Case Studies on Transport Policy 11 (2023) 100938

Contents lists available at ScienceDirect

Case Studies on Transport Policy

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

Impact of working from home on travel behavior of rail and car commuters: A case study in the Tokyo metropolitan area

Ryosuke Abe [a,*], Tatsuya Ikarashi [b], Shin Takada [c], Daisuke Fukuda [d]

[a] Japan Transport and Tourism Research Institute, 3-18-19 Toranomon, Minato-ku, Tokyo 105-0001, Japan
[b] CTI Engineering Co., Ltd., 3-21-1 Nihonbashi Hamacho, Chuo-ku, Tokyo 103-8430, Japan
[c] Japan International Cooperation Agency, 5-25 Niban-cho, Chiyoda-ku, Tokyo 102-8012, Japan
[d] Department of Civil Engineering, The University of Tokyo, 7-3-1, Hongo, Bunkyo-Ku, Tokyo 113-8656, Japan

ARTICLE INFO

Keywords:
Working from home
Trip frequency
Multivariate regression
Commuting mode
Built environment

ABSTRACT

This study empirically analyzes the impact of working from home (WFH) on travel behavior in the Tokyo metropolitan area. We use a large survey sample divided by the usual travel mode for commuting and quantify the impact of WFH on the number of rail, car, and walking and cycling trips made on a weekday. Two types of trip frequency models are examined: (1) a multivariate Poisson-lognormal (MVPLN) regression model that simultaneously explains the number of trips made by multiple modes and (2) a negative binomial regression (NBR) model. Explanatory variables comprise the place of work, the built environment of the place of residence, and individual and household attributes. The estimation results of the MVPLN model show that the error correlation between the number of trips made by a commuting mode and that by other/non-commuting modes is low for both rail and car commuters, which could justify the application of an NBR model. The estimation results of the NBR model show that the average effect of WFH for the full day (compared with working only outside the home) is a reduction of 1.9 rail trips per day for rail commuters and 1.6 car trips per day for car commuters, with car commuters who live in low-density areas tending to reduce car trips to a lesser extent. Meanwhile, few differences are observed in the reduction in rail trips for rail commuters by population density. Rail commuters tend to walk and cycle more if they work from home for the full day.

1. Introduction

Remote working (also known as teleworking and telecommuting) means working in a place different from the office or workplace in which one usually works, facilitated by ICT (MLIT, 2021); working from home (WFH) is one such form. In the Tokyo metropolitan area (TMA), "home-based teleworkers" accounted for 34.1 % of workers (excluding self-employed) in fall 2020, which was a rapid increase from 18.8 % of workers in fall 2019 (MLIT, 2021). In Central Tokyo, they accounted for 42.8 % of workers in December 2020 (Cabinet Office, 2020). Although the future trends are subject to many factors, an estimate suggests that this percentage could potentially reach up to 30–40 % in Japan (Lund et al., 2020), compared to 23 % in fall 2020 (MLIT, 2021). Remote working may become a prerequisite for the activities and lifestyles of more workers than earlier, and related analyses are more required to inform transportation and urban policy. For instance, it is not well known what a scenario where more people work from home means for the number of trips with different modes. In the TMA, the results on the travel impact of WFH could have implications for transit-oriented development and urban rail systems in such a scenario as well as rail companies' operational and business plans.

Recent empirical analyses of the effects of remote working on travel behavior have used indicators of whether an individual works remotely on a specific day as well as highly representative large survey samples. Elldér (2020), using data from the Swedish National Travel Survey, distinguishes between full-day teleworking and part-day teleworking (i.e., teleworking and commuting on the day). The results show that the amount of travel and probability of making a trip decrease if an individual works remotely for the full day, whereas the number of walking and cycling trips increases. Stiles and Smart (2020), using data from the American Time Use Survey, consider workplace, home, café/library, in-vehicle, and a combination of the four as work locations. The results

* Corresponding author at: Institute of Urban Innovation, Yokohama National University, 79-5 Tokiwadai, Hodogaya-ku, Yokohama 240-8501, Japan.
E-mail addresses: abe-ryosuke-vw@ynu.ac.jp (R. Abe), ikarashi@ctie.co.jp (T. Ikarashi), shintakada1995@outlook.jp (S. Takada), fukuda@civil.t.u-tokyo.ac.jp (D. Fukuda).

https://doi.org/10.1016/j.cstp.2022.100938
Received 13 February 2022; Received in revised form 17 November 2022; Accepted 10 December 2022
Available online 13 December 2022

show a decrease in the total amount of travel and travel during peak hours when working only from home. By contrast, the other types of work considered do not affect total travel but may reduce travel at peak times.

Studies have also developed behavioral models of whether and how often workers work remotely and incorporated them into travel demand and activity models. Shabanpour et al. (2018) estimate a model that explains how often workers in the Chicago metropolitan area work remotely by their occupation type and other factors and incorporate the results into an activity-based model. They show the impact of remote working on total daily vehicle miles/hours traveled in that area. Kawai and Fukuda (2020) estimate a model that explains the frequency of satellite office use by employing a stated preference survey of rail commuters in the TMA. The results are then incorporated into an activity-based model, and the impact of satellite offices on daily utility is computed.

This study empirically analyzes the impact of WFH on travel behavior in the TMA. First, we use the results of a survey of individuals with large sample size and divide the sample according to their usual travel mode for commuting. This segmentation is adopted because WFH could change the use of travel modes, and this shift differs by the worker's usual travel mode for commuting. In particular, the proportion of public transit use is relatively large for commuting in Japan's major metropolitan areas, making analysis by commuting mode necessary. However, surveys of daily travel behavior may not capture the commuting mode of those who work from home for the full day since they do not commute on the survey day. The same is true for the survey, the results of which are used in this study. This study predicts the commuting travel mode of those who work from home for the full day by examining their home and work addresses.

Second, it is important not only to examine whether WFH influences travel behavior, but also to quantify such an effect given the increase in the number of remote workers in the TMA and other metropolitan areas. This study thus computes the average effect of WFH on the number of rail, car, and walking and cycling trips. Additionally, the number of trips with different modes could have interdependence. For instance, rail and walking trips may have a positive relationship (in unobservable factors). This study addresses such interdependence in the estimation of the effect. Furthermore, the impact of WFH on travel behavior could differ by the place of residence given that remote workers may spend more time at home. This study examines this difference by using variables that express the built environment of the place of residence at a detailed spatial scale.

The remainder of the paper is organized as follows. The next section summarizes the assumptions of the analysis in this study. Section 3 describes the data used. Section 4 explains the models to be estimated. Section 5 presents the estimation results. The final section summarizes this study's findings and suggestions.

2. Method

2.1. Target groups and definitions of WFH

In this study, the targets of the analysis are the workers who worked on a particular day, as analyzing the impact of WFH using cross-sectional data requires a comparison of the activities of those who worked at home and those who worked outside the home on that day. The workers who worked on a day are classified into the following three categories:

- Those who worked only from home: Respondents who answered that they worked from home and did not commute or make any business trip on the day.
- Those who worked both from home and outside the home: Those who answered that they worked from home and made at least one commute or business trip on the day.
- Those who worked only outside the home: Those who answered that they did not work from home and made at least one commute or business trip on the day.

Whether a commuting trip is taken has been one of the issues in the definition of remote working (e.g., Elldér, 2020; Helminen and Ristimäki, 2006; Mokhtarian et al., 1995), as regardless of the hours worked on the day, work trips result in work outside the home.

