

Measuring the impacts of weather variability on home-based trip chaining behaviour: a focus on spatial heterogeneity

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Published online: 14 May 2015
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Abstract Using the 2011 Swedish national travel survey data, this paper explores the influence of weather characteristics on individuals' home-based trip chaining complexity. A series of panel mixed ordered Probit models are estimated to examine the influence of individual/household social demographics, land use characteristics, and weather characteristics on individuals' home-based trip chaining complexity. A thermal index, the universal thermal climate index (UTCI), is used in this study instead of using directly measured weather variables in order to better approximate the effects of the thermal environment. The effects of UTCI are segmented into different seasons to account for the seasonal difference of UTCI effects. Moreover, a spatial expansion method is applied to allow the impacts of UTCI to vary across geographical locations, as individuals in different regions have different weather/climate adaptations. The effects of weather are examined in subsistence, routine, and discretionary trip chains. The results reveal that the 'ground covered with snow' condition is the most influential factor on the number of trips chained per trip chain among all other weather factors. The variation of UTCI significantly influences trip chaining complexity in autumn but not in spring and winter. The routine trip chains are found to be most elastic towards the variation of UTCI. The marginal effects of UTCI on the expected number of trips per routine trip chain have considerable spatial variations, while these spatial trends of UTCI effects are found to be not consistent over seasons.

Keywords Trip chaining complexity · Weather impact · Thermal index · Spatial heterogeneity

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Introduction

Individuals' trip chaining has grown increasingly complex as modern life becomes busier and they become increasingly time-poor (Currie and Delbosc 2011). The growing challenge of fulfilling errands in a limited time budget leads to the growing propensity of chaining more trips in home–home or home–work trip chains, which are defined as a series of trips with the start and end locations both at home or at either home or the workplace, respectively (McGuckin and Nakamoto 2004; Kitamura and Susilo 2006). Trip chaining behaviour also increases dependency on automobiles, leading to higher car usage, and thus to congested traffic and the expansion of urban peak hours (Ye et al. 2007; Habib et al. 2009; Yun et al. 2014). Studies have also uncovered distinct trip chaining behaviour between workers and non-workers (Chu 2004; Bayarma et al. 2007), implying different trip chaining mechanisms between mandatory errands and non-mandatory errands. Moreover, land use serves as an important factor influencing trip chaining behaviour, and its impacts show a bell shape effect. Noland and Thomas (2007) found more complex trip chaining behaviour in lower density environments in the US while Schmöcker et al. (2010), Susilo and Maat (2007), and Dharmowijoyo et al. (2015) found that in extremely dense areas, such as London, Randstad, and Jakarta, higher density is associated with more complex trip chaining.

Among all possible factors that can potentially affect trip chaining behaviour, individual/household characteristics and land use characteristics have been studied most extensively and have been found to have significant impacts. At the same time, the impact of the weather has rarely been examined in previous studies. Several studies have shown that weather significantly influences the daily number of trips travelled (e.g. Sabir 2011; Liu et al. 2014a), which is likely to also influence trip chaining behaviour. In addition, rather than having a constant impact, weather impacts also vary across different geographical locations in terms of various individual-level travel behaviour indicators, e.g. activity duration, number of trips travelled, etc. (Liu et al. 2014b). It is plausible that such heterogeneity is partly due to weather and land use interaction, as a specific weather condition and a specific land use pattern may form a micro environment that affects an individual's travel choices. Additionally, travellers in a specific geographical location may adapt their travel behaviour to the local climate, thus embodying spatial heterogeneity. However, most previous studies have only treated weather and land use as two separate factors and ignored their interaction. Moreover, almost all previous studies have singled out the effects of certain weather indicators, such as temperature and/or wind speed, and explored the relationship between the travel behaviour change and the variation of those singled-out weather indicators. However, it is well known that different weather indicators always co-occur and they are likely to have interrelated effects. For instance, wind in a hot summer may not be considered unpleasant, while wind in a cold winter may be considered very unpleasant. Thus, in this study, a meteorological thermal index, the universal thermal climate index (UTCI), is constructed by using directly measured weather indicators, air temperature, wind speed, and relative humidity. The use of a meteorological thermal index provides a better approximation of the way the human body perceives weather conditions than the use of directly measured weather indicators. In terms of travel, existing literature has shown that the use of a meteorological thermal index can better explain an individual's attendances of urban recreational sites (e.g. Nikolopoulou and Lykoudis 2007).

