MODELLING MULTIPLE OCCURRENCES OF ACTIVITIES DURING A DAY: AN EXTENSION OF THE MDCEV MODEL

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ABSTRACT
The popularity of activity-based models has led to interest in flexible but tractable models of time use, such as Bhat's Multiple Discrete Continuous Extreme Value (MDCEV) model. MDCEV formulations typically model aggregate time allocation into different activity types during a given period, such as the amount of time spent working and shopping in a day. This ignores disaggregate activity-episodes -for example splitting work into morning and afternoon episodes, with a leisure break in between- which are necessary for activity-based modelling and predicting trips. We propose a modified MDCEV model where an activity-episode, rather than an activity type, is the basic alternative, using a modified utility function to capture the reduced likelihood of later episodes. Two large revealed preference data sets exhibit equivalent forecast accuracy between the traditional and proposed approaches at an aggregate level, but the latter also provides the number and duration of activity-episode engagement, with significant accuracy.

Keywords: time use, MDCEV, episodes, discrete-continuous

1 INTRODUCTION

One of the fundamental differences between trip-based and activity-based travel demand modelling is related to the treatment of “time”. In the trip-based approach to demand modelling, time is merely treated as a cost that a decision maker needs to incur for travelling between an origin and a destination. On the other hand, the activity-based approach – which is strongly grounded on the notion of derived nature of travel – puts much emphasis on understanding and predicting the time use behaviour of the travellers, including why, where, with whom and for how long people spend time (Bhat and Koppelman 1999). Therefore, from the perspective of an activity-based model analysist, people choose how to spend their time, and travelling is but a by-product of that decision, as different activities must be performed at different locations.

Time use decisions can be thought of as deciding on the *activity type* (purpose, e.g. work, education, shopping, etc.), number (count by purpose, i.e. number of *episodes* of a given activity) and *duration* of activities to pursue within a certain time frame. In the last decade, the multiple discrete continuous (MDC) structure has evolved as an elegant framework to model activity participation and time allocation decisions subject to a budget constraint (Bhat 2008, Bhat et al. 2013, Liu et al. 2017, Wang and Li 2011). However, the state-of-the-art MDC models focus on predicting the aggregate *duration* for an *activity type* but fall short of accommodating the time allocation at the *episode* level (Bhat and Mishra 1999, Calastri et al. 2017, Enam et al. 2018). Hence, the time allocation information obtained from the state-of-the-art MDC models can at best act as a constraint (Bhat et al. 2004); but will seldom be (immediately) useful for the representation of downstream travel choices such as mode, destination and route, which rely on episode level activity participation and time allocation decisions (Auld and Mohammadian 2009).

Splitting the time invested in each activity into multiple *episodes* is relevant from a behavioural perspective, as engaging in an extended episode of an activity is different from engaging in multiple episodes of the same type for the same combined duration. For example, working for four hours, having a lunch break and then working for another four hours is not behaviourally equivalent to working for eight hours in one continuous stretch. Likewise, from a practical perspective, the episode-level activity participation and time allocation decisions are required to construct the trips that tie together the consecutive activity episodes and subsequently model the associated travel decisions such as mode, destination, and route, choice among others (Garling 1989). Our example above involving two episodes of work separated by a lunch break will lead to four trips (home-work, work-restaurant, restaurant-work, work-home), but simply knowing that an individual works for eight hours a day does not provide information on the particular number of trips performed on top of the first and last (home-work and work-home). This is a crucial shortcoming of the existing modelling approaches, as trip information is necessary to generate the actual demand for a transportation system which is often the end goal of transportation planning operations and management.

More recently, efforts have been made to use MDC formulations (and variants of it) for the episode level time allocation behaviour (Garikapati et al. 2014, Enam and Konduri 2017). However, the formulation adopted in the above-mentioned studies are best suited for tour-based analysis (Bowman and Ben-Akiva 2001) and not so much for the activity-based analysis of travel demand (Miller and Roorda 2003).

Other approaches to deal with the "episodic consumption of time" have been proposed in the literature. One example, which we will refer to as the *period* approach, consists of splitting the day into several periods (e.g. night, morning, afternoon and evening) and using an MDCEV model for each (see Pinjari and Bhat, 2010). While having the benefit of providing a rough schedule or at least time window inside which each episode is performed, this method imposes fairly arbitrary definitions of the time periods.

Saxena et al. (2019) provide a more recent contribution to the problem of episodic time consumption. Their approach forces orderly consumption of the episodes within each activity by conditioning the error terms in the base utility of the alternatives of later episodes to be smaller than that of the previous episodes. While this approach ensures a consistent modelling and forecasting of the data generation process, it also leads to a new model form different from the MDCEV, which requires specialized programming for implementation.

The objective of the current research is to expand on the activity participation and time allocation research based on MDC formulations with an episode-based analysis framework. The proposed framework can produce time allocation choices at the activity-episode level and therefore compliments the activity-based paradigm of travel analysis. This approach considers an activity episode to be the basic alternative of the MDCEV model, in contrast with the typical use of an activity type. Additionally, the proposed formulation accounts for the increasingly lower likelihood of performing later episodes of an activity type compared to the first. The proposed method also incorporates important changes to the traditional MDCEV forecasting algorithm (Pinjari & Bhat, 2011). We demonstrate the potential of the approach using two large-scale household travel survey datasets, one from Leeds, UK and the other from the Puget Sound Region (PSR), USA.

The remainder of the paper is organised as follows: Section 2 presents the methodology, looking at both estimation and forecasting. Section 3 describes the data sources used for our empirical examples, and Section 4 presents the estimation and forecasting results. Section 5 provides a summary of the work and concludes the paper.

2 ESTIMATION AND FORECASTING METHODOLOGY

In this section, we introduce the MDCEV model (Bhat, 2008) and describe two modelling approaches to time use data based on this model. First, we discuss the traditional or "aggregate" approach, used by most time use applications. Secondly, we describe the episode-based approach which we propose in the present paper.

2.1 The MDCEV model

The MDCEV model is derived from a classical individual utility maximization problem.

$$\max_{x_n} \sum_{k=1}^{K} \psi_{nk}\gamma_{nk} ln\left(\frac{x_{nk}}{\gamma_{nk}}+1\right) \tag{1}$$

$$\text{s.t. } \sum_{k=1}^{K} x_{nk}p_{nk} = B_n, \tag{2}$$

where x_{nk} is the amount of alternative k consumed by individual n. The utility function, as described in equation (1), fulfils the requirements of additive separability and is driven by two different sets of parameters. While the ψ_{nk} parameter represents the marginal *base utility* of alternative k for individual n, γ_{nk} relates to its level of satiation, with a bigger value of γ_{nk} implying a lower satiation for alternative k, i.e. a higher consumption when chosen. Consumption is subject to a budget constraint, as expressed by equation (2), where p_{nk} represents the price per unit of alternative k for person n, and B is the the total budget either in money or time unit (24 hours in the present case).

Stochasticity is included in the model through a random error term ε_{nk} in the base utility of each alternative. Both the base utility ψ_{nk} and the satiation parameter γ_{nk} need to be positive, and can be further parametrized as follows:

$$\psi_{nk} = e^{\delta_k + \beta_k z_{nk} + \varepsilon_{nk}} \quad (3)$$
$$\gamma_{nk} = \theta_k + \lambda_k z_{nk} \quad (4)$$

where δ_k and θ_k are constants for alternative k for the baseline utility and translation parameters, z_{nk} is a vector of attributes of the alternative and/or characteristics of individual n (e.g. a measure of the activity attractiveness, age of the individual, whether this observation was during a weekend, weather during that day, etc.), and β_k and λ_k are estimated parameters capturing the impact of z_{nk}. Many implementations of MDCEV use an exponential transformation in equation (4) to ensure positivity, but we have found that this often leads to slow model convergence and inferior solutions, while unconstrained estimation generally still yields positive estimates. If ε_{nk} is assumed to follow an independent and identical Gumbel (0, σ) distribution across individuals and alternatives, then the following closed form expression for the likelihood of a consumption basket can be derived.

$$Likelihood_n(x_{n1}, \dots, x_{nM}, 0, \dots, 0) = \frac{1}{p_{n1}} \frac{1}{\sigma^{M-1}} \left(\prod_{k=1}^{M_n} f_{nk}\right) \left(\sum_{k=1}^{M_n} \frac{p_{nk}}{f_{nk}}\right) \left(\frac{\prod_{k=1}^{M_n} e^{\frac{V_{nk}}{\sigma}}}{\left(\sum_{k=1} e^{\frac{V_{nk}}{\sigma}}\right)^{M_n}} \right) (M_n - 1)!, \quad (5)$$

where: $f_{nk} = \frac{1}{x_{nk} + \gamma_{nk}}$, (6)

$$V_{nk} = \delta_k + \beta_k z_{nk} - ln\left(\frac{x_{nk}}{\gamma_{nk}} + 1\right) - \ln(p_{nk}) \quad (7)$$

and where alternatives are ordered in such a way that the first M_n are consumed. This formulation corresponds to the MDCEV without outside good (Bhat 2008). In the case of time use applications, all prices become the time unit (in our case, one hour), simplifying the equations and making equation (1) independent of which alternative is labelled as the first one.