The workers in this study exclude the self-employed and family employees. When the impact of remote working on travel behavior is analyzed, the self-employed are often excluded from the analysis (e.g., Lachapelle et al., 2018; Stiles and Smart, 2020). However, they may respond not only as self-employed, but also as company executives or other employment types in the survey data used in this study. Thus, the workers in this study also exclude those whose home and workplace are in the same block/district. They also exclude workers who were not at home in the early morning of the day (e.g., on a business trip and night shift).

2.2. Usual travel mode for commuting

We assume that the usual commuting travel mode for those who worked from home for the full day is the mode with the largest probability of being chosen for commuting between each individual's residence and workplace address (at the postcode level). Note that this prediction is required because those who worked from home for the full day do not commute on the survey day and their (usual) commuting mode is not recorded in the survey data used in this study.

To obtain this probability for each individual, we compute the probability of choosing a principal/main mode for commuting in the TMA rail demand analysis system (MLIT, 2017b; Kato et al., 2017). This method predicts the commuting mode choice at the individual level and the validity of the results is discussed in Section 3.3.2. Specifically, we first obtain the probability of walking or cycling to work between an Origin-Destination (OD) pair by using the average walking and cycling probability by the distance band prepared for non-elderly commuters.

Next, we obtain the probability of using railways, buses, and cars to get to work between an OD pair by employing a mode choice model (multinomial logit) prepared for non-elderly commuters. This model's explanatory variables are total cost, line-haul travel time between an OD pair, the number of cars owned per capita in the departure zone (for cars only), city center (for the arrival zone) and short-distance trip dummies (for cars only), and the accessibility-to-station indicator in the arrival zone (for railways only, detailed in Section 3.2.2), as well as the alternative specific constants. Note that the (McFadden's) pseudo-R-squared of this model is reported to be 0.740 and the percent correctly predicted is 90.3 % (Kato et al., 2017). These values are the second largest among the different mode choice models for travel purposes within that system after the model for commuting to school. The relatively good fitness of the commuting model means that the commuting mode choice in the TMA may be strongly explained by the above-specified factors, where whether the work address is within the city center and the accessibility to the station particularly have an important role. Note also that the TMA Person Trip Survey (PTS) data are used as travel behavior data for estimating this model.

Additionally, the overall TMA rail demand analysis system is reported to reproduce daily passenger flows between all station pairs generally within $\pm$ 10 % of the current situation (Kato et al., 2017).

2.3. Conceptual model

We estimate a model that explains the number of trips made by each mode, for a sample of rail or car commuters, as follows:

$$trip_m = f(WP, BE, SE) \tag{1}$$

where, for a given individual, $trip_m$ is the number of trips made by mode m (rail, car, or walking and cycling) on a weekday; WP is the place of work (home only, home and outside the home, or outside the home only) on the day; BE is the built environment of the place of residence; and SE is the individual and household attributes comprising the driver's license status and car ownership levels, age, gender, physical difficulties in leaving home, household type, and employment type.

As for the *BE* variables in the TMA, we employ rail accessibility, road accessibility, accessibility to rail stations, population density, and width of sidewalks and cycleways for the given place of residence. Built environment factors that affect travel behavior often include such concepts as "density," "diversity (land use mix)," "design," "destination/regional accessibility," and "distance to transit" at a particular location (Ewing and Cervero, 2010). Regional accessibility represents the potential of opportunities for interaction that can be reached from a specific place by the road or public transit network (Geurs and van Wee, 2004; Hansen, 1956). Meanwhile, the issue of residential self-selection has also been pointed out in relation to the *BE* variables (e.g., Cao et al., 2009). This study addresses this issue by enriching the *SE* variables to reduce potential covariates.

Since this model estimates the impact of WFH on the number of trips, the scope of the *SE* variables must be carefully examined. In particular, as a worker's occupation largely affects whether they can work from home (e.g., Beck et al., 2020; Shabanpour et al., 2018), the model does not use an explanatory variable for occupation.

3. Data

3.1. Travel behavior data

This study employs data from the 2018 PTS in the TMA. The survey sampled approximately 1 % of residents (300,000 residents) aged 5 years or older in the TMA. The invitation letter was sent to sampled households, requesting them to respond to the survey online or via mail. The survey was conducted in fall 2018, and respondents provided details of their travel on a specified weekday as well as their individual and household characteristics. The actual reporting day was randomly assigned to each respondent on a Tuesday, Wednesday, or Thursday during the period from September to November 2018. The survey categorized workers into regular staff/employees, temporary/contract employees, part-time workers, company executives, and other workers.

The 2018 survey included questionnaire items on the work style of the respondents who had jobs. One of these items asked, "Did you work from home on the specified day?" The response was either yes or no. The definition of WFH was not given in the questionnaire. Approximately 11 % of the sampled workers did not answer this question and in many cases, part-time workers did not. Thus, these missing values might happen more often among those who virtually cannot work remotely.

The number of rail trips (categorized as 0, 1, 2, 3, and 4 or more), car trips (categorized as 0, 1, 2, 3, 4, and 5 or more), and walking and cycling trips (categorized as 0, 1, 2, 3, 4, and 5 or more) made on a weekday are summarized for each individual and used in the analysis.

3.2. Built environment data

In this study, built environment data from 2015 were obtained for all zones at the postcode level in the TMA. The built environment information was then assigned to the residential address of each respondent in the travel behavior data.

3.2.1. Rail and road accessibility

We compute an index that expresses the ease of reaching destinations within the TMA from a specific place as follows:

$$A_i = \ln\sum_j \frac{X_j}{e^{\beta tt_{ij}}} \tag{2}$$

where A_i is the rail or road accessibility in zone i; X_j is the number of opportunities in zone j (the sum of the population and employment in zone j is used in this study); tt_{ij} is the time (in minutes) required for the shortest path between zones i and j by transit or car; and β is set at 0.2 for this setting (Axhausen et al., 2008).

The National Integrated Transport Analysis System of the Ministry of Land, Infrastructure, Transport and Tourism (MLIT) is used to compute the time required (as of 2015) for the shortest path by transit or car. The path is between the representative point of each zone to the city or town hall (ward office if applicable) of all the municipalities within the TMA. We also employ the destination municipality's population (as of 2015) and the number of jobs in all industries (as of 2014) to compute this index. A caveat in eq. (2) is that the value of β may not necessarily apply to the TMA context as discussed in the transferability issue of accessibility indices (Cascetta et al., 2016). Nonetheless, the results of these indices seem reasonable to represent the overall accessibility levels of zones in the TMA. Additionally, we use an accessibility index that measures the ease of a traveler to reach rail stations as detailed below, given the TMA's travel patterns where rail trips account for a larger share than bus, car, cycling, and walking trips (in the 2018 PTS results).

3.2.2. Accessibility to rail stations

We employ the log-sum term computed from the access mode choice model (multinomial logit), which is a component of the TMA rail demand analysis system (MLIT, 2017b; Kato et al., 2017). The system employs this log-sum term as one of the explanatory variables in mode choice and rail route choice models.

The log-sum term indicates an individual's expected utility obtained from the choice situation in the behavioral models (Train, 2009) and our log-sum term indicates the accessibility of each zone to a station, which is defined as follows:

$$P_{m,i} = \frac{\exp V_{m,i}}{\sum_{m=1}^{M} \exp V_{m,i}} \tag{3}$$

$$AA_i = \ln\sum_{m=1}^{M} \exp V_{m,i} \tag{4}$$

where $P_{m,i}$ is the probability of choosing an access mode m in zone i; M is the number of access modes; $V_{m,i}$ is the deterministic part of utility for using mode m in zone i; AA_i is the log-sum term (i.e., accessibility-to-station indicator) in zone i.