Thus, this paper aims to systematically explore the roles of individual social demographics, household characteristics, weather characteristics, and land use characteristics

towards an individual's trip chaining behaviour, with an emphasis on the impacts of weather variability and spatial heterogeneity. The study uses one-day travel diary data from the Swedish national travel survey in 2011 and the weather record from the Swedish Meteorological and Hydrological Institute (SMHI). UTCI is constructed to approximate the individual's thermal perception. The panel mixed ordered Probit model is chosen to model the number of trips per trip chain so that the fact that several trip chains were made by the same individual can be taken into account. The spatial expansion method is also applied to UTCI variables so that the UTCI impacts can have heterogeneity over space. The outcome of this study helps us not only to understand the cause of the variation in trip chaining, especially the role of weather which has rarely been studied before, but also to reveal how weather impacts can potentially vary in different geographical locations. The findings would also provide several insights on the potential direction in which trip chaining patterns could be influenced.

The next section offers a brief review of the existing knowledge of determinants that affect trip chaining behaviour. This is then followed by a description of the data that is used in this study. The model structure is then proposed and is followed by the model's estimation and a discussion section. The paper ends with a conclusion section.

Weather impacts on trip chaining behaviour

Although a body of studies that has examined weather impacts on travel behaviour has recently emerged (e.g. Winters et al. 2007; Koetse and Rietveld 2009; Böcker et al. 2013a, b; Dijst et al. 2013), the amount of existing literature exploring weather impacts on trip chaining behaviour is still relatively limited. Thus, the impact of the weather on trip chaining complexity is still largely unclear. However, some evidence has revealed that the weather has significant impacts on the number of trips and number of trip chains travelled per day. Liu et al. (2014b) found substantial seasonal variation of the number of trips travelled, more cycling trips but fewer walks and public transport trips in summer compared to winter. Such a seasonal variation, although it was affected by several non-weather factors such as summer vacations, was found to be partially due to changes of weather conditions. In addition, trip scheduling and the perceived stress underlying activity participation decisions were found to be significantly affected by rain (Chen and Mahmassani 2015). For trip chains associated with mandatory activities, this finding may indicate an increased likelihood of trip chaining under rainy conditions, while for trip chains associated with discretionary activities, this finding implies fewer activities scheduled on a given rainy day.

Several studies have examined the role of different weather parameters and found that the impacts vary across different travel modes and different trip purposes. Liu et al. (2014b) found an increasing trend in both the number of trip chains and total number of trips per individual per day as temperature rises, especially for non-commuters, while Saneinejad et al. (2012) showed no significant difference in the commuter trip rate in different temperature conditions. A rise in temperature corresponded to a decrease in daily trips of motorised modes, but an increase of daily cycling trips (Sabir 2011) and daily public bus trips (Arana et al. 2014). Madre et al. (2007) showed that adverse weather, specifically snow, rain, and strong wind, is one of the main reasons for trip cancellation. By counting traffic flows, Keay and Simmonds (2005) found a significant decrease in car flows on rainy days compared to those on sunny days. Since non-motorised modes of transport are less protected against adverse weather, pedestrians and cyclists are believed to be more

strongly affected by the weather than other traveller groups. Several studies have shown that the number of cycling trips decreases significantly in strong wind and heavy rain conditions, especially for recreational purposes (e.g. Bergström and Magnusson 2003; Winters et al. 2007; Gebhart and Noland 2014). On the other hand, although private cars provide protection against adverse weather conditions, drivers are also exposed to dangerous and congested road conditions and drive slowly, thus suffering longer travel times than in normal weather conditions.

It is clear from the research presented above that weather conditions significantly influence the number of trips travelled or activities scheduled in different magnitudes depending on different trip purposes and travel modes. However, it is still largely unknown how the variation of trip chaining behaviour is affected by the variation of weather, as none of the above-mentioned studies took into account trip chain occurrence and composition. An increase in the number of trips does not necessarily imply a longer trip distance or a longer travel time or a more complex trip chaining behaviour. As the weather impacts on the number of trips vary across trip purposes, it is plausible that the weather impacts on trip chaining behaviour may also vary across different trip purposes. While previous studies often model weather and land use as separate factors affecting the number of trips and travel distance, it is important to understand how the weather and land use factors interact with each other in terms of trip chaining complexity, as both are the built environment factors that define a specific travel environment which is perceived by the travellers. These are the purposes of this paper. The next section will describe the data used in the study and then the modelling method that will be used in analysing trip chaining behaviour.

