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Examining the effects of out-of-home and in-home constraints on leisure activity participation in different seasons of the year

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Abstract Using multi-day, multi-period travel diaries data of 56 days (four waves of two-week diaries) for 67 individuals in Stockholm, this study aims to examine the effects of out-of-home and in-home constraints (e.g. teleworking, studying at home, doing the laundry, cleaning and taking care of other household member[s]) on individuals' day-to-day leisure activity participation decisions in four different seasons. This study also aims to explore the effects of various types of working schedules (fixed, shift, partial- and full-flexible) on individuals' decisions to participate in day-to-day leisure activities. A pooled model (56 days) and wave-specific models (14 days in each wave) are estimated by using dynamic ordered Probit models. The effects of various types of working schedules are estimated by using 28 days of two waves' data. The results show that an individual's leisure activity participation decision is significantly influenced by out-of-home work durations but not influenced by in-home constraints, regardless of any seasons. Individuals with shift working hours engage less in day-to-day leisure activities than other workers' types in both spring and summer seasons. The thermal indicator significantly affects individuals' leisure activity participation decisions during the autumn season. Individuals exhibit routine behaviour characterized by repeated decisions in participating in day-to-day leisure activities that can last up to 14 days, regardless of any seasons.

Keywords Panel data · Leisure activity participation · Space–time constraints · Seasons · Dynamic ordered Probit model · Stockholm

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Introduction

Leisure purposes of travel account for a third to a half of total personal travel (Anable 2002; Götz et al. 2002). Kitamura et al. (2006) argued that non-mandatory activities are irregular between days. Intra-personal (within-person) and inter-personal (between-person) variabilities tend to be more obvious in discretionary activities than other types of activities (Tarigan and Kitamura 2009). The decisions on participating in non-mandatory activities are believed to be influenced by the scheduled mandatory activities which refer to the space–time constraints (Susilo and Kitamura 2005; Susilo and Dijst 2010; Susilo and Axhausen 2014), thus forming the day-to-day variability in those non-mandatory activities. The previous days' activity participation (e.g. state dependence) may also influence the day-to-day variability in non-mandatory activities that may lead to the developing of habit persistence for such activities (Ramadurai and Srinivasan 2006).

The growing use of information and communication technology (ICT) has changed human lifestyles and can also affect personal travel demands (Mokhtarian et al. 2006). ICT has offers alternative means of conducting various activities that can change people lifestyles. Salomon (1986) and Mokhtarian (1990) have discussed the impact of ICT on travel demands in which they refer it to substitution (e.g. by using ICT such as teleconference, a person does not have to go to a particular location to conduct activities with others, thus eliminates the travel to that location), neutrality (e.g. by substituting a travel with ICT that eliminate the travel, a person may travel to a new location to conduct new activities) and complementarity (e.g. ICT may stimulate the demand for new location, thus generates travel). Then, Mokhtarian et al. (2006) add a possible impact in which they refer it as modification (e.g. ICT can alter a person's travel although travel is neither generated nor replaced). Humans have moved into a new world where almost anything can be done online (e.g. searching for information and engaging with other people, goods and services) anywhere and anytime (Lyons 2015). Since the early 1980s, the impacts of ICT on travel time and commuting have been a major interest (e.g. Salomon 1986; Nilles 1988; Mokhtarian 1990). Since the term 'telecommuting' has been introduced by Nilles (1988), much research has been done on examining the characteristics of telecommuters (e.g. Mokhtarian et al. 1998; Bélanger 1999). Note that 'telecommuting' is the actual substitution of the commuting trip, while 'teleworking' is working at a distance from the actual workspace (Salomon 2000). In this paper, the term teleworking is used since it is commonly used in Europe. Telework is at the highest for Scandinavian countries, with Sweden falling at the second rank after Finland (ECaTT 2004). In Sweden, 7 % of the work force teleworked, but with no indication of significant increases in teleworking during the latter half of the 1990s, although the technology has rapidly improved (SIKA 2006). Despite substantial research done on the impacts of ICT on telework, however, the impacts of ICT on travel demand, whether it stimulates or reduces the travel, still remains unclear (Aguiléra et al. 2012).

Employment type may also play an important role in stimulating or reducing personal travel demand. Breedveld (1998) hypothesised that the traditional workweek (e.g. work from 9 to 6 on Monday to Friday) will be replaced by the 'flexibilization' and '24/7 society', with individuals working in different days of the week and at different times of the day. Due to this scenario, individuals gain greater autonomy over their time use. Thus, nowadays, various types of work schedules are available to fulfil the public social requirement, especially in the service field that provides 24 h services (e.g. paramedics, police officers, public transport drivers etc.). Different employment types may lead to different working schedule durations (e.g. fixed, shift, partial- and full-flexible), and thus may affect personal travel demands on out-of-home non-mandatory activities, especially leisure activities (e.g. sports, eating outside, meeting friends). For example, individuals who work as paramedics may have shift work types (e.g. early morning shift, night shift etc.), and thus have different activity-travel patterns than individuals who work as clerks and commonly have fixed work types (e.g. from 9 a.m. to 5 p.m.) due to the differences in their working schedules. To date, many efforts have been taken to investigate workers' activity-travel patterns. For example, Bhat and Singh (2000) developed a comprehensive representation to describe workers' activity-travel patterns and captured their work schedules by categorising the work arrival and departure times (e.g. arrival at work before 8 a.m., departure before 4 p.m., departure between 4 and 6 p.m. and departure after 6 p.m.). They found that individuals who work more (who leave work after 6 p.m.) and who spend more time in travel to work, have less time to conduct post-work activities, and thus engage less in such activities than other workers. Susilo and Dijst (2009) analysed individual's travel time ratio (TTR) for activity participation in the Netherland. They found that full-time workers and students have lower TTR values for nonwork activities than do part-timers, suggesting that they spend their nonwork activities close to their home base. Spissu et al. (2009) analysed individual's weekly out-of-home discretionary activity participation and time-use behaviour by using the 2002 dataset of Twelve Week Leisure Travel Survey collected in three different waves in Zurich region. They have compared the results of panel Mixed Multiple Discrete–Continuous Extreme Value (panel MMDCEV) model and cross-sectional MMDCEV model (see Bhat 2005, 2008). They found that the variable 'flexible work time' is positively associated with out-of-home meal activity participation in the panel model and the variable is associated with a higher inclination towards sport activity engagement in the cross-sectional model. Kang and Scott (2010) investigated the variations in individuals' time-use patterns over a seven-day period while accommodating their interactions with other household members. They found that on weekdays, teleworking has a positive effect on joint activity participation and a negative effect on independent activity, but otherwise on weekends. Tarigan et al. (2012) studied intrapersonal variability in leisure activity-travel patterns between one-worker and two-worker households and found that individuals from one-worker households had higher intrapersonal variability for several behavioural patterns than individuals from two-worker households. Bayarma et al. (2007) studied the heterogeneity in travel patterns variations and found that workers who live in the central city tend to have more stable travel patterns, while higher-income workers have more variable travel patterns for shopping and leisure, and for work.

