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Use of repeated cross-sectional travel surveys to develop a Meta model of activity-travel generation process models: accounting for changing preference in time expenditure choices

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The paper presents an investigation of the temporal transferability of activity generation process models. Three repeated cross-sectional household travel survey data sets collected in the Greater Toronto and Hamilton Area in the years 2001, 2006, and 2011 are used for the investigation. A multiple discrete-continuous extreme value model is used to develop an activity-travel generation model and separate models are estimated for non-workers and workers. Models are developed for individual years and then for the pooled data set of three cross-sectional years to develop a Meta model of activity generation processes. Individual year-specific models are used to increase knowledge about the temporal stability of different parameters of the model so that the Meta model could capture the non-linear evolution of some key parameters of the model. Different transferability indices are used to test temporal transferability of cross-sectional year-specific modes and the Meta model. The results show that, in general, the activity-travel generation process model shows good temporal transferability. The Meta models reveal that the use of multiple repeated cross-sectional data sets considered as a pseudo-panel data improves temporal transferability of an activity generation model significantly.

Keywords: temporal transferability; activity generation; MDCEV

1. Background and motivation

Transferability is 'the application of a model, information, or theory about behaviour developed in one context to describe the corresponding behaviour in another context' as defined by Koppelman and Wilmot (1982). Temporal transferability is one of the key and implicit conditions of developing travel behaviour models as these are developed for forecasting future levels of transport demand. Current travel demand modelling practices are focusing on the development of advanced models that better explain current behaviour rather than focusing on the ability of these models in forecasting (Fox and Hess 2010). The importance of producing high temporal transferability of models should not be neglected as these models are used by planners and policy-makers to test policy decisions and to estimate future demands, which are important inputs for infrastructure planning and maintenances. Changes in socio-economic variables and in transportation system performances can lead to changes in individuals' activity-travel-related behaviour and travel demands. This thereby affects the temporal transferability of demand models. Travel demand models should take into account such changes to accurately forecast future demand.

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Activity-based approach of travel demand modelling has gained considerable attention from transportation researchers (Chow and Nurumbetova 2015). However, still, the conventional way of modelling travel demand through capturing the choice preference is by using cross-sectional data set (i.e. one data set collected in a specific year). There have been investigations on activity-travel demand over multiday time periods (Habib and Miller 2008; Arentze, Ettema, and Timmermanns 2013). However, for forecasting medium- to long-term travel demand, only cross-sectional data sets are used to estimate model parameters to forecast travel demands for the future and have applications in a variety of environments (Miller and Roorda 2003; Arentze and Timmermans 2004; Pendyala et al. 2005; Auld and Mohammadian 2012). This practice assumes that the preference structures of activity-travel choices are constant or fixed over time. In fact, the conventional (both trip and activity-based) practices of travel demand modelling do not take the temporal evolution of travel behaviour into consideration. The main components of any activity-based travel demand models are activity generation models; activity scheduling models; mode choice models; and location choice models (Miller and Roorda 2003; Auld and Mohammadian 2012). Among all of these components, the activity generation model is the most critical component defining the patterns of other components and captures fundamental behavioural processes of time expenditure choices (Habib and Miller 2009). Although the efforts to develop an advanced model of activity-travel demand are underway by various researchers worldwide, the investigation of temporal transferability of any activity-based travel demand model is not fully complete as of yet. There have been efforts to test temporal transferability of activity-based model outputs for short durations as well as spatial transferability of activity generation models (Roorda, Miller, and Habib 2008; Sikder and Pinjari 2013). According to our knowledge, any investigation of temporal transferability of an activity generation model is not available in the existing literature. However, it is critical to test how transferable (temporally) the activity generation models are, at least, to gain confidence in an activity-based approach to travel demand modelling.

This paper is concerned with the temporal transferability of activity generation models. Three repeated cross-sectional household travel surveys collected from the same study area over a period of 10 years are used in this investigation. In addition to a series of cross-sectional models, three data sets are pooled to develop a Meta model of activity generation processes. The models are then tested for temporal transferability. The paper is organised in the follow sections: the next section presents a brief literature review. This is followed by sections discussing modelling activity generation process and mathematical formulations, description of data, and the empirical models and temporal transferability. The paper's conclusion contains a summary of the key findings and recommendations for further research.

2. Literature review

The importance of temporal transferability comes from the need to accurately forecast travel behaviour in the future. The temporal transferability was first investigated in the literature in late 1960s. From that time period to the present, the research on this topic is still ongoing. In this section, a review of the existing studies related to this topic is conducted.

An overview of temporal transferability of activity generation models was presented in Fox and Hess (2010). Hill and Dodd used household travel surveys of Toronto from the years 1956 and 1964 (note the boundaries of the City of Toronto in those decades differ from those of Toronto currently) to investigate the aggregate trip generation models (1966). Kannel and Heathington (1973) analysed the temporal transferability of households' disaggregate trip generation models using household surveys of Indianapolis (USA) conducted during the years 1964 and 1971. The authors indicated that the household models based on the 1964 data successfully predicted

1971 data. Downes and Gyenes (1976) compared the forecasting performance of three trip generation techniques that are zone-based regression; category analysis; and household-based regression. The data, collected from Reading, UK, in the years 1962 and 1971, were used to hold the comparison (Downes and Gyenes 1976). Yunker (1976) investigated the transferability of trip generation and distribution models by using data generated in Wisconsin (USA) using data gathered during the years 1963 and 1972. The author found that 1972 trip generation, transit use, and trip length characteristics were successfully predicted with adequate accuracy through the application of the original 1963 models. Smith and Cleveland (1976) used household travel surveys generated from surveys performed in the years 1953 and 1965 to analyse the temporal transferability of household trip generation models for Detroit, Michigan (USA). The key finding for this work was that although the lack of overall statistical time transferability, disaggregate home and work-based trip generation equation for the year 1953 did produce a reasonable prediction of trips that occurred in the year 1965. Doubleday used the same Reading data set, which Downes and Gyenes used in their work, as mentioned above, to analyse the temporal transferability of trip generation models (1977). The author could not provide positive evidence for the overall transferability of a certain trip generation model. The possible reason stated by the author was that there were many limitations in the analysis used. It should be noted that the results related to model transferability conducted by the aforementioned early studies need to be interpreted carefully since most of these studies used simple model structures and/or aggregate modelling techniques (Fox and Hess 2010).

Elmi, Badoe, and Miller (1999) investigated the temporal transferability of aggregate trip distribution models by using the Toronto data generated during the years 1964, 1986, and 1996. The main finding of the paper was that although the models were not transferable, advanced models could enhance the temporal transferability of the models (Elmi, Badoe, and Miller 1999). Valentin, Prashker, and Shiftan (2003) used national travel survey data of the year 1984 and the years 1996–1997 to study temporal and spatial transferability of trip generation models for the cities of Tel-Aviv and Haifa (Israel). Multinomial linear regression and Tobit model structures were applied. They were found not to be temporally transferable. One reason stated by the authors was the land use changed in the study area. The authors also studied person-level trip without separating trip purposes (Valentin, Prashker, and Shiftan 2003). Also, in the same year, Zofka (2005) used two data sets from the years 1990 and 2000 to investigate the temporal and spatial transferability of activity generation and travel time duration for workers in two cities: Twin Cities and Seattle (USA). Generalised least-squares regression models were used by the author in this work. However, the author did not find any temporal transferability among the models (Zofka 2005).

Roorda, Miller, and Habib (2008) validated the activity generation, location choice, and scheduling components of travel and activity scheduling for household agents (TASHA). The model was developed using year 1996 data and validated using year 2001 data from the Transportation Tomorrow Survey (TTS) conducted in the Greater Toronto and Hamilton Area (GTHA). The validation process showed that TASHA activity generation and scheduling model components were stable over the five-year study period. It also successfully replicated the daily activity distribution. However, TASHA was not able to forecast an increase in the activity participation rate (Roorda, Miller, and Habib 2008).