Forecasting with the MDCEV can be done efficiently by using the algorithm by Pinjari & Bhat (2011). Even though this method is proposed for MDCEV models with an outside good, it is easy to generalize it to the case without an outside good, by taking the alternative with the highest base utility (given ε_{nk}) as the first consumed alternative.

2.2 Approach 1: Aggregate

The first approach is the most traditional way of using MDCEV in a time use context. This approach disregards the number of episodes of each activity within a day, focusing only on the total amount of time spent in each activity within 24 hours. One observation is equivalent to one day of data, and the number of alternatives is equal to the number of different activities. The duration of each activity is the sum of the time spent in all episodes of the corresponding activity.

2.3 Approach 2: Episode-based

The episodes-based approach does not aggregate episodes of each activity. Instead, this approach uses an MDCEV model with as many alternatives as the number of episodes conducted during the day for each activity type. The maximum number of episodes per activity must be defined a priori and must be at least as large as the maximum number of episodes observed in the data. This leads to a substantial increase in the number of alternatives - now equal to $\sum_k E_k$, where E_k is the maximum number of instances in which activity k is performed by anyone in the data (see Figure 1 for an example on how the alternatives are coded). The episode-based approach does not entail a higher number of observations, as in both approaches one observation is equivalent to one day of data for one respondent. To avoid an excessive number of alternatives, it is theoretically possible to define a maximum number of episodes smaller than the one observed in the database. For example, even though someone in the database performs seven *drop-off/pick-up* episodes, we can consider only up to five episodes. In such a situation, the analyst can either aggregate the time spent on episodes five, six and seven, into a single episode, or simply truncate the data so episodes above the fifth are ignored. The best approach will depend on each particular dataset.

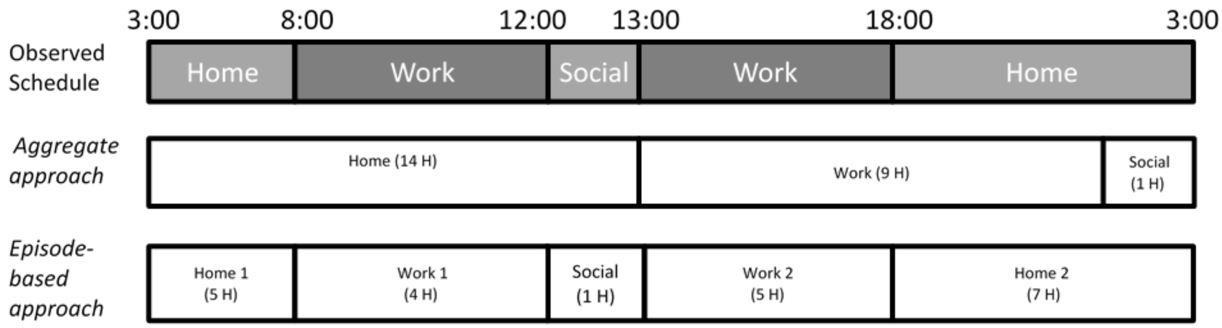

Figure 1 - Example of alternative coding for traditional and episode approach

The high number of alternatives poses a problem in terms of parametrisation. As time use studies generally use data from several hundred respondents who will perform different number of episodes of each activity, it is generally not recommended to use different alternative specific constants (ASC) parameters δ for each alternative (activity-episode pair). However, it is clearly important to allow for variability in the base utility across the episodes of the same activity type, mainly for two reasons. First, engaging in too many episodes of the same alternative is most probably undesirable given the time constraint, so the base utility should decay from the first episode to the higher number of episodes. For example, engaging in two four-hour episodes of work with a rest in between is probably more desirable than engaging in eight one-hour episodes. Secondly, the number of episodes is likely to vary by activity type. For example, if we assume that a day starts at 3 AM as in Figure 1, *being at home* will probably have at least two episodes during the day (morning and evening), while *getting petrol* would probably be performed no more than once a day.

The situation is similar when considering the duration (and satiation effect) of different episodes. For most activities, later episodes will likely be shorter than earlier ones. For example, a third episode of work in the evening will likely be shorter than the previous ones due to fatigue. But behaviour can change across activities. For example, the second *at home* episode might be longer than the first one, depending on commuting time. Using different θ parameters for each activity-episode could help capturing these effects, but again, this is unpractical given the potentially high number of activity-episodes.

To capture these effects, we use a generic baseline constant for each activity type (δ and θ parameters) and add a polynomial *episode penalty* to the base utility ψ and satiation γ of each alternative, depending on the number of the episode. To avoid identification issues, the first episode of each activity does not have any penalty; instead, the penalties begin from the second episode onwards. Penalties can be used for both ψ_{nki} and γ_{nki}. The analyst needs to decide on what degree of polynomials to include, being mindful of the increase in the number of parameters to estimate. We then have:

$$\psi_{nki} = e^{\delta_k + \beta_k z_{nk} + \sum_{p=1}^{P_{\psi_k}} \pi_{\psi kp}(i-1)^p + \varepsilon_{nki}} \tag{8}$$

$$\gamma_{nki} = \theta_k + \lambda_k z_{nk} + \sum_{p=1}^{P_{\gamma_k}} \pi_{\gamma kp}(i-1)^p \tag{9}$$

where *i* enumerates the episode of activity k, P_{ψ_k} and P_{γ_k} represent the number of polynomia terms used for ψ_{nk} and γ_{nk}, and $\pi_{\psi kp}$ (p=1,…, P_{ψ_k}) and $\pi_{\gamma kp}$ (p=1,…, P_{γ_k}) are the associated penalty parameters to be estimated. The penalty is only within activities, i.e. there is no penalty due to the global order of events across activities throughout the day. We did not include a global penalty due to endogeneity concerns. From a behavioural perspective, the choice of what activities to perform, for how long, and in what order (i.e. their scheduling) is most likely done simultaneously, so using one to explain the other could generate endogeneity issues.

To see the effect of penalties more clearly, consider the case of two activities: *at home* and *get petrol*. As the first activity is usually performed twice a day, while the second one is usually performed only once, where would expect penalties for *getting petrol* to be much more negative than for *at home*. Such values would make a second episode of the *getting petrol* activity much less likely than a second episode of the *at home activity*.

2.4 Forecasting

In both approaches, the forecast for each observation is calculated by solving the optimisation problem in eqns. (1) and (2) multiple times, each time with different values of ε_{nki} drawn for the corresponding distribution. The final forecast is the average across solutions for all different ε_{nki}.

Pinjari & Bhat (2011) propose an efficient algorithm to solve the optimisation problem based on an iterative process. First, the baseline marginal utilities are sorted in descending order of magnitude and one alternative is incrementally added to the consumption set, until the choice set gets exhausted or the magnitude of the baseline marginal utility of the next alternative in line becomes less than the Lagrangian multiplier. In a typical application of MDCEV model, each activity type constitutes an alternative; however in the proposed approach an event of an activity type is considered to be an alternative. When forecasting with the episode-based approach, nothing a priori forces individuals to choose event i before event $i+1$. For example, episode 2 will be consumed before episode 1 of activity k if $\varepsilon_{nk1} < \varepsilon_{nk2} + \sum_{p=1}^{P_{\psi_1}} \pi_{\psi 1p}$. A modification to the forecasting algorithm is used to ensure that at each iteration step, exactly one event of an activity type is available for consumption. First, instead of sorting the baseline marginal utilities across all activity-event combination, in the proposed approach, the sorting is performed within the events of the same activity type in the descending order of their magnitude. Next, at each iteration, exactly one event of an activity type is made available for consumption, ensuring that within each activity type, the episodes are consumed in the descending order of their base utility magnitude.

Ordering episodes by their base utility does not guarantee that they are consumed orderly, because the random ε_{nki} makes it impossible to predict which episode will have the higher base utility. So for a given set of ε_{nki} draws, episode $i+1$ could be consumed before episode i. However, when averaging results from a large number of sets of ε_{nki} draws, earlier episodes will be consumed more often than later ones due to the effect of the penalties. Hence, we always recommend using our forecasting algorithm with a large number of draws.