The alternatives of the access mode choice model are walking, cycling, drop-off, and buses. The explanatory variables (included in the deterministic part of utility) are "walking/cycling time = walking or cycling time between the origin/destination and the boarding/alighting station (including bicycle parking time in the station)," "drop-off/bus travel time = drop-off travel time between the aforementioned points (including car-departing/parking time in the origin/destination) or bus travel time between them (including the walk time to and from the bus stop)," "cost = cost required for each mode of travel between them," "cumulative absolute value of elevation differences for walking and cycling between them," and "bus frequency on a weekday between them" as well as the ACSs.

The log-sum term is computed for a path between a zone and the access stations included in the choice set of rail routes for each zone, based on 7 models segmented by travel purpose and age group (i.e., aged 64 or younger, or 65 or older). Among nearby stations accessible from each zone, the value of the station that has the maximum log-sum value (i.e., the most accessible station) for leisure trips or in off-peak hours is used as the log-sum value of this zone in this study.

3.2.3. Population density

We compute the number of residents within a radius of 1500 m from a representative point of each zone using the 2015 Population Census data of a 500 m mesh (Statistics of Japan, 2021). Ewing et al. (2015)

employ population density within a radius of a quarter, half, and one mile (approximately 400, 800, and 1600 m) from each zone in U.S. metropolitan areas to analyze the impact of the built environment on travel behavior. While we also examined the use of the population within a radius of 500 and 1000 m in the model to be estimated, the model fit was best with the population within a radius of 1500 m. Therefore, we used this value.

3.2.4. Average width of sidewalks and cycleways

The average width of sidewalks and cycleways is computed as sidewalk and cycleway area divided by road length for the sections of municipal roads and arterial road networks within a radius of 1500 m from the representative point of each zone using the 2015 Road Traffic Census data (MLIT, 2017a). The radius in meters is determined to reduce the number of zones with no target sections and relates to walking and cycling near home. Note that the sidewalk width of each road section is recorded for the roads having sidewalks in the original data. While this value can be summarized for each zone, the above formula provides a more realistic representation of the average sidewalk level provided in the area.

3.3. Descriptive statistics of respondents

3.3.1. Individual and household attributes and built environment

Table 1 summarizes the individual and household attributes as well as the built environment of the place of residence for the used sample. The number of observations is 90,376, of which 1.5 % worked from home for the full day, 4.8 % worked from home for part of the day, and the rest worked only outside the home.

Of those who worked only outside the home, 72 % are regular staff/employees compared with 54 % of those who worked from home for the full day and 59 % of those who worked from home for part of the day. Although the proportion is slightly lower for those who worked from home for the full day, over half are still regular staff/employees. The other major difference between the three categories is that the 65–74 age group accounts for 5 % of those who worked only outside the home, but 14 % of those who worked from home for the full day or for part of the day. Households with children of 6 years or less account for 13 % of those who worked only outside the home and 8 % of those who worked from home for part of the day, whereas they account for 20 % of those who worked from home for the full day. Finally, the built environment conditions are similar for those who worked from home for the full day and worked only outside the home, whereas those who worked from home for part of the day tend to live in areas with less rail accessibility and lower population density.

3.3.2. Commuting mode and travel behavior

Table 2 summarizes the travel behavior by commuting travel mode for the sample. Recall that the commuting mode of those who worked from home for the full day is that predicted by the method described in Section 2.2. The proportion of rail commuters does not differ significantly between those who worked only outside the home and those who worked from home for the full day, whereas it tends to be lower for those who worked from home for part of the day. The proportion of car commuters tends to be higher among those who worked from home for part of the day.

Table 2 indicates that 1.5 % of rail commuters and 1 % of car commuters worked from home for the full day, suggesting that rail and car commuters are classified reasonably well. For instance, the survey of MLIT (2021) reveals that the proportion of “home-based teleworkers” (defined as those who have worked from home in the past year) in the TMA in fall 2019 and 2020 is higher among rail commuters (13.4 % and 35.8 %, respectively) than among car commuters (4.2 % and 14 %, respectively). The overall percentage of remote workers is lower than that in the MLIT survey since this study defines WFH as whether a worker worked from home on a particular day.

Table 1
Individual and household attributes and the built environment of the place of residence.

	Those who did not work from home	Those who worked from home for the full day	Those who worked from home for part of the day
Number of respondents	84,705	1,353	4,318
Age and gender			
15–24 years	5 %	4 %	4 %
25–34 years	21 %	17 %	13 %
35–44 years	25 %	24 %	17 %
45–54 years	28 %	20 %	27 %
55–64 years	15 %	17 %	21 %
65–74 years	5 %	14 %	14 %
75 years or more	1 %	5 %	3 %
Female	38 %	42 %	41 %
Physical difficulties in leaving home	1 %	3 %	2 %
Employment type			
Regular staff/employees	72 %	54 %	59 %
Temporary/contract employees	9 %	9 %	10 %
Part-time job	14 %	19 %	23 %
Company executives	3 %	11 %	5 %
Other workers	2 %	6 %	3 %
Driver’s license and car ownership			
Licensed, car available for own use	30 %	32 %	37 %
Licensed, family shared car available	28 %	27 %	26 %
Licensed, no car	31 %	25 %	23 %
No license, no car	11 %	16 %	13 %
Household type			
Single-person households	24 %	18 %	19 %
Married-couple households	17 %	17 %	18 %
Two-generation households	49 %	52 %	49 %
Three or more generation households or other households	10 %	12 %	14 %
Households with children of 6 years or less	13 %	20 %	8 %
Household income			
Less than JPY 2 million	2 %	5 %	5 %
JPY 2 to 5.99 million	29 %	30 %	33 %
JPY 6 to 9.99 million	27 %	24 %	25 %
JPY 10 to 14.99 million	13 %	13 %	11 %
JPY 15 million or more	5 %	6 %	5 %
Unknown	23 %	22 %	21 %
Built environment of the place of residence	Mean, standard deviation	Mean, standard deviation	Mean, standard deviation
Rail accessibility	4.9, 4.2	4.8, 4.2	4.3, 4.8
Accessibility to rail stations	−2.1, 1.2	−2.1, 1.3	−2.3, 1.3
Road accessibility	10.9, 1.2	10.8, 1.2	10.7, 1.3
Population density (in ten thousands, within 1.5 km)	7.8, 4.2	7.8, 4.4	7.1, 4.2
Average width of sidewalks and cycleways (in meters, within 1.5 km)	2.6, 0.9	2.6, 1.0	2.5, 0.9

Note: Higher values of accessibility indicators imply higher accessibility.

Table 2
Commuting travel mode and travel behavior.