However, none of the studies mentioned above have focused on the various types of work schedules such as fixed, shift, full- and partial-flexible, which may affect individuals' personal travel demands due to space–time constraints. Limited research has been done to examine the effects of in-home activities other than teleworking (e.g. studying at home, cleaning, doing the laundry etc.) and also seasonal effects on individuals' leisure activity participations due to high constraints (e.g. budget, time and respondents' burdens) in collecting the longitudinal panel data. By using the 2010 American Time Use Survey (ATUS), a study by Bernardo et al. (2015) found that dual-earner households with young children lead to the reduction in both in-home (excluding child care activities) and out-of-home (excluding child care and shopping activities) non-work activity participation. Meanwhile, Bhat and Gossen (2004) and Bhat and Srinivasan (2005) are among few researchers that examined the seasonal effects on out-of-home, non-work/non-school activities (e.g. recreational, maintenance shopping activities etc.) on weekends. Using the

Swedish National Transport Survey (NTS) data of 13 years, Liu et al. (2015a) found the effects of seasonal variations on the number of trips travelled in which there were more cycling trips but fewer walking and public transportation trips in summer than in winter. They also found that the impact of individuals' perceptions on weather differs in different regions and seasons, conditional to the different modes used for travel. For example, cyclists in northern Sweden are more aware of temperature variation than cyclists in central and southern Sweden, especially in spring and autumn seasons. Thus, seasonal variations could possibly influence in-home activity participation and thus affect out-of-home non-mandatory activity participation such as leisure activities.

To fill in the research gaps and gain a better understanding of the effects of out-of-home and in-home constraints that underlie individuals' decisions to participate in day-to-day leisure activities over different seasons, the weather indicators should also be considered. This can be realised only by using multi-day, multi-period data at an individual level that is rich with information on dynamics in travellers' behaviours that may not be available in conventional single-day or single-period cross-sectional surveys that have dominated in travel behaviour research (Pendyala and Pas 2000). The variability of between- and within-person in leisure activity participation can be investigated only by using longitudinal panel data. Understanding these would assist transport planners and local transport operators to manage travel demand strategies across different seasons of the year and provide efficient transportation systems for all individuals that may lead to increases in individuals' activity participation, particularly in leisure activities, and thus increase their well-being. Access and participation in activities can lead to positive psychological well-being (Stanley et al. 2011), and engaging in leisure activities is more essential to human well-being than engaging in mandatory or maintenance activities (Mokhtarian et al. 2006). The growth in leisure activity-travel can be attributed to the rising standards of living, early retirement and trend towards shorter working hours (ECMT 2000). Therefore, it is expected that the demand for discretionary activities will increase due to the increase in global economic prosperity (Mokhtarian et al. 2006).

Given the importance of leisure activities, this paper aims to examine the variability of individuals' leisure activity participations (e.g. number of leisure trips) in different seasons and how these patterns are related to their daily out-of-home mandatory activities and in-home mandatory and maintenance activities by using longitudinal panel data of 56-day travel diaries of four waves for 67 individuals collected in Stockholm, Sweden. The paper also aims to explore the effects of various types of working schedules (fixed, shift, partial- and full-flexible) on individuals' leisure activity participations by using 28-day travel diaries of two waves. The analytical method in this study is similar to Liu et al. (2015b), in which dynamic ordered Probit models are estimated, but with the framework adjusted according to the nature of the leisure trip and activity participation. Note that the pooled model (56-day observations) and wave-specific models (14-day observations each) are estimated separately. The work schedule types are categorised into four working durations—shift, fixed, partial- and full-flexible—but this is applicable only on Wave 3 (spring) and Wave 4 (summer) data, since no information was collected on work schedule types in Wave 1 (autumn) and Wave 2 (winter). Thus, the effects of various types of working schedules are estimated and compared between Waves 3 and 4 only. For comparisons in all waves (56-day data), out-of-home work and study durations were used in the analysis, including in-home activities. In this study, leisure activities refer to the daily out-of-home activities that give pleasure and enjoyment (Meurs and Kalfs 2000) to individuals such as meeting friends, going to the theatre or cinema, sports and training, eating outside, strolling around city, picnicking, walking in nature, bringing children to recreational parks, attending parties and having family days. In-home mandatory activities refer to the telework and study at home activity durations. In-home maintenance activities refer to doing the laundry, cleaning and taking care of other household member(s), represented by dummy variables. The average weather thermal indicator on the daily level is also considered in the models to capture the seasonal variations.

The remainder of this paper consists of five sections, starting with a description of the panel data used and followed by the description of methodology. Next, the descriptive analysis and empirical analysis using multivariate techniques are explained, and then the results are discussed. Finally, the paper's conclusions are summarized, followed by the directions of future research.

Travel diary data

The data contain a travel diary survey for 67 individuals who live in sub-urban areas of Stockholm within two municipalities (Solna and Sundbyberg), and the diaries were collected for four consecutive waves of a seven-month period with two weeks' worth of travel diaries collected in each wave. A total of eight weeks (56 days) of individuals' travel diaries were obtained within this period. It is preferable to have more than two waves of data so that the first wave of data may be treated as a base condition in analysing the subsequent waves (Kitamura 1990). Wave 1 and Wave 2 were collected during the autumn (14th to 27th October 2013) and winter (2nd to 15th December 2013) seasons respectively. Meanwhile, Wave 3 and Wave 4 were collected in the spring (17th to 30th March 2014) and summer (26th May to 8th June 2014) seasons respectively.

The design of the travel diary is similar to the *MobiDrive* six-week travel diary that was implemented in Karlsruhe and Halle in Germany during the fall of 1999 (Axhausen et al. 2002). The diary consists of origin and destination details, mode choice details, trip purpose, departure and arrival time, estimated travel time, estimated travel distance, travel companion details, travel expenses including costs for parking, types of season ticket used and long journey details. Waves 3 and 4 also included questions about the respondents' daily work schedules and the use of travel information and weather forecast services. This travel diary is a self-reported travel diary via the paper and pencil approach. Moreover, the respondents' socio-demographic information was obtained through an on-line questionnaire which has been distributed in each wave. The details on the survey design can be found in Ahmad Termida et al. (2016).

