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Modelling the impacts of COVID-19 measures on activity-travel behavior in the Netherlands: A MDCEV framework

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Abstract

In this study, we used the Netherlands Mobility Panel (MPN) data collected during different phases of the pandemic to understand how people adapt their behavior with the implementation and relaxation of governmental measures. The MPN data is a longitudinal activity-travel diary data collected from a fixed group of approximately 2000 households since 2013. The data is collected annually based on a self-reported diary of 3 consecutive days. As daily activity-travel behavior can be characterized by the multiple discrete-continuous choices, multiple discrete-continuous extreme value (MDCEV) models have widely been used in transport literature. However, MDCEV in the seminal work usually focused on predicting behavior at a daily aggregate level. To model the dynamic aspects of activity duration and mode-choice, we estimate an episode-based mixed multiple discrete-continuous extreme value (MMDCEV) model. The episode-based approach does not aggregate the amount of consumption for each alternative but allows multiple episodes per activity. Based on the empirical study on the time-use and mode-use behavior during the different phases of the COVID-19 pandemic, we found the use of the episode-based approach enriches the behavioral insights.

Keywords: COVID-19, Activity Travel Diary Data, Multiple Discrete-Continuous Extreme Value Model, Activity-Duration Choice, Mode-Duration Choice

1. Introduction

The COVID-19 pandemic has brought about substantial changes in people's activity-travel behavior. In the early phase of the pandemic (March 2020), the Dutch government implemented so-called "intelligent lockdown" to avoid the spread of the virus while minimizing the economic impact (de Haas et al., 2020). Though it was not a complete lockdown, the measure included the cancellation of all leisure/social activities, the closure of catering/leisure facilities and schools, downscaling public transport, work-from-home as a norm, and so forth. As more data become available, some descriptive analyses have been undertaken. For example, recent studies analyzed the impact of the Dutch lockdown on activity-travel behavior (de Haas et al., 2020; Van Der Drift et al., 2021). They both found a decrease in the number of out-of-home activities and travel distance, and more prominent decline in the use of public transport. However, modelling these changes is crucial in the context of preparing post-pandemic and possible similar future scenarios. In this study, we used the Netherlands Mobility Panel (MPN) data collected during different phases of the pandemic to understand how people adapt their behavior with the implementation and relaxation of governmental measures. To model activity duration and mode-choice behavior, based on Palma et al. (Palma et al., 2021), we estimate an episode-based mixed multiple discrete-continuous extreme value (MMDCEV) model.

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2. Methodology

2.1. Episode-based Mixed MDCEV Model

As daily activity-travel behavior can be characterized by the multiple discrete-continuous choices, MDCEV models have widely been used in transport literature (Bhat, 2005). However, MDCEV models in the seminal work usually focused on predicting behavior at a daily aggregate level (either time-use or mode-use). The episode-based approach proposed by Palma et al. (2021) does not aggregate the amount of consumption for each alternative but allows multiple episodes per activity. The utility function of the episode-based MMDCEV model can be formulated as follows:

$$U_{nt}(\mathbf{x}_{nt}) = \sum_{k=1}^{K}\sum_{i=1}^{I_k}\frac{\gamma_{ki}}{\alpha}\psi_{ntki}\left[\left(\frac{x_{ntki}}{\gamma_{ki}}+1\right)^{\alpha}-1\right]$$

$$\text{s.t.} \sum_{k=1}^{K}\sum_{i=1}^{I}x_{ntki}p_k = B_{nt}, \qquad \forall n \in N, t \in T \tag{1}$$

where K is the total number of activity types (or transport modes) considered (we call this as "base alternative" in this paper), and I_k is the daily maximum number of activity episodes or trips (a pre-defined set for base alternative k). $\mathbf{x}_{nt} = \{x_{nt11}, x_{nt12}, \dots, x_{ntKI_k}\}$ is the consumption amount of the i-th episode (i = 1, 2, …, I_k) of base alternative k (k = 1, 2,…, K) by individual n (n = 1, 2,…, N) on day t (t = 1, 2,…, T), and p_k is the unit price of base alternative k. B_{nt} is a daily budget constraint, which is non-zero and positive, related to activity time-use (individual-specific daily time budget except travel time) or mode-use (individual-generic daily proportion of travel distance, i.e., 100%). α is the generic satiation parameter. ψ_{ntki} and γ_{ki} are the baseline utility and the translation/satiation parameter which can be written as follows:

$$\psi_{ntki} = \exp\left(\delta_k + \beta_k z_{nk} + \sum_{s=1}^{S_{\psi k}}\pi_{\psi ks}(i-1)^s + \varepsilon_{ntki}\right) \tag{2}$$

$$\gamma_{ki} = \theta_k + \lambda_k z_{nk} + \sum_{s=1}^{S_{\gamma k}}\pi_{\gamma ks}(i-1)^s \tag{3}$$