	Those who did not work from home	Those who worked from home for the full day	Those who worked from home for part of the day
Usual travel mode for commuting [1]			
Number of rail commuters	51,111 (60 %)	790 (58 %)	2,015 (47 %)
Number of car commuters	19,772 (23 %)	216 (16 %)	1,384 (32 %)
Number of walking/ cycling commuters	11,856 (14 %)	345 (25 %)	778 (18 %)
Number of commuters by other modes	1,966 (2 %)	2 (0 %)	141 (3 %)
Sample of rail commuters (n = 53,916)			
% of those who made a trip on the day (by definition)	100 %	39 %	100 %
% of those who made a trip during 7:30–9:30 am	86 %	6 %	80 %
	Mean	Mean	Mean
Total number of trips	2.43	1.23	2.37
Number of trips by purpose (by definition)			
Commute	0.96	0	0.96
Business	0.19	0	0.17
Personal business, returning home	1.28	1.23	1.24
Number of trips by mode			
Rail	2.12	0.25	2.08
Car	0.08	0.31	0.08
Walking and cycling	0.21	0.61	0.18
Commuting time (in minutes)	Mean, standard deviation	Mean, standard deviation	Mean, standard deviation
Travel time between first boarding and final alighting stations [2]	40.8, 23.3	44.7, 24.9	40.7, 24.3
Walking time between home and the first boarding station [3]	16.9, 13.3	17.4, 15.6	18.5, 16.0
Sample of car commuters (n = 21,372)			
% of those who made a trip on the day (by definition)	100 %	39 %	100 %
% of those who made a trip during 7:30–9:30 am	74 %	12 %	71 %
	Mean	Mean	Mean
Total number of trips	2.57	1.33	2.50
Number of trips by purpose (by definition)			
Commute	0.97	0	0.97
Business	0.29	0	0.24
Personal business, returning home	1.30	1.33	1.28
Number of trips by mode			
Rail	0.02	0.05	0.01
Car	2.39	0.88	2.35
Walking and cycling	0.09	0.32	0.08

Note:
[1] Commuting mode of those who worked from home for the full day is the mode predicted by the method described in Section 2.2.
[2] This variable is computed from network data for the non-elderly commuter's mode choice model described in Section 2.2.
[3] This variable is computed from network data for the non-elderly commuter's access mode choice model described in Section 3.2.2.

In terms of travel behavior of rail commuters, 39 % of those who worked from home for the full day made trips and 6 % of this group traveled during the morning peak hours. These values are much lower than those of the other two categories. Additionally, those who worked from home for the full day tend to make fewer rail trips and more car, walking, and cycling trips than those in the other categories. The average number of rail trips for those who worked from home for the full day is 0.25. If two rail trips (i.e., a round trip) are assumed to be equivalent to a rail traveler, then one out of eight workers who worked from home for the full day (and use rail if they commute) make rail trips. No considerable difference is observed in any of the indicators between those who worked only outside the home and those who worked from home for part of the day. Finally, the commuting time of rail commuters tends to be longer for those who worked from home for the full day than those who worked only outside the home.

For car commuters, the percentages of those who made trips and those who traveled during the morning peak hours are also much lower for those who worked from home for the full day than for the other two categories. Additionally, those who worked from home for the full day tend to make fewer car trips and more walking and cycling trips than those in the other categories. Although the number of car trips (0.88 on average) for that group is lower than that for those who worked only outside the home, the difference is less pronounced. No considerable difference is observed in any of the indicators between those who worked only outside the home and those who worked from home for part of the day. Finally, car commuters make few rail trips in all the categories.

4. Estimated model

4.1. Trip frequency model

This study employs the multivariate Poisson-lognormal (MVPLN) regression model (e.g., Ma et al., 2008; Zhao et al., 2018) and negative binomial regression (NBR) model to address the count data. The first model is applied to address the interdependence among the number of rail, car, and walking and cycling trips and analyze the impact of WFH on the number of trips with different modes.

Meanwhile, trip frequency is treated as count data and an NBR model is applied for its modeling in many studies as reviewed in Ewing and Cervero (2010) possibly because the distribution of a trip frequency variable has many zero values. In this study, the percentage of zero values is 1.3 % for rail trips, 95.7 % for car trips, and 87.1 % for walking and cycling trips in the rail commuter sample and 98.6 % for rail trips, 0.7 % for car trips, and 95.1 % for walking and cycling trips in the car commuter sample. For the non-commuting mode in each sample, it may be preferable to apply NBR models that relax an assumption that the (conditional) mean and variance of the dependent variable are the same rather than Poisson regression models that assume so.

We employ both models to acknowledge the above two issues that might not easily be addressed at the same time.

4.2. MVPLN regression model

The MVPLN regression model is formulated as follows:

$$\mathrm{Prob}(y_{ij}) = \frac{\exp(-\mu_{ij})\mu_{ij}^{y_{ij}}}{y_{ij}!} \tag{5}$$

$$\ln\mu_{ij} = \beta_j' X_{ij} + \varepsilon_{ij} \tag{6}$$

$$\varepsilon_{i.} = \begin{pmatrix} \epsilon_{i1} \\ \varepsilon_{i2} \\ \varepsilon_{i3} \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}, \Sigma \right) \tag{7}$$

where y_{ij} is the number of trips per weekday made by mode j (=1, 2, 3) for individual i; μ_{ij} is a parameter of the Poisson distribution and the expected value of the number of trips for mode j for individual i; and μ_{ij} follows a multivariate lognormal distribution. For the regression model of μ_{ij}, X_{ij} is a vector of variables, $\boldsymbol{\beta}_j$ is a vector of regression parameters, and ε_{ij} is a random term. ε_{ij} follows a multivariate normal distribution with the mean vector being the zero vector and the variance–covariance matrix being Σ.

Σ is an unconstrained variance–covariance matrix with unknown parameters. The parameterization of the diagonal component of Σ (i.e., the variance of the random term) allows us to deal with overdispersion, which is a problem in univariate Poisson regression models (El-Basyouny et al., 2014). The off-diagonal component of Σ describes the correlation structure in the unobserved factors affecting trip frequency between the different modes.

The R package PLNmodels (Chiquetet et al., 2018) is used to estimate the MVPLN regression models. In this package, the approximate maximum likelihood is obtained using a variational algorithm for which gradient descent applies. In doing so, we estimate the model with the weights of each observation. Specifically, we employ the scaling factor assigned to each respondent in the 2018 PTS in the TMA and define the weight of individual i as the scaling factor of individual i divided by the average of the scaling factors in the rail or car commuter sample. Finally, the model fit index R_d^2 defined as (final log-likelihood - initial log-

Table 3
Estimation results of the MVPLN regression model for the trip frequencies of rail commuters.