Methodology

This paper examines whether day-to-day leisure activity participation (e.g. number of leisure trips) varies across individuals and seasons and how these patterns are related to individuals' daily out-of-home and in-home constraints, work schedule types and thermal indicators.

Individuals' work schedule types and built environment data

The data on daily out-of-home work and study durations were collected in all waves. The data on daily work schedule types, however, were collected only in Waves 3 and 4. First, to obtain the information on individuals' work schedule types, the respondents who were employed in a given wave had to mark their answers in a given box of four choices: 1. fixed, 2. completely flexible, 3. flexible with restrictions, 4. schedule/shift. Second, the respondents who had fixed and shift working schedule types had to fill in their daily actual working times from the beginning until the end of their working hours on a given day for a two-week period in each wave, resulting in the total of four weeks (28 days) of observations. Third, for the respondents who had flexible working schedule types, they needed to choose the conditions that best suited them or restrictions that they had (if any) on a given day, including time restrictions (e.g. must arrive at the office before 10 a.m.) for each wave.

The attributes for the built environment consist of the distance from the respondent's home to Stockholm's central business district (CBD) and to the work/study place. The first attribute is used to capture the agglomeration effects of urban areas (e.g. Stockholm city centre) that normally have a higher provision of public goods that are oriented towards leisure than towards sub-urban areas (e.g. Solna and Sundbyberg) such as museums, waterfront parks, architectural variety and other public spaces (Florida 2002). The latter attribute is used to capture the spatial effects of work or study place locations on leisure trips. It is expected that the further the distance from home to CBD and to the work or study place, the lower the trips' demands for leisure activities due to space and time constraints.

Weather data

Weather is considered to be closely related to seasonality effect as weather characteristics can substantially vary in different seasons. In Sweden, the impacts of weather vary across different regions and in different seasons (Liu et al. 2015a), and thus may contribute to the variations in individuals' travel patterns. In this study, the weather data was obtained from Swedish Meteorological and Hydrological Institutes (SMHI) (2015), which includes daily air temperature (degrees Celsius), hourly relative humidity (%) and hourly wind speed (km/hr). Both hourly recorded relative humidity and wind speed were averaged into daily levels, in which hourly records between 7:00 a.m. and 8:00 p.m. were used, since most of the recorded activities in the travel diary were conducted in the daytime. These data are recorded from the nearest weather stations available to the study area. It is assumed that the weather data can represent the actual weather in the study area since the area is small relative to the spatial variation of weather conditions.

A thermal indicator, Universal Thermal Climate Index (UTCI), is used due to its advantages on utilizing knowledge in meteorology and its ability to overcome interdependency issues that may emerge from differences in an individual's subjective perceived weather (Liu et al. 2015a, b). UTCI is constructed by wind speed, relative humidity and air temperature, following the concept of an equivalent temperature that involves a reference environment and also equal physiological conditions (Bröde et al. 2010). Bröde et al. (2010) defined a reference environment as an environment with 50 % relative humidity but with vapour pressure not exceeding 2 kPa, with still air and radiant temperature equalling air temperature, to which all other climate conditions were compared. Equal physiological conditions are based on the equivalence of the dynamic physiological response (e.g. different body core temperature, sweat rate, skin wettedness conditions at different exposure times) predicted by the model for the actual and the reference environment. The detailed review on UTCI can be obtained in the UTCI website (UTCI 2015).

Multivariate analysis

In this study, a dynamic ordered Probit model was used to model individuals' leisure trips on a given day. It can handle taste variation, allow any pattern of substitution and can be used for panel data with temporally correlated errors. The error terms are assumed to be normally distributed (Train 2009). The model structure is similar to Liu et al. (2015b) study on investigating how the subjective weather perception varies among individuals and how those subjective weather perception influences individuals' actual travel behaviour by considering the influence of weather forecast. They have argued that number of leisure activities on the given day t is influenced by space–time constraints (time needed to spend on mandatory activities in day t), habit persistence (number of continuous working days until day t), perceived weather conditions (7-point Likert scale from very bad weather to very good weather) and state dependence (number of leisure trips made in the previous day). However in this study, it is argue that individuals' decisions to participate in leisure activities on a daily basis are believed to be influenced by time spent for out-of-home mandatory activities (Susilo and Kitamura 2005; Susilo and Dijst 2010) and/or in-home mandatory and maintenance activities (space–time constraints) in day t. The more people spend their time for out-of-home mandatory activities and/or in-home mandatory and maintenance activities on a given day, the less time they have to participate in leisure activities, and thus contribute to less leisure trips on that day. Secondly, number of leisure trip participations made in the previous day t-1 (state dependence) (Ramadurai and Srinivasan 2006) may also influenced individuals' decisions to participate in leisure activities on a daily basis. It is believed that if people have participated in leisure activities in the previous day (e.g. $t-1$), it is less likely that they will participate again in leisure activities today and thus contribute to less leisure trips on day t. Thirdly, number of continuous working or studying days until day t (habit persistence) (Liu et al. 2015b) may also influenced individuals' decisions to participate in leisure activities on a daily basis. For example, when people have to work or study continuously for 5 days per week, they may feel too tired to participate in leisure activities on a daily basis compared to the people who work or study also for 5 days per week but not continuously. This will contribute to less leisure trips on a daily basis. Finally, weather conditions represented by thermal indicator (e.g. UTCI) that also capture the impact of seasonal variations, are believed to influence individuals' decisions in leisure activity participations on a daily basis. For example, in a cold weather condition during winter season, people may reluctant to conduct leisure activities on a given day in a given season and thus contribute to less leisure trips. In contrast, people may likely to participate in leisure activities during warm weather condition in summer season and thus contribute to more leisure trips. From methodological point of view, this study also considered several mixed parameters and heteroscedasticity in the model system which makes it different from Liu et al. (2015b) model.