One of the findings Fox and Hess (2010) review was that the models were more accurate in predicting the effect of changes on travel behaviour for short-term (five years) periods rather than longer term forecasting. In addition, the authors noted that using too many variables could lead to overfitting to the base-year data (Fox and Hess 2010). To test whether adding more variables and specification improvement improve transferability, Huntsinger et al. (2013) investigated the temporal transferability of advanced models (logit models and cumulative logistic regression). One of their findings was that the generation choice model using logit model formulation was temporally stable, while adding more socio-economic, demographic, land-use, and accessibility variables did not enhance model transferability (Huntsinger and Rouphail 2013). Finally, Shams, Xia, and Argote (2014) examined the temporal transferability of trip generation models for commuting and shopping trips using multinomial logit models for two data sets from the year 1998 and the year 2010. The results showed some transferability for the commute trip model, while the shopping trip model was not temporally transferable (Shams, Xia, and Argote 2014). There are additional studies that focused on temporal transferability of mode choice. These studies will not be discussed in this paper as their focus is beyond the scope of our discussion (Habib, Swait, and Salem 2012; Forsey et al. 2014).

To review, most of the previous studies on temporal transferability focus on either a specific aspect of activity-travel generation or on other elements of travel demand rather than on generation processes. For example, trip generation models focus on the outcome of activity generation processes rather than on the generation process itself. On the other hand, trip distribution and mode choice models focus on other aspects of travel demand rather than on activity generation. This paper contributes to the existing literature of travel demand forecasting by focusing on activity generation process rather than on the outcome of the activity generation process. It contributes to the activity-based travel demand modelling literature by testing temporal transferability of the basic component of activity-travel demands.

3. Modelling activity generation processes

We consider activity generation process as multiple discrete-continuous choices under time budget constraints. Considering a 24-hour time budget, we model time expenditure choices to multiple activities using the multiple discrete-continuous extreme value (MDCEV) model (Bhat and Sen 2006). The MDCEV model uses a generalised version of translated continuous expenditure system utility function to specify marginal utility of time expenditure choices to different activity types. Equation (1) defines the total utility function of time expenditure to different activities within a time budget. The equation accommodates additively separable sub-utility functions of a number of out-of-home activities as well as the composite activity. Composite activity referees to all activities that are not identified separately, but are important to take into consideration. In our case, the time spent at-home to different at-home activities are considered as a composite activity. Each specific activity sub-utility function is composed of a baseline utility component and an additional utility component.

The base line utility component explains the baseline preference (marginal utility) in spending time in specific out-of-home activity with respect to the composite activity. The additional utility component ensures the possibility of a corner solution (allocation of zero time to specific activity) in the mathematical optimisation and captures satiation effects in time expenditure behaviour. Two specific parameters are used in the specific utility component. The η parameter translates time to ensure corner solutions and also to take into consideration the satiation effects in time expenditure to specific out-of-home activities. The higher the value of η, the less is the satiation effect in the time expenditure to specific out-of-home activities which mean a stronger preference. The second parameter is the ζ parameter that is purely a satiation factor that defines the marginal rate of utility gain and loss in spending each additional unit of time on the activity types under consideration. This parameter is the same for all activities, including the composite activity. Considering the total modelling time frame (T) as a typical day, the total utility function can be written as

$$U_{\text{Total}} = \sum_{j=1}^{\text{No. of Activities}} \left(\frac{\eta_j}{\zeta}\right) \exp((\beta_P X_P)_j + \varepsilon_j) \left(\left(\frac{Y_j}{\eta_j} + 1\right)^{\zeta} - 1\right) + \frac{1}{\zeta}\exp(\varepsilon_C)(C)^{\zeta}, \quad (1)$$

s.t.

$$\sum_j Y_j + C = T,$$

$$Y_j \geq 0,$$

where ε is the error term; Y_j is the total time spent on out-of-home activity $j = d_j x_j$, where d_j is the average duration and x_j is the frequency; C is the composite activity time (at-home activities); T is the total time budget; $\exp((\beta_P X_P)_j + \varepsilon_j)$ is the baseline marginal utility of activity j; $\eta_j = \exp(\beta_a X_a)$ is the translating satiation parameter for activity j and it must be positive; $\zeta = 1 - \exp(-\beta_C X_C)$ is the satiation parameter for the composite activity C and it must be less than 1; and X represents variables and β represents corresponding parameters.

Using Kuhn–Tucker conditions the utility function can be transformed to specify the deterministic utility component of specific and composite activities as follows (Kuhn and Tucker 1951).

The deterministic part (transformed) of the specific activity sub-utility is

$$V_j = (\beta_P X_P)_j + (\zeta - 1)\ln(\eta_j^{-1} Y_j + 1) - \ln(d_j). \tag{2}$$

The deterministic part (transformed) of the composite activity sub-utility is

$$V_C = (\zeta - 1)\ln(C). \tag{3}$$

Now, using the 'transformation of variable theorem' and the error term (ϵ) distributional assumption as Type I extreme value distribution, the probability of spending positive amounts of time (Y) to a set of out-of-home activities can be derived as (see Bhat 2008 for more details):

$$P(Y_1,\ Y_2,\ Y_3,\ Y_4, \ldots,\ 0,\ 0,\ 0,\ Y_j) = \frac{1}{\sigma^{N-1}}\left(\left(\prod_{j=1}^{N} \frac{1-\zeta}{Y_j + \eta_j}\right)\left(\sum_{j=1}^{N} \frac{d_j(Y_j + \eta_j)}{1-\zeta}\right)\right) \times \left(\frac{\prod_{j=1}^{N} \exp(V_j/\sigma)}{\left(\sum_{k=1}^{K} \exp(V_k/\sigma)\right)^N}\right), \tag{4}$$

where σ is the scale parameter of Type I extreme value distribution; N indicates the number of activities with non-zero frequency; and K indicates the number including all specific as well as composite activity.

This is a closed-form likelihood function, which we coded in GAUSS and used a gradient search algorithm for estimating model parameters (Aptech 2014).

4. Data for empirical investigations

The data sets used in this investigation come from the TTS, which is a household trip diary that randomly samples 5% of the GTHA households every five years (DMG 2012). Data from the years 2001, 2006, and 2011 TTS are used for the investigation conducted for this paper. Survey instruments, sampling procedures, and study area of these three surveys remained the same. The level-of-service attributes of automotive and transit modes are generated by using calibrated and validated traffic assignment models of corresponding years (Miller 2007). After eliminating all missing values, a total of 33,263 non-workers and 114,388 workers with a total of 147,651

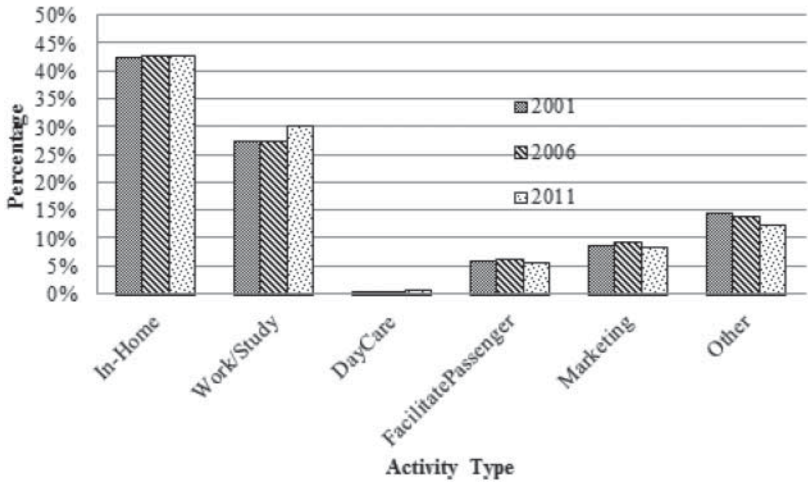

Figure 1. Activity type distribution.

individuals remained for the year 2001, a total of 33,730 non-workers and 112,779 workers with a total of 146,509 individuals remained for the year 2006, and a total of 30,909 non-workers and 107,577 workers with a total of 138,486 individuals remained for the year 2011. All in-home activities are considered in general as the composite activity and all out-of-home activities are broadly classified into five types. The specific out-of-home activity types are

(1) work/school activities,
(2) day care (trips to day care),
(3) facilitate passenger (pick up/drop off person),
(4) marketing (shopping), and
(5) others: all other out-of-home activities that do not fall into the above types.

