design, the data-collection process and the data-analysis methods used to derive empirical results. Section "Results" describes and evaluates the main results. Section "Discussion" discusses the implications of the results, and the contributions and limitations of this study. Section "Conclusion" concludes this study.

## Methodology

An event study design based on the research area was adopted. A data-collection process including raw data acquisition, sampling, commute mode detection and variable calculation was conducted. Event study models were used to quantify post-pandemic shifts in commute mode switch behaviors and carbon emissions. This section gives a detailed description of the methodology involved in research design, data collection and data analysis, and presents descriptive results on sample composition and commute mode split changes.

**Research design**. The current study adopted an *event study design* to examine the effects of the COVID-19 pandemic on commute mode switch behaviors. The event study design is suitable for studying long-term dynamics of treatment effects, and it also enables a straightforward graphic presentation of results (Miller, 2023). Therefore, it is the appropriate research design for this study. An event study typically assigns all research subjects into treatment groups and does not have any control groups; treatment time is set as the time of the event, the study period is divided into several phases, and the outcome of interest is measured for each phase; with appropriate controls, the outcomes of post-event phases are compared with those of pre-event phases to estimate changes caused by the event. Event study designs are widely used in economics and health fields (Dobkin et al. 2018), and they are gaining importance in transportation (Aïkous et al. 2023) and urban studies (Sandler, 2017). In particular, a large number of recent studies have focused on the impact of COVID-19 and pandemic control measures on various aspects of the transportation system, including traffic flow (Zhou et al. 2021), population mobility and infections (Askitas et al. 2021), and airline and shipping stock returns (Gavalas et al. 2022; Maneenop and Kotcharin, 2020).

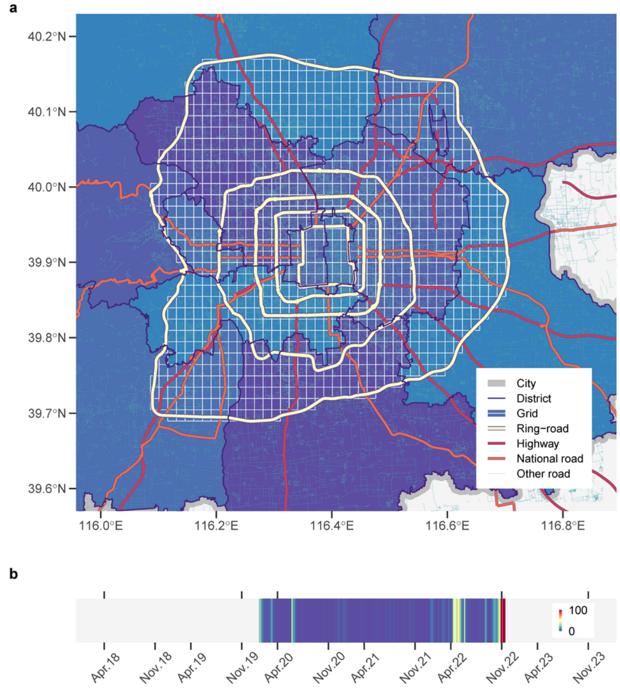


**Fig. 1 Case city.** This figure shows the spatio-temporal context of the case city Beijing. **a** research area: the monocentric urban area of Beijing within its sixth ring-road, which is divided into 1062 1.5 km × 1.5 km uniform grids. **b** COVID-19 pandemic spread: the number of daily confirmed cases after the pandemic outbreak (figures larger than 100 are taken as 100; gray tiles represent periods with no data). Data was obtained from Beijing Municipal Health Commission and web sources (Beijing Municipal Health Commission, 2023; Beijing Bendibao, 2023).

The event study design is a kind of non-experimental research design. In addition to non-experimental studies, randomized controlled experimental studies and natural or quasi-experimental studies have been used to study the effects of certain events, policies, or interventions on certain outcomes of interest (de Vocht et al. 2021; Dunning, 2012; Leatherdale, 2019). The reason randomized controlled experimental designs are not used here is that COVID-19 is not a treatment controllable by researchers; thus, it does not meet the requirements for group comparison, randomization, and manipulation in a true experiment (Dunning, 2012). Although natural experimental designs are used to analyze uncontrollable events, they are not suitable for this study either because the group comparison requirement (Craig et al. 2017) is not met: the unprecedented scale of COVID-19 has made it difficult to build an adequate control group in which individuals have not been exposed to the pandemic.

The spatial area of research is the area within the sixth ring road of the case city Beijing, as shown in Fig. 1a. This area

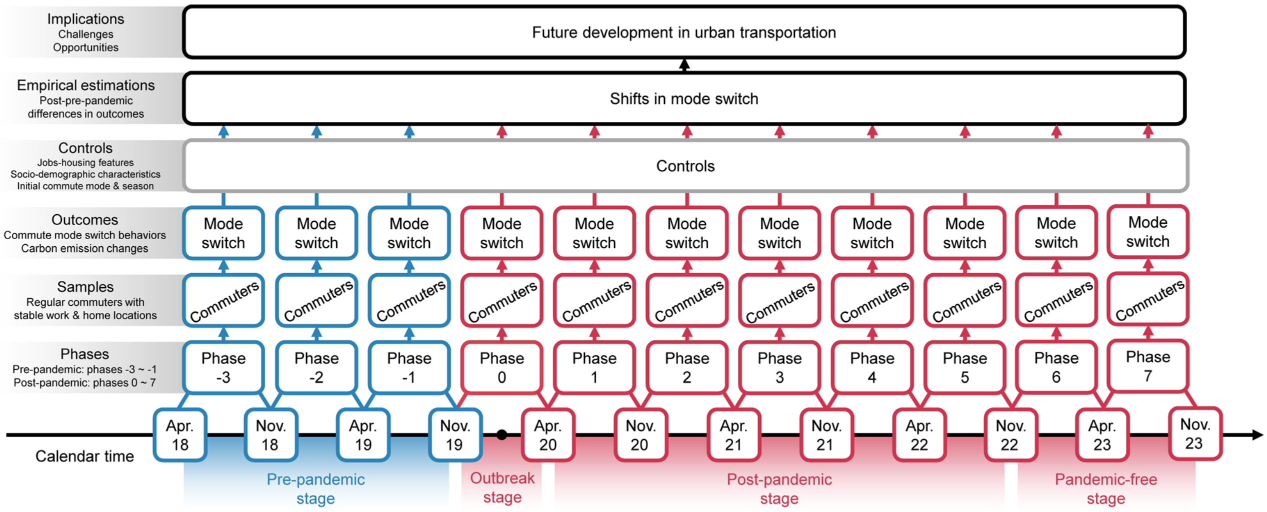


**Fig. 2 Research design.** This figure shows an outline of the event study research design used in this study.

approximates Beijing's central urban area and is the most densely populated and rigorous part of Beijing, making it a suitable research area for this study. It is home to over 75% of the city's 21 million residents, and it has a diverse population with a large number of commuters. It has a monocentric city structure characterized by the ring-road system (2nd–6th ring roads) and radial arterial roads, and it is connected with the public transportation system of Beijing consisting of over 20 subway lines and over 3,000 bus lines. Before the pandemic, this area suffered from traffic congestion, air pollution issues, and public transit overcrowding. During the pandemic, traffic volume dropped and the share of public transit travel decreased, while that of walking and car travel increased (Jiang et al. 2020), and considerable changes in individual travel mode choice-making mechanisms emerged (Wei and Liu, 2022; Zhao and Gao, 2022). After the pandemic, traffic volume resumed. However, the long-term changes in mode split are still unclear.

The period of research was between April 2018 and November 2023. This research period was divided into 11 phases, with three phases in the pre-pandemic era (Phases −3 to −1) and eight in the post-pandemic era (Phases 0 to 7): April 18–November 18 (Phase −3), November 18–April 19, April 19–November 19, November 19–April 20 (Phase 0), April 20–November 20, November 20–April 21, April 21–November 21, November 21–April 22, April 22–November 22, November 22–April 23, and April 23–November 23 (Phase 7). The reason for dividing the research period into half-year phases was to capture changes in commute mode switch behaviors in an even and consistent manner and in a finer temporal resolution. Commute mode split was quite unstable during and after the pandemic outbreak, especially in 2020. Longer phases may not be able to capture these delicate changes. Aprils and Novembers were used as start and end months of phases because they are working months that do not contain and are not near public holidays (including winter vacation in January and February, May Day vacation in May, summer vacation in July and August, and National Day holidays in October), hence data collected for these months generally includes the largest number of commuting trips for any given commuter, and they can provide the most robust information on commuters' jobs–housing locations and travel modes. As Fig. 1b shows, Phases −3 to −1 were in the pre-pandemic stage; among post-pandemic phases, Phase 0 represents the outbreak stage of COVID-19 when the first wave of pandemic occurred and mobility restrictions were the strictest; Phases 1 to 5 represent the post-pandemic stage when relatively mild restrictions were in place and travelers were aware of but not seriously affected by the pandemic; and Phases 6 to 7 represent the pandemic-free stage when government infection control ended and travelers' health concerns reduced considerably, despite the increases in infection numbers.

Figure 2 provides an overview of the event study design, and Table 1 provides details of the variables. After phase division, commuters who met the sampling requirements were studied and their outcome variables were measured. The values of outcome variables in post-pandemic phases were compared with those in pre-pandemic phases conditional on selected control variables. The differences between post- and pre-pandemic outcomes were identified as shifts under the influence of the pandemic. Based on these shifts, the post-pandemic norm of commute mode split was evaluated and implications were presented.