To guarantee the positivity, the exponential form has generally been used for both ψ_{ntki} and γ_{ki}, but the recent study (Palma et al., 2021) suggest that it is harmless or even beneficial in estimation not to use the exponential form for γ_{ki}. The first term δ_k and θ_k represent constants for the baseline utility and satiation parameters, respectively. The second term $\beta_k z_{nk}$ and $\lambda_k z_{nk}$ capture the observed heterogeneity across individuals. The third term $\sum_{s=1}^{S_{\psi k}}\pi_{\psi ks}(i-1)^s$ and $\sum_{s=1}^{S_{\gamma k}}\pi_{\gamma ks}(i-1)^s$ are the polynomial penalty terms imposed to capture fatigue effects in both baseline utility and satiation parameters, where $S_{\psi k}$ and $S_{\gamma k}$ are the polynomial degree which analysts can determine by observing the pattern in the data. $\pi_{\psi ks}$ and $\pi_{\gamma ks}$ are the penalty parameters to be estimated. To accommodate the random panel effect caused by the correlation over the multiple days, the error term ε_{ntki} can be partitioned into two components: $\eta_{nki} = \mu_{ki}\xi_{nki}$, where $\xi_{nki} \sim N(0,1)$ and $\zeta_{ntki} \sim Gumbel(0,\sigma)$. The unconditional probability of an observed set of the continuous choices $\mathbf{x}_{nt}^{*} = \{x_{nt1}^{*}, x_{nt2}^{*}, \dots, x_{ntM_{nt}}^{*}\}$ when the first M_{nt} is consumed ($M_{nt} \geq 1, \forall n, t$) is given by:

$$P\left(x_{nt1}^{*}, x_{nt2}^{*}, \dots, x_{ntM_{nt}}^{*}, 0, 0, \dots, 0\right) =$$

$$\int_{\eta} \frac{1}{p_1}\cdot\frac{1}{\sigma^{M_{nt}-1}}\left[\prod_{m=1}^{M_{nt}} f_{ntm}\right]\left[\sum_{m=1}^{M_{nt}}\frac{p_m}{f_{ntm}}\right]\left[\frac{\prod_{m=1}^{M_{nt}} e^{(V_{ntm}+\eta_{nm})/\sigma}}{\left(\sum_{k=1}^{k}\sum_{i=1}^{I_k} e^{(V_{ntki}+\eta_{nki})/\sigma}\right)^{M_{nt}}}\right](M_{nt}-1)!\,dF(\eta). \tag{4}$$

where M_{nt} is the total number of episodes chosen by individual n on day t, $f_{ntm} = \frac{1}{x_{ntm}+\gamma_m}$, $V_{ntki} = \delta_k + \beta_k z_{nk} + \sum_{s=1}^{S_{\psi k}} \pi_{\psi ks}(i-1)^s + (\alpha-1)\ln\left(\frac{x_{ntki}}{\gamma_{ki}}+1\right) - \ln(p_k)$, and $F(\cdot)$ is the multivariate cumulative normal distribution (Bhat, 2005). Because the integral does not exist in closed form, the model parameters were estimated using the maximum simulated likelihood method with 1000 MLHS draws (Hess et al., 2006). We used Apollo software (Hess & Palma, 2006) for all model estimations. For model identification and operation, some decisions had to be made. As in equation (1), the model represents a "no outside good" case since the data does not exhibit an "outside good". α is generic across alternatives and γ_{ki} is alternative-specific. The unit cost p_k is assumed to be equal (to one) across base alternative k, and thus the scale parameter σ is normalized to one. For the penalty terms $S_{\psi k}$ and $S_{\gamma k}$, a cubic polynomial (degree 3) is initially posed.

2.2. The Netherlands Mobility Panel (MPN) Data

The MPN data is a longitudinal activity-travel diary data collected from a fixed group of approximately 2000 households since 2013 (Hoogendoorn-Lanser et al., 2015). The data is collected annually based on a self-reported diary of 3 consecutive days. In 2020, due to the demanding requests of the data during the pandemic, two additional rounds of the survey were conducted as shown in Table 1.

Table 1. Summary of the MPN data

Phase	Survey period	Number of households	Number of individuals	Number of day-individuals	Number of episodes
Pre-pandemic	2019-09-22 ~ 2019-11-12	2051	2791	8374	29627
Lockdown	2020-03-27 ~ 2020-04-04	1695	2279	6831	14216
Relaxation	2020-06-24 ~ 2020-07-02	1533	2051	6152	17152

3. Results

For model estimation, the sample with zero budget (only for mode-use model) and incomplete observations (less than 3 days) are removed. The number of alternatives is 36 and 29 for activity time-use model and mode-use model, respectively. As shown in Figure 1, only significant alternative-specific constants (δ, θ) and penalty parameters (π_ψ, π_γ) of the activity time-use models are shown for brevity. Regarding activity time-use behavior, the result suggests a significant decrease in education, leisure and services along with increases in touring activity (e.g., walk a dog) during the lockdown period, but soon it recovered to the pre-pandemic state in the relaxation period. In terms of the satiation effect, all else being equal, during the lockdown period, people spent less time on business and education activity whereas home activity duration was increased. The episode-based approach enriches the behavioral insights. The number of episodes was significantly reduced during the lockdown period which also implies a decrease in daily travel. Most of the estimated penalty parameters for both baseline utility (π_ψ) and satiation parameters (π_γ) have negative values indicating the fatigue effects on the repetition of the same activity type. For transport mode-use behavior, the use of public transport (train, bus/tram/metro) significantly dropped during the lockdown period while the use of active modes (walk, bike) is increased. Regarding the penalty parameters on mode-use, the results show somewhat different behavior compared to activity time-use. Several positive penalty parameters were observed indicating the fact that the most daily travel is round trip using the same mode. The association between socio-demographic attributes and activity-travel behavior is intuitive and is consistent with previously reported studies.