Figure 1 represents the pattern of activity participation for 2001, 2006, and 2011 data. It shows that the activity participation behaviour is almost stable over the 10-year period. For each individual in the sample data set, a 24-hour time frame ($24 \times 60 = 1440$ minutes) is considered as the time budget for daily time expenditure. We parameterise the baseline utility, translation, and satiation parameters as functions of the various variables available in the data sets. The variables that are considered are person-specific variables; household-specific variables; and activity-specific variables. For person-specific variables age, gender, having a driver's licence, occupation, etc. are considered for this study. For household-specific variables household size, auto ownership, etc. are additionally taken into consideration. For activity-specific variables activity-specific dummies (constants) and the travel time are considered.

5. Empirical models

We estimate activity generation models for each of the years 2001, 2006, and 2011. Individual year-specific models are used to gain understanding of the stabilities of different parameters for the activity generation process model. Based on this knowledge, a Meta model is used that exploits multiple repeated cross-sectional data sets. Empirical models are discussed in the following.

5.1. *Individual year-specific models*

Three models are estimated for each year: for workers and non-workers separately; and both workers as well as non-workers combined. Estimated model parameters are presented in Tables 1–3.

For evaluating the goodness of fit of the empirical models, the Adjusted Rho-Squared is calculated. The Adjusted Rho-Squared ranged between 0.255 and 0.278 for non-workers' models, 0.625 and 0.646 for workers, and 0.557 and 0.568 for all-data models, which represent a very good fit for this type of model (Ben-Akiva and Lerman 1985). Overall, the models, based on workers' data, provide the best fit. These results are expected because the commuting trip, as a regular trip, would be expected to be recorded with a higher degree of accuracy than other trips. The reported model specifications are the best specifications among a number of different specifications for the systematic utility function, both in terms of better likelihood ratio values and the higher numbers of statistically significant parameters. The statistical significance of the parameters is tested by comparing estimated asymptotic t-statistics with the 95% confidence z-value of 1.96. Most of the parameters are highly significant but the same parameter set is retained for all of the models to allow comparisons across the years under study. The following subsections discuss the parameters of the empirical model.

5.1.1. *Baseline utility components of individual year-specific models*

The baseline utility component captures the baseline preference in evolving into an out-of-home activity with respect to the composite activity. Hence, the baseline utility component should be positive. The utility is expressed as an exponential to force this positivity. The baseline utility function had two components: the systematic component and the random component. The systematic component is modelled as a linear-in-parameter function of different variables. The systematic component of the baseline utility for the composite activity is assumed to be 1 so that it could be the reference utility for all out-of-home activities.

The systematic component of the baseline utility function for each out-of-home activity type is composed of a constant term and a number of socio-economic variables. The final specifications of the models include one constant for work and study activity type as well as a generic constant term for other specific activities in the workers and all-data models. There is one generic constant term for all specific activities in the non-workers' models (there is no work and school activity in the non-workers' model).

Comparing the activity-specific constant term across models, we found in the case of the non-workers' models that these constants did not vary across the years. For the workers' model, work and school constants are higher for the year 2006 rather than the year 2001, and higher for the year 2006 than the year 2011. For the other activity-specific constants, they are higher for the year 2011 compared to the years 2006 and 2001 with almost equal values for the years 2006 and 2011. For the all-data model, the constants did not vary a lot across the years. This suggest that for the year 2011, individuals seem to spend more time in work- and school-related activities more than any other activity types which may be consistent with a study published in Statistics Canada (Turcotte 2007). In this study, the researcher looked at the time workers spent with family members during a typical workday between 1986 and 2005. They found that the average time spent with family has declined and the main cause for this is the increase in average working hours.

Among the other variables in the systematic baseline utility function component gender-specific dummy variables capture the difference of females in spending time on out-of-home activity relative to males. This variable is statistically significant for all activities. The variable had almost consistent effects across the nine models, but with different values. It shows that

Table 1. Year-specific and Meta model parameters for workers' and non-workers' combined models.

	2001	2006	2011	Meta model (1)	Meta model (2)	Meta model (4)	Meta model (3)	Meta model (5)
Adjusted Rho-Squared	0.560	0.557	0.568	0.556	0.582	0.556	0.556	0.583
Baseline Utility								
Constant								
Work/school	– 5.60	– 5.61	– 5.15	– 5.29	– 5.05	– 5.30	– 5.25	– 5.24
Other activities	– 7.67	– 7.49	– 7.50	– 7.54	– 5.78	– 7.55	– 7.49	– 5.54
Age (dummy)								
11–18	1.11	1.24	1.61	1.31	0.91	1.32	1.28	0.95
18–25	0.54	0.53	0.54	0.58	0.22	0.58	0.56	0.23
25–35	0.53	0.49	0.53	0.57	0.19	0.57	0.54	0.21
35–45	0.51	0.51	0.51	0.56	0.19	0.55	0.53	0.21
45–55	0.46	0.50	0.57	0.53	0.18	0.53	0.51	0.19
55–65	0.37	0.42	0.43	0.39	0.09	0.39	0.38	0.09
Full-time worker (dummy)								
Work/school	6.46	6.41	5.57	6.04	6.16	6.05	6.01	6.41
Day care	– 8.73	– 8.88	– 11.59	– 9.24	– 9.28	– 9.21	– 9.27	– 8.97
Facilitate passenger	– 4.06	– 4.03	– 7.59	– 4.75	– 5.13	– 4.73	– 4.77	– 4.88
Marketing	– 4.42	– 4.52	– 8.49	– 5.36	– 6.13	– 5.33	– 5.37	– 5.95
Other	– 2.48	– 2.93	– 6.79	– 3.60	– 4.68	– 3.58	– 3.62	– 4.49
Part-time worker (dummy)								
Work/school	1.10	1.26	2.49	1.41	1.43	1.42	1.39	1.61
Day care	– 8.33	– 8.31	– 11.97	– 9.27	– 9.18	– 9.31	– 9.32	– 8.84
Facilitate passenger	– 3.77	– 3.92	– 7.84	– 4.73	– 4.95	– 4.69	– 4.74	– 4.72
Marketing	– 4.48	– 4.39	– 9.05	– 5.51	– 6.04	– 5.48	– 5.52	– 5.86
Other	– 2.99	– 3.14	– 7.39	– 4.00	– 4.77	– 3.98	– 4.02	– 4.57
Work from home (dummy)								
Work/school	– 0.27	– 0.78	1.74	– 0.91	– 0.85	– 0.89	– 0.94	– 0.53
Day care	– 9.53	– 9.95	– 12.91	– 10.13	– 10.13	– 10.17	– 10.15	– 9.81
Facilitate passenger	– 3.95	– 4.02	– 7.94	– 4.72	– 5.15	– 4.70	– 4.74	– 4.93
Marketing	– 3.70	– 3.47	– 7.85	– 4.38	– 5.38	– 4.37	– 4.41	– 5.18
Other	– 1.86	– 2.14	– 6.31	– 2.85	– 4.09	– 2.83	– 2.87	– 3.88
Full-time student (dummy)								
Work/school	5.45	4.86	4.30	4.78	4.94	4.77	4.77	5.09
Day care	– 7.60	– 7.45	– 8.18	– 7.69	– 8.04	– 7.77	– 7.66	– 8.22
Facilitate passenger	– 2.14	– 2.28	– 3.51	– 2.73	– 3.07	– 2.76	– 2.71	– 3.19
Marketing	– 1.50	– 1.74	– 3.95	– 2.77	– 3.46	– 2.78	– 2.73	– 3.43
Other	0.68	0.19	– 0.79	0.02[a]	– 0.85	0.02[a]	0.04	– 0.84
Part-time student (dummy)								
Work/school	0.71	0.59	0.59	0.65	0.64	0.64	0.65	0.64
Day care	– 3.80	– 3.32	– 4.28	– 3.49	– 3.08	– 3.66	– 3.50	– 3.16
Facilitate passenger	– 0.23	– 0.31	– 0.65	– 0.35	– 0.37	– 0.37	– 0.35	– 0.36
Marketing	– 0.33	– 0.40	– 1.07	– 0.53	– 0.76	– 0.54	– 0.53	– 0.75
Other	0.20	0.13	0.12	0.19	0.04	0.18	0.19	0.05
Transit Pass (dummy)								
Work/school	0.46	0.38	0.32	0.35	0.32	0.36	0.36	0.32
Day care	– 4.28	– 4.40	– 3.35	– 3.83	– 3.34	– 3.81	– 3.82	– 3.48
Facilitate passenger	– 0.79	– 1.03	– 0.84	– 0.96	– 0.89	– 0.95	– 0.93	– 0.90
Marketing	0.16	0.11	0.33	0.12	– 0.02[a]	0.13	0.15	– 0.04
Other	0.33	0.25	0.51	0.28	0.16	0.28	0.30	0.17
Female (dummy)								
Work/school	0.06	0.05	– 0.01	0.01	– 0.15	0.01	0.01	– 0.15

(*Continued*)

Table 1. Continued.