The main outcome variable of interest was commute mode switch behavior, which is a multi-class categorical variable recording the change (or non-change) of commute mode between the start and end months of each phase for each commuter. Note that five commute modes were examined in this study, namely private car (including taxi), bus, subway, bicycle (including e-bike) and walking, but in data analysis they were regrouped into three categories following previous research (Molloy et al. 2021): private car (private, high-carbon), public transit (bus and subway; public, low-carbon), and active travel (bicycle and walking; private, low-carbon). The reason for this simplification was to combine similar travel modes and to enable straightforward interpretations of modeling results. The mode switch behavior variable thereby had nine categories in total. For example, if an individual switched from public transit commuting in November 19 to private car commuting in April 20, then the mode switch behavior variable for this individual in this phase was recorded as public transit to private car. An additional outcome of interest was the change in carbon dioxide emissions per-capita kilometer, which was recorded as the difference between the emission factors of the commute modes adopted in the end and start months of each phase for each individual. In the local context of Beijing, private car (including taxi) had the largest unit distance carbon dioxide emission rates among all commute modes, followed by bus, subway, bicycle (including e-bike), and walking.

Control variables included jobs–housing features, sociodemographic characteristics, initial commute mode, and season. These variables may influence commute mode choice. Therefore, they

**Table 1 Variables used in analysis.**

| Variable name | Type | Description | Impact on mode choice | Source |
|---|---|---|---|---|
| Outcome variables | | | | |
| Commute mode switch behavior | Multi-class categorical | $y_{ij}$ records commute mode switch behavior of each commuter between the start and end months of each phase. $y_{ij} = y_{ij_s} \sim y_{ij_e}$, where $y_{ij_s}$ is the start month commute mode type and $y_{ij_e}$ is the end month commute mode type. $y_{ij_s}$ and $y_{ij_e}$ can take the following three values: private car, public transit, and active travel, thus $y_{ij}$ has nine categories in total. | | |
| Carbon emissions change | Continuous | $y_{ij}$ records carbon dioxide emission change per kilometer of each commuter between the start and end months of each phase due to commute mode switch. | | |
| Treatment variables | | | | |
| Phase | Dummy | $t_j = 1$ if phase is j and $t_j = 0$ if phase is not j. | | |
| Control variables | | | | |
| Gender | Dummy | $X_{ij} = 1$ for male commuters, and $X_{ij} = 0$ for female commuters. | In the pandemic context, men and young people were less sensitive to crowding, and they were more likely to travel by public transit than private cars and active modes. | Das et al. (2021) Basnak et al. (2022) Mussone and Changizi (2023) Liu and Lee (2023) |
| Age | Continuous | $X_{ij} = 27$ for commuter aged 25–29, $X_{ij} = 32$ for commuter aged 30–34, $X_{ij} = 37$ for commuter aged 35–39, $X_{ij} = 42$ for commuter aged 40–44, $X_{ij} = 47$ for commuter aged 45–49, and $X_{ij} = 52$ for commuter aged 50–54. | | |
| Affluence index | Dummy | $X_{ij}$ corresponds to six categories ranging from 3 to 8, with 3 being the least affluent and 8 being the most affluent. The raw data has nine categories ranging from 1 to 9, and categories 1–3 and 8–9 are combined respectively because they contain too few observations. | In the pandemic context, high-income individuals were more sensitive to crowding, and they were more likely to travel by private cars than public transit; low-income individuals had less control over their travel mode choices, and they were more likely to be captive riders of affordable modes such as public transit. | Das et al. (2021) Dingil and Esztergár-Kiss (2021) Parker et al. (2021) Basnak et al. (2022) He et al. (2022) |
| Commute time | Continuous | $X_{ij}$ equals the logarithm of the median commute duration of each commuter in each phase. | In the pandemic context, longer travel time increased the possibility of traveling by private cars versus public transit, and the possibility of traveling by public transit versus active modes; long travel time could prevent mode switch. | Das et al. (2021) Dingil and Esztergár-Kiss (2021) Mussone and Changizi (2023) |
| Spatial position of workplace<br>Spatial position of residence | Dummy | $X_{ij}$ corresponds to five categories ranging from 2 to 6, representing the number of the smallest ring in which each commuter's work/home location is positioned. | In the pandemic context, urban areas with different development levels, land use characteristics and population composition responded differently in terms of travel behavior. | Hu and Chen (2021) Liu and Lee (2023) |

**Table 1 (continued)**

| Variable name | Type | Description | Impact on mode choice | Source |
|---|---|---|---|---|
| Bus accessibility of workplace<br>Bus accessibility of residence<br>Subway accessibility of workplace<br>Subway accessibility of residence | Dummy | $X_{ij} = 1$ if the $1.5km \times 1.5km$ grid containing the commuter's work/home location has at least one bus stop/subway station, and<br>$X_{ij} = 0$ otherwise. | In the pandemic context (and in general), people with higher accessibility to public transit were more likely to travel by public transit. | Cheng et al. (2020)<br>Das et al. (2021) |
| Season | Dummy | $X_{ij} = 1$ for summer phases (Apr-Nov), and<br>$X_{ij} = 0$ for winter phases (Nov-Apr) | In general, travel mode choice is sensitive to weather conditions and seasonality; active modes are most influenced by weather factors. | Böcker et al. (2016)<br>Hyland et al. (2018) |
| Initial commute mode | Dummy | $X_{ij}$ corresponds to five categories (private car, bus, subway, bicycle, and walking) recording each commuter's commute mode in the start month of each phase. | In general, travel mode choice is habitual. | Verplanken et al. (1997)<br>Wood et al. (2002)<br>Zhao and Gao (2022) |

control for initial commute mode switch tendencies, minimizing individual-level confounding. Possible relationships between these variables and travel mode choice presented in previous studies are in Table 1. Jobs–housing features consist of commute time, workplace and residence spatial position, and public transit accessibility. The spatial position of each place was recorded using its location relative to Beijing's ring-road system. This recording method was applied because the ring roads can be used as a natural reference system to determine the position of locations against the monocentric structure of Beijing's central urban area. Sociodemographic characteristics consisted of gender, age, and an affluence index. Individuals' commute mode in the start month of each phase was controlled. A season dummy was also included to control for seasonal fixed effects.

**Data collection**. The main dataset used in this study was a mobile phone signaling data package obtained from one of the largest mobile communication network providers in China. Mobile phone signaling data from the same source were used and tested in many previous studies (Zhao H et al. 2024a; Zhao et al. 2023a; Zhao P et al. 2024b). These data were collected by the network operator through the following steps:

a. all service users' trajectories within the administrative boundary of Beijing were passively recorded by the network, and the raw data contained user coordinates determined by triangulation and corresponding timestamps;
b. the network operator performed data cleaning, stay point identification, and trip segmentation based on undisclosed algorithms;
c. the processed data were provided by month, including stay point data (location, start time, and end time), trip data (origin and destination location, distance, speed, time, and mode label), and user attribute data (gender, age, monthly fee, and affluence index). Note that the affluence index reflects income level, and it was calculated by the operator based on mobile phone users' offline travel, online activities and fixed assets information.

After acquiring the processed data package described above, a sampling process was conducted to collect data for regular commuters used in analysis:

a. for each phase, users with enough recorded data were included by selecting users between 25 and 54 years old who stayed in Beijing for at least 10 days in the start and end months respectively. Only working-age users were selected because this study focuses on commuters, and individuals of other age groups have a much smaller chance of being commuters;
b. users from *Step a* who had stable jobs–housing locations were included by selecting those whose work and home locations in both the start and end months were successfully detected based on the rules below. The stay point with the longest monthly stay time in working (or resting) hours was detected as the user's work (or home) location of that month, if the stay time was longer than half of the user's total monthly stay time in working (or resting) hours, and if the user's monthly total stay time in working and resting hours exceeded the median monthly total stay time in working and resting hours of all users that month; working and resting hours were defined as 9 a.m.–5 p.m. and 9 p.m.–5 a.m. (next day) on work days, respectively;
c. users from *Step b* whose work and home locations were within the research area (the sixth ring road) were selected;

d. users from *Step c* who were commuters and stayers (who neither changed workplace nor relocated residentially) were included by selecting those whose work and home locations remained at least 1.5 km apart and did not change between the start and end months. Studying only stayers can help to prevent any effects of workplace change or residence relocation on commute mode choice switch behaviors from confounding modeling results.

For users selected through the sampling process, a hybrid mode detection method combining fuzzy logic and rule-based models was applied to detect commute mode. The fuzzy logic algorithm was adopted because it is suitable for solving classification problems with subjectivity and uncertainty such as travel decisions by mimicking the process of human thinking in real-life decision-making, and it can be integrated with collective-level supervision using membership functions (Zadeh, 1965, 1973). Fuzzy logic inference has long been used in travel demand modeling including trip generation, trip distribution, mode choice, and traffic assignment (Teodorović, 1999). Among fuzzy-logic-based studies, travel mode choice has received the most attention. Previous studies have often used trip characteristics such as travel time, distance, speed, acceleration, and cost as input features for inference, and they have achieved relatively high prediction accuracies ranging from 68% to 90% (Dell'Orco and Ottomanelli, 2012; Rasmussen et al. 2015; Vythoulkas and Koutsopoulos, 2003; Zhang et al. 2011). The rule-based algorithm was combined with the fuzzy logic algorithm to improve classification accuracy, as previous research has found that when some clear-cut boundaries can be established, combining rule-based detection with other methods can lead to better efficiency and model performance (Chin et al. 2019). Hybrid models with rule-based components have been used in many previous studies to detect travel mode (Graells-Garrido et al. 2018; Qu et al. 2015; Wang et al. 2010).

Besides the hybrid detection model used in this study, existing studies on mobile phone signaling data mode detection have also resorted to single rule-based detection and machine-learning-based detection, and the latter has been further divided into unsupervised learning and supervised learning (Chin et al. 2019; Graells-Garrido et al. 2018). Single rule-based models were not adopted here because they rely entirely on human judgement and Boolean logic, which might be inaccurate in complex situations. Since unsupervised learning might lead to unreasonable classifications and the individual-level actual commute mode choice data is not available for supervised learning, machine learning models are not suitable for this study either.