Travel survey and weather datasets and variation of trip chaining in different weather conditions

The travel survey and weather datasets

The 2011 Swedish national transport survey (NTS) dataset provided the trip and individual/household information for this paper. The NTS data is an individual-level cross-sectional dataset that collects respondents' daily trips in all Swedish municipalities from all days of the week and from every week of the year. A combined stratified sampling method was carried out based on gender, age, and municipality. The interviewer collected travel-related information on each trip, such as travel mode, travel purpose, departure and arrival locations, departure and arrival times, as well as individual and household socio-demographic information (Algers 2001). In NTS, each trip corresponds to a destination/visit where a certain errand is achieved, such as picking up children, visiting friends, etc. Note that changing modes is not defined as an errand. All the trips a respondent took in the given observed day were recorded. The travel survey consists of 8757 respondents, of which 49.4 % are male, 18.2 % are younger than 25, 19.9 % are older than 65, 17.9 % are single, 15.1 % are partnered with young children, 22.8 % have a household annual income less than 150,000 SEK, and 12.1 % do not have cars in their family. Municipality-level land use information (Swedish Statistics Database 2014) was also matched to the departure municipality of each trip. This large-scale cross-sectional travel survey provides a comprehensive set of data on travel behaviour for the whole of Sweden. The trip-based travel data was then aggregated into trip chain level, where only the home and workplace are defined as the anchored points of a trip chain. The trip chains that were not based on home–

work trip chains were not included in this analysis, as the behaviour of those trip chains may be quite different from the trip chains based on home–work chains.

The weather information comes from SMHI. Several weather parameters, including average, minimum and maximum temperatures (only average temperature is used in this paper), precipitation amount (mm), visibility (visible distance measured in km), wind speed (km/h), relative humidity, snow depth, and air pressure, are collected at 3 h intervals every day SMHI (2012). Weather information was assigned to each trip by matching the weather data from the weather station nearest to the departure point of the trip and selecting the weather variable with the measured time closest to the departure time. When trip information was aggregated into the trip chain level, the weather variables of the first trip in the trip chain were used to represent the weather condition of the whole trip chain. Such a procedure assumes that each individual would base his or her travel decision on the weather condition that prevailed at the place of departure and time of the trip chain. Although individuals may make their travel decisions based on other weather information, such as weather forecasts, especially for some planned travel, this assumption is still plausible as the weather at the departure time may still lead to last-minute changes in individuals' travel plans (Cools and Creemers 2013). It is worth noting that the average distance from each weather station to its corresponding municipality centre is around 10 km. One should be aware of the limitation of combining two datasets: the distances from the nearest weather station to the respondent's place of departure vary for each trip, raising questions about the degree to which weather conditions measured at the weather station are the same as those at the place of departure. However, it is worth noting that these distances are shorter for large municipalities such as Stockholm and Gothenburg where more data were collected, while for municipalities with only a few residences, such as some in northern Sweden, that distance is greater. In addition, since the trip-based data were aggregated into the trip chain level, the effect of these uncertainties was reduced at least for short distance trips.

The variation of the trip chaining measure on different trip purposes under different seasons and weather conditions

As discussed before, the impacts of weather may potentially differ in trip chains with different trip purposes. It would be beneficial to provide how the number of trips per trip chain is distributed under different seasons and weather conditions by different trip chain purposes. The main purpose of a trip chain was directly answered by each respondent during the survey in response to the question, "What was the main purpose with the whole trip?" Three types of main trip purposes are categorised (Primerano et al. 2008):

- *Subsistence* defined as the main purpose of a trip chain being for work or school. Such trips usually have a frequency location and timing that are fixed. And they are essential for providing the financial means for pursuing maintenance and discretionary activities.
- *Routine* defined as the main purpose of a trip chain being compulsory to some extent. The destination is usually at a regular base, but with certain characteristics that can vary (time, location, etc.). Examples are: child care, certain shopping types (weekly/grocery), banking, pick-up/drop-off of children, and personal business.
- *Discretionary* defined as the main purpose of a trip chain being optional. The destination usually varies substantially regarding location and time. Examples are: sports, eating out, visiting friends, irregular shopping, etc.