	2001	2006	2011	Meta model (1)	Meta model (2)	Meta model (4)	Meta model (3)	Meta model (5)
Day care	– 5.25	– 5.20	– 4.68	– 5.05	– 5.27	– 5.05	– 5.06	– 5.38
Facilitate passenger	– 0.27	– 0.37	– 0.58	– 0.39	– 0.87	– 0.39	– 0.39	– 0.91
Marketing	1.98	2.12	2.12	2.09	0.89	2.08	2.09	0.87
Other	1.87	2.08	2.04	2.01	0.98	2.00	2.00	0.97
Satiation parameter of specific activities								
Constant	0.64	0.53	0.71	0.60	0.56	0.71	0.59	0.63
Travel time (hours)								
Day care	0.61	0.11	1.01	0.77	0.86	1.49	0.79	1.48
Facilitate passenger	0.87	0.89	1.07	0.90	0.96	1.74	0.90	1.72
Marketing	2.46	1.98	2.21	2.18	2.17	2.07	2.19	2.13
Other	5.63	5.79	6.25	5.82	5.79	4.75	5.81	4.79
Satiation parameter of composite activity								
HH size	– 0.06	– 0.05	– 0.06	– 0.06	– 0.05	– 0.06	– 0.06	– 0.05
No. of vehicles/HH	– 0.11	– 0.06	– 0.04	– 0.07	– 0.07	– 0.07	– 0.07	– 0.06
Apartment *(dummy)*	– 0.06	– 0.05	– 0.05	– 0.05	– 0.05	– 0.05	– 0.05	– 0.04
General office *(dummy)*	– 0.59	– 0.64	– 1.04	– 0.71	– 0.72	– 0.71	– 0.72	– 0.66
Professional /management/technical *(dummy)*	– 0.62	– 0.72	– 1.07	– 0.76	– 0.74	– 0.76	– 0.77	– 0.68
Sales/service *(dummy)*	– 0.66	– 0.67	– 1.04	– 0.75	– 0.73	– 0.75	– 0.76	– 0.68
Construction *(dummy)*	– 0.59	– 0.81	– 1.04	– 0.76	– 0.73	– 0.76	– 0.77	– 0.68
Driver license *(dummy)*	– 0.19	– 0.17	– 0.17	– 0.17	– 0.19	– 0.17	– 0.18	– 0.18
Temporal factors								
Baseline utility								
Work/school	–	–	–	–	0.04	–	–	– 0.02
Day care	–	–	–	–	– 3.06	–	–	– 3.40
Facilitate passenger	–	–	–	–	– 0.73	–	–	– 1.07
Marketing	–	–	–	–	0.13	–	–	– 0.21
Other	–	–	–	–	0.24	–	–	– 0.12
Satiation parameter of specific activities								
Day care	–	–	–	–	–	– 0.30	–	– 0.24
Facilitate passenger	–	–	–	–	–	– 0.34	–	– 0.27
Marketing	–	–	–	–	–	– 0.06	–	– 0.02
Other	–	–	–	–	–	0.09	–	0.14
Satiation parameter of composite activity								
Constant	–	–	–	–	–	–	0.01	– 0.06

Note: HH, household.
[a]Non-significant parameters.

females spent more time on marketing (shopping) and other activity types and less time in drop-off and picking up activities and day-care activities. Although, female workers in the 2011 model tend to spend less time in work/school, marketing, and other activities and more time into day-care activities. The tendency to spend less hours in marketing may be due to the increase of online shopping (McKeown and Brocca 2009).

Table 2. Year specific and Meta model parameters for workers' models.

	2001	2006	2011	Meta model (1)	Meta model (2)	Meta model (3)	Meta model (4)	Meta model (5)
Adjusted Rho-Squared	0.634	0.625	0.646	0.629	0.633	0.630	0.629	0.637
Baseline utility								
Constant								
Work/school	– 2.81	– 3.42	– 1.33	– 2.72	– 2.64	– 2.72	– 2.71	– 2.65
Other activities	– 9.51	– 9.72	– 11.44	– 10.02	– 8.89	– 10.03	– 10.01	– 7.86
Age (dummy)								
11–18	1.06	1.15	1.45	1.25	1.19	1.26	1.25	1.09
18–25	0.25	0.12	0.18	0.22	0.21	0.23	0.21	0.24
25–35	0.22	0.04[a]	0.14	0.20	0.17	0.21	0.19	0.20
35–45	0.17	0.06	0.13	0.16	0.15	0.17	0.16	0.18
45–55	0.13	0.06[a]	0.21	0.15	0.16	0.16	0.15	0.19
55–65	0.14	0.08	0.16	0.12	0.15	0.13	0.13	0.16
Full-time worker (dummy)								
Work/school	4.22	4.92	2.55	4.09	4.03	4.07	4.09	4.23
Day care	– 5.23	– 4.74	– 4.46	– 4.79	– 4.86	– 4.81	– 4.80	– 4.60
Facilitate passenger	– 0.76	– 0.09	– 0.58	– 0.51	– 1.16	– 0.51	– 0.50	– 0.95
Marketing	– 0.22	0.52	– 0.22	– 0.004[a]	– 0.71	– 0.009[a]	0.00	– 0.49
Other	1.78	2.16	1.52	1.78	0.99	1.77	1.79	1.22
Part-time worker (dummy)								
Work/school	0.91	1.38	1.03	1.29	1.21	1.28	1.29	1.31
Day care	– 4.89	– 4.84	– 5.11	– 4.84	– 4.86	– 4.86	– 4.79	– 4.67
Facilitate passenger	– 0.49	– 0.02[a]	– 0.86	– 0.51	– 1.06	– 0.51	– 0.50	– 0.92
Marketing	– 0.03[a]	0.79	– 0.49	0.11	– 0.50	0.10	0.10	– 0.32
Other	1.05	1.84	0.04[a]	1.06	0.53	1.05	1.07	0.76
Full-time student (dummy)								
Work/school	2.79	2.91	0.76	2.34	2.35	2.33	2.35	2.48
Day care	– 6.46	– 6.45	– 5.83	– 6.43	– 6.78	– 6.39	– 6.46	– 6.89
Facilitate passenger	– 1.50	– 1.68	– 0.95	– 1.63	– 2.06	– 1.59	– 1.55	– 2.20
Marketing	– 0.09	– 0.65	– 0.05[a]	– 0.59	– 0.96	– 0.56	– 0.52	– 0.98
Other	2.09	1.12	2.85	1.92	1.43	1.92	1.96	1.39
Part-time student (dummy)								
Work/school	0.43	0.41	– 0.44	0.28	0.27	0.27	0.28	0.26
Day care	– 3.43	– 3.30	– 2.80	– 3.21	– 3.13	– 3.15	– 3.24	– 3.03
Facilitate passenger	– 0.17	– 0.27	0.01[a]	– 0.15	– 0.33	– 0.17	– 0.18	– 0.27
Marketing	0.03[a]	– 0.15	0.32	0.07	– 0.06	0.05	0.06	– 0.02[a]
Other	0.58	0.42	0.78	0.67	0.55	0.68	0.67	0.57
Transit pass (dummy)								
Work/school	0.44	0.37	0.33	0.34	0.35	0.35	0.35	0.34
Day care	– 1.19	– 1.31	– 0.44	– 1.05	– 0.62	– 0.93	– 1.22	– 0.39
Facilitate passenger	– 0.71	– 0.91	– 0.73	– 0.83	– 0.76	– 0.82	– 0.81	– 0.78
Marketing	– 0.08	– 0.18	– 0.14	– 0.19	– 0.13	– 0.20	– 0.18	– 0.14
Other	0.05	– 0.04[a]	– 0.07	– 0.11	– 0.03	– 0.09	– 0.08	– 0.03

(*Continued*)

Table 2. Continued.