Another limitation when forecasting with the episode-based approach is that the maximum number of possible episodes is defined a priori, preventing the model from predicting more than that number of episodes defined by the analyst.

Despite these limitations, the proposed forecasted algorithm has the advantages of being efficient, having a simple implementation, and being accurate when using a large number of draws. The particular number of draws will depend on the dataset being analysed, so it is not possible to recommend a specific number. As usual when working with random draws, our advice is to forecast with an increasing number of draws and stop when further increases do not yield a significant change in prediction.

3 DATA

In order to demonstrate the proposed approach and compare it to traditional time use modelling using the MDC framework, we use two Revealed Preferences data sources. The first one was collected in Leeds, UK, and the other in the Puget Sound Region (PGS), USA.

3.1 Leeds dataset

The Leeds dataset was collected in 2017 within the ERC-funded project "DECISIONS" and time use was only one of the aspects on which the data collection effort was focused (see Calastri et al., 2020 for more details). The study participants first completed a background survey providing data on their socio-demographics, commuting behaviour, and attitudes. At a later stage, they were asked to install the mobility tracking application *rMove* (Resource Systems Group, 2011) on their smartphones. *rMove* record participants' location for two weeks through their phone's GPS. Every time the application detected the end of a trip, it would prompt a short survey asking the participant for the trip purpose, mode, cost (if any), and who was the trip was performed with. At the end of each day of tracking, participants saw a summary of all their daily trips, giving them the opportunity to correct or complete the information if there was any error.

A total of 449 respondents successfully completed the two weeks of tracking, providing full information for at least 95% of all their trips. Most participants lived in the greater Leeds area, yet the sample is not representative of this area's population. The sample is mostly composed of women (58%), and more than two thirds of it (69%) hold a university-level degree. Most participants (30%) are between 30 and 39 years old, with under-25 participants representing only 15% of the sample. The most common personal income in the sample (25%) is between 20 and 30 thousand pounds sterling a year (see Table 1).

Table 1 - Summary of Leeds database: sample socio-demographics

		Female	Male	Total
Participants		260	189	449
University degree		182	126	308
Age	18-24	41	26	67
	25-29	29	14	43
	30-39	81	53	134
	40-49	57	36	93
	50-59	41	40	81
	60-65	7	12	19
	66-75	3	8	11
	>75	1	0	1
Personal income (thousands of £)	Unknown	12	11	23
	<10	43	21	64
	10-20	65	24	89
	20-30	70	44	114
	30-40	51	44	95
	40-50	12	27	39
	50-75	4	16	20
	>75	3	2	5

On the basis of the recorded trips and their stated purposes, it is possible to construct a daily activity schedule for each participant, which we use to model time use for our sample. For our analysis, we aggregated trip purposes into eleven activities: *home* (i.e. being at home), *work* (either at main location or elsewhere), *leisure or social* (e.g. meeting friends, going to the cinema, eating out, etc.), *drop-off/pick-up* (i.e. driving someone else to their activity location, e.g. taking children to school), *exercise* (e.g. spending time at a gym), *shopping* (both maintenance shopping, such as grocery shopping, and non-maintenance, such as leisure shopping), *private business* (e.g. doctor's appointment), *petrol* (i.e. buying petrol for a vehicle), and *education* (e.g. school or university classes). We considered two additional activities: *travelling*, i.e. travelling to an activity location, and an *other/unknown* activity, used in the presence of errors in the tracking (e.g. participant did not provide the purpose of a trip or the end location of a trip did not match -within a tolerance- the beginning of the next trip).

Key to our approach is the observation that people can engage in the same activity across multiple episodes throughout a day. The Leeds data contains 28,839 episodes of all activities. Among these, *home* is the one participants engage with more often and for longer durations, and the only one in the dataset with an average of more than two daily episodes. *Travel* follows it as the second activity in terms of number of episodes, but *work* is the second highest in terms of time spend. Table 2 presents a summary of average daily time use in the Leeds dataset. As the data was collected using geographical tracking, the activities captured where the ones performed at a certain distance from one another, meaning travelling is a pre-requisite to record a new activity. This explains why *travelling* is such a common activity in our sample. This is the same reason why we did not split *travel* into episodes, as their number would have been perfectly correlated with the total number of episodes in a day. We did not disaggregate *other/unknown* into episodes either, as this activity mostly represents errors in data collection. We decided to retain such occurrences to make sure that the 24-hour daily budget would be satisfied.

We limited the number of episodes per activity to five in the Leeds dataset. To achieve this, we aggregated the length of subsequent episodes into the fifth one. We did not simply remove observations with more than five episodes per activity, as this would have implied dropping more than 5% of the sample.

Table 2 - Summary of daily activity engagement and time consumption in the Leeds sample

	Fraction of sample who engage (#)	Average time spent when engaged (Hr)	Average number of episodes when engaged (#)	Average length of episode when engaged (Hr)
At home	0.98	15.38	2.21	6.96
Work	0.46	6.66	1.78	3.74
Exercise	0.17	3.84	1.40	2.74
Education	0.04	3.55	1.43	2.49
Leisure	0.40	3.25	1.66	1.96
Other/unknown*	0.04	3.06		
Travelling*	0.91	2.34		
Drop-off/Pick-up	0.20	2.20	1.68	1.31
Private Business	0.25	1.98	1.49	1.33
Shopping	0.34	1.54	1.55	0.99
Getting petrol	0.03	0.95	1.02	0.94

Exercise and *Drop-off/pick-up* exhibit unusually high average daily time allocations in the Leeds dataset. This is probably due to limitations in the data collection. Several participants tagged leisure activities such as hiking and cycling (quite popular around Leeds) as exercise. On the other hand, *Drop-off/pick-up* episodes often include the time of the following activity in them, because as the time taken to drop-off or pick-up someone was short, the tracking app confused it with a short stop in a longer trip.

To compare the different approaches tested in this study, we set aside 20% of the sample, and estimated the models with the remaining 80%. This led to 4,429 days of data used for estimation, and 1,101 days used for forecasting comparison (i.e. validation). We randomly split the full dataset at the individual level, meaning that all observations from a single individual belong to either the estimation or validation sets, but are never spread across both.

3.2 Puget Sound Region dataset

The Puget Sound Region (PSR) dataset was collected through a household travel survey from four counties (King, Kitsap, Pierce and Snohomish) located in Puget Sound Region (PSR), Washington State. The survey collected information in a trip diary format. The survey was conducted using two modes: a proprietary software was used to administer an online survey, while additionally, the households were given the option to participate in a telephone administered survey. The survey collected travel patterns (for example trip start and end time, origin and destination purpose, transport mode) of the household members on a randomly selected weekday (Tuesday, Wednesday and Thursday) in Spring 2014. A total of 4,786 participants from 2,419 households participated in the survey. The current study uses information from 3,618 participants after filtering based on age (>18).

Table 3 provides a summary of the socio-economic characteristics of the 3,618 survey respondents. The sample is slightly skewed in terms of gender – with 54% being male. The sample over-represents highly educated people with 65% of the sample having a bachelor or higher degree. One third of the sample belong to the 35 to 54 age group, while 43% of the respondents are older than 55. In terms of household income, 37% of the households have an income of more than \$100,000 per year, while 46% of households' income falls between \$25,000 and \$100,000 per year.

Table 3 - Summary of Puget Sound Region (PSR) database: sample socio-demographics

		Male	**Female**	**Total**
Gender		1951 (54 %)	1667 (46 %)	3618 (100 %)
Bachelor degree		1249 (64 %)	1118 (67 %)	2367 (65 %)
Age	18-24	91 (5 %)	78 (5 %)	169 (5 %)
	25-34	359 (18 %)	316 (19 %)	675 (19 %)
	35-44	314 (16 %)	308 (18 %)	622 (17 %)
	45-54	316 (16 %)	264 (16 %)	580 (16 %)
	55-64	415 (21 %)	343 (21 %)	758 (21 %)
	65-74	309 (16 %)	242 (15 %)	551 (15 %)
	75-84	121 (6 %)	95 (6 %)	216 (6 %)
	>85	26 (1 %)	21 (1 %)	47 (1 %)
Household income (thousands of \$ per year)	< 25	---	---	375 (10 %)
	25-50	---	---	593 (16 %)
	50-75	---	---	543 (15 %)
	75-100	---	---	541 (15 %)
	>100	---	---	1335 (37 %)
	Missing	---	---	231 (6 %)

The next task in terms of data preparation was to create an activity diary from the trip data collected in the survey. In this regard, the 16 trip purposes were re-coded into 13 broad categories - *home* (i.e. being at home), *work* (either at main location or elsewhere), *shopping* (both maintenance shopping, such as grocery shopping, and non-maintenance, such as leisure shopping), *education* (e.g. day-care, school or university classes), *medical* (e.g. doctor's appointment), *personal-business* (e.g. bank, post office), *drop-off/pick-up* (i.e. driving someone else to their activity location, e.g. taking children to school), *exercise* (e.g. gym, walk, jog, bike ride), *eat-out* (e.g. go to restaurant to eat/get take-out), *leisure* (e.g. attend social event such as visit with friends, family, co-workers, attend recreational event such as movies, sporting event), *religious* (go to religious/community/volunteer activity), *travel* (e.g. transfer to another mode of transportation such as changing from ferry to bus) and *other*. The first 11 activity types were further subdivided into up to 5 episodes. All the travel undertaken during the day were aggregated into a single travel episode. Similarly, time spent in any other activities were grouped under the other category. Table 4 presents a summary of time engagement from the PSR sample.

