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Publication Date:
2008

Permanent Link:
https://doi.org/10.3929/ethz-a-005704978 →

DYNAMIC MODEL OF ACTIVITY-TYPE CHOICE AND SCHEDULING

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Abstract

This paper presents a model for the choice of activity-type and timing, incorporating the dynamics of scheduling estimated on a six-week travel diary. The main focus of the study is the inclusion of past history of activity involvement and its influence on current activity choice. The econometric formulation adopted, explicitly accounts both for correlation across alternatives and for state dependency. The results indicate that behavioral variables are superior to socio-economic variables and that consideration of the correlation pattern over alternatives clearly improves the fit of the model.
This is a first but significant contribution to changing the current static demand models into dynamic activity based ones. The availability of other multi-week travel surveys and the progress made recently on advanced econometric techniques should encourage the transferability of this study to different regions or model scale.

1. Introduction

Transportation research has seen, in recent years, an increased analysis of the complexity of travel decisions. The need for a more behaviorally sound framework has led to a new generation of transport model systems called activity-based models (Bowman and Ben-Akiva, 2000; Nagel and Rickert, 2001; Bhat and al., 2004; Arentze and Timmermans, 2004; Pendyala and al., 2004; Salvini and Miller, 2005). The general concept is that household and individual travel patterns are generated from the desire to pursue activities in time and space. However, their desires are limited by personal/physical constraints and by the institutional, economic and cultural context. Moreover activity based models are not limited to one single purpose trip or tour, but often account for all trips/tours on a daily basis or on longer periods.
An activity-based model consists of a multi-facet choice process; amongst its various components activity participation has certainly a core position but has seen relatively modest attention. (Arentze and Timmermans, 2000). Activity type preferences are, explicitly, modeled by Hamed and Mannering, 1993 as part of a modeling system estimated for post-work activity patterns. The assumption they made is that a traveler is likely to choose an activity providing the maximum utility. The choice set consists of four alternatives: shopping, free-time, personal business and chain of activities; a number of socio-demographics, working schedule variables and previous activity indicator are estimated using a multinomial logit. Bhat has published (i.e. 2000, 2005) several papers on activity participation both for weekdays and weekends. These studies also develop advanced econometric techniques with flexible structures to accommodate complex error structures among different alternatives. Other approaches using Poisson related methods (Ma and Goulias, 1999), multivariate negative binomial (Kockelman, 1999) and structural equations (Lu and Pas, 1999; Golob, 2000) have been used to predict activity frequencies; all the studies cited here use multi-day

travel surveys, although the number of observation from the same individual is often limited to two days.

It is often argued that past history of activity involvement may have potential influence on current activity choice. However, because the data available to transport modelers are often limited to a single day trip diary, the activity type choice models existing in the literature are estimated with the assumption of independence from past involvements (Hamed and Mannering, 1993). Furthermore, in the 80s and 90s several researchers have pointed out that there is a significant day-to-day variability in travel behavior. A 1988 special issue of *Transportation* provides excellent insight into the analysis of variability in multi-day travel activity behavior. Jones and Clark focus on the policy implication of variability analysis and encourage the collection of more multi-day travel surveys. Eric Pas distinguishes long-term patterns from daily behavior and finds that the latter is independent of individual characteristics, when accounting for both. Hanson and Huff, by using a specific measure of repetition and variability, conclude that a one-week record of travel does not capture longer-term travel behavior[1]. In a more recent work, Pas and Sundar (1995) assess that this variability should have important implications for data collection, model estimation and model interpretation. Data collected over a period of time are still rare, but two recent studies have made available to researchers two continuous surveys on a six-week period (Axhausen *and al.*, 2002; Axhausen *et al.*, 2007) (See Schlich, 2004 for an analysis of the similarity of the activity patterns over time). Longitudinal observations of individual activity behavior allow the estimation of dynamic models. There are very few example of dynamic, disaggregate choice models in the existing activity-based literature. Hirsh *et al.* (1986) estimate a parametric model of dynamic decision-making process for weekly shopping activity behavior. The individual is assumed to proceed from period to period and the observed weekly activity pattern is the outcome of successive decisions. Action plans are then modified on the basis of actual behavior and of the additional information acquired in previous periods. Mahmassani and Chang (1986) investigate the dynamics of departure time of urban commuters in a series of simulation experiments; user departure time decisions are modeled by means of heuristics, which also incorporate the experience cumulated by repeated use of the same facility. Very recently, Khandker and Miller (2007) have presented an econometric model for daily activity program; the estimations are done using CHASE, a one-week travel survey collected in Toronto. The model accommodates dynamics in activity travel behavior; in particular, within-day dynamics in time-use is represented by the number of working hours, while day-to-day dynamics is explained by the number of activities executed the previous day.
Dynamic models have been applied more extensively to explain car ownership behavior; Goodwin and Mogridge (1981) note that "the resistance to change" is one of the aspect that model based on cross sectional data fail to account for. More technical questions arising in dynamic models, like state dependency versus heterogeneity, have also been addressed in household car ownership models by Kitamura (1988) and by Kitamura and Bunch (1990).

The present paper intends to introduce dynamics in travel behavior by explicitly accounting past activity involvement when modeling activity choices and their scheduling. Exogenous variables describing present and past activity involvement are calculated on short-term period (day), medium-term period (week) and long-term period (multi weeks). The survey, from

[1] The longer-term is referred to a five-week period over which the travel survey used was conducted (Uppsala household travel survey, 1971)

which data have been derived, is Mobidrive, a six-week travel survey conducted in Germany; all activities and the related tours are accounted in the framework applied.
The correlation across alternatives and the state dependency across choices made on the same period of time (day or week) or by the same person, are modeled via a mixed logit structure with error components and repeated choices.
The models presented are then validated and applied to reproduce choices on the seven days of the week and during the six weeks.

2. The model formulation

We develop this dynamic activity type choice model based on discrete choice analysis theory. The focus of attention is on mixed logit models (Train, 2003); the formulation adopted here is able to deal with correlation over alternatives in the stochastic portion of utility, and to allow efficient estimation in presence of repeated choices by the same respondent. We assume that each person faces a choice among the alternatives in set J in each of T time periods. The choice set and the number of choice situations can vary over people. The utility that person *n* obtains from alternative *j* in choice situation *t* is:

$$U_{njt} = \beta_n x_{njt} + \mu_n z_{njt} + \varepsilon_{njt} \qquad (1)$$

where:

x_{njt} is a vector of observed variables relating to alternative *j*,

z_{njt} is a vector of error components,

β_n is a vector of unobserved fixed coefficients,

μ_n is a term of random terms with zero mean,

ε_{njt} is an unobserved random term i.i.d. extreme value distributed.

The terms in z_{njt} along with ε_{njt}, define the stochastic portion of the utility. The correlation pattern over alternatives depends on the specification of the vector z_{njt}. Various correlation structures can be, in fact, obtained by an appropriate choice of variables to enter as error components. In this model, we specify a dummy variable for each group *k* that equals 1 for each alternative in the group and zero for alternatives outside the group. Error components are assumed to be independently normally distributed $N(0,\sigma_k)$, where the variance σ_k measures the magnitude of the correlation.