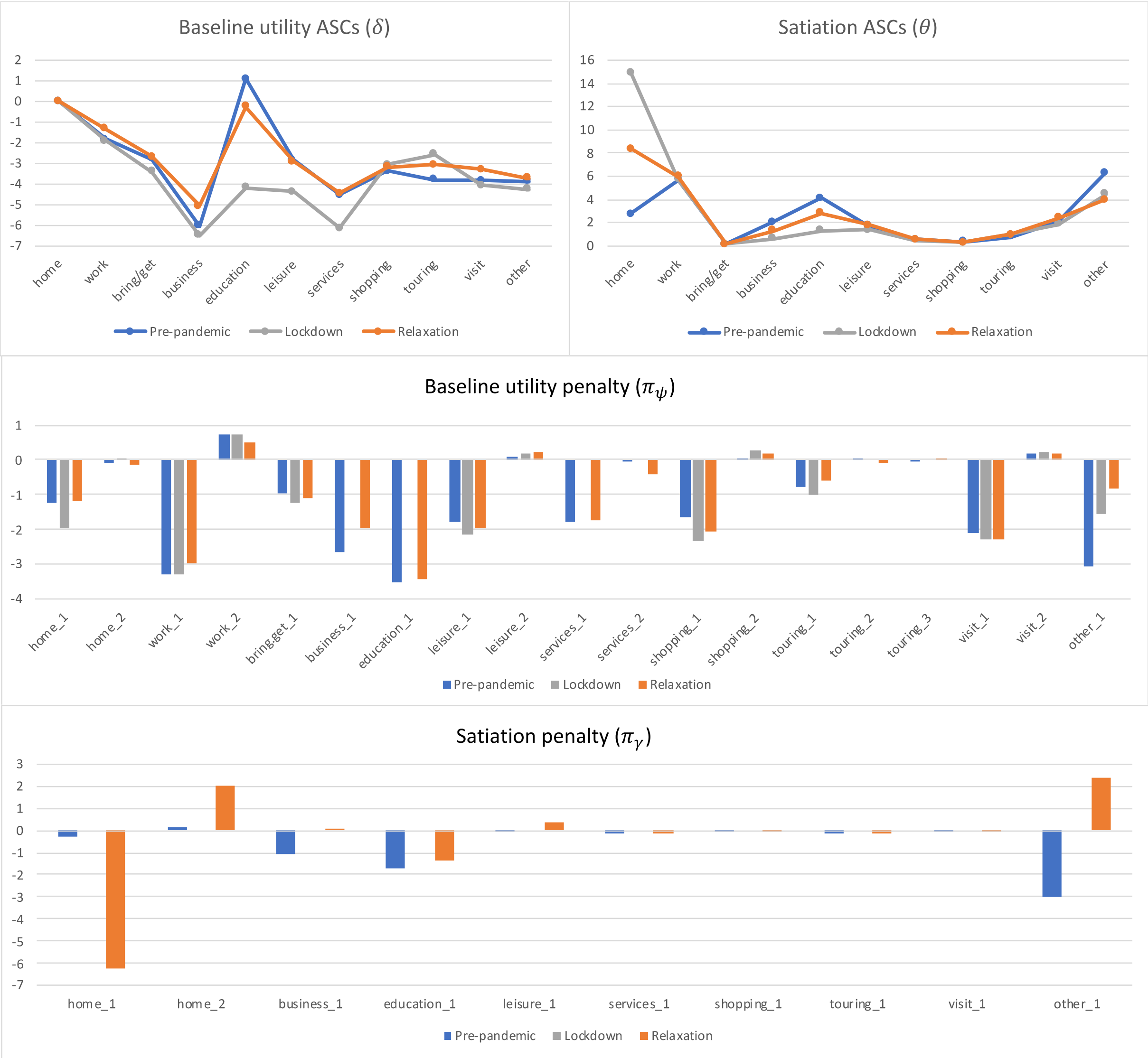

Figure 1: Estimation results for activity time-use

4. Conclusion

We modelled the changes in activity-travel behavior over three different phases of COVID-19 (i.e., pre-pandemic, lockdown, and relaxation) in the Netherlands. With the MPN data collected during pre-pandemic, lockdown, and relaxation period, episode-based MMDCEV models for time-use and mode-use behavior were developed. The behavioral insights obtained from the models confirm results from prior research.

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