We limited the number of episodes per activity to five in the PSR dataset (the same as in the Leeds dataset). To achieve this, we simply dropped observations with more than five episodes of a single activity. These cases constituted less than 5% of the sample.

Table 4 - Summary of activity engagement and time consumption in the PSR sample

Activity	Fraction of sample who Engage (#)	Average time spent when engaged (Hr)	Average number of episodes when engaged (#)	Average length of episode when engaged (Hr)
Home	0.99	15.84	2.47	6.4
Work	0.53	8.07	1.42	5.67
Shopping	0.4	0.71	1.48	0.48
Education	0.03	5.01	1.1	4.53
Medical	0.1	1.46	1.07	1.36
Personal business	0.21	0.79	1.33	0.59
Drop-off/pick-up	0.13	0.39	1.5	0.26
Exercise	0.16	1.21	1.12	1.07
Eat out	0.23	0.92	1.22	0.75
Leisure	0.17	3.33	1.26	2.64
Religious	0.04	2.54	1.25	2.03
Travel*	1	1.7	---	---
Other*	0.06	5.83	---	---

* *Engagement not split across episodes*

Like the Leeds sample, almost 100% of respondents participate in home and travel on the survey day, while 53% and 4% of the sample participate in work and in education activity, meaning increases by 7 and 1 percentage points, respectively, compared to the Leeds sample. Another considerable difference noted in the PSR sample compared to the Leeds sample is that while in Leeds, only 33% of the sample respondents engage in shopping on the survey day, 40% do so in the PSR sample.

In the PSR sample, respondents spend around 16 hours at home on average on a daily basis. Average aggregate duration for work is around 8 hours, which is 1.3 hours greater than in the Leeds sample. Similarly, the average aggregate duration for education is around 1.3 hours greater in the PSR sample (5 hour) compared to the Leeds sample (3.7 hours). On the other hand, discretionary activity durations in the PSR sample are generally smaller compared to the Leeds sample. For example, the average aggregate shopping activity duration in the PSR sample is only about 40 minutes, while the average duration in the Leeds sample is almost 50 minutes higher. Similarly, the average aggregate travel duration in the PSR sample is around 1.7 hours, which is almost 40 minutes smaller than the average in the Leeds sample.

In terms of average number of episode engagement, people tend to engage in 2.5 episodes of home activity during the day – which is intuitive given that one out-of-home activity splits the stay home duration into two episodes. Other than home, an around 1.5 episodes per day average is noted for work, shopping, pick-up/drop-off and personal-business activity – for the rest of the activities an average closer to 1 episode is more probable.

As with the Leeds data, 80% of the PSR sample (3000 observations) is used for model estimation and 20% (~750 observations) was set aside for the validation of the model estimation and forecasting routines.

4 RESULTS

In this section, we present results from the proposed episode-based approach for both the Leeds and PSR datasets. We compare them against MDCEV models using the traditional aggregated approach. We begin by comparing the model parameters, followed by the model fit (using the aggregate Root Mean Squared Error, RMSE), and finish with an analysis of the forecasted episodes as compared to the observed ones.

4.1 Model parameters

The detailed parameter estimates for the Leeds models are shown in Table 6, while those for the PR models are shown in Table 6.

As Table 5 shows, coefficients signs and magnitudes are consistent across the aggregate and episode-based approach for the Leeds data. *Travelling* is the most popular activity (*ceteris paribus*) according to both the aggregate and episode-based model, followed by *education* and *work*. This reflects in these activities having the highest constants in their base utilities. In both models, participants are less likely to engage in *work*, *education* and *other* activities during the weekends, and instead are more likely to engage in *shopping*, *private business, getting petrol*, *leisure* and *exercise* activities during this period. Being at *home* is not significantly influenced by the weekend according to the aggregate approach, but it is instead positively influenced by it according to the episode-based approach. Older participants are less likely to engage in *education* activities according to both models, while there are other consistent effects of sex and income across both approaches. Concerning satiation, *work* exhibits the highest θ in both models, meaning that -*ceteris paribus*- it is consumed for longer than other activities. This effect, however, is mediated by the base utility of the alternative, explaining why home is the activity most consumed in the sample (see Table 2). Satiation parameters are less influenced by the participants' characteristics, with just *drop-off/pick-up*, *exercise*, *home* and *travel* showing significant effects of covariates, all of which are consistent (or not significant) across the aggregate and episode-based approaches.

As Figure 2 shows, all penalties have a net negative effect on the base utility of alternatives. As these only influence the base utility from the second episode onwards (see Eq. 3), we can conclude that the objective of making later episodes less likely to be engaged with is achieved by our functional form. As expected, *getting petrol* is the activity whose penalty becomes negative more quickly, because most participants perform only one episode of this activity a day. Instead, *at home* grows much slower, to make multiple episodes of the activity more likely.

Penalties in the satiation effects were not significant as often as in the base utility, with only a few being kept in the reported model, and all of them including only linear effects. We observe that *work* and *exercise* have negative penalty parameters, meaning that later episodes of these activities tend to be shorter. *Leisure*, on the other hand, has a positive penalty, meaning that later episodes tend to be longer than previous ones, because later episodes are usually performed during the evening, when individuals have more time to spend in recreational activities.

Table 5 - Parameter estimates of aggregate and episode-based approach of the Leeds models (robust t-ratios in parenthesis)

	Baseline parameters					Satiation parameters			
	Aggregate		Episodes			Aggregate		Episodes	
Drop-off / Pick-up									
δ	-3.116	(-19.17)	-3.062	(-28.37)	θ	0.282	(7.19)	0.136	(7.88)
					$\lambda_{weekend}$	0.242	(2.00)	0.116	(2.60)
					$\pi_{\gamma 1}$			-0.955	(-16.40)
Work									
δ	-1.773	(-11.93)	-1.766	(-22.38)	θ	4.456	(20.01)	2.076	(13.04)
$\beta_{weekend}$	-2.175	(-13.65)	-2.057	(-11.61)	$\pi_{\gamma 1}$			-0.947	(-5.51)
$\pi_{\psi 1}$			-1.108	(-20.39)					
$\pi_{\psi 2}$			0.070	(4.76)					
Education									
δ	0.147	(0.20)	0.639	(0.87)	θ	2.613	(6.77)	1.549	(6.86)
β_{age}	-1.076	(-5.01)	-1.248	(-5.43)					
β_{income}	-0.967	(-4.94)	-1.015	(-5.04)					
$\beta_{weekend}$	-2.254	(-5.09)	-2.536	(-5.69)					
$\pi_{\psi 1}$			-1.274	(-7.18)					
Shopping									
δ	-2.888	(-18.89)	-2.900	(-30.15)	θ	0.364	(17.38)	0.230	(20.62)
β_{female}	0.293	(3.19)	0.312	(2.93)					
$\beta_{weekend}$	0.672	(9.18)	0.786	(9.64)					
$\pi_{\psi 1}$			-1.311	(-24.29)					
$\pi_{\psi 2}$			0.068	(3.69)					
Private business									
δ	-3.154	(-19.96)	-3.102	(-30.45)	θ	0.511	(12.04)	0.282	(13.02)
β_{female}	0.246	(2.16)	0.229	(1.67)					
$\beta_{weekend}$	0.463	(5.82)	0.493	(6.08)					
$\pi_{\psi 1}$			-1.308	(-18.34)					
$\pi_{\psi 2}$			0.074	(3.33)					
Get petrol									
δ	-5.376	(-24.00)	-5.321	(-31.08)	θ	0.091	(4.04)	0.093	(3.94)
$\beta_{weekend}$	0.527	(2.76)	0.518	(2.69)					
$\pi_{\psi 2}$			-3.755	(-6.93)					
Leisure									
δ	-2.618	(-17.04)	-2.611	(-30.06)	θ	1.455	(20.10)	0.678	(16.29)
β_{female}	0.143	(1.69)	0.109	(1.17)	$\pi_{\gamma 1}$			0.116	(2.29)
$\beta_{weekend}$	0.973	(16.14)	1.126	(17.16)					
$\pi_{\psi 1}$			-1.215	(-28.71)					
$\pi_{\psi 2}$			0.069	(5.17)					
Exercise									
δ	-3.642	(-22.31)	-3.656	(-32.26)	θ	1.736	(9.49)	1.332	(8.97)
$\beta_{weekend}$	0.712	(8.18)	0.889	(8.60)	$\lambda_{weekend}$	0.464	(1.50)	-0.203	(-1.43)
$\pi_{\psi 1}$			-1.495	(-14.20)	$\pi_{\gamma 1}$			-0.696	(-5.57)
$\pi_{\psi 2}$			0.123	(3.93)					
At home									
δ	0.000	((fixed))	0.000	((fixed))	θ	2.030	(6.40)	0.845	(15.99)
β_{female}	0.118	(1.68)	0.136	(1.90)	$\lambda_{weekend}$	2.839	(3.87)	0.684	(8.04)
$\beta_{weekend}$	-0.146	(-1.04)	0.204	(3.94)	$\pi_{\gamma 1}$			1.577	(15.53)
$\pi_{\psi 1}$			-1.367	(-38.91)					
Travel									
δ	0.666	(4.36)	0.869	(9.26)	θ	0.115	(13.40)	0.098	(14.32)
					$\lambda_{fullTimeWork}$	0.024	(3.56)	0.022	(4.02)
Other									
δ	-4.840	(-25.98)	-4.792	(-34.54)	θ	0.612	(2.83)	0.612	(2.83)