	2001	2006	2011	Meta model (1)	Meta model (2)	Meta model (3)	Meta model (4)	Meta model (5)
Female (dummy)								
Work/school	– 0.17	– 0.17	– 0.20	– 0.17	– 0.18	– 0.17	– 0.17	– 0.19
Day care	– 2.08	– 2.73	– 0.83	– 1.78	– 1.36	– 1.81	– 1.77	– 1.60
Facilitate passenger	0.14	0.09	– 0.12	0.11	0.01[a]	0.10	0.10	– 0.002[a]
Marketing	0.68	0.66	0.32	0.59	0.51	0.58	0.58	0.49
Other	0.42	0.51	0.20	0.43	0.35	0.43	0.43	0.32
Satiation parameter of specific activities								
Constant	0.62	0.49	0.71	0.58	0.58	0.72	0.58	0.41
Travel time (hours)								
Day care	0.82	0.95	0.47	0.44	0.41	1.22	0.36	1.24
Facilitate passenger	0.60	0.61	0.65	0.61	0.62	1.55	0.61	1.63
Marketing	2.19	1.85	1.81	1.95	1.97	1.64	1.96	1.77
Other	4.54	4.62	4.65	4.61	4.62	3.54	4.62	3.57
Satiation parameter of composite activity								
HH size	– 0.13	– 0.15	– 0.15	– 0.14	– 0.13	– 0.37	– 0.14	– 0.10
No. of vehicles/HH	– 0.17	– 0.13	– 0.11	– 0.14	– 0.13	– 0.39	– 0.14	– 0.10
Apartment *(dummy)*	– 0.11	– 0.11	– 0.11	– 0.11	– 0.11	– 0.04	– 0.11	– 0.07
General office *(dummy)*	– 0.09	0.03	– 0.23	– 0.09	– 0.11	0.10	– 0.09	– 0.08
Professional /management/technical *(dummy)*	– 0.04	– 0.03	– 0.25	– 0.11	– 0.13	– 0.14	– 0.11	– 0.10
Sales/service *(dummy)*	– 0.13	0.04	– 0.19	– 0.09	– 0.10	– 0.14	– 0.10	– 0.07
Driver license *(dummy)*	– 0.38	– 0.47	– 0.51	– 0.43	– 0.43	– 0.11	– 0.44	– 0.29
Temporal factors								
Baseline utility								
Work/school	–	–	–	–	– 0.02	–	–	– 0.21
Day care	–	–	–	–	– 1.67	–	–	– 2.83
Facilitate passenger	–	–	–	–	– 0.35	–	–	– 1.61
Marketing	–	–	–	–	– 0.31	–	–	– 1.59
Other	–	–	–	–	– 0.24	–	–	– 1.53
Satiation parameter of specific activities								
Day care	–	–	–	–	–	– 0.09	–	– 0.11
Facilitate passenger	–	–	–	–	–	– 0.11	–	– 0.13
Marketing	–	–	–	–	–	– 0.09	–	0.23
Other	–	–	–	–	–	– 0.43	–	0.41
Satiation parameter of composite activity								
Constant	–	–	–	–	–	–	0.01	– 0.22

Note: HH, household.
[a]Non-significant parameters.

Individual's age had almost the same effect on all activity types except for the 11–18 age category. It seems that individuals from the 11–18 age categories had a tendency to spend more time in out-of-home activities. This trend is the same among non-workers, workers, and all-data models. On the other hand, being a full-time worker appears to increase time expenditure on work and school activity type differing from part-time workers and workers from home. This

Table 3. Year-specific and Meta model parameters for non-workers' models.

	2001	2006	2011	Meta model (1)	Meta model (2)	Meta model (3)	Meta model (4)	Meta model (5)
Adjusted Rho-Squared	0.273	0.278	0.255	0.269	0.383	0.275	0.270	0.398
Baseline utility								
Constant	– 9.39	– 9.40	– 9.33	– 9.37	– 7.51	– 9.45	– 9.45	– 6.52
Age (dummy)								
11–18	0.26[a]	0.33[a]	0.29[a]	0.24[a]	0.01[a]	0.17[a]	0.26	– 0.23
18–25	– 0.37	– 0.32	– 0.22	– 0.30	– 0.38	– 0.32	– 0.26	– 0.20
25–35	– 0.45	– 0.46	– 0.45	– 0.44	– 0.44	– 0.47	– 0.37	– 0.22
35–45	– 0.38	– 0.41	– 0.39	– 0.38	– 0.39	– 0.40	– 0.31	– 0.16
45–55	– 0.29	– 0.24	– 0.25	– 0.24	– 0.30	– 0.27	– 0.21	– 0.14
55–65	– 0.10	– 0.11	– 0.08	– 0.10	– 0.13	– 0.12	– 0.08	– 0.06
Female (dummy)								
Day care	– 4.78	– 5.03	– 4.69	– 4.83	– 6.04	– 4.83	– 4.86	– 6.06
Facilitate passenger	1.33	1.03	0.54	0.97	– 0.41	0.99	0.96	– 0.43
Marketing	4.37	4.54	4.35	4.42	1.61	4.47	4.41	1.64
Other	5.24	5.34	5.18	5.25	1.96	5.18	5.25	2.01
Transit pass (dummy)								
Day care	– 5.45	– 5.52	– 5.41	– 5.46	– 5.51	– 5.48	– 5.48	– 5.69
Facilitate passenger	0.48	– 0.32	– 0.07	0.02[a]	– 0.75	– 0.05[a]	0.05[a]	– 1.03
Marketing	2.30	2.28	2.38	2.34	0.81	2.36	2.35	0.73
Other	3.22	3.10	3.11	3.14	1.45	3.07	3.11	1.40
Satiation parameter of specific activities								
Constant	1.20	1.07	1.09	1.12	1.06	1.11	1.14	0.87
Travel time (hours)								
Day care	0.23[a]	0.21[a]	0.16[a]	– 0.85	– 0.80	– 0.73	– 0.84	– 0.38
Facilitate passenger	– 0.58	– 0.73	– 0.82	– 0.64	– 0.51	1.02	– 0.77	1.01
Marketing	0.48	0.55	0.16	0.45	0.50	1.44	0.45	1.84
Satiation parameter of composite activity								
HH size	– 0.09	– 0.11	– 0.10	– 0.10	– 0.11	– 0.10	– 0.09	– 0.07
No. of vehicles/HH	– 0.15	– 0.13	– 0.14	– 0.14	– 0.15	– 0.15	– 0.13	– 0.05
Apartment *(dummy)*	– 0.09	– 0.11	– 0.10	– 0.10	– 0.10	– 0.11	– 0.09	– 0.12
Driver license *(dummy)*	– 0.24	– 0.21	– 0.23	– 0.22	– 0.23	– 0.23	– 0.21	– 0.41
Temporal factors								
Baseline utility								
Day care	–	–	–	–	– 3.75	–	–	– 6.05
Facilitate passenger	–	–	–	–	– 0.57	–	–	– 2.98
Marketing	–	–	–	–	0.74	–	–	– 1.64
Other	–	–	–	–	1.06	–	–	– 1.50
Satiation parameter of specific activities								
Day care	–	–	–	–	–	– 0.34	–	0.13
Facilitate passenger	–	–	–	–	–	– 0.53	–	– 0.08
Marketing	–	–	–	–	–	– 0.28	–	0.09
Other	–	–	–	–	–	0.31	–	0.84
Satiation parameter of composite activity								
Constant	–	–	–	–	–	–	– 0.03	– 0.04

Note: HH, household.
[a]Non-significant parameters

effect is similar between the workers and all-data models. Also, being a full-time student appears to increase the time expenditure on work and school activity type more than part-time students.