Considering a sequence of specific activity patterns, one for each time period $\dot{\mathrm{j}} = \{j_1, ..., j_T\}$, the probability that the person makes this sequence of choices is the product of logit formulas (Revelt and Train, 1998):

$$L_{nj}(\beta,\mu) = \prod_{t=1}^{T} \left[\frac{e^{\beta_n x_{nj_t t} + \mu_n z_{nj_t t}}}{\sum_j e^{\beta_n x_{nj_t t} + \mu_n z_{nj_t t}}} \right] \qquad (2)$$

where j_t is the alternative choice made by the individual n on time period t.
The unconditional probability is the integral of this product over all values of μ:

$$P_{nj} = \int L_{nj}(\mu) f(\mu) d\mu \qquad (3)$$

The integrand is a product of logit formulas, one for each time period or group of choice situations.

We consider here four time periods/activity episodes: (1) the single activity episode, (2) the day, (3) the week, (4) and the entire set of individual activity episodes.

We include in our dynamic model past and future exogenous variables, they are added to the utility for a given activity episode to represent lagged responses and anticipatory behavior. In our specification the coefficients β_n are assumed to be constant over individuals and over choice situations for a given period. This assumption is appropriate if the decision-maker's tastes are stable over the observed time period.

The vector of unknown parameters is then estimated by maximizing the log-likelihood function, i.e. by solving the equation:

$$\max_{\mu} LL(\mu) = \max_{\mu} \sum_{1}^{N} \ln P_{nj_t}(\mu) \tag{4}$$

This involves the computation of $P_{nj_t}(\mu)$ for each individual n, n = 1, ..., N, which is impractical since it requires the evaluation of one multidimensional integral per individual. The value of $P_{nj_t}(\mu)$ is therefore replaced by a Monte-Carlo estimate obtained by sampling over μ, and given by

$$SP_{nj_t}^{R} = \frac{1}{R} \sum_{r=1}^{R} L_{nj_t}(\mu) \tag{5}$$

where R is the number of random draws μ_r, taken from the normal distribution. As a result, μ is now computed as the solution of the simulated log-likelihood problem

$$\max_{\mu} SLL^{R}(\mu) = \max_{\mu} \frac{1}{N} \sum_{n=1}^{N} \ln SP_{nj_t}^{R}(\mu) \tag{6}$$

We will denote by a μ_R^* solution of this last approximation (often called Sample Average Approximation, or SAA), while μ^* denote the solution of the true problem (4).
Our model has been calibrated using the software AMLET, which uses an adaptive stochastic programming algorithm to estimate the objective function (Bastin *et al.*, 2006).

3. The data and the framework

The multi-day database used for the dynamic activity type model is derived from a six-week travel diary held in Karlsruhe (Germany) in 1999, part of the *Mobidrive* survey, which involved 160 households and 360 individuals in the main survey. Further details on data collection techniques and descriptive results on rhythm of daily life can be found in Axhausen, Zimmermann, Schönfelder, Rindsfüser and Haupt, 2002 and PTV AG, Fell, Schönfelder and Axhausen, 2000[2]. The recorded days were structured according to the framework proposed by Bhat and Singh, 2000 and extended by Cirillo and Toint, 2001. We briefly describe the principal elements of the schema adopted here to define the activity chains on a daily basis. The schema is also presented in Figure 1, where activities considered

[2] See also http://www.ivt.ethz.ch/vpl/research/mobidrive for a list of the papers employing the Mobidrive data.

and their possible schedules are schematically represented. We distinguish working days, i.e. days including a commute or school trip, and non-working days. Given the multi-week nature of the survey, the days of one individual can belong to either category. All trips are grouped into tours. A tour is the sequence of trips performed by an individual, starting from a given base (usually home or workplace) until the individual returns to this base. Each tour has a main activity defined by duration, purpose and main mode.
For each daily chain we define: the *main activity* of the day as work/education for working days and the *principal activity* of the day as the longest duration out-of-home activity for non-working days. All daily activity chains are represented in relation with this pivotal activity.
The work tour is divided into outbound and return legs, which are called the *morning* and *evening commute*. All activities that take place before the morning commute will be referred to as *morning activities* and the associated displacements grouped into one or more *morning tours*; they constitute the *morning pattern*. Similarly, all activities taking place after the return from work to home (the evening commute) will be referred to as *evening activities* and the associated displacements grouped into one or more *evening tours*; which together constitute the *evening pattern*. Additionally, all activities taking place outside the work location after the morning, but before the evening commute will be called *midday activities* and the associated displacements, whose origin and destination are at work, are grouped into one or more *midday tours,* in turn aggregated into the *midday pattern*.

We organize the daily pattern of the non-working days in a similar manner. The morning pattern represents the activities and travel undertaken before leaving home to perform the principal activity of the day. The *principal activity pattern* represents the activities and travel performed within the tour comprising the principal activity of the day; the principal activity tour is divided into outbound and return legs. Note that this definition implies that the principal activity pattern always consists of a single tour. The (afternoon and) evening pattern comprises the activities and travel of individuals after their return home from their principal activity. By applying this framework to Mobidrive we obtained 4952 activity episodes, 3212 daily schedules, 773 weekly schedules and 144 individual schedules. Table 1 shows the number of activity episodes for each purpose and the relative scheduling for working and non-working days.

4. Choice set, model structure and variable definition.

The model developed to generate the activity programs is disaggregate and based on individual choices. The alternatives are discrete and are exogenously defined by the analyst. A number of assumptions/hypothesis needed to be made in order to define the choice set. In fact, one of the main difficulties in modeling activity patterns is that analysts usually observe just the chosen pattern and it is difficult to reconstruct the entire set of alternatives available to the individuals. In this study, we consider only out-of home activities. Individuals are supposed to make a two-step choice: first they choose the type of activity to be pursued and then they schedule the chosen activity within a specific time frame. Four activity types are possible: shopping, leisure, personal business and pick up/drop off. In the original data set more activity categories were available (i.e. long term shopping vs. short term shopping); however, in order to reduce the total number of discrete alternatives and to avoid a low number of observations for each category, we grouped them into the above main activities. Moreover, the activity "other-purposes" was excluded given the small number of observations reported for this category. The scheduling is intended to be the decision regarding the specific time frame when the activity is executed; in this model time frames are defined with respect to the main activity of the day. As follows from the framework described in Section 3, the main activity of the day is by definition the work activity for working days and it is the activity with the longest duration for non-working days. For working days the possible times frame are: morning tour, morning commute, evening commute and evening tour; work based tour to home during lunch time are also considered. Similar is the choice set for non-working days; the main difference consists in the possibility to execute secondary activities on the outbound and return leg of the principal tour. The combinations of activity types and of time frames define the alternatives in the choice set. A total number of thirty-eight alternatives are modeled; the relative choice set is reported in Figure 1.

The availability of each alternative for a given individual was then determined on the basis of the activity patterns reported during the entire survey period. In particular, if an activity type was never reported by a respondent during the six-week period, this activity type is considered not available for the individual. Shopping alternatives are available from 8:00am to 6:00pm; they are not available on Sundays except if they have been chosen[3].