Loglikelihood	-41499.86	-79633.72
Number of parameters	40	57

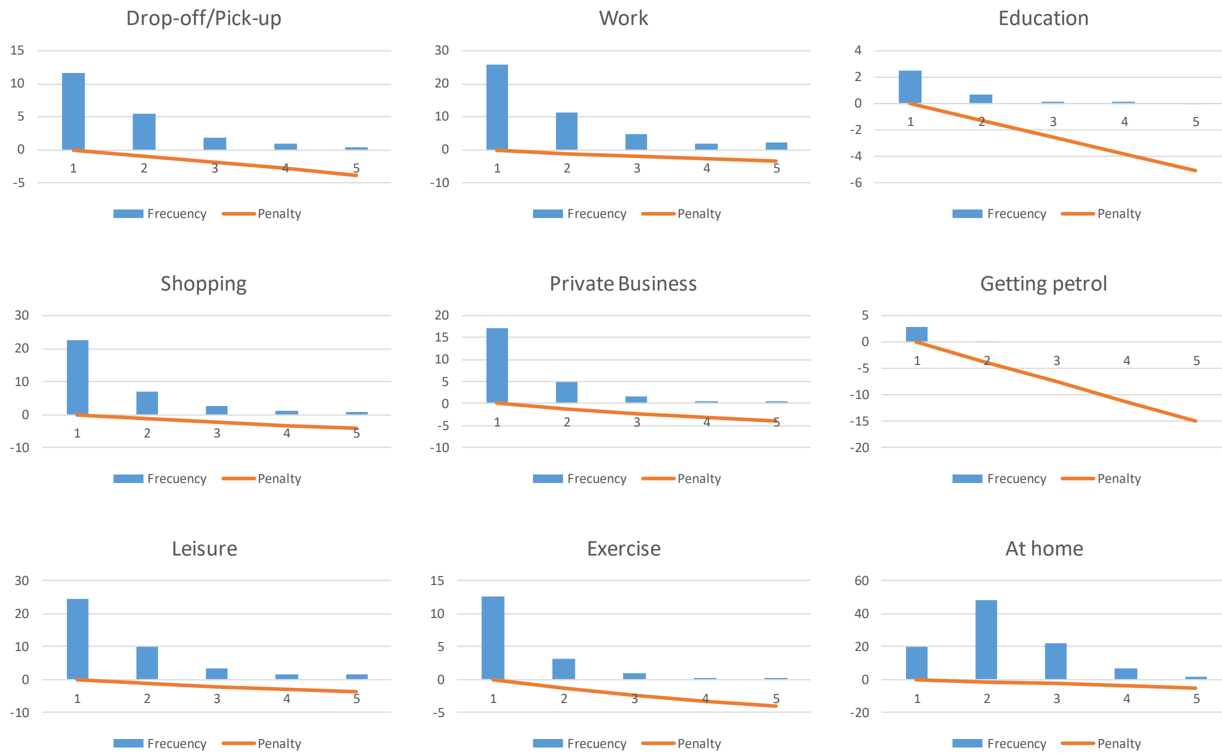

Figure 2 - Frequency of episode engagement (%) and size of base utility penalty in the Leeds dataset

According to the aggregate PSR model, home is the most likely activity to participate in followed by shopping and personal business. The episode model also identifies home as the most likely activity to participate in, but then it places work as the second most likely activity. This difference is probably due to the different covariates used in each model, based on their significance. Men are less likely than women to participate in work and more likely to participate in shopping, medical, personal business, pick-up/drop-off, leisure and religious activities according to the both the aggregate and episode model. As expected, people above 75 years old are less likely to participate in work according to both models. Yet only the episode model points to them being more likely to participate in medical and shopping activities. Income has no impact on the episode model, while it does significantly influence shopping (base utility), work, exercise, eating out and leisure (satiation) in the aggregate model. The constants of the satiation parameters exhibit similar sign in both the aggregate and in the episode model. Work has the highest positive value of the satiation constant followed by education indicating people's propensity to spend longer duration into these activities when they participate in these activities. Home and leisure have very similar magnitude for satiation parameter constant.

Table 6 - Parameter estimates of aggregate and episode-based approaches of the PSR models (robust t-ratios in parenthesis)

Baseline Parameters

	Aggregate*	Episode*
Home		
δ_{Home}	-5.04 (-4.92)	-13.09 (-116.26)
$\beta_{Age\ 18\ to\ 34}$	-0.62 (-6.75)	
$\beta_{Age\ 55\ to\ 74}$	-0.5 (-5.34)	
$\beta_{Age\ above\ 75}$		0.294 (3.07)
$\pi_{\psi,Home,1}$		0.118 (1.89)
$\pi_{\psi,Home,2}$		-0.716 (-12.64)
$\pi_{\psi,Home,3}$		0.099 (9.08)
Work		
δ_{Work}	-10.7 (-9.97)	-14.63 (-118.77)
β_{Male}	-0.27 (-5.25)	-0.233 (-4.11)
$\beta_{Age\ 18\ to\ 34}$	3.06 (8.39)	
$\beta_{Age\ 35\ to\ 54}$	3.05 (8.4)	0.503 (8.78)
$\beta_{Age\ 55\ to\ 74}$	2.22 (6.09)	
$\beta_{Age\ above\ 75}$		-2.272 (-8.4)
$\beta_{HH\ Income\ \$50k\ to\ \$100k}$	0.11 (1.44)	
$\pi_{\psi,Work,1}$		-1.586 (-27.55)
$\pi_{\psi,Work,2}$		0.09 (3.86)
Shopping		
$\delta_{shopping}$	-7.71 (-7.57)	-15.12 (-106.27)
β_{Male}	0.16 (2.33)	0.258 (3.82)
$\beta_{Age\ 18\ to\ 34}$	-1.11 (-7.93)	
$\beta_{Age\ 35\ to\ 54}$	-0.97 (-7.25)	-0.336 (-4.52)
$\beta_{Age\ 55\ to\ 74}$	-0.44 (-3.47)	
$\beta_{Age\ above\ 75}$		0.647 (3.71)
$\beta_{HH\ Income\ \$50k\ to\ \$100k}$	-0.2 (-2.57)	
$\pi_{\psi,Shopping,1}$		-1.3 (-21.35)
$\pi_{\psi,Shopping,2}$		0.038 (1.61)
Education		
$\delta_{Education}$	-11.8 (-11.41)	-17.6 (-91.7)
$\beta_{Age\ 18\ to\ 34}$	1.74 (6.93)	
$\beta_{Age\ 35\ to\ 54}$		-0.914 (-3.18)
$\beta_{Age\ 55\ to\ 74}$	-0.86 (-2.06)	
$\pi_{\psi,Education,1}$		-2.262 (-5.18)
Medical		
$\delta_{Medical}$	-9.11 (-8.87)	-16.91 (-97.18)
β_{Male}	0.32 (2.58)	0.278 (1.95)
$\beta_{Age\ 18\ to\ 34}$	-1.77 (-7.59)	
$\beta_{Age\ 35\ to\ 54}$	-1.33 (-6.76)	
$\beta_{Age\ 55\ to\ 74}$	-0.83 (-4.52)	
$\beta_{Age\ above\ 75}$		0.931 (4.24)
$\beta_{HH\ Income\ \$50k\ to\ \$100k}$	-0.23 (-1.66)	
$\pi_{\psi,Medcial,1}$		-2.663 (-12.1)
Personal business		
$\delta_{Personal\ business}$	-8.48 (-8.31)	-15.97 (-117.25)
β_{Male}	0.23 (2.74)	0.233 (2.44)
$\beta_{Age\ 18\ to\ 34}$	-1.43 (-8.42)	
$\beta_{Age\ 35\ to\ 54}$	-1.05 (-6.88)	-0.231 (-2.26)
$\beta_{Age\ 55\ to\ 74}$	-0.55 (-3.76)	
$\beta_{Age\ above\ 75}$		0.738 (4.29)