The hybrid commute mode detection method used in this study is described below, and a visualization of this process is in Fig. 3:

a. for each month, every regular commuter selected by the sampling process who had enough recorded commute trips was extracted;
b. for each regular commuter from *Step a*, every single commuting trip of the commuter recorded during rush hours in the studied month was extracted for mode detection. Trips with abnormal speeds were excluded from mode detection;
c. for each trip from *Step b*, commute mode was detected as *subway* if the trip contained subway labels. Base stations located in the subway system of Beijing have unique identifiers so that mobile phone signaling records linked to these base stations are clearly labeled by the network operator, and it is assumed that any trip containing subway labeled records are traveled by subway;
d. for each trip from *Step b*, if it was not a subway trip, then the fuzzy logic architecture containing fuzzification, fuzzy rule decision, and defuzzification was applied:
   d-1)the fuzzification step converted input features (trip speed, time, and distance) into a set of degrees of membership (DoMs) using membership functions. These membership functions were the probability density functions of trip features for different transportation modes derived by the following steps:
   d-1-1)a travel mode detection process was conducted by the network operator for 2 days in November 2019;
   d-1-2)trip distance, speed, and time data of the trips with successfully detected modes was used to estimate log-normal probability density functions of trip characteristics for private car (including taxi), bus, bicycle (including e-bike) and walking trips, as shown in Supplementary Equation S1 and Supplementary Table S1;
   d-2)the decision-making step used the fuzzy rule below to obtain the fuzzy membership set of the trip:
   d-2-1)the sums of the trip's DoMs in all three dimensions for private car (including taxi), bus, bicycle (including e-bike), and walking were calculated;
   d-2-2)the fuzzy membership of the trip was the set of sums of DoMs calculated, and in this case the fuzzy membership set contained four elements, one for each mode;
   d-3)the defuzzification step assigned a commute mode to the trip based on the decision-making step below:
   d-3-1)the mode with the largest sum of DoMs was detected as the commute mode of the trip;
e. for each regular commuter from *Step a*, after all trips were processed by *Steps c–d*, the most frequently used commute mode of the month was detected as the user's monthly commute mode;
f. repeat *Steps a–e* for all commuters in all months.

For regular commuters whose commute modes were all successfully detected, the following steps were used to calculate other necessary variables used in analysis:

a. affluence index data provided by the mobile network operator were available for over 80% of commuters, while for the rest, their affluence information was inferred based on gender, age, monthly fee, housing price of residential grid, and workplace and residence spatial position data through Naive Bayes, a probabilistic classifier widely used in data science (Wickramasinghe and Kalutarage, 2021);
b. a geographical dataset containing a map of Beijing and its road network, 1.5 km × 1.5 km uniform grids, public transit points of interest (POI) data, and real estate resale price data were used to calculate control variables. The public transit POI dataset consisted of spatial coordinates of all bus stops and subway stations in Beijing as of 2024, and it was obtained from an online data service provider (Lifangshujuxueshe, 2024). The housing price dataset was obtained in 2021 from the website of one of the largest real estate agencies in China (Lianjia, 2021);
c. a carbon emissions dataset containing local emission factors for every travel mode was used to calculate carbon emissions per-capita kilometer, as shown in Supplementary Table S2.

The resulting sample size for each phase from selected steps of the above data collection process is in Fig. 4. The final sample used for data analysis after the calculation of necessary variables was $N = 2,121,131$ in total and on average 192,830 per phase. The gender, age, and affluence index distributions of the final sample compared with those of whole population in Beijing are in Fig. 5.

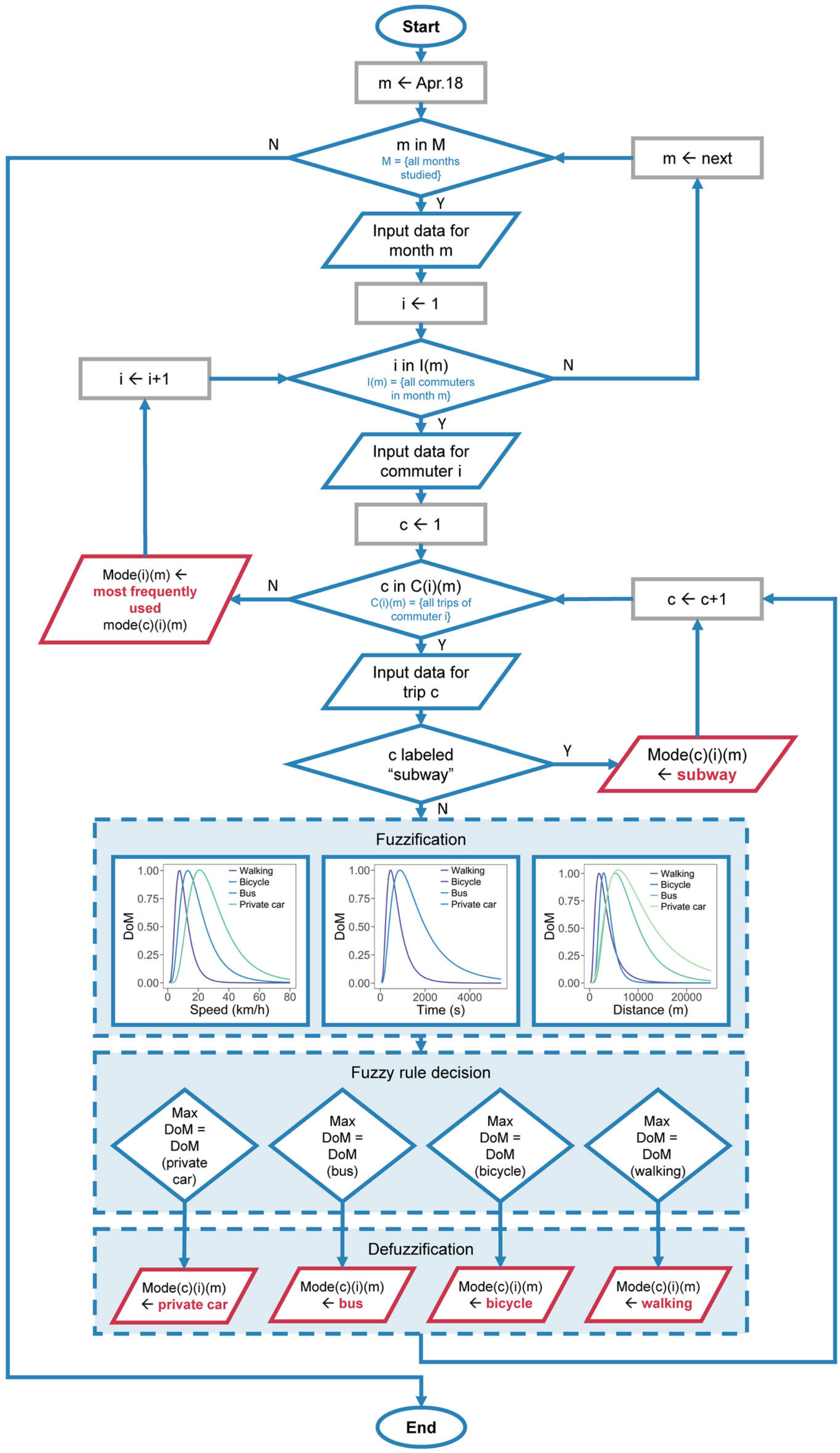


**Fig. 3 Commute mode detection method.** This figure shows the process of commute mode detection, which is a hybrid method combining rule-based and fuzzy logic algorithms.

The sample contains larger percentages of men and young people in the 25–29 and 30–34 age groups than the actual population, because these groups use mobile phone more often and have larger chances of being captured by signaling records. Another explanation for the overrepresentation of men is that sometimes phone cards of family members are registered under the name of the head of the household, and men are more likely than women to take this role in general. The sample also contains larger percentages of high-income individuals than the actual population, probably because only regular commuters who have stable jobs and residences were selected, and these groups tend to be more affluent than the general population. This issue was addressed by resampling in model evaluation.

Commute mode detection results for the final sample are in Fig. 6. On a monthly average, private car, bus, subway, bicycle, and walking commuters accounted for 38.3%, 10.7%, 36.5%, 9.5%, and 5% of the sample, respectively. In comparison, a commuting survey of Beijing residents in 2019 ($N = 565$) showed that 19.8%, 16.1%, 37.5%, 11.5%, and 13.5% of residents preferred these modes as their first-choice commute mode, respectively (Zhao and Bi, 2021). The shortage of walking commutes in the detection results is due to the fact that individuals with jobs–housing distances less than 1.5 km were excluded during sampling. The large number of private car commutes was probably caused by sample composition, as the sample was more affluent than the actual population of Beijing. Taking these factors into consideration, the mode detection results are relatively consistent with the actual commute mode split of Beijing residents.

Figure 6 provides a preview of commute mode split change during the research period. Before the pandemic, mode split was stable, and the average mode shares of private car, bus, subway, bicycle, and walking before April 20 were 34.1%, 12.4%, 39.6%, 8.6%, and 5.2%, respectively. After the pandemic, there were both shock-rebound responds and steady changes in commute mode split. In general, the average mode shares of private car, bus, subway, bicycle, and walking in and after April 20 were 41.1%, 9.2%, 35.6%, 9.4%, and 4.7%, respectively, meaning that the share of private car commuting increased and the share of public transit commuting decreased.

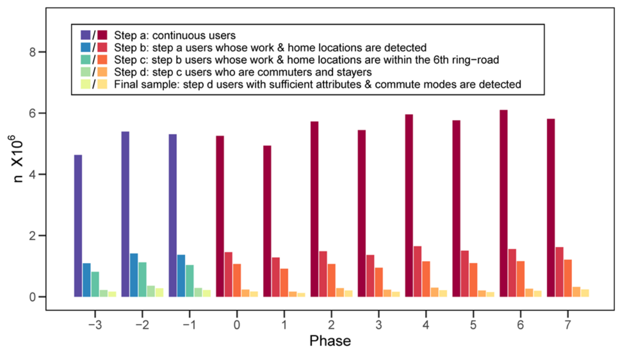


**Fig. 4 Sampling results.** This figure shows the sample sizes for each phase after selected steps of the data collection process. Step 5 represents the final sample, consisting of $N = 2,121,131$ commuters in total and on average $N = 192,830$ commuters per phase.