It is worth noting that a trip chain with a main purpose may consist of trips with more than one trip purpose. For example, a subsistence trip chain from home to work may consist of one routine trip/visit (dropping off a child at school) and one subsistence trip/visit (going to a workplace). In this paper, trip chains were categorised based on the main purposes discussed above. Thus an increase in the number of trips per subsistence trip chain may be due to routine/discretionary trips, such as dropping off children at kindergarten, being chained in the subsistence trip chain. The descriptive analysis of trip chaining in terms of the main purposes of the trip chain is shown in Table 1.

As shown in Table 1, there is no substantial seasonal variation of the number of trips per subsistence trip chain. Results from a one-way ANOVA show that the mean values of the number of trips per subsistence trip chain are not significantly different for all possible pairs of season combinations at a 5 % significance level. This indicates that patterns of subsistence trip chains are generally stable across seasons, even given the fact that there are fewer subsistence trip chains in summer as fewer individuals work in summer. The number of trips per routine trip chain in summer is on average 0.30 fewer (significant at 1 % level) than that in spring, which is the highest of all seasons. This is likely due to the long summer holiday when schools and some services are closed, thus relaxing some time constraints and pressures of the travellers and subsequently reducing the number of trips attached to the routine trip chains. The number of trips in a discretionary trip chain is fewer in summer and autumn than that in spring and winter (significant at 1 % level), but the difference is smaller than that in routine trip chains. Precipitation and bad visibility show little influence on the variation of the number of trips per subsistence trip chain. The number of trips per routine trip chain tends to be 0.1 trips fewer (significant at 5 % level) in rain conditions compared to in conditions with no precipitation. However, leisure trip chaining is not affected by precipitation. It is worth noting that snow significantly affects trip chaining behaviour. The subsistence trip chains under snow conditions have on average 0.4 trips more than those without snow. That number for routine and discretionary

Table 1 Average number of trips per trip chain per individual on a given day, by season and weather conditions

	Subsistence trip chain	Routine trip chain	Discretionary trip chain
<i>Season</i>			
Spring	1.258 (0.610)	2.270 (0.780)	1.873 (0.905)
Summer	1.226 (0.581)	1.966 (0.814)	1.751 (0.895)
Autumn	1.283 (0.670)	2.075 (0.874)	1.757 (0.901)
Winter	1.275 (0.654)	2.227 (0.754)	1.828 (0.868)
<i>Weather conditions</i>			
No precipitation	1.258 (0.630)	2.150 (0.822)	1.805 (0.883)
Drizzle: precipitation < 1 mm	1.268 (0.634)	2.143 (0.838)	1.771 (0.928)
Rain: precipitation \geq 1 mm	1.287 (0.660)	2.058 (0.771)	1.800 (0.905)
Visible distance up to 1 km	1.270 (0.634)	2.132 (0.817)	1.791 (0.884)
Visible distance over 1 km	1.251 (0.640)	2.146 (0.823)	1.850 (0.931)
Ground without snow	1.261 (0.632)	2.130 (0.813)	1.800 (0.892)
Ground with snow	1.657 (0.845)	2.438 (1.052)	2.088 (1.047)

Note standard deviation in parentheses

trip chains is around 0.3 and 0.28, respectively. Similar trends are further found in both urban and rural areas. Presumably, snow-related activities are likely being chained in the trip chains. Moreover, since the “indirect cost” of travel increases due to snow (with bus delays, the inconvenience of walking and cycling, etc.), chaining errands in snow-covered ground situations is more attractive than separating errands into different trip chains. The descriptive results above clearly show the correlation between weather and trip chaining behaviour. However, such correlations vary across trip chains with different main purposes and the reasons and interactions that underlie such correlations are far from straightforward. Thus, a multivariate analysis was conducted, the detailed procedure of which is described in the following sections.

Model specification

Similarly to previous studies (Noland and Thomas 2007; Schmöcker et al. 2010), a multivariate model was chosen to examine the impacts of socio-economic factors, land use patterns, and weather impacts. The dependent variable is the number of trips per trip chain. The number of trips per trip chain is equal to the number of visits (stops) per trip chain, which was used as the dependent variable in some previous studies, plus one. The distributions of the number of trips per subsistence/routine/discretionary trip chain are presented in Table 2.