Satiation Parameters

	Aggregate*	Episode*
Home		
θ_{Home}	0.53 (3.21)	0.607 (33.7)
$\lambda_{Age\ 35\ to\ 54}$	-0.72 (-7.93)	
$\lambda_{HH\ Income\ \$50k\ to\ \$100k}$	-0.05 (-1.18)	
Work		
θ_{Work}	2.04 (55.31)	1.388 (39.98)
$\lambda_{HH\ Income\ \$50k\ to\ \$100k}$	-0.14 (-2.24)	
Shopping		
$\theta_{Shopping}$	-1.11 (-21.29)	-1.307 (-53.65)
$\lambda_{Age\ 35\ to\ 54}$	-0.09 (-1.46)	
$\lambda_{HH\ Income\ \$50k\ to\ \$100k}$	0.09 (1.41)	
λ_{Male}	0.15 (2.55)	
Education		
$\theta_{Education}$	1.44 (7.71)	1.519 (9.96)
$\lambda_{Age\ 18\ to\ 34}$	0.56 (2.79)	
$\lambda_{HH\ Income\ \$50k\ to\ \$100k}$	-0.34 (-1.71)	
Medical		
$\theta_{Medical}$	-0.05 (-0.77)	-0.025 (-0.5)
$\lambda_{Age\ 35\ to\ 54}$	0.2 (1.71)	
Personal business		
$\theta_{Personal\ business}$	-1.23 (-23.12)	-1.468 (-32.21)
Pick-up/Drop-off		
$\theta_{Pickup/Dropoff}$	-1.49 (-12.21)	-1.849 (-47.29)
$\lambda_{HH\ Income\ \$50k\ to\ \$100k}$	-0.15 (-1.11)	
$\lambda_{HH\ Income > \$100k}$	-0.2 (-1.68)	
λ_{Male}	0.12 (1.14)	
Exercise		
$\theta_{Exercise}$	-0.58 (-4.73)	-0.307 (-5.77)
$\lambda_{Age\ 35\ to\ 54}$	0.16 (1.32)	
$\lambda_{Age\ 55\ to\ 74}$	0.33 (2.9)	
$\lambda_{HH\ Income\ \$50k\ to\ \$100k}$	0.26 (2.07)	
$\lambda_{HH\ Income > \$100k}$	0.41 (3.52)	
Eat out		
θ_{Eatout}	-0.83 (-7.97)	-0.849 (-19.3)
$\lambda_{Age\ 35\ to\ 54}$	-0.23 (-2.03)	
$\lambda_{Age\ 55\ to\ 74}$	0.15 (1.47)	
$\lambda_{HH\ Income\ \$50k\ to\ \$100k}$	0.25 (2.16)	
$\lambda_{HH\ Income > \$100k}$	0.36 (3.36)	
Leisure		
$\theta_{Leisure}$	0.63 (7.37)	0.655 (12.65)
$\lambda_{Age\ 55\ to\ 74}$	0.2 (1.96)	
$\lambda_{HH\ Income\ \$50k\ to\ \$100k}$	0.27 (2.4)	
$\lambda_{HH\ Income > \$100k}$	0.24 (1.98)	
Religious		
$\theta_{Religious}$	0.9 (11.49)	0.554 (5.88)
Travel		
θ_{Travel}	-7.56 (-7.48)	-14.171 (-128.4)
Other		
θ_{Other}	1.35 (6.47)	1.413 (7.21)
$\lambda_{HH\ Income > \$100k}$	0.59 (1.74)	

$\pi_{\psi,Personal\ Business,1}$		-1.289 (-20.57)
Pick-up/Drop-off		
$\delta_{Pickup/Dropff}$	-10.31 (-10.14)	-17.23 (-98.49)
β_{Male}	0.42 (3.83)	0.511 (4.11)
$\beta_{Age\ 35\ to\ 54}$	0.77 (7.19)	0.89 (7.92)
$\pi_{\psi,Pickup/Dropoff,2}$		-0.712 (-10.78)
$\pi_{\psi,Pickup/Dropoff,3}$		0.114 (6.42)
Exercise		
$\delta_{Exercise}$	-9.25 (-9)	-16.16 (-124.79)
β_{Male}	0.1 (1.07)	
$\beta_{Age\ 18\ to\ 34}$	-0.39 (-1.94)	
$\beta_{Age\ 35\ to\ 54}$	-0.49 (-2.49)	-0.114 (-1.02)
$\beta_{Age\ 55\ to\ 74}$	-0.25 (-1.31)	
$\pi_{\psi,Exercise,1}$		-1.97 (-15.59)
Eat out		
$\delta_{Eat\ out}$	-9.11 (-9.01)	-15.62 (-127.89)
$\beta_{Age\ 35\ to\ 54}$		-0.219 (-2.36)
$\pi_{\psi,Eatout,1}$		-1.792 (-23.34)
Leisure		
$\delta_{Leisure}$	-9.05 (-8.86)	-16.12 (-111.29)
β_{Male}	0.33 (3.5)	0.24 (2.25)
$\beta_{Age\ 18\ to\ 34}$	-0.69 (-4.02)	
$\beta_{Age\ 35\ to\ 54}$	-0.91 (-5.3)	-0.399 (-3.57)
$\beta_{Age\ 55\ to\ 74}$	-0.41 (-2.53)	
$\pi_{\psi,Leisure,1}$		-1.586 (-17.15)
Religious		
$\delta_{Religious}$	-10.04 (-9.64)	-17.97 (-86.28)
β_{Male}	0.26 (1.36)	0.514 (2.24)
$\beta_{Age\ 18\ to\ 34}$	-1.66 (-4.88)	
$\beta_{Age\ 35\ to\ 54}$	-1.46 (-4.87)	
$\beta_{Age\ 55\ to\ 74}$	-0.76 (-2.84)	
$\beta_{Age\ above\ 75}$		1.131 (2.95)
$\pi_{\psi,Religious,1}$		-1.412 (-6.36)
Other		
δ_{Other}	-10.54 (-10.32)	-17.18 (-120.67)
β_{Male}	0.28 (1.8)	
$\beta_{Age\ 18\ to\ 34}$	-0.3 (-1.54)	
$\beta_{Age\ 35\ to\ 54}$	-0.28 (-1.62)	

Aggregate Model	Log-likelihood	-27665.9	Episode Model	Log-likelihood	-51957.0
	# of Parameters	89		# of Parameters	62

As figure 3 shows, all activities have negative value for penalty term except for home. The positive linear penalty for home indicates that, home activity is more likely to be participated in two episodes than in one episode like rest of the activity types (please recall that the penalty term is applied starting from the second episode of an activity type and not on the first episode of the activity type). This is in line with the observed statistics and indicate the polynomial penalty terms were able to replicate the episode participation propensity of the individuals. Work and education activity have very negative penalties indicating these activities are more likely to be participated in one episode than in more episodes. On the other hand, the much lower magnitude of the negative penalty terms in the shopping and personal business activity indicate that for many people it is probable to participate into multiple episodes on these activities during the day compared to participating in multiple episodes of work and education activity.

The log-likelihood of the two models is not comparable. While the aggregate approach in the Leeds sample has a final log-likelihood of -41,500, the episode-based approach peaks at -79,634. Similarly, for the PR sample the likelihood peaks at -27,665 for the aggregate model and at -51,957 for the episode model. The difference is due to the episode-based approach trying to fit more alternatives with essentially the same amount of the data, so the log-likelihood becomes much lower. Due to the unsuitability of the LL as a measure of fit of the models, we assess the goodness of fit by comparing their precision when forecasting out-of-sample, as described in the next section.