**Data analysis**. The empirical models used in the current study were inspired by the nonparametric event study model of Dobkin et al. (2018), which takes the form of Eq. 1:

$$y_{it} = \gamma_t + X_{it}\alpha + \sum\nolimits_{r \in R \setminus r_b} \mu_r + \varepsilon_{it}. \tag{1}$$

where $y_{it}$ is the outcome variable for individual $i$ at calendar time $t$, $\mu_r$ s are the coefficients of interest that represent the change in $y_{it}$ in phase $r$ relative to the baseline phase $r_b$ (the baseline phase is the omitted category in phase dummies), $\gamma_t$ represents calendar time fixed effect, and $X_{it}$ represents a set of other control variables.

This model used by Dobkin et al. (2018) was designed for continuous outcome variables, and the treatment phases $r$ do not correspond to calendar time $t$. However, the main outcome variable of the current study, commute mode switch, is a multi-class categorical variable, and treatment phases correspond to calendar time. Therefore, this model was transformed into a multinomial logistic regression model as used in other travel choice studies (Dingil and Esztergár-Kiss, 2021; Myftiu et al. 2024), and adjustments were made to the time fixed effect term and the control variables to suit the needs of the current study. The model adopted for data analysis in this study took the form of Eq. 2:

$$\begin{gathered} \textit{For observations with } y_{ij_s} = mode_0 \\ \ln\left(\frac{P\left(y_{ij_e} = mode_k\right)}{P\left(y_{ij_e} = mode_0\right)}\right) = \sum_{j=0}^{6} \mu_j + \beta X_{ij} + \gamma_j + \varepsilon_{ij} \\ mode_0 \in M, mode_k \in M \setminus mode_0, M = \{private\ car, public\ transit, active\ travel\} \end{gathered} \tag{2}$$

where the outcome variable commute mode switch $y_{ij}$ equals $y_{ij_s}$ to $y_{ij_e}$, where $y_{ij_s}$ and $y_{ij_e}$ are the commute modes used by commuter $i$ in the start and end months of phase $j$ respectively. $\mu_j$ s are the coefficients of interest, i.e., the coefficients for phase dummy variables $t_j$ s (pre-pandemic Phases −3 to −1 are taken as baseline phases). $X_{ij}$ represents the control variables. $\gamma_j$ represents seasonal fixed effect, i.e., the coefficient of the season dummy. Observations are divided into groups according to their initial commute modes $y_{ij_s}$ s, and Eq. 2 was estimated for each group using different $y_{ij_s}$ s as the base values.

To assist model interpretation, an example is given below. In the model for the sample group whose initial commute mode was public transit ($y_{ij_s} = public\ transit$), the base value of the end month commute mode was designed to be public transit

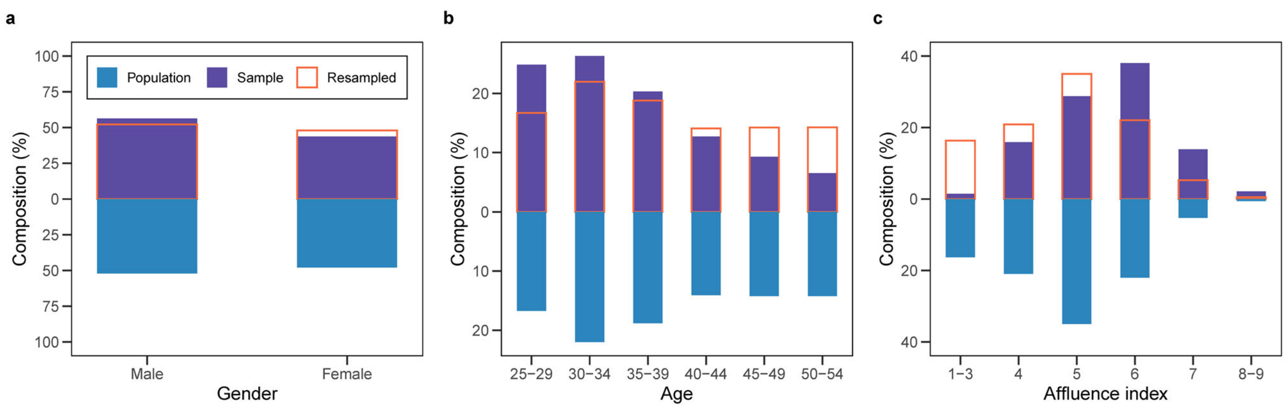


**Fig. 5 Sample composition.** This figure shows the composition of the final sample (and the resampled sample) compared with that of Beijing's whole population. **a** gender. **b** age. **c** affluence index. Socio-demographic information of the whole population were obtained from census data (Office of the Leading Group of the State Council for the Seventh National Population Census, 2020) and the mobile network operator.

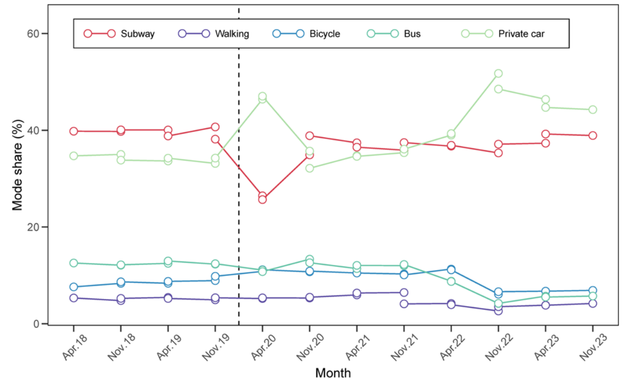


**Fig. 6 Variations in commute mode split.** This figure shows the variations in the mode shares of private car, bus, subway, bicycle and walking over the research period.

($mode_0 = public\ transit$), and an estimated coefficient of $\hat{\mu}_j$ for phase $j$ when the analyzed value of end month commute mode was private car ($mode_k = private\ car$). This indicates that the relative risk for public transit commuters switching to private car commuters instead of remaining transit commuters in post-pandemic phase $j$ was $\exp(\hat{\mu}_j)$ times that in pre-pandemic phases; in other words, public transit commuters were $\exp(\hat{\mu}_j)$ times more or less likely to change their commute mode to private car in phase $j$ than in phases −3 to −1. When $\hat{\mu}_j>0$ or $\exp(\hat{\mu}_j)>1$, transit commuters were more likely to switch to private cars in post-pandemic phase $j$ than in pre-pandemic phases; when $\hat{\mu}_j<0$ or $\exp(\hat{\mu}_j)<1$, transit commuters were less likely to switch to private cars in post-pandemic phase $j$ than in pre-pandemic phases.

After estimating the above model for the whole sample, analyses were conducted to explore differences in commute mode switch behavior between income and commute time groups. For income group analysis, the sample was divided using a median affluence index value of 6, and Eq. 2 was estimated separately for middle-income commuters (affluence index <6; $n = 975{,}923$) and high-income commuters (affluence index ≥6; $n = 1.145.208$). For commute time group analysis, the sample was divided using the median initial commuting time of each travel mode: 24 min for private car, 34 min for public transit, and 9 min for active travel, and Eq. 2 was estimated separately for short-commute commuters ($commute\ time \le 24$ min $if\ y_{ij_s} = private\ car, commute\ time \le 34$ min $if\ y_{ij_s} = public\ transit, commute\ time \le 9$ min $if\ y_{ij_s} = active\ travel$; $n = 1,072,622$) and long-commute commuters ($commute\ time > 24$ min $if\ y_{ij_s} = private\ car,.\quad commute\ time > 34$ min $if\ y_{ij_s} = public\ transit, commute\ time > 9$ min $if\ y_{ij_s} = active\ travel; n = 1,048,509$).

To examine carbon emissions change per-capita kilometer, a linear model similar to the model of Dobkin et al. (2018) was estimated. This model is in Eq. 3:

$$\text{For all observations}$$
$$y_{ij} = \sum_{j=0}^{6} \mu_j + \beta X_{ij} + \gamma_j + \varepsilon_{ij} \cdot \tag{3}$$

where $y_{ij}$ is the outcome variable carbon emissions per-capita kilometer, $\mu_j$ s are the coefficients of phase dummy variables, $X_{ij}$ is the control variables, and $\gamma_j$ is the seasonal fixed effect. An estimated coefficient $\hat{\mu}_j$ for phase $j$ indicated that the change in per-capita kilometer carbon emissions due to commute mode switch in post-pandemic phase $j$ was $\left|\hat{\mu}_j\right|$ larger or smaller than in the pre-pandemic phases. Equation 3 was estimated for the whole sample.

## Results

The event study models described above were estimated to address the three research questions of this study. This section reports modeling results in the order of research questions, and it presents model evaluation details including fitting information for the main models and fitting results of alternative specifications.

**Shifts in commute mode switch behaviors**. To answer the first research question, how have commute mode switch behaviors changed since the pandemic, the modeling results of Eq. 2 based on the whole sample are reported below.

Figure 7a–c shows the results of the private-car-based model. As expected, in Phase 0, private car commuters were 0.63 times less likely to switch to public transit commuting than before the pandemic. This trend was temporarily reversed due to post-pandemic rebound of the public transit system in Phase 1, when private car commuters were 1.99 times more likely to adopt public transit than before the pandemic. However, through Phases 2–7, the probability of commute mode switch behavior from private car to public transit compared with pre-pandemic level remained below 1, averaging 0.70 with the lowest value equaling 0.34 in Phase 5, meaning that in the long run the pandemic discouraged private car commuters from switching to public transit. Surprisingly, private car commuters became more willing to adopt active travel modes after the pandemic. On average the probability for private car users to switch to walking in Phases 0–6 was 1.37 times that in pre-pandemic phases.