We now turn our attention to the variables used in model estimation. Variables types and their categories are listed in Table 2. We estimate (1) socio-economic variables, (2) level of service variables and (3) individual activity involvement variables. Age (by categories), number of young children in the household, number of working hours per week, employment status and sex enter the final specification. Level of service variables are included through the logsum of a mode choice model. This model is a simplified version of an existing mode choice model (Cirillo and Axhausen, 2006), which is estimated on five alternatives (car as driver, car as passenger, transit, walk and bike) and contains a full set of alternative specific constants, travel time and travel cost. To account for the variability in value of travel time savings, four mode choice models were estimated, one for each activity-type considered in our final activity programs. For the non-chosen activity-type alternatives time and cost variables are calculated as the average on all the locations visited by each individual for the same purpose. Each individual is supposed to know the average durations of the possible activities to be performed and the travel times and travel costs to reach the relative locations. Pattern-related variables are defined on three different time horizons: the day, the week and the entire survey period. For non-chosen alternatives the activity durations are drawn from the vector of activity (with the same purpose) durations, reported by the same individual, over the entire survey period. Again this is a strong assumption, but it is reasonable to assume that individuals are aware of the possible durations and of the locations of their activities and that they consider the time to be spent at the destinations when deciding their activity agenda. In discrete-continuous choice model of activity-type and duration time is allocated just if the activity is chosen (Munizaga et al., 2008). The implicit assumption of hazard joint model of activity type choice and duration is that the day is planned coherently in one step (Bhat, 1996). We make here the assumption of independence of the forward looking choices. The variables then are only the result of past choices, which are then assumed to be taken as given by the traveler. Time availability for shopping activities and weekly frequency were specified has in Hirsh and al., 1986. The definition of policy related variables responds to the need of more accurate forecasting in activity-based models. In fact, the model proposed in this paper is sensible to both work duration and time availability before and after working activities. Day-to-day dynamics is explained by the variable that counts the number of days passed since the same activity was performed last. Individual past history is also represented by the number of days spent at home since the beginning of the survey period.

[3] Sunday trading is still the exception in Germany, and it was more so in 1999, when the survey was conducted. Still, a limited number of outlets at train stations, gas stations and bakeries were available.

To conclude this Section, it is important to say that we are observing the extension of daily models into multi-day time horizons (Buliung, 2005); in order move on in that direction it is necessary to use appropriate data but also to understand how activity and scheduling variables should enter our model specifications.

Table 1 Number of activity episodes

	Type	Shop-ping	Leisure	Person al busi-ness	Pick up / drop off	No extra activi ties	Home from Work	All
Working day	Morning tour (MT)	41	14	41	5			101
	Morning Commute (MC)	44	24	65	26			159
	Evening Commute (EC)	207	103	105	40			455
	Evening Tour (ET)	143	376	90	54			663
	Work as the only activity (W)					547		547
	Work-Home-Work (WHW)						159	159
Non working day	Morning Tour (MT)	372	126	163	72			733
	Principal tour outbound leg (PT out-leg)	88	35	90	54			267
	Principal Tour (PT)	404	658	251	64			1377
	Principal tour return leg (PT ret-leg)	73	59	40	14			186
	Evening Tour (ET)	97	93	62	53			305
Total		1469	1488	907	382			4952

Figure 1: Activity-scheduling choice tree

	Activity-type	**Scheduling**
Working day	1. Work only	
	2. Work-Home-Work	
	Shopping	3. Morning tour 4. Morning commute 5. Evening commute 6. Evening tour
	Leisure	7. Morning tour 8. Morning commute 9. Evening commute 10. Evening tour
	Personal Business	11. Morning tour 12. Morning commute 13. Evening commute 14. Evening tour
	Pick up Drop off	15. Morning tour 16. Morning commute 17. Evening commute 18. Evening tour

	Activity-type	**Scheduling**
Non working day	Shopping	19. Morning tour 20. Principal tour outbound leg 21. Principal tour 22. Principal tour return leg 23. Evening tour
	Leisure	24. Morning tour 25. Principal tour outbound leg 26. Principal tour 27. Principal tour return leg 28. Evening tour
	Personal Business	29. Morning tour 30. Principal tour outbound leg 31. Principal tour 32. Principal tour return leg 33. Evening tour
	Pick up Drop off	34. Morning tour 35. Principal tour outbound leg 36. Principal tour 37. Principal tour return leg 38. Evening tour

Table 2 List of independent variables used

Level	Variables	Description / Categories	Type
Day	Activity duration (min)	It is randomly drawn from the vector of activity (with the same purpose) durations, reported by the same individual, over the entire survey period.	continuous
Day	Time budget (min)	It is calculated as 24 hours minus the time spent on previous activities (time at home included) and previous travel.	continuous
Day	Available time before work (min)	It is the time available between the shop opening hour (8:00 am) and the arrival time to work.	continuous
Day	Available time after work (min)	It is the time available after the departure from work and the assumed shop closing time (6:00 pm).	continuous
Week	High week episode	Dummy variable, which is 1 if, for the week considered, the number of activity episodes with a specific purpose is greater than two.	dummy
Six-week	Last time	Number of days since the day when the same activity was undertaken last	discrete
Six-week	Immobile days	Number of days that the individual spent at home since the first day of the reporting period.	discrete
Level of Service	Logsum	Logsum of the mode choice model.	Continuous
Individual	Age	Age 6-18/ Age 26-35/ Age 51-65	dummy
Socio-Economic Variables	Presence of children	Number of Children under 12	dummy
	Professional Status	Number of working hours per week	continuous
		Full time worker	dummy
		Female and employed part-time	dummy

5. Model estimations results

In Table 4 we report the results of the model estimation. Estimated coefficients and relevant statistics are given for five model formulations: logit model, mixed logit model with error components, mixed logit model with error components and correlation across repeated observations from the same day, the same week and the same individual. The final specifications include fifteen socio-economic variables, thirty activity/scheduling related variables, the logsum of the mode choice model and four error components. Error components are specific to activity types, which induces correlations across activities of the same type performed at different time frames. Given the high number of alternatives specified the model is certainly identified (Walker, 2001). We have tried to include a number of different socio-economic variables and their combinations, but they turned out to be not significant and were excluded from the final specification. Behavioral variables are estimated as specific to activity types (where it was possible). Activity durations including work duration, estimated as specific to tour types, are found to be negative and significant. Negative value for shopping activity durations have been also found by Hirsh and al. (1986) in their dynamic model of weekly activity pattern. The time budget variables are highly significant, highlighting that more mandatory activities, such as private business and pick up/drop off have a different status from the others. The same is true for period since the last activity performance, which captures in a rough way the rhythms reported in detail by Schönfelder, 2006. The time available for shopping before work is found to be negative due to the low number of shopping activity episodes in the morning tours. This means that temporal constraints remain significant for workers. Time available for shopping after work is instead positively evaluated by our sample. The high week episode variable is found to be highly significant as already outlined in a previous dynamic model proposed by Hirsch and al. (1986). Moreover, the variable specific for pick up/drop off and shopping have the highest values given their fixed commitment nature. The number of days passed since an activity type was done last time is also affecting positively the probability of doing again the same activity. We also find that the same variable specified for leisure and pick up/drop off purposes affect negatively the probability of working all day. Immobile days increase the likelihood of out-of-home activities during the following days. The logsum of the mode choice model is positive and less than one, which is consistent with random utility maximization theory (Ben-Akiva and Lerman, 1985); this variable is significant in all the model specifications shown in that paper. A number of socio-economics attributes are also part of the explanatory set of variables. Young people have a low probability to go home for lunch; individuals between 36 and 50 year old are less likely to go out for leisure, while adults over 50 are more likely to be engaged in picking up/dropping off other members of the family. Turning to individuals' working status, it is interesting to see that full time workers are not frequently engaged in activities other than work; the increasing number of working hours per week also affects the probability of work only alternative. By contrast, being female and working part-time highly affect the complexity of daily patterns.