5.1.2. *Satiation parameters of specific activities*

The satiation parameter of specific activities is the translating parameter that reflects the satiation effect in time expenditure to the specific out-of-home activities with respect to the composite activity. It ensures the possibility of a corner solution of time expenditure. This parameter is expressed as an exponential function of a number of activity-specific variables. The higher value of satiation parameters of specific activities indicates a higher willingness to spend more time on the specific activity. The constant term of the satiation parameters of specific activities captures the unexplained behaviour in the satiation effect. In this model specification, it is not possible to identify the satiation parameters of specific activities for the work and school activity type and it is assumed to be 1. We use a generic constant for other activity types and it is highly significant for the nine models. The workers and all-data models had nearly the same value for the generic parameters with a little decrease towards the year 2011's models. The non-workers' models had higher constants than other models, which meant that non-workers had tendency to spend more time in out-of-home activities. This is intuitive since non-workers have more time than workers to do household-related activities like grocery, day care and facilitate passenger.

For the travel time variable, it had positive sign for the nine models except for the facilitate passenger activity type in the non-workers' models, and also for all models it had highly significant parameter values. It is also difficult to get significant parameters for the other activity in the non-workers' models. We, therefore, decided against using it. In most of the cases, this variable had a positive effect on the parameter. It indicates that a higher value of travel time decreases the satiation in spending time on specific out-of-home activities which is logical, because an individual will be willing to spend more time in a specific activity if he/she travelled long time to participate in this activity. The parameter values are higher for the marketing and the other activity types than day-car and facilitate passenger activity types.

5.1.3. *Satiation parameter for composite activity*

The satiation parameter for composite activity represents the satiation effects in time expenditure by reducing the marginal utility with increasing consumption of the composite activity, which in this case is the in-home activity. It is established that the higher the value of the satiation parameter for composite activity, the lower the satiation effects are. Different socio-economic variables such as the household size; household auto ownership; living in an apartment; occupation; and having a driver's licence are tested within the specification. All variables are found to be significant in the nine models. For the household size, the increase in the household size increases the satiation effects and hence decreases the time spent in in-home activities. This may be explained by having a big family means the increase in out-of-home activities like marketing, day care, facilitate passengers, and leisure activities. In the non-workers' and workers' models, there is almost no variation among the three years under study. Also, the increase in the household auto ownership decreases the time expenditure for in-home activities which is logical since the increase in vehicles in the household will encourage spending more time in out-of-home activities. The years 2001, 2006, and 2011 non-workers' models had almost the same parameter value. The workers' and all-data models for the years 2001, 2006 and 2011 had a variation in the parameter value among the three years studied. For 2011, this factor seems to have less effect than 2001 and 2006. Regarding having a driver's licence, it increases the satiation effects in relation to in-home activities, which is rational, since having a driver's licence will encourage participating in out-of-home activities. Living in an apartment decreases the willingness to participate in in-home activities compared to that of living in a house. This finding is the same among the non-workers', workers', and all-data models for the three years. In terms of the occupation groups studied, there is no variation between them, but there is an increase in the variable effect for 2011.

5.2. *Temporal transferability of activity generation models and the Meta model*

The first step in developing a Meta model of activity generation processes is to compare the year-specific model parameters graphically to identify the parameters causing a higher deviation from one model to the another (Swait and Bernardino 2000; Habib, Swait, and Salem 2012). Figures 2–4 present the comparisons of the model parameters. In each plot, the straight red line represents the line on which all dots should align if both comparing models had exactly the same parameter values. It is found that the parameters for the year 2001 all-data model are almost closer to the year 2006 parameters, and the year 2011 parameters show a relatively high deviation

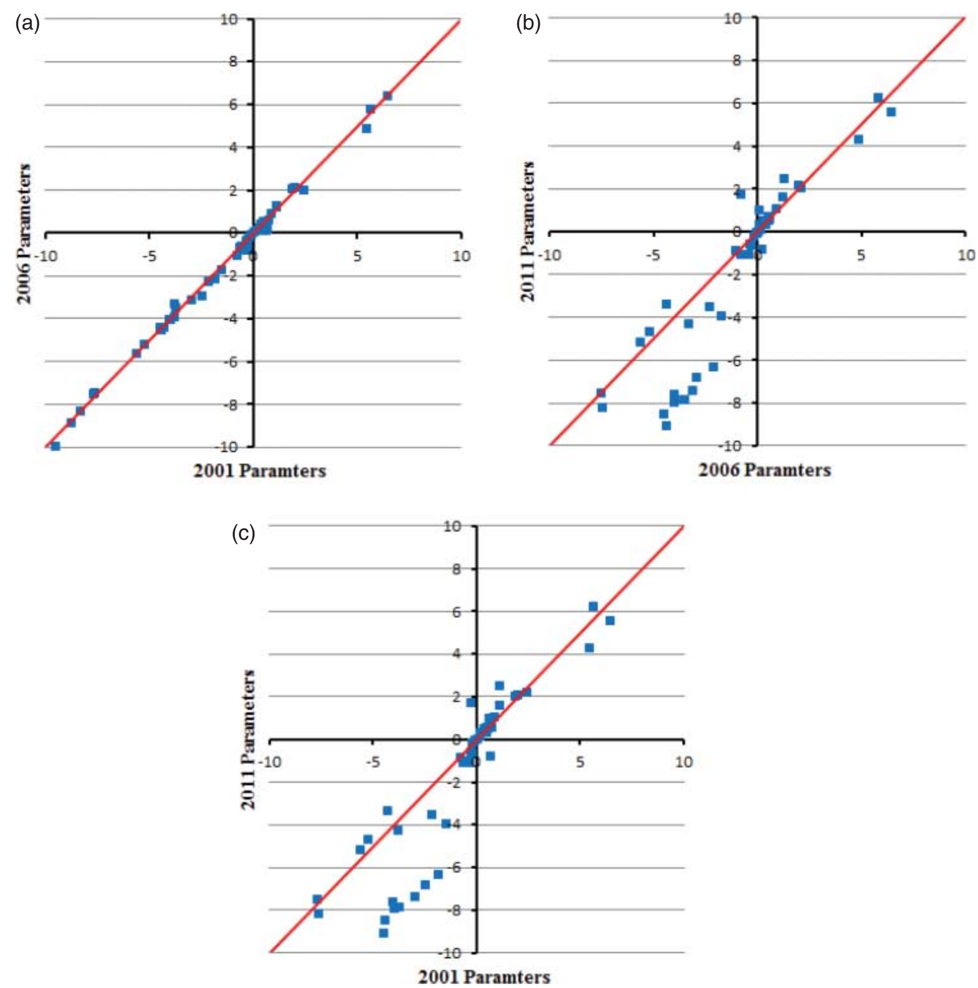

Figure 2. Comparison of year-specific model parameters for workers and non-workers combined: (a) 2001 vs. 2006 model parameters, (b) 2006 vs. 2011 model parameters, and 2001 vs. 2011 model parameters.

