Validation of latent class models to account for the effect of flexibility in departure time choices

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Several major cities are facing congestion problems. Congestion is (especially) related to commuting in dense urban areas, where the demand is condensed in peak-hours. Since people are more likely to change their departure time rather than changing their transport mode to avoid congestion, understanding the departure time choice from an individual perspective is important to develop policies aimed to address growing congestion issues. The predominant approach to study departure times is the Scheduling Model (Small, 1982), which assumes a trade-off between travel time and a "scheduling penalty" with respect to the preferred arrival time.

Crucial in departure time for commuting trips is whether individuals are flexible or not in their choices. Flexible individuals are more likely to reschedule their departure/arrival time in order to reduce the increase in their travel time due to congestion and demand elasticity is expected to be high. This has been recognised since the early studies, though the discussion in the literature has mainly focused on temporal flexibility at work for morning commuting trips (see e.g. de Jong et al., 2003; Hess et al., 2007). Moreover, most of the studies on departure time account only for constraints at the work location, assuming that (different types of occupations at) work is the main source of heterogeneity in departure time flexibility. Activity-based studies have shown that the choice of when to realize a given trip is (often) related to the full daily activity schedule (Bowman and Ben-Akiva, 2000). Since time/space constraints in one activity may form restrictions in the flexibility of other activities, these affect the preference for the related departure time. To correctly account for flexibility, one needs to consider the full daily activity pattern and if these activities and trips are constrained in multiple dimensions, such as temporal, spatial, and social constraints. However, this is seldom done. To our knowledge Thorhauge et al. (2016) is the only study that has explicitly incorporated the effect of several constraints for the daily activities into the departure time model and showed that neglecting constraints in other daily activities can lead to an overestimation of individuals' flexibility and substitution patterns in forecasting. However, measuring and modelling flexibility beyond work hour starting times is non-trivial and it is likely that departure time studies will continue to neglect the several sources of constraint due to the comprehensive requirements during the data collection phase, and hence to overestimate the demand elasticity to transport policies (Thorhauge et al., 2016).

The objective of this paper is to explicitly use detailed information about individuals' temporal, spatial, and social flexibility to validate that socio-demographics can be used as a proxy for flexibility. We hypothesizes that especially the household compositions play an important role in defining individuals flexibility. More specifically, we expect that individuals with spouse and kids are more likely to be inflexible, and we expect this to be particular true for woman, who are often more involved in the practical tasks within the household. Similar, we expect singles to be more likely to being flexible.

Since socio-demographics are easier to collect and often available from national sources, this paper proposes to use a latent class model where socio-demographic information is used to infer the individual's activity structure and the constraints that this structure imposes on the departure time. More specifically, each class in the latent class model represents a segment of individuals with a specific level of flexibility and thus similar willingness (ability) to shift departure time.

The data were collected mainly in the Greater Copenhagen Region. We collected information about all activities and trips individuals performed during a 24H period. Furthermore, a customized stated choice experiment containing 9 choice task was presented to each individual pivoted around their reported commuting trip. Seven flexibility statement were collected for each trip:

1. **Exclude:** Could you have omitted this trip/activity? (yes/no)
2. **AltPlace:** Could you have carried out this activity at another location? (yes/no).
3. **AltDay:** Could you have done this activity another day? (yes/no)
4. **AltTime:** Could you have done this activity at another time of the day? (yes/no).
5. **DepTime:** Were there any restrictions to how early you could have departed? (yes/no)
6. **ArrTime:** Were there any restrictions to how late you could have arrived? (yes/no)
7. **AltPerson:** Could another person have done this activity for you? (yes/no)

The trips were aggregated into trip chains covering home-work (HW), work-home (WH), and after work (AW). Since two of the indicators contained no variability in the observed response, a total of $3 * 7 – 2 = 19$ indicators where available to be estimated for all classes.

The latent class choice model (LCCM) is estimated based on 3686 observations from 438 individuals using PythonBiogeme v2.5 (Bierlaire, 2016, 2003), and contains three components: 1) class specific (discrete) departure time choice model based on the Scheduling Model, 2) class membership model using socio-demographics, and 3) class specific indicators based on detailed statements about individuals flexibility. Results indicate that a latent class model is able to approximate the effect of flexibility in departure time choices, see Table 1. Three classes were identified:

- Class 1: "Flexible" consists of 30.1% of the individuals, who are flexible both with respect to the morning commute, but also in terms of constraints later in the day during the afternoon and work. This group has the highest marginal disutility for travel time and lowest marginal disutility for rescheduling departure times. Individuals in this class are more likely to being single males without child(ren), who work more than the standard work week (37 hours/week), have a medium income, and flexible work hours.

- Class 2: "Restricted morning" consists of 16.7% of the individuals, who are generally very restricted in the morning. This class have the highest marginal disutility for both early and late arrival of among all three classes. This indicate that they to a large extend care about the exact arrival time, which is likely caused by having temporal restrictions. Individuals in this class are more likely to be male, have a spouse and child(ren), have high income, and not least having fixed work hours.

- Class 3: "Restricted evening" consists of 53.2% of the individuals, who are more likely to be restricted in the afternoon and evening. The third class is the only class for which the discrete latent penalty is negative (and significant), and fairly large, while the time dependent penalties for rescheduling is fairly low (in fact, similar to that of class 1 for both early and late arrival). This indicates that it is not temporal constraints in this morning that are important for individuals in this class (there is not much difference in arriving 5 minutes late compared to 8 minutes late), instead they do not want to reschedule due to restrictions later in the day, which is then captured by the discrete lateness dummy instead. Individuals in this class are more likely to have a spouse and child(ren), have high income, and not least having fixed work hours.