Looking at the final log-likelihood values and adjusted rho-squared (on the basis of the degrees of freedom) we observe that the inclusion of error components definitely improves the fit of the model. However, when accounting for correlation across observations (from the same day, the same week and the same respondent) this improvement is less remarkable; the best model is the one obtained by including error components and without accounting panel effects. This result differs from what recently found by Cherchi and Cirillo (2007), who used the same panel data to estimate a mode choice model with different temporal correlation patterns. Their results show that for mode choice model the correlation due to panel effect was very significant and that the best model was the one accounting for correlation across the observations from the same individual. In Table 3 we also report the rho-squared adjusted obtained by calibrating a series of models of increasing richness. The basic model includes just socio-economic variables; the followings gradually include daily behavioral variables, weekly behavioral variables and long-term variables. The low fit obtained by including just socio-economic variables clearly shows the superiority of behavioral variables in the context of activity–type choice models and scheduling.

In one case (mixed logit model with error components specified on socio-economic and day variables) the convergence was not achieved after 1500 iterations, which is the maximum number of iterations set for our runs. The main reason of that failure is the high value assumed by the error component related to the leisure activity.

Table 3 Model fit (Final Log-likelihood / Rho-squared adjusted)

Model	Degrees of freedom	Logit	Mixed – err comps	Mixed – Day	Mixed - Week	Mixed - Individuals
Socio-economic variables	16 + 4 e.c.	-11952.6 0.024	-11845.1 0.033	-11850.8 0.032	-11685.3 0.046	-11351.8 0.073
Day behavioral variables	32 + 4 e.c.	-10777.7 0.119	convergence not achieved	-10643.9 0.129	-10495.3 0.142	-10154.3 0.169
Week behavioral variables	36 + 4 e.c.	-9868.7 0.193	-9797.0 0.198	-9847.3 0.194	-9862.6 0.193	-9758.1 0.201
Long-term behavioral variables	46 + 4 e.c.	-9194.9 0.247	-9134.9 0.251	-9179.7 0.248	-9189.3 0.247	-9149.0 0.250

*e.c. = error component

The best model in terms of goodness of fit has been applied to test the ability of the model to forecast observed choices. Figures 2 and 3 compare observed and predicted choices for Monday and Friday, Figures 4 and 5 report the same statistics for the weekend days, while in Figures 6 and 7 the model application to the first and last week of the survey is given. This exercise aims at testing if one dynamic model can reproduce activity choices and scheduling over different days and weeks. Models estimated on panel data are usually estimated for each single day to capture day-to-day variability (Hirsh and al, 1986; Khandker and Miller, 2007). The model does a quite good job in reproducing choices for weekdays and for the different weeks of the survey. There are clearly some effects that are not captured. On Saturdays the number of shopping tours is underestimated during the morning and the principal tour, while on Sundays shopping tours are overestimated and leisure tours underestimated. More detailed information about the shopping opening hours on weekend days could perhaps help to set appropriate alternative availabilities and reduce the gap between choices observed and predicted. One could also propose to estimate different models for the weekend days, but that will destroy the temporal continuity of our model structure. Overall, we can conclude that the dynamic model proposed is able to reproduce choice patterns and that it also adapts well to the variability of rhythms of daily life.

Table 4 Model results

		Logit		Mixed – err comps		Mixed – Day		Mixed - Week		Mixed - Individuals	
Variable	Alternative	Estimates	t-stat	Estimates	t-stat	Estimates	t-stat	Estimates	t-stat	Estimates	t-stat
Activity duration	MT Wday	-0.0162	5.94	-0.0166	5.74	-0.016	5.74	-0.0163	6.06	-0.0164	5.22
	MC Wday	-0.0195	8.62	-0.0193	8.14	-0.020	8.15	-0.0195	6.80	-0.0198	4.16
	EC Wday	-0.0044	5.93	-0.0044	5.43	-0.004	5.41	-0.0044	4.83	-0.0044	3.01
	ET Wday	-0.0012	3.03	-0.0013	2.70	-0.001	2.84	-0.0012	2.92	-0.0013	2.39
	MT NWday	-0.0080	13.19	-0.0077	12.95	-0.008	11.24	-0.0080	10.90	-0.0081	9.66
	PT out-leg NWday	-0.0200	10.45	-0.0196	10.89	-0.020	9.60	-0.0200	9.21	-0.0200	9.06
	PT NWday	-0.0025	12.03	-0.0034	10.65	-0.003	8.44	-0.0025	6.41	-0.0026	5.09
	PT ret-leg NWday	-0.0207	8.97	-0.0204	9.70	-0.021	8.84	-0.0207	7.73	-0.0208	7.30
	ET NWday	-0.0159	10.67	-0.0155	11.61	-0.016	10.34	-0.0158	8.98	-0.0159	7.45
	W-H-W	-0.0063	4.88	-0.0052	4.40	-0.006	4.56	-0.0064	4.82	-0.0068	3.48
Time budget	Shopping	-0.2621	19.19	-0.4001	12.38	-0.277	17.66	-0.2647	18.58	-0.2721	11.80
	Leisure	-0.6555	35.46	-0.9463	12.10	-0.682	32.87	-0.6679	31.97	-0.7019	14.11
	Personal Business	-0.3014	25.00	-0.4727	13.64	-0.313	21.59	-0.3029	23.59	-0.3122	14.85
	Pick up/drop off	-0.4375	24.46	-0.7697	11.65	-0.474	22.83	-0.4592	21.45	-0.4830	12.24
Available time before work	Shopping	-0.0018	2.14	-0.0040	3.90	-0.002	2.19	-0.0018	2.19	-0.0020	2.15
Available time post work	Shopping	0.0039	6.67	0.0078	10.10	0.004	6.40	0.0040	5.64	0.0042	6.25
High week episode	Shopping	1.4918	18.43	2.6685	12.35	1.605	21.91	1.5057	29.99	1.4461	16.28
	Leisure	0.4874	6.00	0.7568	7.52	0.509	7.23	0.4699	5.86	0.4623	4.42
	Personal Business	1.0966	15.03	1.7625	11.80	1.142	17.77	1.1091	22.58	1.1124	12.23
	Pick up/drop off	2.0591	15.10	3.7895	9.80	2.207	26.75	2.0947	20.82	1.8323	7.82
Last time	Shopping	0.5463	7.87	1.0072	7.22	0.617	7.83	0.5536	9.94	0.5548	5.32
	Leisure	4.2962	31.08	6.6242	12.81	4.540	38.88	4.4205	38.72	4.6440	12.84
	Personal Business	0.2111	10.49	0.4130	8.34	0.234	10.06	0.2111	12.19	0.2093	8.47
	Pick up/drop off	0.0020	4.17	0.0042	6.44	0.003	4.09	0.0025	2.76	0.0029	3.09
Last time leisure	Work only	-0.2431	3.06	0.1558	1.09	-0.191	2.24	-0.2451	4.82	-0.2555	2.85
Last time PB	Work only	-0.1359	2.17	-0.1170	1.61	-0.136	2.19	-0.1357	2.96	-0.1300	1.75