	Number of rail trips			Number of car trips			Number of walking and cycling trips		
	Coefficient	*t*-value		Coefficient	*t*-value		Coefficient	*t*-value	
Place of work (reference = outside the home only)									
WFH for the full day	−1.845	−10.5	**	4.718	36.3	**	2.196	17.9	**
WFH for the full day × Population density of the place of residence	0.067	4.2	**	−0.235	−12.5	**	0.017	1.5	
WFH for part of the day	−0.032	−0.9		−0.172	−1.0		−0.601	−4.1	**
WFH for part of the day × Population density of the place of residence	0.002	0.5		0.026	1.3		0.052	3.8	**
Built environment of place of residence									
Rail accessibility	0.001	1.0		−0.006	−1.0		0.012	2.5	*
Accessibility to rail stations	0.002	0.6		−0.067	−3.7	**	0.100	6.9	**
Road accessibility	0.002	0.4		0.044	2.1	*	0.005	0.3	
Population density (within 1.5 km)	0.002	1.6		−0.014	−2.1	*	0.036	9.3	**
Average width of sidewalks and cycleways (within 1.5 km)	0.000	−0.1		0.073	4.3	**	0.072	5.9	**
Driver's license and car ownership status (reference = no license, no car)									
Licensed, own car available	0.018	1.5		1.364	17.5	**	−0.070	−1.8	
Licensed, family shared car available	0.016	1.4		0.982	12.6	**	−0.026	−0.7	
Licensed, no car	0.015	1.5		0.338	4.3	**	0.092	2.9	**
Age (reference = 15–24 years) and gender									
25–34 years	0.010	0.6		−0.002	0.0		0.345	5.4	**
35–44 years	0.018	1.1		0.157	1.5		0.556	8.8	**
45–54 years	0.026	1.6		0.225	2.2	*	0.614	9.8	**
55–64 years	0.029	1.7		0.003	0.0		0.527	8.1	**
65–74 years	0.026	1.2		0.298	2.6	**	0.336	4.3	**
75 years or more	0.005	0.1		−0.053	−0.3		0.103	0.7	
Female	−0.004	−0.6		−0.230	−6.0	**	0.501	23.3	**
Physical difficulties in leaving home	−0.014	−0.4		−0.028	−0.2		−0.500	−3.3	**
Household type (reference = three or more generations and other households)									
Single-person households	0.023	1.9		0.240	3.8	**	0.627	14.8	**
Married-couple households	0.012	0.9		0.011	0.2		0.195	4.4	**
Two-generation households	0.001	0.1		−0.187	−3.6	**	0.008	0.2	
Households with children of 6 years or less	0.006	0.6		0.385	8.2	**	0.518	15.9	**
Employment type (reference = regular staff/employees)									
Temporary/contract employees	−0.014	−1.3		−0.215	−3.7	**	−0.020	−0.6	
Part-time job	−0.023	−1.9		0.064	1.0		0.219	6.1	**
Company executives	0.036	2.2	*	0.833	14.0	**	0.484	10.0	**
Other workers	−0.012	−0.4		0.322	2.9	**	0.066	0.8	*
Constant	0.674	14.5	**	−6.273	−26.4	**	−4.033	−24.7	**
Error variance and covariance									
Between rail and rail trips	0.000								
Between car and car trips	4.221								
Between walking/cycling and walking/cycling trips	1.941								
Between rail and car trips	0.000								
Between rail and walking/cycling trips	0.000								
Between car and walking/cycling trips	0.044								
Number of parameter estimates	93								
Number of observations	53,809								
Final log-likelihood	−265,251								
R_d^2	0.657								

Significance level: ** p <.01 * p <.05.
Note: Weighted estimation using the scaling factor of each observation.

likelihood) / (maximum log-likelihood - initial log-likelihood) that has been used in univariate Poisson regression models (Greene, 2003), is also used in MVPLN (Chiquetet et al., 2018).

4.3. NBR models and average effects

While univariate Poisson regression models have an assumption that the (conditional) mean and variance of the dependent variable are the same, this assumption is relaxed in NBR models that can deal with the problem of overdispersion. Suppose the conditional mean of the probability distribution of y_{ij} is $\lambda_{ij}(=e^{\beta_j' X_{ij}})$; then, the conditional variance is $\lambda_{ij}+1/\theta$ in the NBR model (Greene, 2003). The larger the value of θ (the dispersion parameter) to be estimated, the smaller the difference between the results of the two models becomes. The parameters of an NBR model are estimated using the maximum likelihood approach and weights of each observation as described in Section 4.2.

An NBR model is used to compute the average effects of the *WP* (place of work) variables on the number of trips. First, the estimated NBR model is used to compute the effect on the expected number of trips when the *WP* variable (dummy variable) is varied for all individuals, other things being equal. Next, we compute the sample mean of this effect by weighting each observation. We also compute the same effect when the population density of each individual's place of residence is fixed at the 25th or 75th percentile or the median in the rail or car

Table 4
Estimation results of the MVPLN regression model for the trip frequencies of car commuters.

	Number of rail trips			Number of car trips			Number of walking and cycling trips		
	Coefficient	*t*-value		Coefficient	*t*-value		Coefficient	*t*-value	
Place of work (reference = outside the home only)									
WFH for the full day	1.803	3.5	**	0.314	2.7	**	2.928	12.2	**
WFH for the full day × Population density of the place of residence	−0.012	−0.1		−0.106	−3.5	**	−0.027	−0.6	
WFH for part of the day	−0.069	−0.2		−0.024	−0.8		−0.490	−2.4	*
WFH for part of the day × Population density of the place of residence	−0.043	−0.6		0.001	0.2		0.042	1.8	
Built environment of place of residence									
Rail accessibility	0.056	3.1	**	0.001	1.1		0.017	2.1	*
Accessibility to rail stations	0.168	3.1	**	−0.001	−0.3		0.114	4.6	**
Road accessibility	−0.004	−0.1		−0.002	−0.4		0.134	4.2	**
Population density (within 1.5 km)	0.038	1.8		0.001	0.3		0.103	10.2	**
Average width of sidewalks and cycleways (within 1.5 km)	0.149	3.0	**	0.004	0.8		0.047	1.8	
Driver's license and car ownership status (reference = no license, no car)									
Licensed, own car available	−2.067	−9.0	**	0.083	2.2	*	−1.240	−8.9	**
Licensed, family shared car available	−0.963	−4.1	**	0.101	2.6	*	−0.175	−1.2	
Licensed, no car	0.359	1.4		0.075	1.5		1.057	7.0	**
Age (reference = 15–24 years) and gender									
25–34 years	−0.317	−1.1		0.038	1.0		−0.222	−1.1	
35–44 years	−0.679	−2.4	*	0.090	2.6	*	0.104	0.5	
45–54 years	0.594	−2.2	*	0.107	3.1	**	0.094	−0.5	
55–64 years	−0.577	−2.0	*	0.093	2.7	**	−0.035	−0.2	
65–74 years	−0.668	−2.1	*	0.105	2.8	**	−0.082	−0.4	
75 years or more	−1.582	−2.4	*	0.070	1.4		−0.209	−0.8	
Female	0.208	1.8		0.001	0.1		0.188	3.4	**
Physical difficulties in leaving home	−0.969	−1.6		−0.042	−0.8		−0.383	−1.7	
Household type (reference = three or more generations and other households)									
Single-person households	0.444	2.2	*	0.058	3.2	**	0.604	6.5	**
Married-couple households	0.256	1.4		0.012	0.8		−0.101	−1.1	
Two-generation households	−0.052	−0.3		0.015	1.1		−0.144	−1.9	
Households with children of 6 years or less	0.243	1.5		0.029	1.9		0.336	4.5	**
Employment type (reference = regular staff/employees)									
Temporary/contract employees	0.259	1.4		−0.005	−0.3		0.063	0.6	
Part-time job	−0.350	−2.0	*	0.045	3.2	**	0.512	7.4	**
Company executives	0.490	2.8	**	0.079	4.1	**	0.734	9.2	**
Other workers	−0.114	−0.3		0.033	1.0		0.035	0.2	
Constant	−3.984	−5.8	**	0.669	9.4	**	−5.514	−14.5	**
Error variance and covariance									
Between rail and rail trips	3.575								
Between car and car trips	0.000								
Between walking/cycling and walking/cycling trips	4.113								
Between rail and car trips	0.000								
Between rail and walking/cycling trips	0.066								
Between car and walking/cycling trips	0.000								
Number of parameter estimates	93								
Number of observations	20,003								
Final log-likelihood	−93,286								
R_d^2	0.529								

Significance level: ** p <.01 * p <.05.
Note: Weighted estimation using the scaling factor of each observation.

commuter sample to examine the difference in the average effect by place of residence.

As a preliminary analysis, we estimated a hurdle model, which can consider the determinants of zero truncation and in our case incorporates binomial logit and negative binomial distribution. We then confirmed that the average effect computed from this hurdle model is almost the same as that from the NBR model. Therefore, this paper presents the results of the NBR model only.

