On commuting duration and the daily travel time budget

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BACKGROUND

There has been accumulated evidence that individuals' average daily travel time is relatively constant at a regional or national scale[1]. This constant, around or slightly more than an hour, is referred to as the travel time budget or Marchetti's constant, assumed to reflect a behavioral regularity of humans[2, 3].

Among the everyday travel purposes, commuting trips (i.e., individuals' travels between their places of residence and work) play a crucial role in urban mobility[4]. Considering the diverse distribution of commuting time within a city[5], we may ask the following question: Would residents with longer commuting times spend less time traveling for other purposes? The answer seems to be yes, as a consequence of the daily travel time budget. Here, we present contrary evidence from the individual-level travel diary data in the Île-de-France (IDF) region (referred to as the NetMob25 dataset hereinafter): residents' daily non-commuting travel time, averaged over a week, remains relatively stable to the change of commuting time.

DATA AND METHODS

The NetMob25 data[6] is collected from a GPS-based mobility survey from October 2022 to May 2023, covering 3,337 volunteer residents aged 16 to 80 in the IDF region. For each resident, the travel diary dataset contains the start/end time and the purpose (activity type at the origin and the destination) of each trip during a week. Among the seven recorded days for each individual, we first exclude days with no traces or when the resident is outside IDF, and label the remaining days as *valid*. Furthermore, a *valid* day is labeled as a workday if and only if it involves any work or study activity. For each resident, we calculate T_{tot} as the average daily travel time over *valid* days, and T^{w}_{tot} as the average travel time over workdays.

To estimate the average commuting time of each individual, a common approach is to classify the trips into commuting and non-commuting trips. However, one may stop at other locations on the way of commuting, resulting in a chain of multiple trips. The commuting time would be overestimated if all these trips were considered commuting. To avoid such bias, we only consider direct trips between home and work (or school) which are not separated by other stops, and define their average duration as the individual commuting time T_{comm}.

Next, the average daily non-commuting travel time T_{ncom} for each individual is calculated as

$$T_{ncom} = \frac{T_{tot} \times \#\text{valid\_days} - T_{comm} \times \#\text{comm\_trips}}{\#\text{valid\_days}} \quad (1)$$

where #comm_trips is the number of commuting trips (possibly with intermediate stops) over the week. In other words, we subtract T_{comm} from the total travel time for each commuting trip, then average over *valid* days. Similarly, we compute the average non-commuting travel time for workdays as T^{w}_{ncom}. Our analysis considers 2,240 individuals with at least 3 *valid* days and 3 direct commuting trips to mitigate the effect of data uncertainty. For analysis over workdays, we further exclude residents with fewer than 3 workday records, resulting in 1,917 residents.

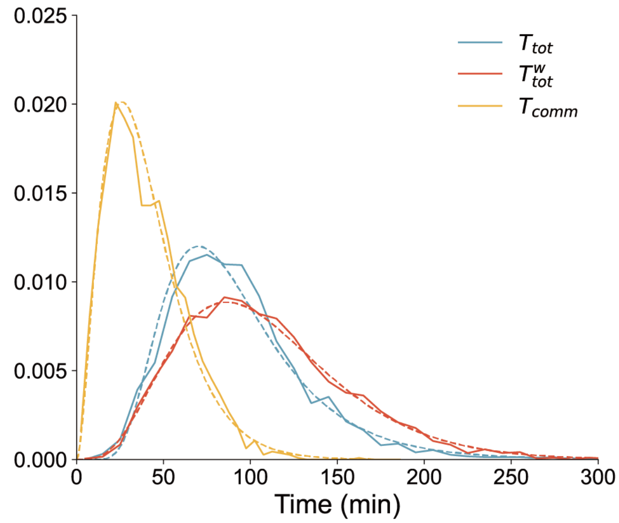

Fig. 1. Distribution of the average daily travel time T_{tot}, the average daily travel time on workdays T^{w}_{tot}, and average commuting time T_{comm} over the volunteer residents. T_{tot} is fit with a lognormal distribution, while the other two curves are fit with gamma distributions.

RESULTS

Figure 1 shows the distribution of T_{tot}, T^{w}_{tot}, and T_{comm}, where each point represents a resident. The daily travel time T_{tot} has a mean of 92.5 min and a median of 86.5 min. Generally, residents spent more time traveling on workdays, yielding a mean of 108.8 min and a median of 101.3 min for T^{w}_{tot}. The average commuting time over 2,240 residents is 40.0 min, and the quartiles are 23 min, 36 min, and 54 min. The distribution of T_{comm} is best modeled with a gamma distribution according to the Akaike information criterion (candidates include lognormal, gamma, exponential, and Pareto), with the probability density function

$$f(t) \propto x^{\alpha-1} e^{-\frac{x}{\theta}} \quad (2)$$

where $\alpha = 5.67$ and $\theta = 16.32$. The gamma property still holds when we consider the duration distribution of the 14,627 direct commuting trips, and when the trips are grouped by the department of residence or the professional group of the individuals. These results suggest the gamma distribution as a stable temporal property of urban commuting.