Immobile days	Shopping	0.0063	1.35	0.0097	1.46	0.006	1.11	0.0065	1.09	0.0066	0.74
	Leisure	0.0063	1.38	0.0101	1.52	0.007	1.14	0.0065	1.10	0.0068	0.77
	Personal Business	0.0067	1.46	0.0107	1.59	0.007	1.21	0.0069	1.18	0.0070	0.81
	Pick up/drop off	0.0060	1.30	0.0096	1.42	0.006	1.07	0.0063	1.06	0.0065	0.73
Logsum (Mode choice)	All	0.1157	1.95	0.1965	2.11	0.128	2.05	0.1473	2.35	0.2027	1.91
Age 36-50	Leisure	-0.4089	1.96	-0.5514	1.97	-0.415	2.78	-0.4567	3.17	-0.6149	2.68
Age 51-65	Pick up/Drop off	0.4383	4.20	0.7369	6.87	0.443	4.76	0.4952	6.62	0.5898	7.31
Age 6-18	W-H-W	-0.3353	1.92	-0.0664	0.40	-0.305	1.78	-0.3231	3.32	-0.2489	1.40
Number of children under 12	Leisure	0.1502	2.46	0.3471	3.97	0.169	2.75	0.1532	2.63	0.2023	2.22
	Pick up/Drop off	0.4722	5.87	0.8920	6.97	0.515	9.79	0.5244	7.71	0.7264	8.66
Number of working hours per week	Work only	0.0240	9.02	0.0318	8.52	0.025	9.21	0.0240	8.20	0.0234	5.04
Full time worker	Shopping	-0.6940	3.35	-1.4388	4.88	-0.795	3.81	-0.7093	2.90	-0.5629	1.07
	Leisure	-1.0277	4.88	-1.7898	6.34	-1.128	5.46	-1.0418	4.16	-0.8856	1.55
	Personal Business	-0.5937	2.80	-1.1476	4.06	-0.670	3.17	-0.6093	2.47	-0.4726	0.88
	Pick up/drop off	-0.4466	1.97	-0.9747	3.25	-0.497	2.13	-0.4829	1.75	-0.3146	0.54
	Work only	-1.6649	7.99	-2.6170	8.85	-1.780	8.79	-1.6817	7.27	-1.6275	3.00
Female and part time	Shopping	0.5714	3.93	0.6456	3.83	0.577	4.11	0.5725	4.51	0.6851	11.60
	Leisure	0.4363	2.98	0.6079	4.03	0.441	3.21	0.4274	3.36	0.4625	4.55
	Personal Business	0.6801	4.67	0.8423	5.17	0.677	4.82	0.6802	5.37	0.7736	8.91
	Pick up/drop off	0.5211	2.49	0.7080	4.24	0.588	3.13	0.5709	2.85	0.7632	6.38
Error components	Shopping	-	-	2.4667	11.78	0.693	11.37	-0.0013	0.03	0.2413	3.13
	Leisure	-	-	0.6685	0.96	-0.077	0.74	0.2569	3.21	0.5161	5.62
	Personal Business	-	-	2.2663	10.31	0.464	4.25	0.0068	0.23	-0.1685	1.75
	Pick up/drop off	-	-	2.8491	8.43	0.774	8.84	0.5549	6.50	0.5597	4.80
Number of observations		4952		4952		4952		4952		4952	

N. of observations with repetitions		4952	4952	3212	773	144
Log likelihood at zero		-12268.27	-12268.27	-12268.27	-12268.27	-12268.27
Log likelihood final		9194.9	9134.9	9179.7	9189.3	9149.02
rho squared adjusted		0.2468	0.2514	0.2477	0.2469	0.2502

Legend:
Wday = working day
NWday = non-working day
MT = morning tour
MC = morning commute
EC = evening commute
ET = evening tour
PT = principal tour
PT out-leg = principal tour outbound leg
PT ret-leg = principal tour return leg
W-H-W = work-home-work

6. Conclusions

The paper has implemented a model of activity type and timing choice, which extends the argument of Cirillo and Axhausen, 2006, that one should improve the formulation of the systematic utility function by including variables that describe the dynamics of the day. Here again, the bulk of the explanatory power rests in those dynamic variables, which give a real insight into the constraints and usefulness of the activities. We model the sequential choice of the tour elements, i.e. the dynamic choices over the course of the day: the estimates confirm that previous choices impact through the restrictions on the degrees of freedom, particular vis-a-vis time. This is intuitively obvious, but shown here for the first time in a discrete choice framework. Previous work used independent hazard models to look at these sequential choices, or only at the rhythms of identical activities/tour elements. The socio-demographic variables, in other models dominant, loose their prominence. The personal preferences here are captured exclusively with the activity type specific error components.

There are various avenues for further research. It would be interesting to test if non-linear formulations of the variables, in particular of prior activity durations and budgets, would improve the fit. Equally, one could try to capture the known regularities of activity performance through the introduction of relevant interaction terms with the variables describing the interval to the previous activity performance. Within the framework of the current model, it would make sense to differentiate leisure further, as the large differences between leisure activities are well known, or to integrate effects of the weather. One could improve the estimates of the variables for the non-observed choices further, for example using models which account for sample selectivity, one could estimate the duration, modes and travel times more appropriately. The same is true for shopping on Sundays, which is mostly grocery shopping. In the same vein, one could analyze the impact of the censoring affecting the variables describing the first observations of each respondent.

The availability of the second half of the Mobidrive data collected in Halle and the more recent 2003 Thurgau survey (Axhausen et al., 2007), raise the question of how stable the parameters and model structure are. We hope to address this question of transferability, or better stability in the future.

The main application of the work undertaken here is the simulation of the dynamics of the activity program over time. We can now undertake to model weeks or even longer time periods, while accounting for the impacts of shocks to transport system.

References:

Arentze, T.A. and H.J.P. Timmermans (2000). *Albatross*: A Learning Based Transportation Oriented Simulation System. EIRASS.

Arentze, T.A. and H.J.P. Timmermans (2004). A learning-based transportation oriented simulation system. *Transportation Research Part B*, 38 (7) 613-633.

Axhausen, K.W., A. Zimmermann, S. Schönfelder, G. Rindsfüser and T. Haupt (2002). Observing the rhythms of daily life: A six-week travel diary. *Transportation*, 29 (2) 95-124.

Axhausen, K.W., M. Löchl, R. Schlich, T. Buhl and P. Widmer (2007) Fatigue in long duration surveys, *Transportation,* 34 (2) 143-160.

Bastin, F., C. Cirillo and P.L. Toint (2006). Application of an adaptive Monte Carlo algorithm to mixed logit estimation. *Transportation Research B*, 40 (7) 577-593.

Ben-Akiva, M. and S.R. Lerman (1985). *Discrete Choice Analysis: Theory and Application to Travel Demand*. MIT Press.

Bhat, C.R. (1996). A Generalized Multiple Durations Proportional Hazard Model with an Application to Activity Behavior During the Work-to-Home Commute", *Transportation Research Part B*, 30 (6) 465-480.

Bhat, C. R. and S.K. Singh (2000). A comprehensive daily activity-travel generation model system for workers. *Transportation Research A*, 34 (1) 1-22.

Bhat, C.R., J.Y. Guo, S. Srinivasan, and A. Sivakumar (2004) Comprehensive Econometric Microsimulator for Daily Activity-Travel Patterns. *Transportation Research Record*, 1894, 57-66.

Bhat, C.R., and S. Srinivasan (2005). A Multidimensional Mixed Ordered-Response Model for Analyzing Weekend Activity Participation. *Transportation Research Part B*, 39 (3) 255-278.

Bowman, J.L. and M. Ben-Akiva (2000). Activity-based disaggregate travel demand model system with activity schedules. *Transportation Research A*, 35 (1) 1-28.

Buliung, R.N. (2005). Activity/travel behavior research: Approach and findings with identification of research themes and emerging methods. Working paper series. McMaster University.