5. Results

5.1. Model estimation results

Tables 3 and 4 show the estimation results of the MVPLN regression model for the number of trips made by rail and car commuters, respectively, following eq. (1). The coefficients of each variable can be interpreted as the rate of change of the effect on the expected value of the number of trips (μ_{ij}). The model also includes an interaction term between the *WP* (place of work) variable and the population density of the place of residence to deal more flexibly with the differences in the impact of WFH by levels of population density.

The model fit index R_d^2 shows that the rail commuter model improves the explanatory power by 65.7 % and the car commuter model by 52.9 %, up to the value in the model with a perfect fit.

The error variance for the number of trips made by a commuting mode is almost zero in both models. These results suggest that overdispersion does not arise when explaining it.

The error covariance associated with the commuting mode is also estimated to be zero in both models. These results suggest that the number of trips made by a commuting mode may be modeled without accounting for the number of trips made by other/non-commuting modes (e.g., by an NBR model) when using a sample by commute mode and this set of explanatory variables.

The error covariance between car trips and walking and cycling trips in the rail commuter model and between rail trips and walking and cycling trips in the car commuter model is estimated to be positive. These results suggest that considering the error correlation may be important between non-commuting modes in our setting, but the error correlation coefficients are low in both cases.

5.2. Impact of WFH on the number of trips

The purpose of the model estimation is to analyze the impact of WFH on the number of trips with different modes. The reference category of this impact is "working outside the home only" on a weekday. The second column of Table 3 shows the impact of WFH on the number of rail trips made by rail commuters. The results show that WFH for the full day (on a weekday) reduces the number of rail trips (on that day). The positive interaction term of this impact implies that the absolute value of this impact decreases somewhat as the population density of the place of residence increases. Said differently, rail commuters living in higher-density areas are (very slightly) less likely to reduce the number of rail trips if they work from home for the full day. Meanwhile, the model also incorporates the other factors that may affect trip frequency as formulated in eq. (1). However, the results show that the other variables do not have a significant effect, indicating that rail use behavior among rail commuters may not differ considerably by the built environment of the place of residence and individual and household attributes.

Columns 3 and 4 of Table 3 show the impact of WFH on the number of car trips and walking and cycling trips made by rail commuters, respectively. The results show that WFH for the full day increases the number of both trips and that the impact on car trips decreases as the population density of the place of residence increases. WFH for part of the day has also a significant impact on the number of walking and cycling trips, but this impact is negligible in size as shown in the next section. Many of the variables for the built environment, driver's license, and car ownership have significant effects and their signs are as expected overall. Therefore, these variables help explain the number of car trips and walking and cycling trips made by rail commuters. The variables for the other individual and household attributes also seem to have reasonable results overall.

Next, the third column of Table 4 shows the impact of WFH on the number of car trips made by car commuters. WFH for the full day and its intersection term have a significant impact. Given the level of population density in the interaction term, WFH for the full day reduces the number of car trips in most cases. Meanwhile, we also consider the other factors that may affect the number of car trips as formulated in eq. (1). The built environment has no significant effect, similar to the case of the number of rail trips made by rail commuters. The variables for driver's license, car ownership, and other individual and household attributes also have significant effects.

Columns 2 and 4 of Table 4 show the impact of WFH on the number of rail trips and walking and cycling trips made by car commuters, respectively. WFH for the full day increases the number of both trips. Many of the variables for the built environment, driver's license, and car ownership have significant effects, and the signs are as expected overall. This observation is also similar to that of the effect on the number of car trips and walking and cycling trips made by rail commuters. The variables for the other individual and household attributes also have significant effects.

5.3. Average effect

Tables 5 and 6 show the estimation results of the NBR model for the number of trips made by rail and car commuters, respectively. The final models do not include the variables that are not significant at the 5 % level. The results of the impact of WFH correspond to those of Tables 3 and 4 in terms of signs and whether significant, excluding that WFH for the full day has no significant impact on the number of rail trips and WFH for part of the day has no significant impact on the number of walking and cycling trips in the car commuter model (Table 6).

Table 7 summarizes the average effect of WFH, which is computed from the results of Tables 5 and 6. First, rail commuters make an average of 1.9 fewer rail trips when they work from home for the full day than when they work only outside the home; this reduced travel is roughly equivalent to a round trip to the workplace. Additionally, there is only a small difference in this effect by place of residence, indicating a similar effect across the residential areas in the TMA. When rail commuters work from home for the full day, they increase their number of car trips by 0.2 and their walking and cycling trips by 0.4 on average, while those who live in low-density areas tend to increase their car use to some extent. However, the overall effect on car trips is quantitively small. While rail commuters may make walking trips particularly near the workplace (e.g., offices) and home when they work only outside the home, they make more walking trips if they work from home for the full day and possibly many of those walking trips are based at home.

Next, car commuters reduce their car trips by an average of 1.6 times when they work from home for the full day. Compared to the case of rail commuters (i.e., a decrease of 1.9 trips on average), the decrease for car commuters is smaller. Furthermore, the decrease in car use tends to be smaller for car commuters living in low-density areas. When car commuters work from home for the full day, they increase their number of walking and cycling trips by 0.2 on average. Car commuters living in densely populated areas are more likely to increase their number of walking and cycling trips, but the overall effect on the number of walking and cycling trips is quantitively small.

The average effect of WFH for part of the day is either quantitatively small or non-significant.

Table 5
Estimation results of the NBR model for the trip frequencies of rail commuters.

	Number of rail trips			Number of car trips			Number of walking and cycling trips		
	Coefficient	*t*-value		Coefficient	*t*-value		Coefficient	*t*-value	
Place of work (reference = outside the home only)									
WFH for the full day	−3.042	−15.8	**	2.203	5.0	**	1.038	11.1	**
WFH for the full day × Population density of the place of residence	0.093	5.6	**	−0.148	−3.1	**			
WFH for part of the day							−0.508	−2.6	**
WFH for part of the day × Population density of the place of residence							0.045	2.4	*
Built environment of place of residence									
Rail accessibility									
Accessibility to rail stations				−0.076	−2.5	*	0.092	4.8	**
Road accessibility							0.040	2.1	*
Population density (within 1.5 km)	0.003	4.3	**				0.033	6.6	**
Average width of sidewalks and cycleways (within 1.5 km)				0.076	2.5	*	0.064	3.8	**
Driver's license and car ownership status (reference = no license, no car)									
Licensed, own car available	0.032	2.8	**	1.289	11.6	**			
Licensed, family shared car available	0.025	2.4	*	0.974	9.2	**			
Licensed, no car	0.024	2.5	*	0.406	4.0	**	0.116	3.8	**
Age (reference = 15–24 years) and gender									
25–34 years							0.333	5.0	**
35–44 years							0.529	7.9	**
45–54 years				0.248	3.8	**	0.577	8.7	**
55–64 years							0.510	7.1	**
65–74 years				0.308	2.3	*	0.344	3.6	**
75 years or more									
Female				−0.276	−4.5	**	0.464	16.1	**
Physical difficulties in leaving home							−0.499	−2.7	**
Household type (reference = three or more generations and other households)									
Single-person households	0.016	2.2	*	0.216	2.8	**	0.585	16.6	**
Married-couple households							0.182	4.5	**
Two-generation households				−0.144	−2.1	*			
Households with children of 6 years or less				0.381	4.5	**	0.498	10.9	**
Employment status (reference = regular staff/employees)									
Temporary/contract employees									
Part-time job							0.201	3.9	**
Company executives	0.046	2.6	**	0.578	4.1	**	0.454	6.0	**
Other workers				0.483	2.3	*			
Constant	0.692	60.3	**	−3.790	−24.4	**	−3.390	−16.9	**
Dispersion parameter	114,632	1.7		0.045	28.5	**	0.241	39.5	**
Number of parameter estimates	10			17			22		
Number of observations	53,809			53,809			53,809		
Final log-likelihood	−73,055			−12,230			−28,674		

Significance level: ** p <.01 * p <.05.
Note: Weighted estimation using the scaling factor of each observation. The models presented here do not include the variables that are not significant at the 5% level.