As shown in Table 2, most subsistence trip chains (81 %) are simple home–work/work–home trip chains. 85 % of routine trip chains contain more than one trip, meaning trip chaining behaviour, while that number for discretionary trip chains is 58 %. It is also worth

Table 2 Frequencies of the number of trips per trip chain

Number of trips	Subsistence trip chain		Routine trip chain		Discretionary trip chain	
	Frequency	Percentage	Frequency	Percentage	Frequency	Percentage
1	5799	81.1	554	15.1	2238	42.1
2	979	13.7	2412	65.9	2287	43.0
3	259	3.6	442	12.1	503	9.5
4	71	1.0	151	4.1	177	3.3
5	24	0.3	60	1.6	64	1.2
6	10	0.1	20	0.5	21	0.4
7	4	0.1	13	0.4	14	0.3
8	5	0.1	6	0.2	7	0.1
9	1	0.0	2	0.1	5	0.1
10	0	0.0	1	0.0	0	0.0
11	0	0.0	0	0.0	0	0.0
12	1	0.0	0	0.0	0	0.0
13	1	0.0	0	0.0	0	0.0
14	0	0.0	0	0.0	0	0.0
15	0	0.0	0	0.0	1	0.0
Total	7154	100	3661	100	5317	100

noting that the percentages for more than four trips per chain in all three categories are very small—0.6 % for subsistence trip chains, 2.8 % for routine trip chains, and 2.1 % for discretionary trip chains. Poisson family models (Poisson/Negative binomial/zero inflated Negative binomial models) or an ordered Probit model are possible model candidates for modelling those count variables. Poisson family models and an ordered Probit model were all tested and compared, while trip chains with more than four trips were categorised into one category in an ordered Probit model. In all three types of trip chains, the ordered Probit model showed a better fit. Thus, the ordered Probit model was chosen for the multivariate modelling. Compared with the Poisson family models, the ordered Probit model has the advantage of eliminating the impact of outliers (e.g. one trip chain had more than twenty trips recorded) (Noland and Thomas 2007; Kim and Susilo 2013). However, the drawback of the ordered Probit model is that the categories being aggregated are treated identically, and thus no further inference can be derived from the ordered Probit model about the difference between the categories being aggregated, e.g. the difference between six trips per chain and seven trips per chain.

In addition, the fact that several trip chains were made by the same individual on a given day was often ignored in previous studies. The variation of the number of trips per trip chain due to unobserved attributes at the individual level is likely to be substantial. Thus, in this paper a mixed ordered Probit model with panel data is chosen to account for the heterogeneity at the individual level. The model has the following structure:

$$y_{ik}^* = X_{ik}\beta + \varepsilon_i + \varepsilon_{ik} \tag{1}$$

where i refers to the individual index, k refers to the trip chain index, y_{ik}^* refers to the latent variable associated with the observed number of trips per trip chain y_{ik} for trip chain k made by individual i . β is the vector of coefficients of the explanatory variable sets X_{ik} , ε_i is the random error term at the individual level, and ε_{ik} is the random error term at the trip chain level. All the random error terms are assumed to be normally distributed and independent from each other. The individual-level random error term captures the unobserved heterogeneity at the individual level after controlling for the observed individual/household characteristics and municipality land use characteristics.

The latent variable y_{ik}^* is associated with the observed number of trips per trip chain y_{ijk} with the following formula:

$$y_{ik} = \begin{cases} 1, & \text{if } -\infty < y_{ik}^* < \mu_1 \\ 2, & \text{if } \mu_1 < y_{ik}^* < \mu_2 \\ \dots & \\ m, & \text{if } \mu_{m-1} < y_{ik}^* < +\infty \end{cases} \tag{2}$$

where μ_m is the threshold to be estimated. The product of the probabilities of all observations from individual i is then:

$$L_i = \prod_{k=1}^K L_{ik} = \int_{-\infty}^{+\infty} \prod_{k=1}^{K_i} (\Phi(\mu_n - X_{ik}\beta - \varepsilon_i) - \Phi(\mu_{n-1} - X_{ik}\beta - \varepsilon_i)) f(\varepsilon_i) d\varepsilon_i \tag{3}$$

where K_i denotes the number of observations from individual i . $f(\varepsilon_i)$ is the probability density function of random error terms ε_i . Φ denotes the standard normal cumulative density function. All random error terms are assumed to be normally distributed and independent of each other, $f(\varepsilon_i) = \phi(0, \sigma_i)$, where ϕ denotes the standard normal density

function, σ_i is the standard deviation of the individual specific error terms to be estimated. The likelihood function is then the product of $P(y_{ik} = n|X_{ik})$ for observed n of each observation. In this paper, $m = 1 \dots 5$, which represents the number of trip(s) per trip chain; from one trip (no extra stop within the given journey, a simple trip from origin to destination) to five trips or more (having four or more extra stops within the given journey).