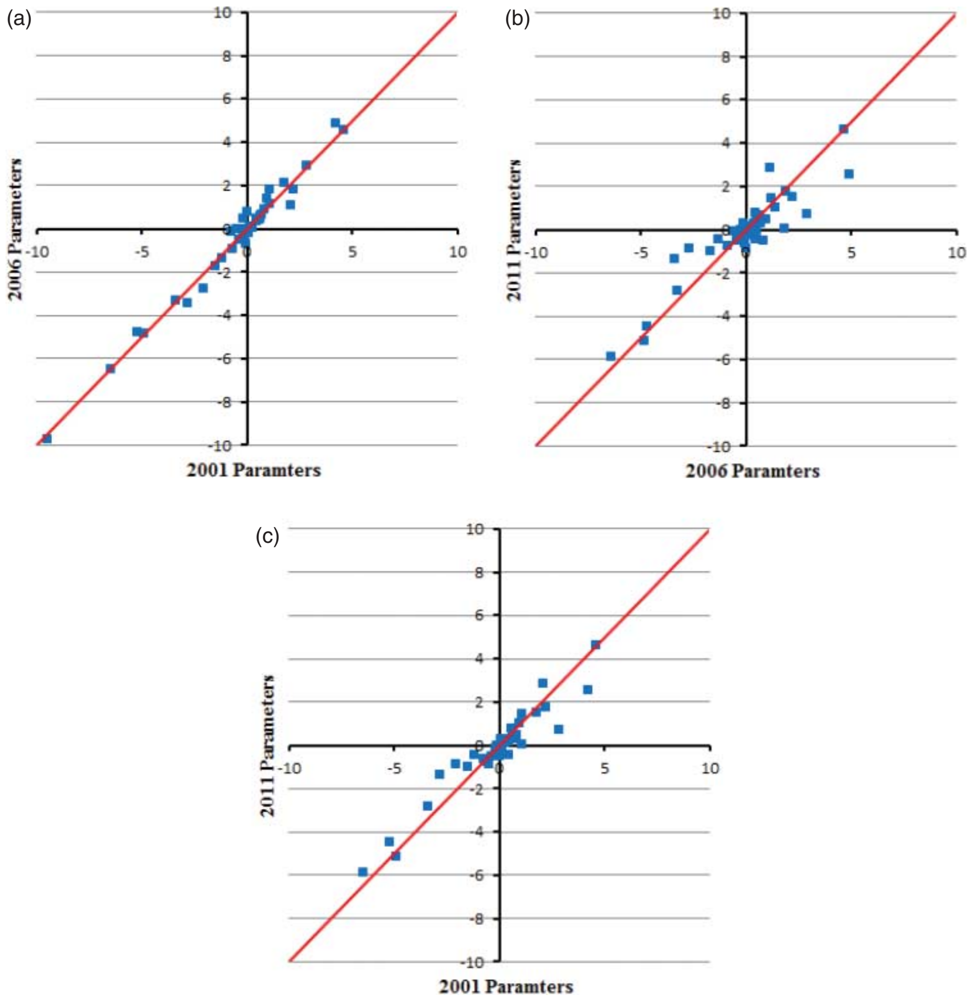

Figure 3. Comparison of year-specific model parameters for workers: (a) 2001 vs. 2006 model parameters, 2006 vs. 2011 model parameters, and 2001 vs. 2011 model parameters.

compared to the year 2001 and the year 2006 model parameters. This trend is almost the same for the workers' models. Interestingly, when the parameters of the three-year-specific non-workers' models are compared, it is found that they show an almost perfect alignment with each other, which meant that travel behaviour for non-workers did not change a great deal through years. We note also that the parameters that cause deviation had a high magnitude. These parameters will cause errors when used to forecast future demand. Thus, one way to enhance temporal transferability is to pool the data sets for the three years together and to estimate new model parameters and to use these parameters in forecasting. Another method is to consider year-specific constants in each part of the utility function: the base line utility and the satiation parameters (Habib, Swait, and Salem 2012). The year 2001 is considered as the base year and we include an additional component to each constant in each part to identify the corresponding year of each individual 'temporal factors' (Habib, Swait, and Salem 2012). A polynomial and logarithmic functions are tested as temporal factors. The polynomial function did not converge. Thus, for the pooled data

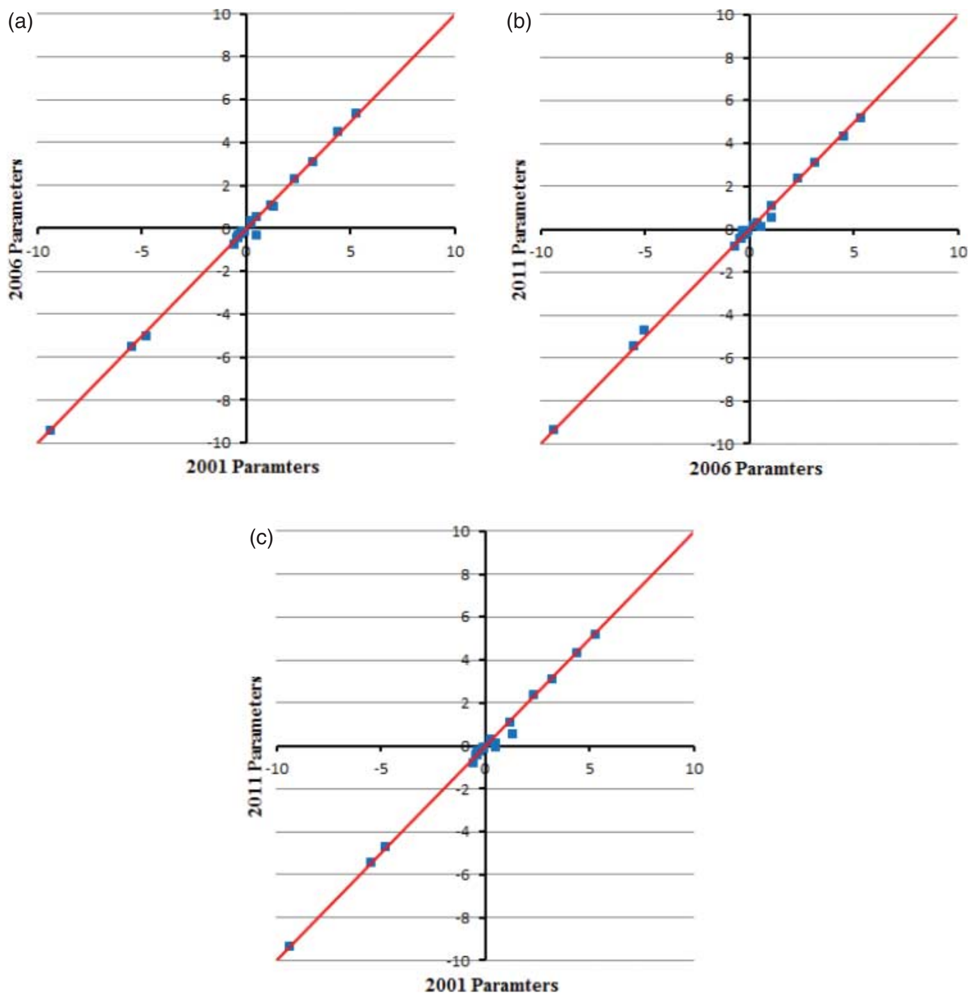

Figure 4. Comparison of year-specific model parameters for non-workers: (a) 2001 vs. 2006 model parameters, 2006 vs. 2011 model parameters, and 2001 vs. 2011 model parameters.

over the years 2001, 2006, and 2011, we propose to use the following formulation for the baseline utility component of the MDCEV model:

- baseline utility component:

$$V_j = (\mathrm{ASC} + \beta X)_j + \theta_{\mathrm{ASC}} \ln(t), \tag{5}$$

- satiation parameter of specific activities:

$$\eta_j = \exp((\mathrm{ASC} + \beta X)_j + \theta_{\mathrm{ASC}} \ln(t)), \tag{6}$$

- satiation parameter of composite activity:

$$\zeta = 1 - \exp(-(\mathrm{ASC} + \beta X) + \theta_{\mathrm{ASC}} \ln(t)), \tag{7}$$

where $t = 1$ if year $= 2001$, $t = 5$ if year $= 2006$, and $t = 10$ if year $= 2011$; θ are parameters.

So, five different Meta models are estimated for each year:

(1) Meta model (1): naively pooling data sets,
(2) Meta model (4): adding temporal factors to baseline utility(V_j) only,
(3) Meta model (2): adding temporal factors to the satiation parameter of specific activities (η_j) only,
(4) Meta model (3): adding temporal factors to the satiation parameter of composite activities (ζ) only, and
(5) Meta model (5): adding temporal factors to the three components of the utility equation.

To test the transferability of the models, we calculate two disaggregate transferability measures: the transferability index (TI) and likelihood ratio (Transfer Rho-Squared) (Habib, Swait, and Salem 2012; Sikder and Pinjari 2013). The transfer index is calculated as follows:

$$\mathrm{TI} = \frac{\mathrm{LL}_j(\theta_i) - \mathrm{LL}_j(\text{Null Model})}{\mathrm{LL}_j(\theta_j) - \mathrm{LL}_j(\text{Null Model})}, \tag{8}$$

where $\mathrm{LL}_j(\theta_j)$ indicates the log-likelihood value for the context year j of the model developed by using jth year's data; $\mathrm{LL}_j(\theta_i)$ indicates the log-likelihood value for the context year j of the model developed by using ith year's data; and LL_j (Null Model) denotes the log-likelihood of the null model for the application context j. TI is a relative measure of strength of the transferred model over a null model in comparison to the originally estimated model. Also, we use the TI measure to assess the effect of the proposed models' improvement on the temporal transferability. If the TI value approaches one, this means that the transferred model is almost performing like the original model.