Thus, the dependent variable used in this study is the count of leisure trips conducted by individual i on a given day t in a given wave (e.g. season). The model has the following structure:

$$y*_{i,t} = X_{i,t}(\beta + \xi_i) + y_{i,t-1}(\gamma + \theta_i) + v_i + \varepsilon_{i,t}. \tag{1}$$

The latent dependent variable $y*_{i,t}$ is associated with the number of daily observed leisure trips made by individual i on given day t, $y_{i,t}$ by the following formula:

$$y_{i,t} = \begin{cases} 0, if -\infty < y*_{i,t} < \mu_0 \\ 1, if \mu_0 < y*_{i,t} < \mu_1 \\ \cdots \\ m, if \mu_{m-1} < y*_{i,t} < +\infty \end{cases} \quad (2)$$

where i is the individual index and t is the day index. $X_{i,t}$ is the time variant explanatory variables that influence individual i's leisure activity participation decisions on a given day t. $y_{i,t\text{-}1}$ refers to the number of leisure trips conducted by individual i on the previous day, t-1. v_i is the individual specific error term and $\varepsilon_{i,t}$ is the iid error term in which they are assumed to be normally distributed and independent with each other. m is the highest category of number of daily leisure trips made by the respondents.

Theoretically, the leisure activity participation in a given t is not only influenced by the leisure activity participation on the previous day t-1, but also by the leisure activity participation from day 0 to day t-2. One alternative to treat the previous days' outcomes as explanatory variables is by using lagged effects, $X_{i,t} = f(y_{i,t\text{-}1}, y_{i,t\text{-}2}, \ldots)$, and to estimate a static panel version model. Such lagged effect variables are defined by the researcher and they can be the number of leisure trips made in the previous week or in the previous weekend, the number of days that the respondent has not made leisure trips since the last day when the respondent conducted leisure activities, or many more possibilities. Cherchi and Cirillo (2014) is the example of a previous study that used lagged effect variables in discrete choice models. However, by doing so, the probability of having n leisure activities on day t is then not only conditional on the probability on day $t-1$, but also the probability on days $t-2$, $t-3$ etc. The consistent estimators given such a time serial correlation in the family of the ordered Probit model is not tractable due to the well-known initial condition problem (Anderson and Hsiao 1982), especially when the time period is not very long, which is 14 days in this case. Meanwhile, from a Markov chain perspective, it is still valid to assume the number of leisure trips on day t is only conditional on that number on day $t-1$ since the effects of the number of leisure trips on day $t-2$ to day 1 are all implicitly reflected in the probability function of the observation on day $t-1$. Thus, in this study, a dynamic ordered Probit model with the outcome of y_t, which is dependent only on the previous day's outcome, $y_{t\text{-}1}$, is chosen. The initial condition problem of the model described in Eq. (1) and (2) can be solved by specifying the distributions of the error terms conditional on the initial condition of the model (Wooldridge 2005) as indicated in Eq. (3). In the model, several mixed parameters have been considered to allow the effects of variables $X_{i,t}$ and $y_{i,t-1}$ to vary among individuals. A heteroscedastic variance of mixed parameters is also considered. This heteroscedasticity reveals the different inter-personal variability in different socio-demographic groups. This can be done by specifying the distributions of the mixing parameters as shown in Eq. (3):

$$y*_{i,t} = X_{i,t}(\beta + \xi_i) + y_{i,t-1}(\gamma + \theta_i) + v_i + \varepsilon_{i,t} \quad (3)$$

[from Eq. (1)]where,

$$\begin{cases} v_i \sim Normal(\alpha_0 y_{i,0} + Z_i\alpha_1, \sigma_v^2) \\ \varepsilon_{i,t} \sim Normal(0, 1) \\ \theta_i \sim Normal(0, X^{\gamma}\delta) \\ \xi_i \sim Normal\left(0, X^{\beta}\varphi\right) \end{cases} \quad (3)$$

where $y_{i,0}$ is the number of leisure trips conducted by individual i in day 0 of each period or season. Z_i refers to the vector of individual level explanatory variables, which in this case are the individual i's socio-demographic variables. The random part of v_i denotes as κ_i, thus $\kappa_i \sim$ *Normal* $(0, \sigma_v^2)$. θ_i and ξ_i are random error terms of mixed parameters which are assumed to follow normal distributions with individual specific standard error. X^γ and X^β specify the individual characteristics that influence the standard error of θ_i and ξ_i. δ and φ are the corresponding parameters associated with X^γ and X^β. α_0, α_1 and σ_v are parameters used to specify the distribution of v_i. Table 1 shows the list of variables used in the model, including the descriptive statistics.

The space–time constraints are captured by the time spent on mandatory activities such as out-of-home work and study durations and also various types of work schedule durations (fixed, shift, partial-flexible and full-flexible). Note that the effects of various types of work schedule durations are examined and compared by using Waves 3 and 4 data due to the availability of the data. The effects of in-home mandatory (e.g. teleworking and studying at home) and also in-home maintenance (e.g. doing the laundry, cleaning and taking care of other household members) activities on day-to-day leisure activity participation are included in the separate models. It is expected that the higher the in-home mandatory and maintenance constraints, the lower the number of leisure trips that are conducted by individual i in a given day t. In order to avoid bias of the effect of long distance journeys on leisure activity participation in a given day (e.g. not conducting any leisure activities on day t due to feeling tired caused by the long distance journey in previous day[s]), long distance trips made on the given day by respondent i are totally removed and excluded from the model estimations. An extension from the maximum likelihood estimator (Wooldridge 2005), the maximum simulated likelihood estimator, is used to estimate the mixed parameters and heteroscedasticity. The likelihood function of observing a series of leisure trip participation for individual i can be expressed as:

$$L_i = \int\limits_{\Omega_{v_i,\theta_i,\xi_i}} \left[\prod_{Period} \prod_{t=1}^{T} L_{i,t}^{k} f(\kappa_i) f(\xi_i) f(\theta_i)\right] d\kappa_i d\xi_i d\theta_i \tag{4}$$

where $L_{i,t}^k$ is the likelihood of observing respondent i on day t choosing to have *kth* category of number of leisure trips:

$$\begin{aligned} L_{i,t}^k = {} & \phi\left[\mu_k - X_{i,t}(\beta + \xi_i) - y_{i,t-1}(\gamma + \theta_i) - \alpha_0 y_{i,0} - Z_{i\alpha 1} - \kappa_i\right] \\ & - \phi\left[\mu_{k-1} - X_{i,t}(\beta + \xi_i) - y_{i,t-1}(\gamma + \theta_i) - \alpha_0 y_{i,0} - Z_{i\alpha 1} - \kappa_i\right]. \end{aligned} \tag{5}$$

Results and discussion

Descriptive statistics

Table 2 shows the statistics of leisure trips data used in this study as compared to the Swedish National Transport Survey (NTS) in 2011 for Sundbyberg and Solna municipalities in which the respondents resided. It can be seen that the number of leisure trips per person per day was substantially higher in the NTS 2011 data than in this study. It is suspected that fatigue may contribute to a lower number of leisure trips made by respondents per day due to under-reported trips. An increase in subsequent waves of the survey also increased levels of trip under-reporting (Meurs et al. 1989).