6. Conclusions

This study analyzed the effects of WFH on the trip frequencies of different modes using a sample of workers segmented by their usual travel mode for commuting in the TMA. The results showed that the error correlation between the number of trips made by a commuting mode and that by other/non-commuting modes is small given the segmented sample and the set of explanatory variables used. For both sets of commuters, the place of work, particularly whether the worker worked from home for the full day, had a significant effect on the trip frequencies of all modes and the built environment of the place of residence also had a significant effect on the number of walking and cycling trips.

Additionally, the average effect of WFH for the full day was a reduction of 1.9 rail trips for rail commuters and 1.6 car trips for car commuters, with car commuters who live in low-density areas tending to reduce car trips to a lesser extent. Few differences were observed in the reduction in rail trips for rail commuters by population density. Rail commuters tended to walk and cycle more if they worked from home for the full day.

The further issues of this study are summarized as follows. First, we predicted the (usual) commuting mode of those who work from home for the full day on the survey day, but this approach could further be improved. Ideally, the large-scale travel behavior survey in the TMA may need to include questions on the usual travel mode for commuting and the location of work to better capture the daily travel behavior. Second, the accessibility indices developed as the rail and road accessibility in Section 3.2.1 could further be improved in terms of the parameter used and the incorporation of the active or passive accessibility theory.

The research and policy implications of this study are summarized as follows. First, this study divided the sample according to the usual travel mode for commuting. This approach facilitated the interpretation of the impact of WFH on the number of trips with different modes. A similar approach might be effective in the analysis of that impact in other metropolitan areas where the share of transit users is relatively large

Table 6
Estimation results of the NBR model for the trip frequencies of car commuters.

	Number of rail trips			Number of car trips			Number of walking and cycling trips		
	Coefficient	*t*-value		Coefficient	*t*-value		Coefficient	*t*-value	
Place of work (reference = outside the home only)									
WFH for the full day				−0.803	−7.0	**	1.284	4.5	**
WFH for the full day × Population density of the place of residence				−0.066	−2.2	*			
WFH for part of the day									
WFH for part of the day × Population density of the place of residence									
Built environment of place of residence									
Rail accessibility	0.066	3.89	**						
Accessibility to rail stations	0.199	3.50	**				0.110	3.2	**
Road accessibility							0.130	2.9	**
Population density (within 1.5 km)							0.107	6.7	**
Average width of sidewalks and cycleways (within 1.5 km)	0.142	2.29	*						
Driver's license and car ownership (reference = no license)									
Licensed, own car available	−2.169	−12.56	**	0.092	2.7	**	−0.918	−10.5	**
Licensed, family shared car available	−1.027	−5.34	**	0.113	3.2	**			
Licensed, no car				0.090	2.1	*	0.824	4.9	**
Age (reference = 15–24 years) and gender									
25–34 years	0.398	2.56	*						
35–44 years				0.056	3.9	**	0.197	2.2	*
45–54 years				0.074	5.3	**			
55–64 years				0.058	3.7	**			
65–74 years				0.070	3.4	**			
75 years or more									
Female							0.203	2.3	*
Physical difficulties in leaving home	−1.230	−2.00	*						
Driver's license and car ownership status (reference = no license, no car)									
Single-person households	0.513	3.15	**	0.047	3.3	**	0.635	6.0	**
Married-couple households									
Two-generation households									
Households with children of 6 years or less				0.036	2.5	*	0.295	2.6	**
Employment status (reference = regular staff/employees)									
Temporary/contract employees									
Part-time job				0.045	3.6	**	0.507	4.8	**
Company executives				0.088	4.6	**	0.813	5.9	**
Other workers									
Constant	−2.458	−8.36	**	0.697	20.3	**	−3.974	−9.0	**
Dispersion parameter	0.077	7.63	**	109,291	1.0		0.089	17.2	**
Number of parameter estimates	10			15			14		
Number of observations	20.003			20,003			20,003		
Final log-likelihood	−1,794			−30,093			−5,079		

Significance level: ** p <.01 * p <.05.
Note: Weighted estimation using the scaling factor of each observation. The models presented here do not include the variables that are not significant at the 5% level.

among commuters. Second, WFH for the full day implies more walking and cycling trips for rail commuters, who make a relatively larger number of walking trips even if they work only outside the home on a weekday. This evidence might be related to the benefit of transit-oriented development in a scenario where more people work from home. Third, we confirmed that rail commuters are less likely to make rail trips on a weekday if they work from home for the full day, implying that a smaller number of frequent rail commuters is directly translated to a decrease in weekday transit ridership. In the TMA, this decrease produces the benefit of alleviating rail in-vehicle congestion during peak hours, which is one of the long-standing issues in Tokyo's transportation planning. It also implies modifications to the rail operation and business plans in such a scenario.

Finally, the scenario where more people work from home is more likely to happen in the period following the COVID-19 pandemic, and the changes brought about by the pandemic, such as the increasing adoption/use of remote working, web conferencing, and e-commerce, have affected urban transportation. Tokyo's rail companies are increasing the speed of reform efforts regarding management strategies; those include projects related to responding to diversifying lifestyle needs, urban development based on local characteristics, and building platforms that connect local services and other travel modes (JTTRI, 2021). The results on the impact of WFH can serve as evidence in the development of Tokyo's transportation and mobility plans by the public (e.g., the Council for Transport Policy) and private sectors.

Table 7
Average effect of WFH on trip frequency (per capita on a weekday) for rail and car commuters.

	Number of rail trips	Number of car trips	Number of walking and cycling trips
Rail commuters			
WFH for the full day	−1.9	+0.2	+0.4
Population density fixed at the 75th percentile	−1.8	+0.1	+0.4
Population density fixed at the median	−1.9	+0.1	+0.3
Population density fixed at the 25th percentile	−1.9	+0.2	+0.3
WFH for part of the day	—	—	0.0
Population density fixed at the 75th percentile	—	—	0.0
Population density fixed at the median	—	—	0.0
Population density fixed at the 25th percentile	—	—	0.0
Car commuters			
WFH for the full day	—	−1.6	+0.2
Population density fixed at the 75th percentile	—	−1.7	+0.2
Population density fixed at the median	—	−1.5	+0.2
Population density fixed at the 25th percentile	—	−1.4	+0.1
WFH for part of the day	—	—	—
Population density fixed at the 75th percentile	—	—	—
Population density fixed at the median	—	—	—
Population density fixed at the 25th percentile	—	—	—

Note:
— = not significant at the 5 % level in the original model.
The estimation results of the NBR model, presented in Tables 5 and 6, are used to compute the average effect. The reference category of the effect is "working only outside the home".

Author contributions

The authors confirm contribution to the paper as follows: study conception and design: R. Abe, D. Fukuda; data collection: R. Abe, T. Ikarashi, S. Takada; analysis and interpretation of results: R. Abe, D. Fukuda; draft manuscript preparation: R. Abe. All authors reviewed the results and approved the final version of the manuscript.