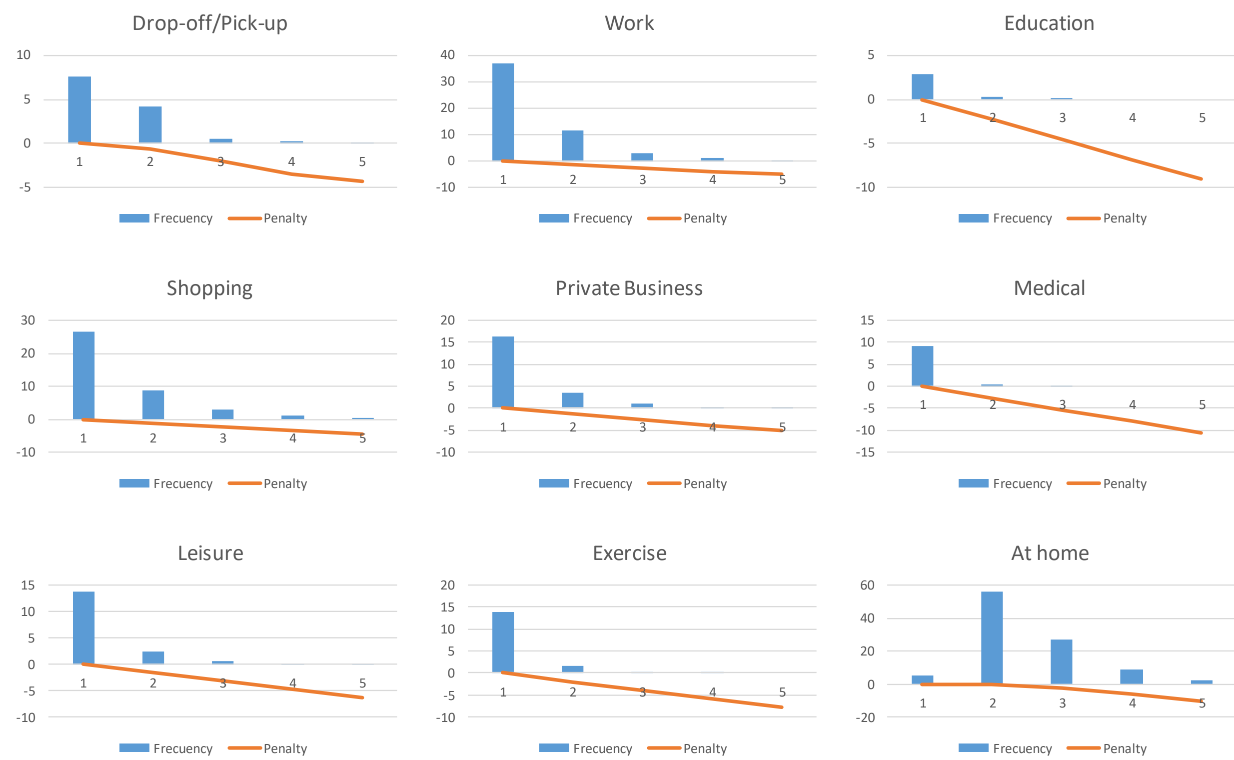

Figure 3 - Frequency of episode engagement (%) and size of base utility penalty in the PR dataset

4.2 Forecast fit comparison

To measure the forecasting accuracy of both the aggregate and episode-based approach, we estimated the model with 80% of the whole sample, and then used that model to forecast for the remaining 20% of the data i.e. the holdout sample. All fit measurements presented in this and the following subsections are based on the holdout sample only. We measured the fit using the Root Mean Squared Error (RMSE) at the sample level, which we defined as follows.

$$RMSE = \sqrt{K^{-1}\sum_{k}\left(\sum_{n}\sum_{t}\sum_{i}x_{nki} - \sum_{n}\sum_{t}\sum_{i}\hat{x}_{nki}\right)^{2}} \qquad (9)$$

Where $\hat{x}_{ntki}$ are the forecasted time consumption of episode i of activity k for individual n, with the observed values given by x_{nki}. K is the total number of different activities.

Table 7 presents forecast and fit indices for the Leeds sample. Under the “Time (hours)” heading, we present the observed and forecasted aggregated consumption of each activity. The forecasts are very similar for the aggregated and episode-based approach, with the second achieving a 15% smaller RMSE. Under the “Activities (obs)” heading, we present the observed and forecasted number of observations that engage in each activity, i.e. the number of observations that perform at least one episode of the corresponding activity. Once again, we see that the forecast is very similar between the aggregated and episode-based approaches, with the episode-based approach having a slightly (4%) smaller RMSE. Under the “Episodes (episodes)” heading, we present the observed and forecasted number of episodes engaged with across the sample, i.e. the total number of episodes in the whole sample. As the aggregate approach cannot predict more than one episode, its forecast is the same as the number of observations that engage in the activity. As expected, we observe a big difference in this aspect between the forecast of the aggregated and episode-based approach, which leads to the episode-based approach achieving a significantly (71%) lower RMSE than the aggregate approach.

We observe a similar pattern in the PSR sample, as presented in Table 8. The aggregated and episode-based approach achieve very similar fit in terms of aggregated time consumption (column “Time”) and activity engagement (column “Activities”) with the exception that the episode-based approach is performing better while predicting the number of individuals engaging in different activities (unlike the Leeds data). However, the episode-based approach reaches a much lower RMSE when it comes to forecasting the number of episodes of each activity in the whole sample.

Table 7 - Forecast fit comparison in the Leeds sample

	Time (hours)			Activities (obs)			Episodes (episodes)		
	Obs	Forecast		Obs	Forecast		Obs	Forecast	
		Agg.	Epi.		Agg.	Epi.		Agg.	Epi.
Drop-off/Pick-up	372	250	231	210	189	277	350	189	309
Work	3304	3609	3263	488	450	548	814	450	733
Education	194	193	199	52	39	50	77	39	54
Shopping	642	481	485	398	311	396	656	311	459
Private Business	418	434	400	264	234	309	368	234	344
Petrol	3	11	12	31	26	26	31	26	26
Leisure	1357	1636	1542	424	393	501	722	393	618
Exercise	1016	603	554	249	148	191	335	148	202
Home	16808	15742	16247	1088	1051	1073	2377	1051	2061
Travel	2205	3395	3421	996	1023	1045	996	1023	1045
Other	105	69	69	46	38	37	46	38	37
TOTAL	26424	26424	26424	4246	3901	4452	6772	3901	5887
RMSE (sample)		**517**	**436**		**47**	**45**		**447**	**128**

Table 8 - Forecast fit comparison in the PSR sample

	Time (hours)			Activities (obs)			Episodes (episodes)		
	Obs	Forecast		Obs	Forecast		Obs	Forecast	
		Agg.	Epi.		Agg.	Epi.		Agg.	Epi.
Home	11361	10489	10481	714	705	693	1777	705	1323
Work	2928	2837	2836	356	305	353	492	305	398
Shopping	207	359	387	296	224	268	459	224	310
Education	145	114	117	27	17	19	34	17	19
Medical	105	145	141	83	55	55	88	55	55
Personal business	134	144	148	154	119	138	223	119	148
Drop-off/Pick-up	42	65	70	83	71	94	129	71	100
Exercise	135	209	201	122	86	91	135	86	93
Eat out	151	229	233	163	125	139	193	125	145
Leisure	523	433	444	139	95	108	167	95	112
Religious	92	100	106	36	23	27	45	23	27
Travel	1274	2019	1987	724	725	725	724	725	725
Other	257	210	201	40	34	32	40	34	32
TOTAL/ Budget	17354	17354	17354	2937	2583	2742	4506	2583	3487
RMSE (sample)		**353**	**350**		**37**	**21**		**339**	**152**

4.3 Episodes forecast analysis

In this subsection, we analyse the results from the episode-based approach more in detail, in particular its prediction of the number and length of episodes. As the aggregated approach can only forecast a single episode per activity, we ignore it in this section. We begin by analysing the results from the Leeds dataset.

Table 9 and 10 present, under the "Total time (hours) per episode" column, the observed and forecasted total time spent in each episode for each activity, from the first to the fifth episode. We observe that the total amount of time spent in the whole sample is decreasing with the order of the episodes, a phenomenon reproduced by our modelling.

While the RMSE of the total time expenditure is higher for the first episode in both samples, this is only a scale effect. If we look at the RMSE as a percentage of the average consumption of each episode across activities, we obtain 26, 5, 49, 35, and 51% for the first, second, third, fourth, and fifth episodes in the Leeds sample, and 53, 49, 140, 160, and 210% in the PSR sample. This points to bigger errors for sparsely consumed episodes or, in other words, the model predicts less accurately for those activities that are less common in the sample.