Table 1 List of variables included in the models and its descriptive statistics

	Variable/mixed variable	Category	Descriptions	All waves (N = 3072) Mean (SD)	Wave 1 (N = 802) Mean (SD)	Wave 2 (N = 854) Mean (SD)	Wave 3 (N = 812) Mean (SD)	Wave 4 (N = 604) Mean (SD)
$y_{i,t}$	N_leisure	Count	Number of leisure activities conducted by individual *i* on day *t*	0.68 (0.85)	0.64 (0.83)	0.73 (0.89)	0.66 (0.82)	0.70 (0.85)
$y_{i,t-1}$	N_leisure_prev	Count	Number of leisure activities conducted by individual *i* in the previous day	0.62 (0.84)	0.59 (0.82)	0.67 (0.89)	0.61 (0.81)	0.61 (0.82)
X^{γ}	Married							
$y_{i,0}$	N_leisure_0	Count	Number of leisure activities conducted by individual *i* on day 0 of the given period	0.61 (0.80)	0.57 (0.71)	0.65 (0.88)	0.55 (0.66)	0.71 (0.94)
	Ooh_workonly_dur	Continuous	Out-of-home working hours on day *t*	2.12 (3.73)	1.89 (3.49)	2.21 (3.80)	2.30 (3.86)	2.08 (3.78)
	X^{β} *associated with*							
	'Ooh_workonly_dur'							
	Distance_CBD							
	High_income							
	Age21_40							
	Ooh_study_dur	Continuous	Out-of-home studying hours on day *t*	0.39 (1.63)	0.49 (1.78)	0.43 (1.63)	0.31 (1.43)	0.32 (1.64)
$X_{i,t}$	Fixed_dur	Continuous	Out-of-home fixed working hours type on day *t*	NA	NA	NA	0.99 (2.76)	0.99 (2.91)
	X^{β} *associated with*							
	'Fixed_dur'							
	Married							
	Shift_dur	Continuous	Out-of-home shift/schedule working hours type on day *t*	NA	NA	NA	0.23 (1.39)	0.41 (1.82)
	X^{β} *associated with*							
	'Shift_dur'							

Table 1 continued

	Variable/mixed variable	Category	Descriptions	All waves (N = 3072) Mean (SD)	Wave 1 (N = 802) Mean (SD)	Wave 2 (N = 854) Mean (SD)	Wave 3 (N = 812) Mean (SD)	Wave 4 (N = 604) Mean (SD)
	Single							
	Part_flexi_dur	Continuous	Out-of-home partial flexible working hours type on day t	NA	NA	NA	0.33 (1.67)	0.24 (1.34)
	Full_flexi_dur	Continuous	Out-of-home full flexible working hours type on day t	NA	NA	NA	0.74 (2.48)	0.44 (1.91)
	Telework_dur	Continuous	Work at home (in hours) on day t	0.01 (0.16)	–	–	0.01 (0.16)	–
	In_home_study_dur	Continuous	Study at home (in hours) on day t	0.02 (0.18)	–	–	0.01 (0.12)	0.02 (0.20)
	Work_period	Count	Number of days working (out-of-home) since the last non-working day	0.69 (1.45)	0.72 (1.53)	0.68 (1.42)	0.75 (1.49)	0.55 (1.31)
	X^{β} *associated with*							
	'Work_period'							
Xi,t	Distance_work							
	Study_period	Count	Number of days studying (out-of-home) since the last non-studying day	0.14 (0.70)	0.18 (0.79)	0.17 (0.78)	0.13 (0.67)	0.07 (0.41)
	UTCI	Continuous	Universal Thermal Climate Index on day t (in degree Celsius)	−1.64 (7.25)	2.10 (5.33)	−7.47 (5.44)	−4.47 (4.34)	5.47 (5.91)
	In_home_maintenance	Dummy	The respondent i is staying at home on day t to do maintenance tasks	1.8 %	1.7 %	2.7 %	1.4 %	1.2 %
			(e.g. laundry, cleaning and taking care of other household members)					

Table 1 continued

	Variable	Category	Descriptions	Categorical variable (%)	Continuous variable	
					Mean	SD
	Male	Dummy	The respondent i is male (reference)	23.9	–	–
	Female	Dummy	The respondent i is female	76.1 7.5	–	–
	Age ≤ 20	Dummy	The respondent i is 20 years old and younger		–	–
	Age21_40	Dummy	The respondent i is between 21 to 40 years old	34.3	–	–
	Age41_65	Dummy	The respondent i is between 41 to 65 years old (reference)	37.3	–	–
Z_i	Age > 65	Dummy	The respondent i is older than 65 years old	20.9	–	–
	Low_income	Dummy	The respondent i has gross monthly income less than 15,000 SEK	16.4	–	–
	Middle_income	Dummy	The respondent i has gross monthly income between	47.7	–	–
			15,000–54,999 SEK (reference)		–	–
	High_income	Dummy	The respondent i has gross monthly income more than 55,000 SEK	35.7	–	–
	Main_sample	Dummy	The respondent i is a main sample	79.1	–	–
	Control_sample	Dummy	The respondent i is a control sample (reference)	20.9	–	–
	Car_ownership	Discrete	The respondent i's household has no car	37.3	–	–
			The respondent i's household has a car	53.7	–	–
			The respondent i's household has two cars	7.5	–	–
			The respondent i's household has more than two cars	1.5	–	–
	With_child	Dummy	The respondent i's household has dependent children	50.7	–	–
	Without_child	Dummy	The respondent i's household has no dependent children (reference)	49.3	–	–
	Single	Dummy	The respondent i is single	14.9	–	–
Z_i	Married	Dummy	The respondent i is married	43.3	–	–
	Live_wt_others	Dummy	The respondent i is living with others (e.g. partner/relatives/friends/others)	28.4	–	–
	Other_status	Dummy	The respondent i is living independently (e.g. divorced or widowed) (reference)	13.4	–	–
	hh_size	Count	Total number of household members in the respondent i's household	–	2.42	1.13
	Distance_CBD	Continuous	The respondent i's home distance from Stockholm City Center (in kilometres)	–	7.26	1.40

Table 1 continued

Variable	Category	Descriptions	Categorical variable (%)	Continuous variable	
				Mean	SD
Distance_work	Continuous	The respondent i's home distance from work or study place (in kilometres)	–	7.88	5.71
Weekend	Dummy	Day t is weekend	26.1	–	–
Weekday	Dummy	Day t is weekday (reference)	73.8	–	–

SD means standard deviation, value in () is standard deviation, 'NA' means data is not available, '–' means no data in the given category for count or continuous variable

Variability analysis

A two-way within-subjects analysis of variance (ANOVA) design was conducted to assess the effects of seasons (waves) and time-scale (weekends and weekdays) on number of leisure trips as well as the between-person variability.