The results shows that it is possible to capture flexibility (and thereby departure time preferences) using socio-demographic. And since the class membership model is only estimated using socio-demographics, this means that transport modelers can use a latent class model to include flexibility when forecasting using national sources where information on flexibility (typically) is not available.

	Class 1: Flexible		Class 2: Restricted morning		Class 3: Restricted evening	
	Value	T-test	Value	T-test	Value	T-test
Class specific model						
ASC, early dep. time	-0.93	-1.30	-2.37	-2.14	-0.38	-0.81
ASC, late dep. time	-0.60	-0.82	-0.40	-0.31	-0.01	-0.03
TC	-0.24	-5.95	-0.18	-3.48	-0.09	-3.94
ETT	-0.29	-6.11	-0.18	-2.21	-0.13	-4.98
ESDE	-0.03	-2.36	-0.10	-2.29	-0.04	-3.96
ESDL	-0.06	-3.62	-0.42	-5.37	-0.06	-6.17
DL	0.49	1.58	-0.06	-0.12	-0.47	-2.33
SIGMA_1	1.64	5.71	4.24	5.13	-1.23	-6.01
SIGMA_3	3.28	7.67	-3.28	-4.90	1.72	9.39
RHO_3	2.68	5.52	-0.21	-0.84	-2.51	-10.18
Class indicators						
HW Fix_AltDay	∞	N/A	4.60	3.15	3.97	7.76
HW Fix_AltPlace	1.33	5.77	∞	N/A	2.43	9.06
HW Fix_AltTime	-3.76	-5.22	-0.62	-2.02	-0.44	-2.56
HW Fix_ArrFlex	-∞	N/A	∞	N/A	1.06	4.82
HW Fix_DepFlex	-1.78	-5.88	-1.43	-3.35	-0.16	-1.03
WH Fix_AltDay	4.09	5.64	∞	N/A	4.54	6.34
WH Fix_AltPerson	4.79	4.74	∞	N/A	5.24	5.20
WH Fix_AltPlace	4.09	5.64	∞	N/A	5.24	5.20
WH Fix_AltTime	-2.02	-5.21	-∞	N/A	0.09	0.49
WH Fix_ArrFlex	-2.21	-4.57	-2.76	-4.21	0.28	1.55
WH Fix_DepFlex	-1.12	-4.01	1.19	3.69	1.04	5.54
WH Fix_Exclude	4.79	4.74	∞	N/A	∞	0.01
AW Fix_AltDay	2.86	2.75	1.32	1.59	∞	N/A
AW Fix_AltPerson	∞	N/A	2.14	2.06	∞	N/A
AW Fix_AltPlace	2.86	2.75	2.14	2.06	∞	N/A
AW Fix_AltTime	-0.11	-0.23	-∞	N/A	1.69	3.70
AW Fix_ArrFlex	-1.37	-2.15	-∞	N/A	1.54	3.57
AW Fix_DepFlex	-∞	N/A	-2.19	-1.91	0.94	2.62
AW Fix_Exclude	2.86	2.75	2.14	2.06	∞	N/A
Class membership model						
ASC			-4.50	-3.39	-0.89	-1.55
Male			1.06	1.78	-0.04	-0.10
Has Spouse			1.54	1.97	0.66	1.56
Female * Has Children <6 years			1.31	1.40	1.21	1.93
Female * Has Children 7-12 years			0.95	1.26	1.05	1.75
Female * Has Children 13-17 years			0.08	0.09	0.01	0.01
Fixed Work Hours			3.65	5.55	2.07	3.83
Work Hours p. week <37			1.59	1.65	1.14	1.51
Work Hours p. week >37			-0.25	-0.49	-0.35	-0.96
Income <450			0.77	0.98	-0.02	-0.04
Income >650			1.99	3.01	1.28	2.61
MissObs, Income			1.16	1.61	-0.04	-0.09
MissObs, Male			0.49	0.33	1.04	1.00

Table 1: Parameter estimates of the LCCM

Key references

Bierlaire, M., 2016. PythonBiogeme : a short introduction, in: Report TRANSP-OR 160706, Series on Biogeme. p. Transport and Mobility Laboratory, School of Archi.

Bierlaire, M., 2003. BIOGEME: A free package for the estimation of discrete choice models, in: Proceedings of the 3rd Swiss Transportation Research Conference. Ascona, Switzerland.

Bowman, J.L., Ben-Akiva, M.E., 2000. Activity-based disaggregate travel demand model system with activity schedules. Transp. Res. Part A Policy Pract. 35, 1–28. https://doi.org/10.1016/S0965-8564(99)00043-9

de Jong, G., Daly, A., Pieters, M., Vellay, C., Bradley, M., Hofman, F., 2003. A model for time of day and mode choice using error components logit. Transp. Res. Part E Logist. Transp. Rev. 39, 245–268.

Hess, S., Polak, J.W., Daly, A., Hyman, G., 2007. Flexible substitution patterns in models of mode and time of day choice: new evidence from the UK and the Netherlands. Transportation (Amst). 34, 213–238.

Small, K.A., 1982. The Scheduling of Consumer Activities : Work Trips. Am. Econ. Rev. 72, 467–479. https://doi.org/10.1126/science.151.3712.867-a

Thorhauge, M., Cherchi, E., Rich, J., 2016. How flexible is flexible? Accounting for the effect of rescheduling possibilities in choice of departure time for work trips. Transp. Res. Part A Policy Pract. 86, 177–193. https://doi.org/10.1016/j.tra.2016.02.006