The effect of the penalty is perhaps clearer when the forecasted number of episodes is analysed. In the "Observations per episodes" columns in Table 9 and 10, we present the observed and forecasted number of observations that engage in one, two, three, four or five episodes for each activity. In this case, we did not consider the order in which the episodes were performed in the forecast, but only the total number of episodes engaged with. This is due to our forecasting algorithm not enforcing the order in which the episodes should be engaged with, as discussed in section 2.3. To calculate these numbers, we register for each set of draws ε_{nki} the number of episodes an individual engages with. We then calculate the frequency of engaging in one, two, three, four or five episodes across all draws, which are our estimate for the probabilities of an individual engaging in each possible number of episodes. Finally, we can obtain the expected number of individuals performing each number of episodes by summing these probabilities across individuals.

Table 9 - Detailed episode forecasting in the Leeds sample

	Time (hours) per episode										Observations per episode									
	Observed					Forecasted					Observed					Forecasted (Epi.)				
Episode:	1st	2nd	3rd	4th	5th	1st	2nd	3rd	4th	5th	1	2	3	4	5	1	2	3	4	5
Drop-off/Pick-up	248	54	40	5	26	142	56	22	8	3	120	60	17	6	7	246	29	1	0	0
Work	2476	538	192	57	42	2272	578	239	114	61	297	109	45	21	16	388	136	22	1	0
Education	142	37	5	9	0	144	39	12	3	1	35	12	2	3	0	46	4	0	0	0
Shopping	456	102	43	22	19	335	99	33	13	5	253	80	33	16	16	337	55	4	0	0
Private Business	308	65	29	7	10	274	81	28	11	5	201	37	15	7	4	277	31	1	0	0
Petrol	3	0	0	0	0	12	0	0	0	0	31	0	0	0	0	26	0	0	0	0
Leisure	863	303	113	37	41	964	361	134	56	27	247	106	38	16	17	395	94	10	1	0
Exercise	794	143	67	11	0	452	66	22	9	5	191	36	17	4	1	180	11	0	0	0
Home	9256	5218	1819	392	123	9069	5247	1450	383	97	226	536	245	61	20	323	531	202	17	0
Travel	2205					3421					996					1045				
Other	105					69					46					37				
RMSE (sample)						**394**	**37**	**125**	**21**	**15**						**80**	**19**	**23**	**18**	**12**

Table 10 -Detailed episode forecasting in the PSR sample

	Total time (hours) per episode										Observations per episode									
	Observed					Forecasted					Observed					Forecasted				
Episode:	1st	2nd	3rd	4th	5th	1st	2nd	3rd	4th	5th	1	2	3	4	5	1	2	3	4	5
Home	4485	4314	1912	471	179	5537	3601	1057	222	65	39	391	203	58	23	248	279	149	17	0
Work	2464	370	76	18	0	2148	497	132	42	16	257	71	20	7	1	309	42	1	0	0
Shopping	143	39	17	6	2	273	79	24	8	3	194	60	27	11	4	229	37	2	0	0
Education	124	18	3	0	0	107	9	1	0	0	21	5	1	0	0	19	0	0	0	0
Medical	99	4	1	0	0	132	9	1	0	0	79	3	1	0	0	54	0	0	0	0
Private business	91	29	9	6	0	108	30	8	2	1	108	28	14	3	1	129	9	0	0	0
Drop-off/Pick-up	27	12	2	1	0	39	23	7	1	1	48	27	5	3	0	87	6	0	0	0
Exercise	121	14	1	0	0	169	28	4	1	0	111	10	0	1	0	89	2	0	0	0
Eat out	122	24	2	2	0	194	33	5	1	0	140	18	3	2	0	133	6	0	0	0
Leisure	419	80	11	12	0	350	74	16	3	1	118	16	3	2	0	105	3	0	0	0
Religious	78	13	0	1	0	86	16	3	1	0	29	6	0	1	0	27	0	0	0	0
Travel	1274					1987					724	0	0	0	0	725				
Other	257					201					40	0	0	0	0	32				
RMSE						**399**	**219**	**258**	**75**	**35**						**68**	**37**	**19**	**13**	**7**

The (expected) number of individuals consuming each number of episodes confirms that the penalty parametrisation works as expected. In both the Leeds and PSR samples we observe, that most individuals engage in two episodes of the *home* activity. On the other hand, no one engages in more than one episode of getting *petrol* in the Leeds sample, just as in the observed data. Similarly, *education*, *medical* and *religious* activities are only performed once per day in the PSR sample.

Once again, we observe that the RMSE of the "observations per episode" forecast decreases with the number of episodes, but again this is just a scale effect. If we calculate the ratio between these RMSE values and the average number of people engaging in each number of episodes, we obtain 33, 17, 50, 120, and 131% for the first, second, third, fourth, and fifth episodes in the Leeds sample, and 46, 64, 77, 163 and 263% for the PSR sample. In other words, the earlier episodes are predicted more accurately than the later ones. This is because our data contains many observations with a few number of episodes being performed, and few observations with many episodes.

5 DISCUSSION

In this paper, we propose a framework to modify our perspective on how time use data is analysed using the popular models in the MDCEV family. In particular, instead of modelling the total amount of time allocated to each activity across a whole day (or any other unit of time), we propose to model the duration of each instance or *episode* of the performed activities. In this framework, an *episode* is a continuous amount of time during which an individual engages in a given activity. There can be several episodes of the same activity within a single day, e.g. working in the morning, then performing another activity, then working again in the afternoon.

The proposed approach is especially relevant when used in the context of activity-based modelling. Considering multiple episodes of each activity can lead to significantly more trips during a day resulting from changes in location for consecutive activity participation. Furthermore, our proposed approach provides richer information that can help with the prediction of individuals' schedules in simulation studies.

Our approach consists in creating multiple alternatives per activity, representing unique episodes. In terms of parameterization, all alternatives belonging to the same activity would share the same parameters pertaining to the characteristics of the individuals and the activity. At the same time, polynomial penalties are used to differentiate between the utilities of the multiple episodes of the same activity type. Additionally, we propose a forecasting technique which can be applied to this approach by modifying the forecasting routine of the traditional MDCEV model proposed by Pinjari & Bhat (2011).

Our results indicate that the proposed episode-based approach to time use modelling is an improvement over current practice using the MDCEV model. While it does not increase the fit of the aggregate consumption as compared to a traditional MDCEV model, it does provide additional information in the form of the number of episodes each individual is likely to engage with. This additional information does not impose additional burden in data collection, as most time use datasets are constructed from individuals' diaries recording their schedule. As a result, coding the information into aggregate time consumption per activity, or disaggregated time consumption across several episodes does not imply additional costs, other than some extra data management. In other words, our approach provides additional information at marginally no cost.

While the proposed model structure represents a relevant contribution to the set of techniques for time use modelling, we acknowledge two main limitations of the present framework. The first and most relevant one is that the current formulation does not enforce the orderly performance of episodes when forecasting. In other words, for an individual set of draws of the error terms, an individual might consume episode 2 of a given activity before consuming episode 1. While this remains a theoretical issue, it will not be a problem in most applications, because the final forecast is an average of multiple draws, and the penalty terms ensure that on average consumption of the first episode is more likely than the later episodes. In cases where the model is used for simulation, the order of the episode consumption should be ignored, instead focusing only on the number of episodes consumed. Probably the most notable of these cases is during activity-based trip simulations, where traditionally only one set of draws would be used for each simulation run. However, if multiple runs of the simulation are performed, once again the penalty terms will ensure that early episodes are consumed more often than later ones.

The episode-based approach does not consider individuals' overall schedule, instead looking at episodic consumption in a simultaneous way. It is reasonable to believe there might be scheduling effects across activities (Allahviranloo et al. 2017). For example, if an individual has engaged in many episodes throughout the day, he or she might be more inclined to limit the number of episodes in the evening. However, including scheduling in the formulation of the problem would inevitably lead to an integer optimisation problem, and to a huge increase in complexity. Our approach instead seeks to be efficient and as simple as possible. If scheduling is needed, this can easily be achieved in a later stage with an additional algorithm.

In summary, the proposed modelling approach achieves two goals: to extend and further methodology in time use research, and to do it in way that makes it more compatible with activity-based modelling, the state-of-the-art approach to large scale transport simulation. The proposed episode-based approach is capable of offering additional information at virtually no additional cost compared to the traditional time use modelling approach. Furthermore, it can be applied using any software capable of estimating MDCEV models, as it does not require any modification to the estimation process, or the formulation of the model. This extra information can be key in the activity-based modelling framework, or more generally, when the total number of trips during a day is of interest, in addition to the time expenditure.

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