Declaration of Competing Interest

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

Acknowledgements

The authors would like to thank Hirotaka Yamauchi for comments on improving the quality of this study and all those who provided comments and suggestions at conferences and seminars. We also thank the Ministry of Land, Infrastructure, Transport and Tourism for providing the Person Trip Survey dataset of the TMA and allowing the use of the National Integrated Transport Analysis System as well as Creative Research and Planning Co. Ltd. for its support in using the rail demand analysis system of the TMA. This work was supported in part by JSPS KAKENHI Grant Number JP18K13854. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the authors' organization.

References

Axhausen, K.W., Dolci, C., Fröhlich, P.h., Scherer, M., Carosio, A., 2008. Constructing Time-Scaled Maps: Switzerland from 1950 to 2000. Transp. Rev. 28, 391–413. https://doi.org/10.1080/01441640701747451.

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

Cabinet Office, 2020. Second Survey on Changes in Attitudes and Behaviors in Daily Life under the Influence of Novel Coronavirus Infection, Government of Japan. [in Japanese] https://www5.cao.go.jp/keizai2/keizai-syakai/future2/20210119/shiryou3-1.pdf (accessed July 10, 2021).

Cao, X., Mokhtarian, P.L., Handy, S.L., 2009. Examining the impacts of residential self-selection on travel behaviour: a focus on empirical findings. Transp. Rev. 29, 359–395. https://doi.org/10.1080/01441640802539195.

Cascetta, E., Cartenì, A., Montanino, M., 2016. A behavioral model of accessibility based on the number of available opportunities. J. Transp. Geogr. 51, 45–58. https://doi.org/10.1016/j.jtrangeo.2015.11.002.

Chiquet, J., Mariadassou, M., Robin, S., 2018. Variational inference for probabilistic Poisson PCA. Ann. Appl. Stat. 12, 2674–2698. https://doi.org/10.1214/18-AOAS1177.

El-Basyouny, K., Barua, S., Islam, M.T., 2014. Investigation of time and weather effects on crash types using full Bayesian multivariate Poisson lognormal models. Accid. Anal. Prev. 73, 91–99. https://doi.org/10.1016/j.aap.2014.08.014.

Elldér, E., 2020. telework and daily travel: new evidence from Sweden. J. Transp. Geogr. 86, 102777 https://doi.org/10.1016/j. jtrangeo.2020.10277.

Ewing, E., Cervero, R., 2010. Travel and the Built Environment. J. Am. Plann. Assoc. 76, 265–294. https://doi.org/10.1080/01944361003766766.

Ewing, R., Tian, G., Goates, J., Zhang, M., Greenwald, M.J., Joyce, A., Kircher, J., Greene, W., 2015. Varying influences of the built environment on household travel in 15 diverse regions of the United States. Urban Stud. 52, 2330–2348. https://doi.org/10.1177/0042098014560991.

Geurs, K.T., van Wee, B., 2004. Accessibility evaluation of land-use and transport strategies: review and research directions. J. Transp. Geogr. 12, 127–140. https://doi.org/10.1016/j.jtrangeo.2003.10.005.

Greene, W.H., 2003. Econometric Analysis, 5th Edition, Upper Saddle River.

Hansen, W.G., 1959. how accessibility shapes land use. Journal of the American Institute of planners 25, 73-76. 10.1080 /01944365908978307.

Helminen, V., Ristimäki, M., 2007. Relationships between commuting distance, frequency and telework in Finland. J. Transp. Geogr. 15, 331–342. https://doi.org/10.1016/j.jtrangeo.2006.12.004.

JTTRI. Symposium on Addressing Mid- and Long-Term Issues for Railways in the Tokyo Metropolitan Area and the COVID-19 pandemic: Improving the Attractiveness of Railway Lines Based on Population and Demand Trends, Presentation Materials, 2021. https://www.jttri.or.jp/events/2021/symposium210705.html (accessed January 3, 2022) [in Japanese].

Kato, H., Fukuda, D., Yamashita, Y., Iwakura, S., Yai, T., 2017. Latest urban rail demand forecast model system in the TMA. Transp. Res. Rec. 2669, 60–77. https://doi.org/10.3141/2668-07.

Kawai, T., Fukuda, D., 2020. Railway commuter's intention of center-based telecommuting and their activity pattern in Tokyo metropolitan area. J. City Plan. Inst. Jpn. 55, 174–181. https://doi.org/10.11361/journalcpij.55.174.

Lachapelle, U., Tanguay, G.A., Neumark-Gaudet, L., 2018. Telecommuting and sustainable travel: reduction of overall travel time, increases in non-motorised travel and congestion relief? Urban Stud. 55, 2226–2244. https://doi.org/10.1177/0042098017708985.

Lund, S., Madgavkar, A., Manyika, J., Smit, S., 2020. what's next for remote work: an analysis of 2,000 tasks, 800 jobs, and nine countries. McKinsey Global Institute, available at https://www.mckinsey.com/featured-insights/future-of-work/whats-next-for-remote-work-an- analysis-of-2000-tasks-800-jobs-and-nine-countries (accessed July 10, 2021).

Ma, J., Kockelman, K.M., Damien, P., 2008. A multivariate Poisson-lognormal regression model for prediction of crash counts by severity, using Bayesian methods. Accid. Anal. Prev. 40, 964–975. https://doi.org/10.1016/j.aap.2007.11.002.

Ministry of Land, Infrastructure, Transport and Tourism (MLIT), 2021. 2020 Telework Population Survey results, MLIT. [in Japanese] https://www.mlit .go.jp/toshi/daisei/telework_index.htm (accessed July 10, 2021).

Ministry of Land, Infrastructure, Transport and Tourism (MLIT), 2017a. 2015 Road Traffic Census, MLIT. [in Japanese] https://www.mlit.go.jp/road/ census/h27/index.html (accessed July 10, 2021).

Ministry of Land, Infrastructure, Transport and Tourism (MLIT), 2017b. Technical Report on Rail Demand Analysis Method, MLIT. [in Japanese] http:// www.mlit.go.jp/common/001138608.pdf (accessed July 10, 2021).

Mokhtarian, P.L., Handy, S.L., Salomon, I., 1995. Methodological issues in the estimation of the travel, energy and air quality impacts of telecommuting. Transp. Res. A 29, 283–302. https://doi.org/10.1016/0965-8564(94)00029-A.

Shabanpour, R., Golshani, N., Tayarani, M., Auld, J., Mohammadian, A., 2018. Analysis of telecommuting behaviour and impacts on travel demand and the environment. Transp. Res. Part D: Transp. Environ. 62, 563–576. https://doi.org/10.1016/j.trd.2018.04.003.

Statistics of Japan, 2021. Statistics Map of Japan (Statistics GIS), available at https://www.stat.go.jp/english/data/kokusei/index.html (accessed July 10, 2021). accessed July 10, 2021).

Stiles, J., Smart, M.J., 2020. Working at home and elsewhere: daily work location, telework, and travel among United States knowledge workers. Transportation. https://doi.org/10.1007/s11116-020-10136-6.
Train, E.T., 2009. Discrete Choice Methods with Simulation, Second Edition. Cambridge University Press, New York.
Zhao, M., Liu, C., Li, W., Sharma, A., 2018. Multivariate Poisson-Lognormal Model for Analysis of Crashes on Urban Signalized Intersections Approach. J. Transp. Saf. Secur. 10, 251–265. https://doi.org/10.1080/19439962.2017.1323059.