Figure 7d–f shows the results of the public-transit-based model. According to the results, the pandemic drove public transit commuters into private car and active commuting, also as expected. In Phase 0, the probabilities for public transit commuters to switch to private car and active travel were 5.11 and 3.75 times those in pre-pandemic phases respectively. Mild rebounds were found in Phase 1, but the long-term trends indicate commute mode shifts away from public transit: public transit commuters were on average 1.73 and 1.39 times more likely to switch to private car and active commuting in Phases 2–7 than before the pandemic, respectively.

Figure 7g–i shows the results of the active-travel-based model. Similarly, commute mode switch behaviors among active commuters also exhibited a shock-rebound reaction to the pandemic. In Phase 0, the probabilities of active commuters switching to private car and public transit were 1.35 and 0.88 times those before the pandemic, respectively, while in Phase 1 these trends reversed. In Phases 2–4, mode switch probabilities of active commuters fluctuated around pre-pandemic level. In Phases 5–7, their probabilities of adopting private car and public transit commuting compared with that before the pandemic increased sharply.

**Group differences in commute mode switch behavior shifts**. To answer the second research question, how have different income and commuting time groups reacted to the pandemic and what are the differences in their reactions, the modeling results of Eq. 2 based on income and commuting time sample groups are reported below.

Table 2 presents the modeling results for income group analysis. Because commute mode switch behavior shifts after Phase 0 were similar between two income groups, only estimation results for Phase 0 are included here. Visualizations of the full

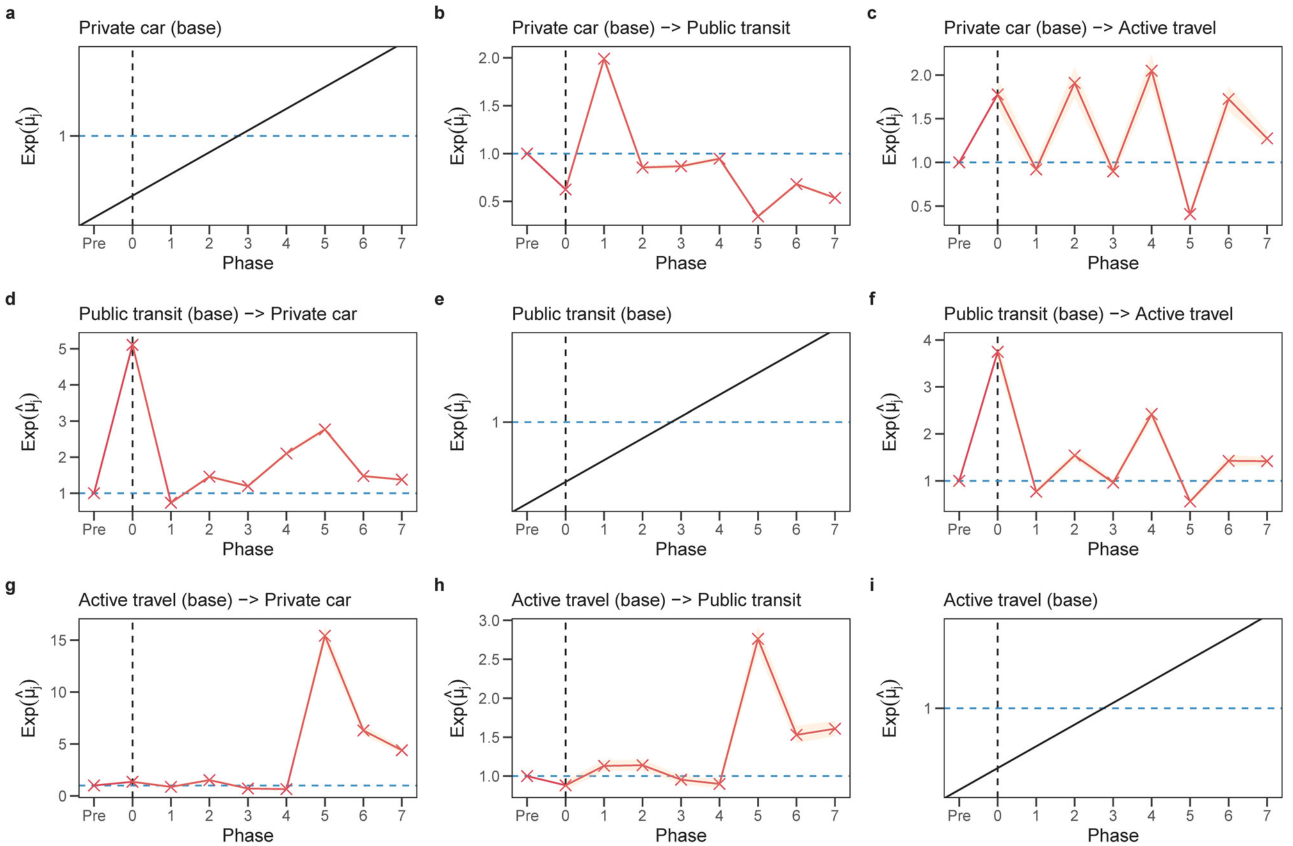


**Fig. 7 Shifts in commute mode switch behaviors.** This figure shows the post-pandemic (phases 0 to 7) shifts in commute mode switch behaviors, relative to pre-pandemic norms. The natural exponents of estimated coefficients of the multinomial logistic models ($\exp\left(\hat{\mu}_j\right)$) and their 95% confidence intervals are shown. **a-c** commute mode switch from private car (base) to public transit and active travel. **d-f** commute mode switch from public transit (base) to private car and active travel. **g-i** commute mode switch from active travel (base) to private car and public transit.

**Table 2 Differences between income groups in commute mode switch behavior shifts.**

| Commute mode switch | $\boldsymbol{Middle - income(M)}$: $\boldsymbol{affluence\ index<6}$ | | $\boldsymbol{High - income(H)}$: $\boldsymbol{affluence\ index \geq 6}$ | | $\left\lvert 1 - \mathrm{Exp}\left(\hat{\mu}_0\right)\right\rvert$ comparison |
|---|---|---|---|---|---|
| | $\mathrm{Exp}\left(\hat{\mu}_0\right)$ | P-value | $\mathrm{Exp}\left(\hat{\mu}_0\right)$ | P-value | |
| Private car (base) → Public transit | 0.677 | 0.000 | 0.590 | 0.000 | *H>M* |
| Private car (base) → Active travel | 1.736 | 0.000 | 1.832 | 0.000 | *H>M* |
| Public transit (base) → Private car | 3.781 | 0.000 | 6.041 | 0.000 | *H>M* |
| Public transit (base) → Active travel | 2.869 | 0.000 | 4.362 | 0.000 | *H>M* |
| Active travel (base) → Private car | 1.322 | 0.000 | 1.378 | 0.000 | *H>M* |
| Active travel (base) → Public transit | 1.032 | 0.542 | 0.777 | 0.000 | *H>M* |

results are available in Supplementary Fig. S1. As Table 2 shows, in all circumstances, relative to pre-pandemic levels, the magnitudes of high-income commuters' commute mode switch behavior shifts were larger than those of middle-income commuters. This suggests that the high-income group was more flexible in its choice of commute mode during the shock, while the middle-income group was more captive to its initial commute mode.

Table 3 presents the modeling results for commute time group analysis. Similar to income group analysis, only the estimation results for Phase 0 are presented here, and the full results can be found in Supplementary Fig. S2. As Table 3 shows, in all circumstances, relative to pre-pandemic levels, long-time commuters were less likely to switch to public transit and active commuting, and were more likely to switch to private car commuting. This indicates that long-time commuters relied more on private cars, while short-time commuters enjoyed more freedom when choosing commute modes because their time constraints were not as strong.

**Shifts in carbon intensity trends**. To answer the third research question, what are the shifts in carbon dioxide emission per-capita kilometer trends caused by commute mode switch behavior shifts after the pandemic. The modeling results of Eq. 3 based on the whole sample are reported below.

Figure 8 shows the modeling results for the carbon emissions model. This model is not estimated separately for different income and commute time groups because the variances in commute mode switch behavior shifts between groups were small in general. The results suggested that in Phase 0, the change in carbon emissions due to commute mode switch increased by

**Table 3 Differences between commute time groups in commute mode switch behavior shifts.**

| Commute mode switch | ***Short* − *commute*(*S*) : *commute time* ≤ *median*** | | ***Long* − *commute*(*L*) : *commute time*>*median*** | | **Exp$(\hat{\mu}_0)$ comparison** |
|---|---|---|---|---|---|
| | **Exp$(\hat{\mu}_0)$** | **P-value** | **Exp$(\hat{\mu}_0)$** | **P-value** | |
| Private car (base) → Public transit | 0.664 | 0.000 | 0.559 | 0.000 | *S*>*L* |
| Private car (base) → Active travel | 1.774 | 0.000 | 1.227 | 0.579 | *S*>*L* |
| Public transit (base) → Private car | 4.479 | 0.000 | 5.894 | 0.000 | *S*<*L* |
| Public transit (base) → Active travel | 3.457 | 0.000 | 2.956 | 0.000 | *S*>*L* |
| Active travel (base) → Private car | 1.171 | 0.020 | 1.565 | 0.000 | *S*<*L* |
| Active travel (base) → Public transit | 0.931 | 0.240 | 0.858 | 0.000 | *S*>*L* |

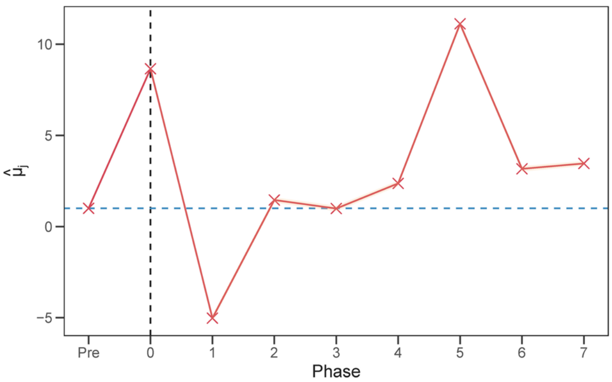


**Fig. 8 Shifts in carbon intensity trends.** This figure shows the post-pandemic (phases 0 to 7) shifts in carbon dioxide emission change per-capita kilometer due to commute mode switch, relative to pre-pandemic norms. The estimated coefficients of the linear model ($\hat{\mu}_j$) and their 95% confidence intervals are shown.