Cherchi, E. and C. Cirillo (2007). A mixed logit mode choice model on panel data: accounting for systematic and random variations on responses and preferences. Proceedings of the 87th TRB meeting Washington DC.

Cirillo, C. and K.W. Axhausen (2006). Evidence on the distribution of values of travel time savings from a six-week travel diary. *Transportation Research A*, 40 (5) 444-457.

Cirillo, C. and Ph. L. Toint (2001). A multinational comparison of travel behaviour using an activity-based approach. Working paper Transportation Research Group, FUNDP, Namur.

Goodwin, P.B. and J.H. Mogridge (1981). Hypothesis for a fully dynamic model of car ownership. *International Journal of Transport Economics*, 8 (3) 313-326.

Hamed, M.M. and F.L. Mannering (1993). Modeling travelers’ postwork activity involvement: toward a new methodology. *Transportation Science*, 27 (4) 381-394.

Hanson, S. and J.O. Huff (1988). Systematic variability in repetitious travel. *Transportation 15,* pp. 111-135.

Hirsh, M., J. Prashker and M. Ben-Akiva (1986). Dynamic model of weekly activity pattern. Transportation Science, 20 (1) 24-36.

Jones, P. and M. Clarke (1988). The significance and measurement of variability in travel behaviour. *Transportation 15* (1/2) 65-87.

Khandker, M.N.H and E.J. Miller (2007). Modeling activity program generation considering within day and day-to-day dynamics in activity travel behavior. Paper presented at 86th TRB Annual Meeting Washington D.C.

Kitamura, R. (1988). A dynamic model system of car ownership, trip generation and modal split: model development and simulation experiments. In the proceedings of the 14th Australian road research board conference, Part 3, 96-111. Australian Road Research Board, Vermont South, Victoria.

Kitamura, R. and D.S. Bunch (1990). Heterogeneity and state dependence in household car ownership: a panel analysis using ordered-response probit models with error components. *Transportation and traffic theory*, Reprint n.52, 477-496.

Kockelman, K.M. (1999). Application of a utility-theory-consistent system of demand equations approach to household activity travel choice. Paper presented at the 78th Annual Meeting of the Transportation Research Board, Washington, D.C., January 10-14.

Golob, T.F. (2000). A simultaneous model of household activity participation and trip chain generation, *Transportation Research*, **34B** (5) 355-376.

Lu, X. and E.I. Pas (1999). Socio-demographics, activity participation and travel behavior. *Transportation Research, Part A*, **33**, 1-18.

Ma, J. and K.G. Goulias (1999). Application of Poisson regression models to activity frequency analysis and prediction. Paper presented at the 78th Annual Meeting of the Transportation Research Board, Washington, D.C., January 10-14.

Mahmassani, H. and G.L. Chang (1986). Experiments with departure-time choice dynamics of urban commuter. *Transportation Research B*, 20, 298-320.

Munizaga, M., S. Jara-Diaz, P. Greeven, and C.R. Bhat (2008). Econometric Calibration of the Joint Time Assignment – Mode Choice Model, *Transportation Science*, Vol. 42, No. 2, pp. 208-219.

Nagel, K. and M. Rickert (2001). Parallel implementation of the TRANSIMS microsimulation. *Parallel Computing*, 27(12): 1611-1639.

Pas, E.I. (1988). Weekly travel-activity behavior. *Transportation 15*, pp. 89-109.

Pas, E.I. and S. Sundar (1995). Intra-personal variability in daily urban travel behavior: Some additional evidence. *Transportation* 22, 135-150.

Pendyala, R., R. Kitamura and A. Kikuchi (2004). FAMOS: The Florida Activity Mobility Simulator, Presented at the Conference on “Progress in Activity-Based Analysis”, Vaeshartelt Castle, Maastricht, The Netherlands, May 28-31, 2004

PTV AG, B. Fell, S. Schönfelder and K.W. Axhausen (2000). Mobi*drive* questionaires, *Arbeitsberichte Verkehrs- und Raumplanung*, **52**, Institut für Verkehrsplanung, Transporttechnik, Strassen- und Eisenbahnbau, ETH Zürich, Zürich.

Revelt, D. and K. Train (1998). Mixed logit with repeated choices, *Review of Economics and Statistics*, **80** (4) 647-657.

Salvini, P. and E.J. Miller (2005). ILUTE: An Operational Prototype of a Comprehensive Microsimulation Model of Urban Systems, Network and Spatial Economics, pp. 217-234.

Schlich, R. (2004) Verhaltenshomogene Gruppen in Längsschnitterhebungen, Dissertation, ETH Zürich, Zürich.

Schönfelder, S. (2006). Urban rythms: Modelling the rythms of individual travel behaviour, Department Bau, Umwelt und Geomatik, ETH, Zürich

Train, K. (2003). *Discrete Choice Analysis with Simulations*. Cambridge University Press, New York.

Walker, J. (2001). Extended Discrete Choice Models: Integrated Framework, Flexible Error Structures, and Latent Variables. PhD Thesis MIT.