ANOVA analysis, based on the Huynh–Feldt Epsilon, reveals that the main effect of number of leisure trips conducted in different seasons was statistically significant: F(2.794, 184.391) = 4.020, $p = 0.01$, partial $\eta^2 = 0.06$. The main effect of type of time-scale was also statistically significant: F(1, 66) = 66.084, $p < 0.001$, partial $\eta^2 = 0.50$. However, the interaction effect between number of leisure trips in different seasons and time-scale types was not statistically significant: F(2.758, 182) = 0.593, $p = 0.61$, partial $\eta^2 = 0.01$. These imply that seasons (waves) and time-scale (weekends and weekdays) significantly influenced the number of leisure trips conducted by the respondents. However, in general, the patterns of leisure trips are similar between weekends and weekdays in each season. Moreover, the test of between-subjects effects was statistically significant: F(1, 66) = 145.518, $p < 0.001$, partial $\eta^2 = 0.688$.

Based on the variability analysis using the Pas (1987) method, more than 94 % of the total variability in the number of leisure trips is due to inter-personal variability while intra-personal variability contributes only about 4–5 % of the total variability. Both analyses yield the importance of considering individuals' heterogeneity in the model structure due to higher inter-personal variability than intra-personal variability.

Model results

To examine day-to-day variation in leisure activity participation given work and study durations including weather conditions, four specific models (14 days of observation each) and a pooled model (56 days of observation) are estimated and compared. Three estimations are conducted by using the same model structure. The first estimation does not include the various types of working schedule durations (fixed, shift, partial-flexible and full-flexible) as time variant variables but considers all out-of-home and in-home

Table 2 Leisure trip statistics

Descriptions	Panel survey data used in this study					NTS 2011	
	All waves (All seasons)	Wave 1 (Autumn)	Wave 2 (Winter)	Wave 3 (Spring)	Wave 4 (Summer)	Sundbyberg	Solna
No. of person	67	67	67	67	67	21	42
No. of observations (day)	56	14	14	14	14	1	1
Total number of trips	6616	1755	1837	1629	1395	123	183
Number of leisure trips	2808	735	787	745	541	36	68
Percentage of leisure trips[a] (%)	42.4	41.9	42.8	45.7	38.8	29.3	37.2
Leisure trips/person/day	0.75	0.78	0.84	0.79	0.58	1.71	1.62

'NTS' means Swedish National Transport Survey

[a] Percentage of leisure trips calculated over the total number of trips made

constraints. However, the results show that all the in-home constraints are insignificant regardless of any seasons due to the data issues. Therefore, the second estimation includes only out-of-home mandatory activities (out-of-home work and study durations). While the third estimation includes various types of working schedule durations and only being examined and compared between spring (Wave 3) and summer (Wave 4) seasons due to the unavailability of the working schedule type's data in Waves 1 and 2. The second and third estimation results are shown in Tables 3 and 4, respectively. Note that only the significant coefficients are shown in the tables. The UTCI variables are included only in the wave-specific models since it is not relevant to include the variables in a pooled model due to the substantial differences in weather characteristics across different seasons, particularly in Stockholm.

All the models can be considered fit with McFadden's rho of in between 0.2 and 0.4 (Louviere et al. 2000; Lee 2013). Thus, the results are interpreted. The effect of the previous day's leisure activity participation $y_{i,t-1}$ was expected to be negative since it is believed that individuals may not conduct leisure activities continuously for several days a week because leisure activity is not similar with maintenance activity (e.g. walking the dog), which needs to be conducted almost continuously. Arentze et al. (2011) argued that leisure activity is a need that may take time to accumulate for the activity to be conducted. The estimation results in Table 3, however, show significantly positive coefficients of $y_{i,t-1}$ in all seasons and the summer period, which indicates that the number of leisure trips conducted by the respondents on a given day is significantly influenced by the previous day's leisure activity participation. This could be because the effects of weather in summer seasons that are much warmer than other seasons can lead to increases in leisure activity participation. In Sweden, longer leisure activity duration in warmer months is mainly due to more leisure activities being conducted and not due to a longer duration per leisure activity (Liu et al. 2014). The result of heteroscedastic variance of mixed parameter (X^{γ}) for the $y_{i,t-1}$ effect in the pooled-model reveals that inter-personal variability for married individuals is significantly larger than non-married individuals for the effect of the previous day's leisure activity participation in all seasons. The coefficient of $y_{i,0}$ is positively significant in all models, indicating that individuals in this study exhibit routine behaviour characterized by repeated decisions of participating in leisure activities that can last up to 14 days, regardless of any seasons.

As expected, the effect of out-of-home work duration is significantly negative in all models, suggesting that the longer the out-of-home work duration, the fewer the number of leisure trips conducted by the respondents due to the less time available to conduct leisure activities. As for the heteroscedasticity, the result shows that inter-personal variability for individuals who live near to Stockholm city center is significantly smaller than individuals who live far from the city center for the effect of out-of-home work duration during winter season. For the same effect in spring, the result reveals that inter-personal variability for high income individuals is significantly larger than other individuals. While in summer, inter-personal variability for adult individuals is slightly larger than other individuals also for the same effect. Although the work period coefficient is not significant in all seasons, the inter-personal variability for individuals who live near to Stockholm city center is significant for the effect of work period in spring season. The effect of out-of-home study duration is also significantly negative, as expected, in all seasons except in winter and summer seasons. This finding is in line with Bhat and Gossen's (2004) study in which less participation took place in out-of-home recreational activities during weekends in February and March (spring) and also in March (spring) and October (autumn) for pure recreational activity participation in San Francisco. In Sweden, particularly in Stockholm, it is common

Table 3 Estimation results of dynamic ordered Probit models with only out-of-home mandatory activities