The second test is called Transfer Rho-Squared and is defined by calculating the goodness of fit of the transferred model against the null model of the target year:

$$\text{Transfer Rho} - \text{Squared} = 1 - \frac{\mathrm{LL}_j(\theta_i)}{\mathrm{LL}_j(\text{Null Model})}. \tag{9}$$

A higher value indicates better goodness of fit against the null model. If the Transfer Rho-Squared values are close to the locally estimated models, this means that the transferred models are very transferable. We estimate two sets of Meta models, the first one using 2001 and 2006 data sets only and transfer these models to 2011 data. In the second one, 2001, 2006, and 201 data sets are used. Table 4 shows TI and Transferred Rho-Squared for Meta models and the year-specific models, when transferred to individual models. Overall, all of the TI values are higher than 0.80 except for only two models, which reflects a very good indication; also we had some values that are above 1. This might indicate that the Meta models outperform the original model or an overfitting problem. In the case of Transfer Rho-Squared measures, the values are very close to the year-specific models. Estimated model parameters of the Meta models are presented in Tables 1–3.

Regarding the Meta models parameters, we found that most of the socio-economic variables had smaller parameter values in the Meta models than in the individual year-specific models. It seems that accommodation for the temporal factors reduces the effects of the socio-economic variables that seem to cause variations among the year-specific models.

In terms of temporal effects, the logarithmic function for temporal progression reveals different effects on the model constants. Generally, the logarithmic function captures the temporal evolution of the constants with a negative effect for non-workers, workers, and all-data models except for the baseline utility parameter for marketing and other activity types for non-workers Meta model (2); the satiation parameter of specific activities constant for other activity type in

Table 4. Transferability index and Transferred Rho-Squared for year-specific and Meta models when transferred to individual years.

From	All	Workers	Non-workers	All	Workers	Non-workers	All	Workers	Non-workers
Transferability index									
2001	1	1	1	0.993	0.949	0.995	0.953	0.961	0.988
2006	0.991	0.992	0.995	1	1	1	0.949	0.955	0.996
2011	0.940	0.961	0.991	0.978	0.918	0.959	1	1	1
Meta model (1)[a]	0.998	0.998	0.999	0.998	0.998	0.999	0.953	0.960	0.994
Meta model (2)[a]	0.998	0.998	0.998	0.998	0.999	1.001	0.949	0.955	0.997
Meta model (3)[a]	0.998	0.998	0.996	1.000	1.000	1.029	0.954	0.961	1.021
Meta model (4)[a]	0.989	0.997	0.895	1.081	1.013	1.639	0.986	0.960	1.708
Meta model (5)[a]	0.989	0.995	0.881	1.083	1.017	1.868	0.987	0.954	− 11.567
Meta model (1)[b]	0.995	0.995	0.997	0.993	0.993	0.999	0.974	0.981	0.997
Meta model (2)[b]	0.995	0.996	0.994	0.993	0.992	1.003	0.975	0.981	1.002
Meta model (3)[b]	0.988	0.995	0.993	0.960	0.995	1.029	0.903	0.983	1.031
Meta model (4)[b]	0.975	0.995	0.802	1.077	1.003	1.693	1.053	0.989	1.824
Meta model (5)[b]	0.972	0.989	0.797	1.080	1.008	1.756	1.058	1.010	1.935
Transferred Rho-Squared									
2001	0.560	0.634	0.273	0.553	0.593	0.277	0.541	0.621	0.252
2006	0.555	0.629	0.272	0.557	0.625	0.278	0.539	0.618	0.254
2011	0.527	0.609	0.271	0.555	0.593	0.277	0.568	0.646	0.255
Meta model (1)[a]	0.559	0.633	0.273	0.555	0.624	0.278	0.541	0.620	0.253
Meta model (2)[a]	0.559	0.633	0.273	0.556	0.624	0.278	0.538	0.617	0.254
Meta model (3)[a]	0.559	0.633	0.272	0.556	0.625	0.286	0.542	0.621	0.260
Meta model (4)[a]	0.554	0.632	0.245	0.602	0.633	0.456	0.559	0.620	0.436
Meta model (5)[a]	0.554	0.631	0.241	0.603	0.636	0.519	0.560	0.617	− 2.949
Meta model (1)[b]	0.557	0.631	0.273	0.553	0.621	0.278	0.553	0.634	0.254
Meta model (2)[b]	0.557	0.632	0.272	0.553	0.620	0.279	0.553	0.634	0.255
Meta model (3)[b]	0.553	0.631	0.272	0.534	0.622	0.286	0.513	0.635	0.263
Meta model (4)[b]	0.546	0.631	0.219	0.600	0.627	0.471	0.597	0.639	0.465
Meta model (5)[b]	0.544	0.627	0.218	0.601	0.630	0.488	0.600	0.653	0.493

[a]Meta Models using 2001 and 2006 data sets.
[b]Meta Models using 2001, 2006, and 2011 data sets.

the non-workers Meta model (3); the satiation parameter of specific activities constant for marketing and other activity type in the non-workers and workers Meta model (5); the satiation parameter of the composite activity in workers Meta model (4); the baseline utility parameter for work/school, marketing, and other activity types for all-data Meta model (2); the satiation parameter of the composite activity in all-data Meta model (3); the satiation parameter of specific activities constant for other activity type in the all-data Meta models (4) and (5).

At the end, after comparing the TI, Transfer Rho-Squared, and temporal factors, we can conclude that adding logarithmic temporal factors to the satiation parameter of specific activities outperforms year-specific models and other Meta models in capturing temporal transferability of activity generation models.

6. Conclusion and recommendations for future research

This study uses three cross-sectional data sets from the TTS to investigate the transferability of activity generation models through the years. An MDCEV model is used to analyse the variations in the daily time expenditure behaviour among all of the possible activities. The MDCEV adopts a Kuhn–Tucker-based demand system model that assumes that every individual maximises his or her total utility in allocating time (resource) to all specific activity types under time budget constraints. The time budget here is defined as a typical day. The activities are classified into two main categories. The first category is in-home activities and the second category is out-of-home activities. Furthermore, out-of-home activities are then classified into five general activity types. All of these possible activity types are modelled jointly by using the MDCEV model, which is developed to capture the complex trade-offs in time expenditure on the different activity types. Three models are developed for each year: one for non-workers only; one for workers only; and one for the all-data set together. Goodness of fit of the empirical models indicates good performances against the constant-only model. The individual year-specific models are used to examine the temporal changes and to know which variables cause the high deviation that resulted. Then, Meta models that captured the evolution of the constants over time are developed. We consider the year 2001 as the base year and add temporal factors in the form of a logarithmic function of time to capture the evolution of the activity generation process. We add these temporal factors to each part of the utility function: baseline utility; the satiation parameter of specific activities; and the satiation parameter of composite activity. The Meta models outperform year-specific models in terms of model transferability. We note also that accommodation of temporal factors reduces the effects of socio-economic variables and the constants that seem to give rise to variations among year-specific models. This finding encourages using Meta models that accommodate temporal factors in forecasting to reduce the problems of overestimating or underestimating demand as we know that activity generation is the first step in any activity-based travel demand models.

The paper contributes to activity-based travel demand literature in two ways. First of all it proves that activity generation process models show good temporal transferability. Thus, it bolstered the argument of the move towards the activity-based approach of travel demand modelling as opposed to trip or tour-based travel demand modelling. Second, the paper presents a unique approach to combining multiple repeated cross-sectional data sets to develop a Meta model of activity generation processes. Thereby it improves temporal transferability to an even greater degree. Methodologically, the paper presents an efficient way of combining multiple cross-sectional data sets to capture the evolution of behavioural parameters of activity generation models. The importance of this study originates in its emphasis on temporal transferability and its effect on the legitimacy of the activity generation models and the consequent decisions of transportation policies and planning. The next step for this research is to test the temporal transferability of activity scheduling process models and to test more functions as temporal factors.

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