Figure 2 - Model application: Monday

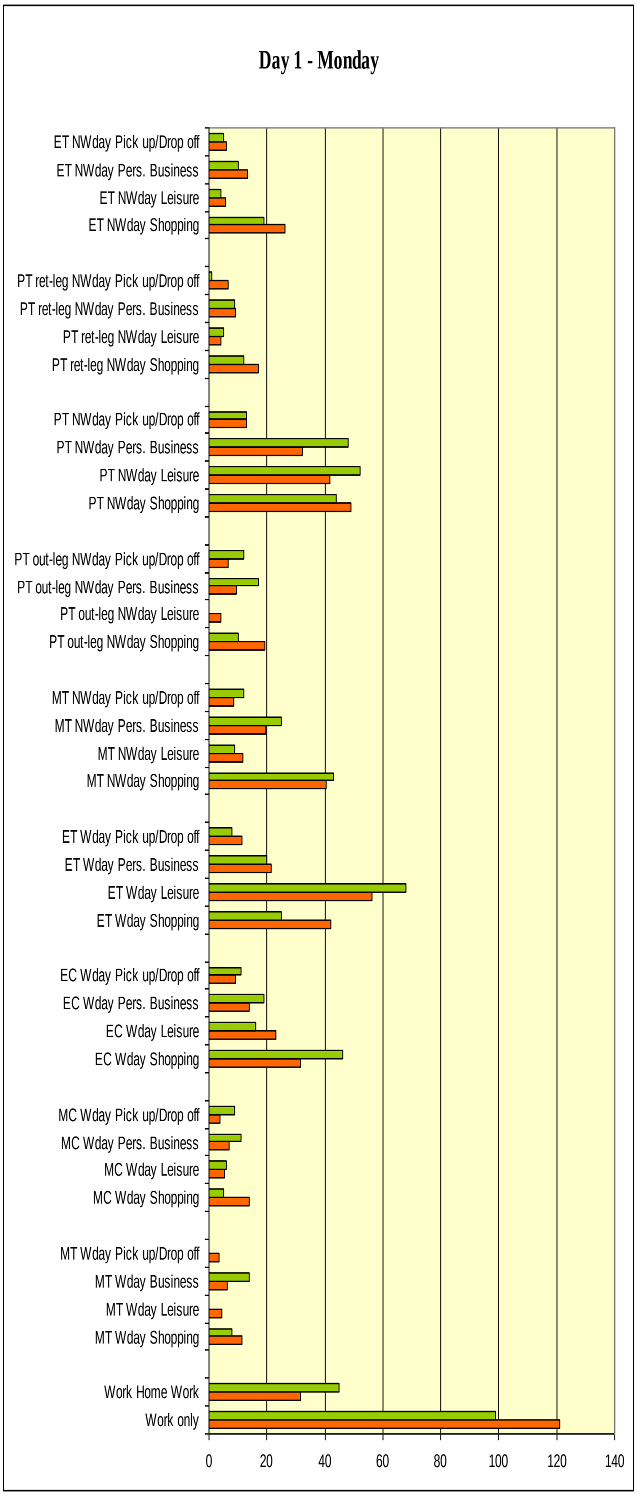
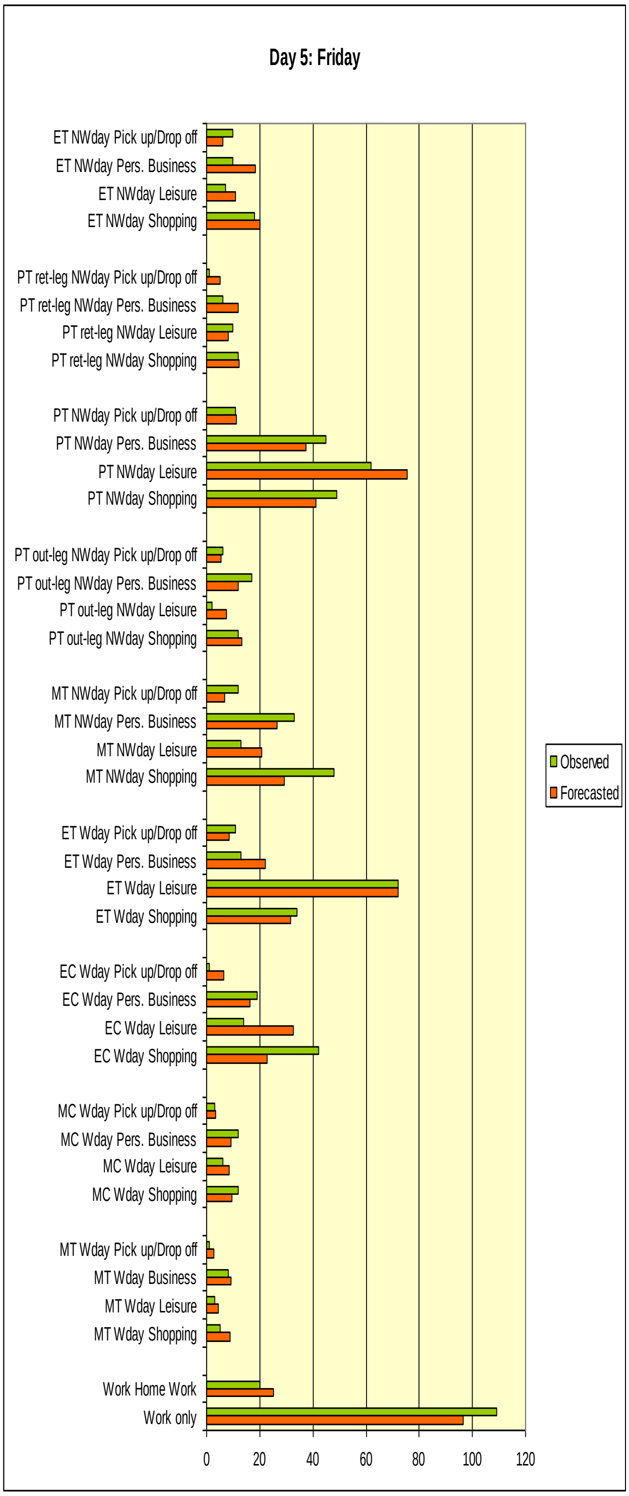


Figure 3 - Model application: Friday



	Observed
	Forecast

Figure 4 - Model application: Saturday

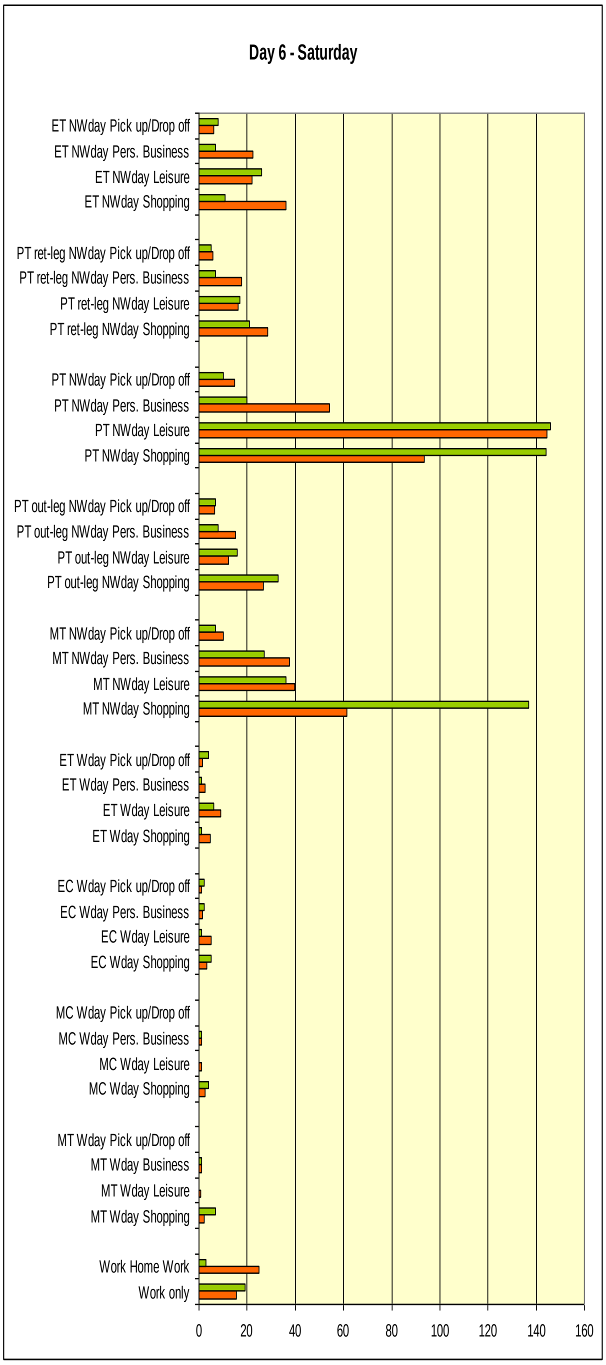
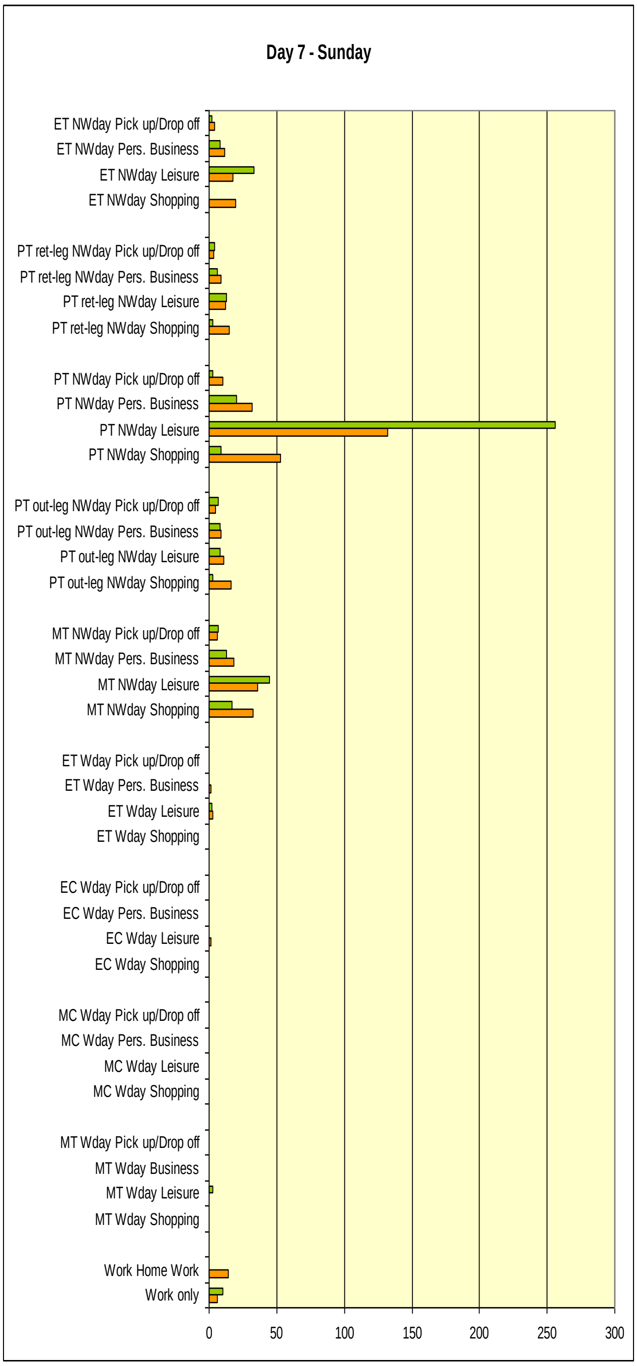