	With out-of-home mandatory activities									
	All waves (all seasons)		Wave 1 (autumn)		Wave 2 (winter)		Wave 3 (spring)		Wave 4 (summer)	
	Estimates	t value	Estimates	t value	Estimates	t value	Estimates	t value	Estimates	t value
The previous day's leisure activity participation										
$y_{i,t-1}$	0.20	5.65***							0.21	2.58***
Standard deviations										
X^{γ}										
Intercept	0.10	2.48**								
Married	−0.18	−2.41**								
Time variant variables, $X_{i,t}$										
Ooh_workonly_dur	−0.12	−10.39***	−0.14	−5.03***	−0.15	−4.67***	−0.19	−5.55***	−0.19	−4.66***
Standard deviations										
X^{β} associated with										
'Ooh_workonly_dur'										
Intercept					0.25	2.59***	−0.13	−3.16***	0.15	2.92***
Distance_CBD					−0.02	−1.88*				
High_income							0.18	2.97***		
Age21_40									−0.16	−1.87*
Ooh_study_dur	−0.11	−3.84***	−0.13	−2.79***			−0.25	−3.37***		
Work_period										
Standard deviations										
X^{β} associated with										
'Work_period'										
Intercept										
Distance_work							−0.03	−2.00**		
Study_period					−0.17	−1.78*	0.33	2.60***		

Table 3 continued

	With out-of-home mandatory activities									
	All waves (all seasons)		Wave 1 (autumn)		Wave 2 (winter)		Wave 3 (spring)		Wave 4 (summer)	
	Estimates	t value	Estimates	t value	Estimates	t value	Estimates	t value	Estimates	t value
UTCI[a]			0.02	1.94*						
Standard deviations										
X^{β} associated with										
'UTCI'										
Intercept					−0.05	−4.75***				
Time invariant variables, Z_i										
$y_{i,0}$	0.23	6.22***	0.44	3.02***	0.50	5.14***	0.68	3.49***	0.36	3.09***
Female			−0.55	−2.06**						
Age <20	−0.50	−1.66*			−1.13	−2.96***	−1.45	−1.83*		
Age21_40										
Age >65										
Low_income									−0.64	−2.02**
High_income										
Main_sample										
Car_ownership	0.24	2.49**	0.34	2.27**	0.33	2.89***				
With_child										
Single										
Married										
Live_wt_others										
hh_size										
Distance_CBD										
Distance_work	−0.03	−1.86*			−0.03	−1.78*				
Weekend										

Table 3 continued

	With out-of-home mandatory activities									
	All waves (all seasons)		Wave 1 (autumn)		Wave 2 (winter)		Wave 3 (spring)		Wave 4 (summer)	
	Estimates	t value	Estimates	t value	Estimates	t value	Estimates	t value	Estimates	t value
Thresholds										
μ_1										
μ_2	2.02	3.66***	1.73	2.03**	1.55	2.11**	2.09	1.94*	2.12	2.88***
μ_3	2.95	5.33***	2.66	3.11***	2.60	3.51***	3.14	2.90***	3.01	3.22***
μ_4	3.63	6.52***	3.34	3.86***	3.36	4.46***	3.91	3.58***	3.64	3.83***
μ_5	4.53	7.69***	4.17	4.50***	3.96	5.05***				
μ_6	4.67	7.76***			4.20	5.18***				
μ_7	4.88	7.73***								
Standard deviations										
Individual level error term κ_i	0.47	9.73***	0.57	6.41***	0.26	2.30**	0.81	8.15***	0.53	4.86***
iid error term $\varepsilon_{i,t}$	1	Fixed	1	Fixed	1	Fixed	1	Fixed	1	Fixed
Model fit										
Number of observations	2808	735	787	745	541					
Number of individuals	67	67	67	67	61					
Log-likelihood at converge	−2511.52	−647.42	−718.03	−622.69	−459.99					
Log-likelihood at zero	−3682.41	−846.58	−976.44	−962.55	−672.24					
McFadden's rho	0.32	0.24	0.26	0.35	0.32					

a UTCI variable only being included in the wave-specific models

* Significant at level 0.1, ** significant at level 0.05 and *** significant at level 0.001

Table 4 Estimation results of dynamic ordered Probit models with different types of working hours

	With various types of working durations			
	Wave 3 (spring)		Wave 4 (summer)	
	Estimates	t value	Estimates	t value
The previous day's leisure activity participation				
$y_{i,t-1}$			0.23	3.02***
Standard deviations				
X^{γ}				
Time variant variables, $X_{i,t}$				
Ooh_study_dur	−0.24	−3.34***		
Fixed_dur	−0.15	−4.28***	−0.16	−3.20***
Standard deviations				
X^{β} associated with				
'Fixed_dur'				
Intercept			0.19	2.45**
Married			−0.20	−1.96**
Shift_dur	−0.33	−2.84***	−0.24	−3.78***
Standard deviations				
X^{β} associated with				
'Shift_dur'				
Intercept				
Single	0.41	2.22**		
Part_flexi_dur	−0.10	−2.28**	−0.17	−2.89***
Full_flexi_dur	−0.18	−4.59***	−0.11	−2.87***
Work_period				
Standard deviations				
X^{β} associated with				
'Work_period'				
Intercept	−0.21	−1.71*		
Distance_work	0.04	2.72***		
Study_period	0.32	2.60***		
UTCI				
Time invariant variables, Z_i				
$y_{i,0}$	0.63	3.16***	0.33	2.95***
Female				
Age <20				
Age21_40				
Age >65				
Low_income			−0.56	−1.86*
High_income				
Main_sample				
Car_ownership				
With_child	0.66	1.96**		
Single				
Married				

Table 4 continued

	With various types of working durations			
	Wave 3 (spring)		Wave 4 (summer)	
	Estimates	t value	Estimates	t value
Live_wt_others				
hh_size				
Distance_CBD				
Distance_work				
Weekend				
Thresholds				
μ_1				
μ_2	2.32	2.07**	2.21	2.47**
μ_3	3.37	2.99***	3.10	3.44***
μ_4	4.14	3.65***	3.73	4.06***
Standard deviations				
Individual level error term κ_i	0.83	7.59***	0.51	4.97***
iid error term $\varepsilon_{i,t}$	1	Fixed	1	Fixed
Model fit				
Number of observations	745		541	
Number of individuals	67		61	
Log-likelihood at converge	−619.71		−457.68	
Log-likelihood at zero	−1047.39		−698.10	
McFadden's rho	0.41		0.34	

* Significant at level 0.1, ** significant at level 0.05, *** significant at level 0.001

that students are more active and busy with their studies in autumn and spring seasons compared to other seasons due to long summer holidays in between the spring and autumn seasons. Moreover, it is found that in spring, the significant positive coefficient of the study period suggests that a long study period contributes to the accumulation of needs of leisure activity participation that triggers the leisure activity participation. In contrast, the significant negative coefficient of the study period is obtained in winter season indicating that a long study period contributes to less leisure activity participation in this season. Therefore, both results yield that the out-of-home study constraints have larger effects in spring seasons on leisure activity participation than other seasons.