**Table 4 Fitting information of the multinomial logistic model on the whole sample.**

| Initial commute mode (base) | Number of obs. | Pseudo $R^2$ | LLR p-value |
|---|---|---|---|
| $y_{ij_s}$ = *private car* | 802,246 | 0.090 | 0.000 |
| $y_{ij_s}$ = *public transit* | 1,023,021 | 0.203 | 0.000 |
| $y_{ij_s}$ = *active travel* | 295,864 | 0.123 | 0.000 |

**Table 5 Fitting information of the multinomial logistic model on income groups.**

| Sample group | Initial commute mode (base) | Number of obs. | Pseudo $R^2$ | LLR p-value |
|---|---|---|---|---|
| Middle-income (M) | $y_{ij_s}$ = *private car* | 361,621 | 0.086 | 0.000 |
| | $y_{ij_s}$ = *public transit* | 471,307 | 0.218 | 0.000 |
| | $y_{ij_s}$ = *active travel* | 142,995 | 0.121 | 0.000 |
| High-income (H) | $y_{ij_s}$ = *private car* | 440,625 | 0.093 | 0.000 |
| | $y_{ij_s}$ = *public transit* | 551,714 | 0.192 | 0.000 |
| | $y_{ij_s}$ = *active travel* | 152,869 | 0.124 | 0.000 |

**Table 6 Fitting information of the multinomial logistic model on commute mode groups.**

| Sample group | Initial commute mode (base) | Number of obs. | Pseudo $R^2$ | LLR p-value |
|---|---|---|---|---|
| Short-commute (S) | $y_{ij_s}$ = *private car* | 406,337 | 0.082 | 0.000 |
| | $y_{ij_s}$ = *public transit* | 523,026 | 0.192 | 0.000 |
| | $y_{ij_s}$ = *active travel* | 143,259 | 0.110 | 0.000 |
| Long-commute (L) | $y_{ij_s}$ = *private car* | 395,909 | 0.058 | 0.000 |
| | $y_{ij_s}$ = *public transit* | 499,995 | 0.157 | 0.000 |
| | $y_{ij_s}$ = *active travel* | 152,605 | 0.129 | 0.000 |

**Table 7 Fitting information of the linear model on the whole sample.**

| Number of obs. | $R^2$ | F p-value |
|---|---|---|
| 2,121,131 | 0.209 | 0.000 |

8.65 g/person.km, and a rebound decrease of 5.02 g/person.km occurred in Phase 1. In Phases 2–7, the changes in carbon emissions due to commute mode switches were consistently larger than pre-pandemic levels, with an average increase of 3.76 g/person.km, and a peak increase of 11.12 g/person.km in Phase 5, at the end of the post-pandemic stage. This means that in general, post-pandemic commuting behaviors became less environmentally friendly then before the pandemic.

**Model evaluation**. The fitting information for Eq. 2 based on the whole sample, Eq. 2 based on the income and commute time sample groups, and Eq. 3 based on the whole sample is shown in Tables 4–7, respectively. Table 4 corresponds to modeling results in Fig. 7, Tables 5–6 correspond to modeling results in Tables 2–3 and Supplementary Figs. S1–S2, and Table 7 corresponds to Fig. 8. In all models, the *p*-values of the Log-Likelihood Ratio (or *F* statistic) were below 0.001, meaning that all models passed the overall significance test at a significance level of 0.001. As Fig. 7, Supplementary Figs. S1–S2, and Fig. 8 show, the 95% confidence intervals of most coefficients of the phase dummies do not include 0, meaning that most treatment variables pass the *t* test at a significance level of 0.05 or lower. This indicates that the estimation results of the main models are adequate for further interpretation, and that post-pandemic shifts in commute mode switch behaviors are statistically significant. The pseudo $R^2$s (or $R^2$s) in all models were small, ranging between 0.058 and 0.218. However, since this study focuses on examining the effects of the treatment variables on the outcome variables, rather than explaining the variances in the outcome variables, small values in the $R^2$ statistic are acceptable as long as the overall model and the treatment variables pass significance tests.

To evaluate the robustness of the main modeling results, three alternative model specifications for Eqs. 2–3 were estimated. Selected results from alternative models compared with the baseline model are in Tables 8–11, and full results and fitting information of alternative models are in Supplementary Tables S3–S10.

**Table 8 Robustness evaluation of the multinomial logistic model estimated on the whole sample.**

| Commute mode switch | Phase | Baseline model | | Alternative model 1: without seasonal fixed effect | | Alternative model 2: resampled by gender-age | | Alternative model 3: resampled by affluence index | |
|---|---|---|---|---|---|---|---|---|---|
| | | $\text{Exp}\left(\hat{\mu}_j\right)$ | P-v. | $\text{Exp}\left(\hat{\mu}_j\right)$ | P-v. | $\text{Exp}\left(\hat{\mu}_j\right)$ | P-v. | $\text{Exp}\left(\hat{\mu}_j\right)$ | P-v. |
| Private car (base) → Public transit | $t_0$ | 0.625 | 0.000 | 0.545 | 0.000 | 0.615 | 0.000 | 0.683 | 0.000 |
| | $t_1$ | 1.990 | 0.000 | 2.181 | 0.000 | 1.978 | 0.000 | 1.676 | 0.000 |
| | $t_7$ | 0.537 | 0.000 | 0.588 | 0.000 | 0.535 | 0.000 | 0.544 | 0.000 |
| Private car (base) → Active travel | $t_0$ | 1.778 | 0.000 | 1.304 | 0.000 | 1.718 | 0.000 | 1.590 | 0.003 |
| | $t_1$ | 0.920 | 0.071 | 1.111 | 0.016 | 0.987 | 0.857 | 0.852 | 0.297 |
| | $t_7$ | 1.275 | 0.000 | 1.541 | 0.000 | 1.386 | 0.000 | 1.304 | 0.009 |
| Public transit (base) → Private car | $t_0$ | 5.108 | 0.000 | 4.548 | 0.000 | 5.329 | 0.000 | 4.324 | 0.000 |
| | $t_1$ | 0.735 | 0.000 | 0.796 | 0.000 | 0.720 | 0.000 | 0.740 | 0.000 |
| | $t_7$ | 1.376 | 0.000 | 1.489 | 0.000 | 1.407 | 0.000 | 1.429 | 0.000 |
| Public transit (base) → Active travel | $t_0$ | 3.748 | 0.000 | 3.049 | 0.000 | 3.906 | 0.000 | 2.721 | 0.000 |
| | $t_1$ | 0.768 | 0.000 | 0.875 | 0.000 | 0.781 | 0.000 | 0.869 | 0.266 |
| | $t_7$ | 1.419 | 0.000 | 1.615 | 0.000 | 1.494 | 0.000 | 1.324 | 0.006 |
| Active travel (base) → Private car | $t_0$ | 1.354 | 0.000 | 1.020 | 0.610 | 1.255 | 0.002 | 1.303 | 0.09 |
| | $t_1$ | 0.867 | 0.001 | 1.036 | 0.409 | 0.846 | 0.017 | 0.800 | 0.131 |
| | $t_7$ | 4.393 | 0.000 | 5.253 | 0.000 | 4.633 | 0.000 | 3.760 | 0.000 |
| Active travel (base) → Public transit | $t_0$ | 0.882 | 0.000 | 0.784 | 0.000 | 0.837 | 0.001 | 1.040 | 0.718 |
| | $t_1$ | 1.131 | 0.000 | 1.225 | 0.000 | 1.084 | 0.091 | 1.172 | 0.130 |
| | $t_7$ | 1.608 | 0.000 | 1.743 | 0.000 | 1.559 | 0.000 | 1.444 | 0.000 |

Alternative Model 1 was specified to evaluate the main models' robustness without controlling for seasonal fixed effects. Alternative Model 2 evaluated the main models' robustness by using a sample drawn according to the joint distribution of gender–age in the whole population of Beijing. This sample was drawn from the final sample used to estimate the main models using stratified random sampling. Similarly, Alternative Model 3 evaluated the main models' robustness by using a sample drawn according to the distribution of affluence index in Beijing's population. These two models were estimated based on a resampling correction for the sample composition problem described in data collection, and their results may be more representative of the general population in the case city.

Table 8 shows that the results of all alternative models were in line with the baseline model, despite some minor differences. In all alternative models, rebound effects (Phase 1) of private car commuters switching to active travel and of active commuters switching to private car were less significant than those in the baseline model, probably indicating that commute mode switch between private car and active travel in the general population was more persistent than the baseline model suggests. In Alternative Model 2, the rebound effect (Phase 1) of active commuters switching to public transit was less significant than that in the baseline model, indicating that public transit avoidance was probably more persistent in the general population than in the sample, as the general population had larger percentages of women and older commuters. In Alternative Model 3, travel avoidance in active commuters was not significant in Phases 0 and 1 compared with the baseline model, probably because the general population had more low- to middle-income commuters, and they were not able to avoid public transit as high-income commuters did. Tables 9–10 show that in the estimation results of all alternative group analysis models, in most circumstances, high-income commuters had stronger reactions than medium-income commuters towards the pandemic, and long-commute commuters were less likely to switch to public transit and active travel than short-commute commuters, which are consistent with the main results with few noteworthy differences. Table 11 also shows that the estimation results for carbon intensity trends were consistent between baseline and all alternative models. In Alternative Model 3, the scope of fluctuation in per-capita kilometer emission change was smaller than that in the baseline model, suggesting that the environmental effects of mode choice shift in the general population were probably milder than indicated by the baseline model. Nevertheless, the directions of these fluctuations remained stable across different model specifications.

## Discussion

The results obtained from event study models may hold important implications for the future development of Beijing's urban transportation system. This section interprets these results in terms of challenges and opportunities, paying attention to the impacts of the pandemic on transport equity, transport management, and carbon emissions. The contributions and limitations of the current study are also discussed at the end of this section.