Figure 5 - Model application: Sunday



(green)	Observed
(orange)	Forecast

Figure 6 - Model application: Week 1

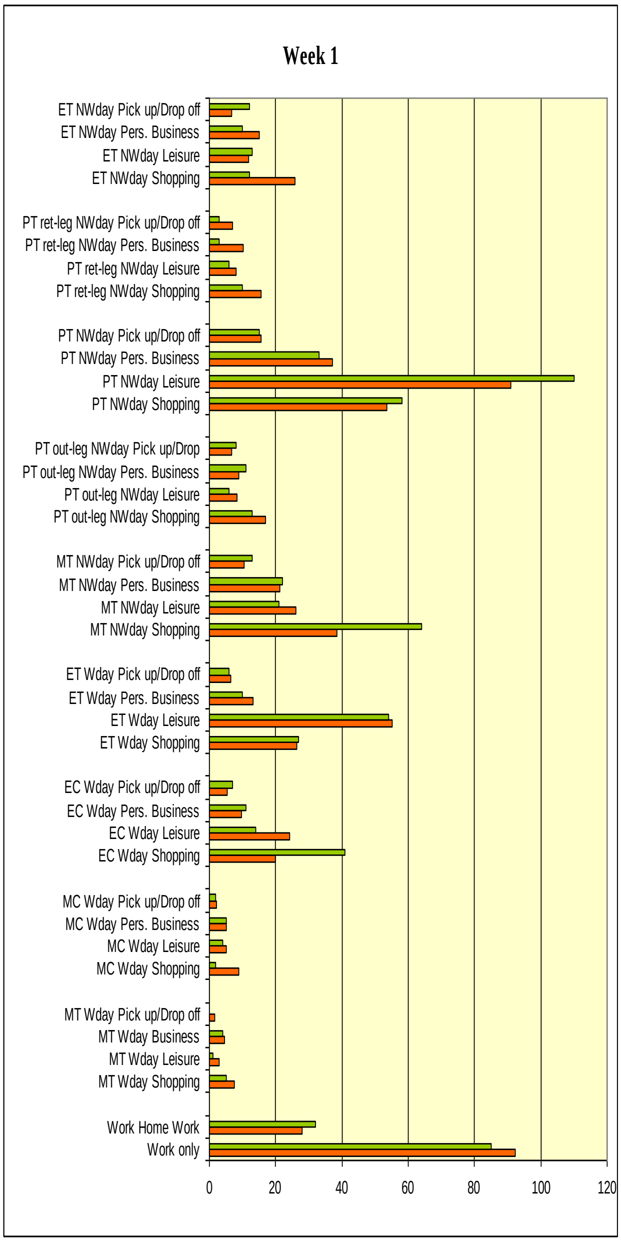
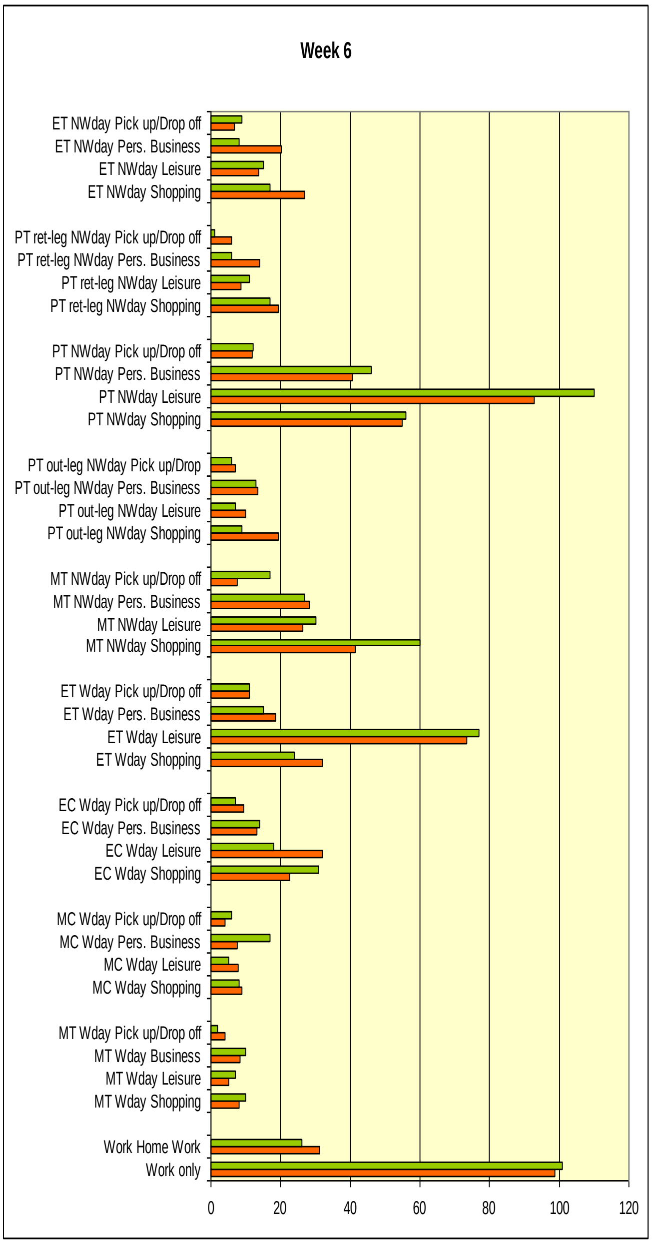


Figure 7 - Model application: Week 6



	Observed
	Forecast