The thermal indicator variable (UTCI) is positively significant in the autumn season only, suggesting that the higher the equivalent ambient temperature (°C) of a reference environment in autumn, the more leisure activities are conducted compared to other seasons. Note that the autumn season in Stockholm, particularly, is normally cloudy and rainy, and thus, a slight increase in the air temperature could encourage individuals to conduct more leisure activities than in other seasons.

The number of car(s) available in the household influences individuals to participate more in leisure activities during the colder months (autumn and winter seasons) than during other seasons. Generally in Sweden, private car share remains stable but is quite high when the temperature is extremely low (around −20 °C) (Liu et al. 2015a). Individuals with low incomes are less likely to conduct leisure trips in the summer than in other seasons. The possible reason is that this group may have a second job during the summer season or work more than the middle and high income groups, in which most people take their long summer holidays. The further the distance from the individual's home to work/study place, the less the individual participates in leisure activities during winter compared to other seasons. This could be the effect of low temperature in winter that may discourage people to participate in such activities.

Table 4 shows the effects of different working schedule durations on leisure activity participation during spring (Wave 3) and summer (Wave 4) seasons. All the models satisfactorily fit with the value of McFadden's rho, being in between 0.2 and 0.4. Thus, the results are interpreted but only focusing on the effects of various working schedule durations and heteroscedasticity, since all other significant variables in this third estimation are similar to the results shown in Table 3 and have already been discussed. As expected, all types of working schedule durations (fixed, shift, partial-flexible and full-flexible) are negatively significant in both seasons, implying that the longer the working durations of all types, the less likely it is for individuals to participate in leisure activities. The highest magnitude was obtained by the shift working duration type in both seasons, implying that individuals who have shift working duration types are most likely to conduct fewer leisure activities in spring and summer seasons than other workers. This is probably due to the shift work type that is normally available in the service field, which provides 24 h services such as operators, public transportation drivers, emergency response teams (e.g. paramedics, firemen) and shop assistants at 24 h retail shops, and thus may lead to different leisure activity participation trends than others. The result of heteroscedastic variance of mixed parameter for the shift work type effect in spring season reveals that inter-personal variability for single household individuals is significant. It is important to note here that, in this model, the effects of the night shift are not captured. Moreover, in the partial- and full-flexible working duration types, the magnitudes are slightly different in spring and in the summer season, while for the fixed working duration type the effects are similar in both seasons. In summer, individuals who have fixed and partial-flexible working schedules have a similar effect on day-to-day leisure activity participation. The plausible reason is that the working durations between these two types of working schedules may not be substantially different. For example, individuals who have partial-flexible working schedule types may still spend 8 h working although they arrive a little bit later than individuals who have fixed working schedule types (e.g. from 9 a.m. to 5 p.m.) due to their flexibility in time. As for the heteroscedasticity, the result shows that inter-personal variability for married individuals is slightly larger in summer season than non-married individuals for the effect of fixed working schedule type. In spring, inter-personal variability for the effect of work period is significantly smaller for individuals who live near to their work place than other individuals.

Conclusion and further directions of the study

This paper examines the effects of both out-of-home and in-home constraints that underlie an individual's decision to participate in day-to-day leisure activities in different seasons by incorporating the thermal indicator (UTCI) in the model estimations. The paper also explores the effects of various types of working schedule durations (e.g. fixed, shift, partial- and full-flexible) on an individual's day-to-day leisure activity participation. The paper also examines the heteroscedasticity for several mixed parameters that reveals the different inter-personal variability in different socio-demographic groups. This is realised by using 56-day travel diary survey data conducted in Stockholm, Sweden, within four different periods, i.e. October 2013, December 2013, March 2014, and May–June 2014. Dynamic ordered Probit models were used to analyse the decision making processes that incorporate the space–time constraints, state-dependence, habit persistence and thermal indicators on leisure activity participation in different seasons.

As expected, the longer the time spent for work, the less the leisure activity participation conducted by individuals, regardless of any seasons. It is found that individuals in this study exhibit routine behaviour characterized by repeated decisions in participating in leisure activities that can last up to 14 days, regardless of any seasons. This may be due to the Swedish lifestyle that tries to maintain work and life balances for people's well-being. The previous day's effects exhibited in the summer season only, implying that individuals in this study maintain to participate in leisure activities on a daily basis during the summer season, which may be due to warmer weather condition compared to other seasons. Liu et al. (2014) found that a one unit increase in monthly temperature would increase number of leisure trips of non-commuters in central Sweden (including Stockholm) overall by 0.02 trips.

The UTCI is significant only in the autumn season. As mentioned previously, the weather in Stockholm during the autumn season is normally rainy and cloudy. Therefore, it is expected that the slight increase in temperature during the autumn period would have an impact on individuals' perceived thermal environments (Liu et al. 2015b) and thus affecting their leisure activity participation decisions compared to other seasons. Physiologically Equivalent Temperature (PET), or the thermal conditions that make one consider physiological factors such as heat resistance of clothing and also activity of humans, may also influence leisure activity participation in different seasons. Creemers et al. (2015) found that PET has the highest influence on households' trip motives and mode choices in the Netherlands compared to other thermal indicator types including UTCI. Therefore, subjective weather perceptions and/or thermo-physiological elements could have an impact on individuals' activity-travel patterns, especially on leisure activities, and this is worth researching in the future.

By using the 28-day travel diary data of two periods (Waves 3 and 4), it is found that the individuals who have shift working duration types have the most constraints in participating in leisure activities in both spring and summer seasons due to their tighter time constraints than other types of workers. However, no concrete conclusion can be made based on this finding due to the unavailability of data in autumn and winter seasons and also due to the small sample size used in this study. Thus, it is recommended that detailed investigations on working schedule effects that also include day and night shifts are worth investigating in future by using more comprehensive panel data than in this study. This is important to explore so that all types of workers can participate in leisure activities equally, thus minimising the social exclusion that may have led to growing isolation and depression which affected their well-being. It is recognized that there is a link between transport mobility and well-being (Stanley et al. 2011; Spinney and Scott 2009), in which access and participation in activities can lead to positive psychological well-being (Stanley et al. 2011). Therefore, if there is an opportunity to collect longitudinal panel data on a larger scale than this study, then understanding these would assist transport planners and local transport operators to manage travel demand strategies across different seasons of the year and also to provide efficient transportation systems for all types of people that may affect their well-being in a longer-term perspective. The effects of seasonal variation on mandatory, maintenance and leisure activity-travel patterns are also some of the main interests that will be investigated in the future.

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