To explore the association between commuting time and non-commuting travel time, the simple linear regression yields

$$\begin{aligned} T^{w}_{ncom} &= \underset{(1.646)}{38.612} - \underset{(0.037)}{0.199}\, T_{comm}, R^2 = 0.015 \quad (3) \\ T_{ncom} &= \underset{(1.416)}{48.795} - \underset{(0.031)}{0.053}\, T_{comm}, R^2 = 0.001 \quad (4) \end{aligned}$$

where standard errors are given in parentheses. The slope estimate suggest that non-commuting travel time is only slightly affected by the change of commuting time. In contrast, assuming T^{w}_{tot} is constant, the slope parameter in Eq. 3 should be

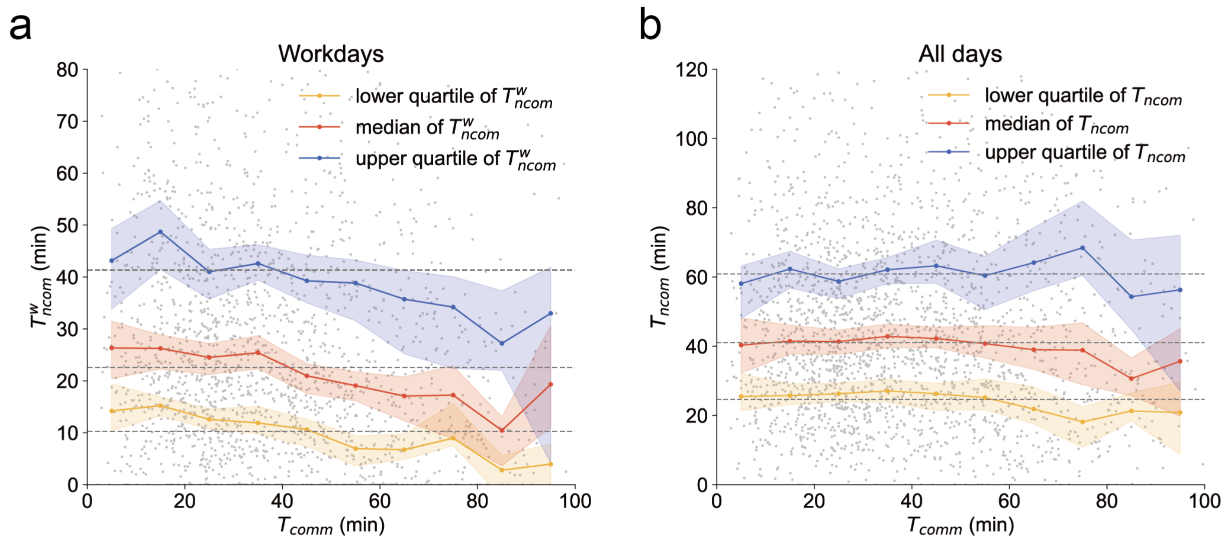

Fig. 2. The relationship between daily non-commuting travel time and commuting time over (a) workdays (T^w_{ncom} against T_{comm}) and (b) all days (T_{ncom} against T_{comm}). Each gray dot represents a resident in the dataset. Yellow, red, and blue lines show the quartiles of non-commuting travel time for each 10 min interval of commuting time with 95% confidence interval from the bootstrap method. Gray dashed lines are the overall quartiles.

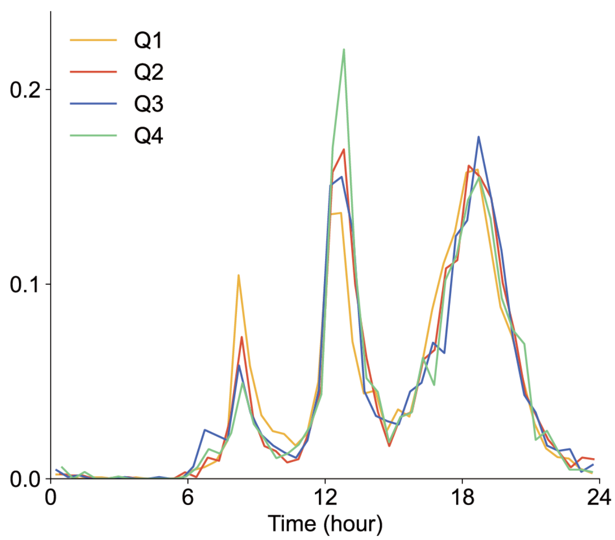

Fig. 3. Start time distribution of non-work activities throughout the day for quartile groups of commuting time.

around -2.0 given two commuting trips per day. Furthermore, if weekends are included, the association is not even significant ($p = 0.087$ in Eq. 4). This finding is further supported by Fig. 2, where we group the residents using commuting time intervals of 10 min and consider non-commuting travel time of each group. For the medians, the non-commuting travel time on workdays of the 50-60 min group is only 7.3 min less than the 0-10 min group (Fig. 2a). If weekends are included, non-commuting travel time remains remarkably stable around the overall median of 41.0 min (Fig. 2b). Instead of the daily travel time budget, these empirical results seem to suggest a hypothesis of "non-commuting travel time budget": the daily non-commuting travel time is relatively stable regardless of the time spent on commuting.

The association between non-commuting travel time and commuting time exhibits heterogeneity among professional groups. A linear regression model of $\ln T_{ncom}$ against $\ln T_{comm}$ (with gender, age, car ownership, and professional groups as dummy control variables) gives an elasticity of -0.076 ± 0.028. When adding interaction terms of T_{comm} and dummy variables indicating professional groups, workers exhibit the strongest elasticity (-0.385 ± 0.126) of all groups. This may indicate potential inequality in access to spare-time activities faced by workers with lower socioeconomic status.

DISCUSSION

We find that the non-commuting travel time of individuals is not necessarily affected by commuting burden, indicating a basic need for spare-time activities such as shopping, recreation, and accompanying. We assume residents accommodate longer commuting time in two possible ways: (i) arranging more non-commuting travels on weekends to compensate for the loss of spare time on workdays, as evidenced in Fig. 2; (ii) rescheduling some non-commuting travels from the morning before work to the lunch break, as suggested in Fig. 3.

Our analysis is currently confined to the IDF region, limiting the generality of results. In the future, we will incorporate individual-level mobility data from other countries to validate our findings.

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Data availability. This work was performed using data from the Netmob 2025 Data Challenge [6].

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