**Implications for the urban transportation system**. The COVID-19 pandemic steered the transportation system away from its previous development course, posing new challenges and opportunities for policy makers. Four years since the initial outbreak, it is crucial to recognize the current status of the urban transportation system, and to propose development strategies accordingly. In response to the absence of long-term evidence, the current study represents an attempt to shed light on the long-term effects of the pandemic on urban daily travels by examining commute mode choice shifts based on an event study design and the case city, Beijing. It can be concluded from the empirical results that the present situation of Beijing's transportation system is most in line with the neutral scenario's prediction (Abdullah et al. 2021). Commute mode split has recovered promptly and to a large extent after the initial shock, but there have also been persistent differences in post-pandemic commute mode decision making compared with pre-pandemic norms, and alarming trends have begun to emerge after the ceasing of government-level pandemic controls. This means that in the context of Beijing, the pandemic's long-term impacts on

**Table 9 Robustness evaluation of the multinomial logistic model estimated on the income groups.**

| Commute mode switch | Sample group | Baseline model | | Alternative model 1: without seasonal fixed effect | | Alternative model 2: resampled by gender-age | | Alternative model 3: resampled by affluence index | |
|---|---|---|---|---|---|---|---|---|---|
| | | Exp$(\hat{\mu}_0)$ | P-v. | Exp$(\hat{\mu}_0)$ | P-v. | Exp$(\hat{\mu}_0)$ | P-v. | Exp$(\hat{\mu}_0)$ | P-v. |
| Private car (base) → Public transit | M | 0.677 | 0.000 | 0.589 | 0.000 | 0.666 | 0.000 | 0.680 | 0.000 |
| | H | 0.590 | 0.000 | 0.515 | 0.000 | 0.584 | 0.000 | 0.688 | 0.000 |
| | $\lvert 1-\text{Exp}(\hat{\mu}_0)\rvert$ | $H>M$ | | $H>M$ | | $H>M$ | | $H>M$ | |
| Private car (base) → Active travel | M | 1.736 | 0.000 | 1.292 | 0.000 | 1.598 | 0.000 | 1.511 | 0.021 |
| | H | 1.832 | 0.000 | 1.324 | 0.000 | 1.844 | 0.000 | 1.876 | 0.040 |
| | $\lvert 1-\text{Exp}(\hat{\mu}_0)\rvert$ | $H>M$ | | $H>M$ | | $H>M$ | | $H>M$ | |
| Public transit (base) → Private car | M | 3.781 | 0.000 | 3.290 | 0.000 | 3.953 | 0.000 | 3.453 | 0.000 |
| | H | 6.041 | 0.000 | 5.441 | 0.000 | 6.230 | 0.000 | 6.209 | 0.000 |
| | $\lvert 1-\text{Exp}(\hat{\mu}_0)\rvert$ | $H>M$ | | $H>M$ | | $H>M$ | | $H>M$ | |
| Public transit (base) → Active travel | M | 2.869 | 0.000 | 2.357 | 0.000 | 2.663 | 0.000 | 2.148 | 0.000 |
| | H | 4.362 | 0.000 | 3.507 | 0.000 | 4.862 | 0.000 | 3.990 | 0.000 |
| | $\lvert 1-\text{Exp}(\hat{\mu}_0)\rvert$ | $H>M$ | | $H>M$ | | $H>M$ | | $H>M$ | |
| Active travel (base) → Private car | M | 1.322 | 0.000 | 0.961 | 0.492 | 1.061 | 0.592 | 1.102 | 0.607 |
| | H | 1.378 | 0.000 | 1.068 | 0.212 | 1.430 | 0.000 | 1.834 | 0.032 |
| | $\lvert 1-\text{Exp}(\hat{\mu}_0)\rvert$ | $H>M$ | | | | $H>M$ | | $H>M$ | |
| Active travel (base) → Public transit | M | 1.032 | 0.542 | 0.907 | 0.030 | 0.901 | 0.213 | 1.033 | 0.802 |
| | H | 0.777 | 0.000 | 0.699 | 0.000 | 0.793 | 0.001 | 1.059 | 0.784 |
| | $\lvert 1-\text{Exp}(\hat{\mu}_0)\rvert$ | $H>M$ | | $H>M$ | | $H>M$ | | | |

"M" represents middle-income group, and "H" represents high-income group.

**Table 10 Robustness evaluation of the multinomial logistic model estimated on the commute time groups.**

| Commute mode switch | Sample group | Baseline model | | Alternative model 1: without seasonal fixed effect | | Alternative model 2: resampled by gender-age | | Alternative model 3: resampled by affluence index | |
|---|---|---|---|---|---|---|---|---|---|
| | | Exp$(\hat{\mu}_0)$ | P-v. | Exp$(\hat{\mu}_0)$ | P-v. | Exp$(\hat{\mu}_0)$ | P-v. | Exp$(\hat{\mu}_0)$ | P-v. |
| Private car (base) → Public transit | S | 0.664 | 0.000 | 0.613 | 0.000 | 0.670 | 0.000 | 0.759 | 0.000 |
| | L | 0.559 | 0.000 | 0.461 | 0.000 | 0.526 | 0.000 | 0.569 | 0.000 |
| | Exp$(\hat{\mu}_0)$ | $S>L$ | | $S>L$ | | $S>L$ | | $S>L$ | |
| Private car (base) → Active travel | S | 1.774 | 0.000 | 1.307 | 0.000 | 1.726 | 0.000 | 1.615 | 0.002 |
| | L | 1.227 | 0.579 | 1.244 | 0.495 | 0.799 | 0.714 | | |
| | Exp$(\hat{\mu}_0)$ | $S>L$ | | $S>L$ | | $S>L$ | | | |
| Public transit (base) → Private car | S | 4.479 | 0.000 | 3.952 | 0.000 | 4.549 | 0.000 | 3.464 | 0.000 |
| | L | 5.894 | 0.000 | 5.308 | 0.000 | 6.364 | 0.000 | 5.694 | 0.000 |
| | Exp$(\hat{\mu}_0)$ | $S<L$ | | $S<L$ | | $S<L$ | | $S<L$ | |
| Public transit (base) → Active travel | S | 3.457 | 0.000 | 2.818 | 0.000 | 3.577 | 0.000 | 2.452 | 0.000 |
| | L | 2.956 | 0.000 | 2.212 | 0.000 | 2.932 | 0.000 | 1.373 | 0.642 |
| | Exp$(\hat{\mu}_0)$ | $S>L$ | | $S>L$ | | $S>L$ | | $S>L$ | |
| Active travel (base) → Private car | S | 1.171 | 0.020 | 0.928 | 0.192 | 1.051 | 0.635 | 1.011 | 0.962 |
| | L | 1.565 | 0.000 | 1.117 | 0.036 | 1.517 | 0.000 | 1.666 | 0.019 |
| | Exp$(\hat{\mu}_0)$ | $S<L$ | | $S<L$ | | $S<L$ | | $S<L$ | |
| Active travel (base) → Public transit | S | 0.931 | 0.240 | 0.793 | 0.000 | 0.963 | 0.688 | 1.372 | 0.076 |
| | L | 0.858 | 0.000 | 0.779 | 0.000 | 0.784 | 0.000 | 0.879 | 0.353 |
| | Exp$(\hat{\mu}_0)$ | $S>L$ | | $S>L$ | | $S>L$ | | | |

"S" represents short-commute group, and "L" represents long-commute group. In the public-transit-based alternative model 3 for the long-commute group, control variable affluence index was further recategorized into four categories to ensure convergence. In the private-car-based alternative model 3 for the long-commute group, coefficients were not estimated for mode switch behavior from private car to active travel due to a lack of observations after resampling.

sustainable mobility are not as destructive, but as of today, time may be limited for policy maneuvers to guide the city towards low-carbon development. Sufficient and imperative attention should be given to urban transportation management by scholars and governments to prevent the emergence of high-carbon transportation.

A major challenge for future transportation management is the persistent decrease in public transit ridership and accompanying increase in private car dependency. Descriptive results show that after the pandemic, on average, the percentage of bus and subway commuters decreased by 13.80% compared with pre-pandemic baseline levels, while the share of private car commuters increased

**Table 11 Robustness evaluation of the linear model estimated on the whole sample.**

| Phase | Baseline model | | Alternative model 1: without seasonal fixed effect | | Alternative model 2: resampled by gender-age | | Alternative model 3: resampled by affluence index | | Phase |
|---|---|---|---|---|---|---|---|---|---|
| | $\hat{\mu}_j$ | P-v. | $\hat{\mu}_j$ | P-v. | $\hat{\mu}_j$ | P-v. | $\hat{\mu}_j$ | P-v. | |
| $t_0$ | 8.654 | 0.000 | 8.752 | 0.000 | 8.910 | 0.000 | 7.265 | 0.000 | $t_0$ |
| $t_1$ | −5.024 | 0.000 | −5.095 | 0.000 | −5.141 | 0.000 | −3.787 | 0.000 | $t_1$ |
| $t_7$ | 3.461 | 0.000 | 3.391 | 0.000 | 3.615 | 0.000 | 3.416 | 0.000 | $t_3$ |

by 20.39%. Modeling results also show that after November 20, the probabilities of public transit commuters switching to other commute modes remained higher than before the pandemic, while the probabilities of private car commuters switching to public transit remained lower than before the pandemic. In particular, public transit commuters were on average 1.73 times more likely to turn to private car commuting than in the pre-pandemic situation. These changes are not catastrophic, yet they may add more obstacles to the already bumpy road of sustainable development. In November 22, the share of private car commuters suddenly increased, and although it decreased gradually afterwards, private car dependency seemed to have stabilized at a level higher than that of April 21, which was already higher than the pre-pandemic level. As of November 23, the percentage of private car commuters was 29.77% higher than the pre-pandemic baseline, and public transit commuters and active commuters were and 1.38 and 4.39 times more likely to switch to private cars, respectively. It is possible that in November 22, residents' travel choices were impacted by the large infection wave at the start of the pandemic-free stage, but this pandemic wave ended around February 23, meaning that descriptive and modeling results from April 23 to November 23 may reflect the new norms of the pandemic-free stage rather than commuters' shock reactions to the infection wave. This indicates that the second pandemic wave may have strengthened driving habits.

Mode choice shifts after the pandemic can also provide opportunities for the future development of sustainable urban mobility. One promising sign is the increase in active travel mode use. Descriptive results showed that compared with the pre-pandemic baseline, bicycle commuting increased by 23.58% between November 20 and April 22. This increase was the largest in magnitude among changes in other transport modes during the same period. Modeling results also show that public transit commuters between November 20 and April 22 were 1.64 times more likely to switch to active commuting than their counterparts before the pandemic, suggesting that cycling is an important sustainable alternative that can absorb spill-out travel demand from public transit. However, after April 22 and especially in November 22, the mode shares of bicycle and walking decreased. As of November 23, the percentage of bicycle commuters and walking commuters were 20.12% and 19.27% below their baseline levels, respectively. Between April 22 and November 23, the average probabilities of active commuters switching to private car and public transit commuting were 8.71 and 1.97 times higher than before the pandemic, respectively. This indicates that those who resorted to active travel to avoid crowding as well as regular users of active travel modes began to rely on motorized transport. Possible reasons include active modes' lack of comfort and safely while traveling, their vulnerability to bad weather, the relatively low speed, etc. Therefore, future research should make more attempts to find effective ways of increasing travelers' loyalty towards active mobility, probably also by conducting behavioral experiments. As the window of opportunity is gradually closing, quick actions are needed to consolidate active travel habits.

Disparities between income and commute time groups in their post-pandemic travel mode choice shifts underline important spatio-economic inequities. In a time of crisis, it is essential to distinguish between mode choice, reflecting deliberate actions, and mode use, reflecting forced actions (Zarabi et al. 2024). The group analyses in this study shed some light on this topic. The results suggest that, at least in the outbreak stage of the pandemic, middle-income commuters were captives of their initial commute mode and exhibited less flexibility during the first pandemic wave than high-income commuters, and that travel mode choices of individuals suffering from long commutes were more limited, especially to private motorized transport, than those with short commutes under the pandemic. Many previous studies have discussed similar transport inequity issues during the pandemic. Regarding income-induced transport inequity, research on public transit found that low-income individuals had less control over their use of public transit due to the lack of other travel options (Parker et al. 2021), hence the public transit trips they took during the pandemic were more likely to be forced than voluntary (He et al. 2022) and might have increased their psychological burdens (Zhao and Gao, 2022). The findings of this study are consistent with these results, as mode switch behaviors from public transit to private car and active travel are considerably more prominent in the high-income group than in the middle-income group. A study specifically focusing on pandemic commuting behavior pointed out that the probability of changing commute modes among individuals with the lowest income level was 82% lower than that of individuals with the highest income level (Dingil and Esztergár-Kiss, 2021). This result is consistent with the current study, although a much smaller gap of 6% between two groups was found here, probably because the sample was only divided into two income groups. Regarding commute time or distance induced inequity, one study pointed out that switching behavior from public transit to private car was more often found for longer trips (Das et al. 2021), while another found that the transport modes chosen for longer trips were more likely to be public transit than active travel (Mussone and Changizi, 2023), indicating that the priority ranking of travel modes was private car > public transit > active travel for long trips. This is also in line with the findings of the current study. Dingil and Esztergár-Kiss (2021) believed that long commutes prevented mode switches like low income levels did, but the current study argues that the ways through which commute distance and income level affect pandemic commute mode choice are different, and that long distances mainly influence mode preferences, while low income levels influence mode switch abilities.

Implications for transportation management and sustainable development can be derived from the above analyses and discussions. In terms of transportation management, increased car dependency may have intensified traffic congestion problems. Although new car purchase is restricted in Beijing by a lottery system, car commuting has still increased substantially since the pandemic because more trips are traveled using existing private vehicles and taxis, with the latter including both city-owned taxis and numerous ride-hailing vehicles in the private sector. Increased distances traveled by vehicles with small loading factors may impose more pressure on transportation infrastructure such as roads and parking facilities as traffic volume grows. Also, with more individuals choosing to travel by active modes, the risk of traffic accidents may rise. The conflicts between motorized vehicles and pedestrians, bikes, and especially vehicles with relatively high speed capacities such as e-bikes and motorcycles, may require extra attention from traffic administration and law enforcement. In terms of sustainable transport, modeling results show that the post-pandemic change in carbon dioxide emission per-capita kilometer due to commute mode switch behaviors was generally above pre-pandemic level, with an average post-pre-pandemic difference of +2.51 g/person.km. This provides direct prof that Beijing's transportation system has indeed been embarking on a less sustainable path of development. Since the pandemic, a series of policies has been implemented to resume human activity and mobility (Zhao et al. 2023b), and to encourage sustainable travel; for example, Beijing provided customized bus services, subway service reservations, and strictly applied disinfection routines. Most of these measures were suggested by previous studies (e.g., Das et al. 2021; He et al. 2023; Thombre and Agarwal, 2021), but their effects so far have been trivial. Faced with the persistent long-term effects of the pandemic, behavioral experiments that can help to identify the reasons behind the ineffectiveness of these policies or provide better solutions are urgently needed. In addition to changing travel mode choice, it is also recommended for policy makers to consider reducing traffic flows to reduce adverse environmental effects, since the volume of emissions depends on both (Ceccato et al. 2022; Javadinasr et al. 2022). For example, providing better access to amenities may help to shorten daily trips in the long run. Also, according to the results of this study, it should be easier for commuters to switch to active travel modes if their commute times are short. These measures may be able to help to break private car dependencies and foster more sustainable travel habits.

**Contributions and limitations**. The contributions of the current study are as follows. First, this study extends the temporal and spatial scope of existing research. The question of how the pandemic has altered travel mode decision among residents in the long run is not fully discussed by the existing literature. Previous longitudinal studies (e.g., Hamad et al. 2024) and large-sample analyses (e.g., Myftiu et al. 2024) have not yet filled this research gap To address it, the longest observation of post-pandemic travel mode change so far is provided here, reaching 4 years into the pandemic and covering over 2.1 million urban dwellers. Second, this study used an event study approach, providing a novel research framework for post-pandemic tracking studies. The unpredictability of the pandemic was utilized to develop a research framework that could single out the long-term effects of the pandemic on commute mode choice. Both the long-term result of mode choice shifts and its change processes during these 4 years were provided by studying eight continuous post-pandemic phases. In each phase, mode switch behaviors were analyzed instead of static mode choices to understand the dynamic trends of post-pandemic mobility better. Third, this study yields results with important policy implications. The results show that 4 years after the pandemic, Beijing's transportation system has partially recovered but is less sustainable, and that the opportunity to reverse this negative situation is gradually slipping away. These findings provide a clear starting point for future policy interventions, and they underline the importance of swift action.

The limitations of the current study are as follows. First, this study is susceptible to the sampling bias problem of mobile phone big data also described in previous research (Huang et al. 2019). The sample overrepresents male, young, and high-income commuters. To solve this problem, two resampled datasets based on the gender-age and affluence index composition of Beijing's whole population, were also used for model estimation. Despite minor differences between the main modeling results and those of the alternative models due to variations in risk perception and the ability to make adjustments between socio-demographic groups, the main modeling results are robust in general. Second, the accuracy of the hybrid mode detection method could not be testified based on individual-level ground truth data due to a lack of such data. However, the detection results are consistent with collective-level mode split data (Zhao and Bi, 2021). Therefore, the identification accuracy is likely to be sufficient for this study. Third, although policy suggestions are given, detailed evidence of the effectiveness of specific policy interventions on travel mode choice is not examined. This is because the main goal of this study was to evaluate the current situation of the transportation system after 4 years of pandemic influence by analyzing commute mode switch behaviors and their environmental effects. Further research is still needed to identify specific ways to deal with the emerging high-carbon urban mobility after the pandemic.

## Conclusion

This study has traced the long-term changes in commute mode switch behaviors after the COVID-19 pandemic in Beijing. Event study models were estimated based on commute modes of regular commuters and other features extracted from a mobile phone signaling dataset containing 12 months of individual trajectory information spanning from April 2018 to November 2023.

The results show that in the outbreak stage, the probabilities of public transit riders switching to private car and active travel skyrocketed, while the probabilities of private car drivers and active travelers switching to public transit dropped sharply. Inequities occurred between different income and commute time groups, as medium-income commuters were often held captive to their initial travel modes and long-commute commuters had difficulties using public transit and active modes. In the post-pandemic stage, significant rebounds in commute mode switch behaviors occurred, but they did not offset the changes brought by the outbreak stage. Persistent changes remained, with public transit riders more likely to switch to private cars, private car drivers less likely to switch to public transit, and both public transit riders and private car drivers more likely to switch to active travel. In the pandemic-free stage, compared with the post-pandemic stage, private car drivers became much less likely to switch to public transit, while active travelers became much more likely to switch to private cars. It was also found that increases in per-capita kilometer commute carbon emissions due to mode switch behaviors became significantly larger in the post-pandemic era then before the pandemic. This suggests that the window of opportunity to build a greener transportation system is closing, and that prompt actions should be taken to find efficient ways of travel behavior intervention.

## Data availability

The mobile phone signaling dataset analyzed in the current study is not publicly available due to confidentiality agreement with the cellular network operator, but an example of the dataset used for estimating event study models in this study is available by contacting the corresponding author (if permission from the cellular network operator is granted). Other datasets used in the current study are publicly available (cited in references) or available from the corresponding author on reasonable request.

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Yukun Gao: Conceptualization, data analysis, methodology, writing- draft preparation, revision. Pengjun Zhao: Supervision, writing- reviewing and editing.

## Competing interests

The authors declare no competing interests.

## Ethical approval

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## Informed consent

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## Additional information

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