Similarly to other mixed models with panel data, such as the panel mixed logit model, the one-dimensional integral in Eq. (3) can be handled by either numerical integration or simulation techniques. In this paper, 10-point Hermite–Gauss quadrature was used to approximate this integral. Due to the identification problem, the intercept was fixed at zero while the standard deviation of the trip chain level error term was fixed at one. The model was run in a routine programmed in the Matlab environment.

Various individual/household social demographic variables, weather characteristic variables, and land use characteristic variables were included in the explanatory variable set, as they were found from the literature review to have significant impacts on trip chain behaviour.

The universal thermal climate index (UTCI)

In a departure from most previous studies, which directly used weather variables such as temperature, relative humidity, etc., this study applied a thermal comfort variable constructed from measured weather variables. Intuitively, the use of a thermal comfort variable is more appreciated, as different weather parameters contribute to the thermal environment which is actually perceived by each individual. Only a few studies have applied weather constructs instead of directly using measured weather parameters (Böcker et al. 2013b). Among several possible candidates for the thermal comfort variable, physiologically equivalent temperature (PET) and the Universal Thermal Climate Index (UTCI) were found suitable for application in travel behaviour research (Creemers et al. 2014). Thus, in this paper UTCI values were calculated. UTCI is expressed as an equivalent ambient temperature ($^{\circ}\text{C}$) of a reference environment that provides the same physiological response of a reference person as the actual environment (Blazejczyk et al. 2012). In comparison to directly measured weather parameters, the use of a thermal indicator has the advantage of incorporating the knowledge in biometeorology and can avoid the interrelated effects of measured weather parameters. An available programme for calculating UTCI values can be found on the UTCI official website (UTCI 2014). Several methodologies were applied to control for this heterogeneity to help interpret the UTCI effects, including a seasonal segmentation to control for the seasonal difference and a spatial expansion method to control for the potential spatial heterogeneity of UTCI perception. Different UTCI values can be categorised in terms of different thermal stress (UTCI 2014), as shown in Table 3 below.

UTCI values vary from -46.77 to 26.09 $^{\circ}\text{C}$ for all recorded trip chains in the 2011 NTS. This suggests that only cold stress was found in the sample, according to Table 3. UTCI values were first segmented into different intervals according to the categories in Table 3 in order to test whether UTCI values had a bell shape effect. The results suggested a linear assumption of the effect of UTCI was valid. The coefficients of UTCI were then segmented into different seasons to capture potentially different impacts of UTCI variations in different seasons, as the clothing type of each individual can be different in different seasons. The detailed explanatory variable sets are shown in Table 4.

Previous studies (e.g. Liu et al. 2014a) showed that weather had different impacts on activity–travel patterns depending on activity purposes, as work activities are less affected

Table 3 Universal thermal climate index (UTCI) thermal stress category

UTCI range (°C)	Stress category
(+46, +∞)	Extreme heat stress
(+38, +46]	Very strong heat stress
(+32, +38]	Strong heat stress
(+26, +32]	Moderate heat stress
(+9, +26]	No thermal stress
(+9, 0]	Slight cold stress
(0, -13]	Moderate cold stress
(-13, -27]	Strong cold stress
(-27, -40]	Very strong cold stress
(-∞, -40]	Extreme cold stress

Table 4 Explanatory variables used in the models

Explanatory variables	Description
<i>Individual socio-demographics</i>	
Gender (D)	Male (reference) Female
Age (D)	Age under 25 years old Age from 26 to 40 years old (reference) Age from 41 to 64 years old Age over 65 years old ^a
Physical disability (D)	Respondent has physical disability
<i>Household socio-demographics</i>	
Household size (D)	Household member is no more than 3 (reference) Household member is more than 3
Household type (D)	Single family and has no child Single family and has one or more children while the youngest child is between 0 and 6 years old Single family and has one or more children while the youngest child is between 7 and 18 years old Partnered family and has no child (reference) Partnered family and has one or more children while the youngest child is between 0 and 6 years old Partnered family and has one or more children while the youngest child is between 7–18 years old
Household Income (D)	Household annual income is lower than 150,000 SEK (reference) Household annual income is between 150,000 and 400,000 SEK Household annual income is higher than 400,000 SEK
Car ownership (C)	Number of cars in household
<i>Trip chain characteristics</i>	
Trip chain departure time (D)	The trip chain departure time at 7:00–9:00 morning peak The trip chain departure time at 17:00–19:00 afternoon peak

Table 4 continued

Explanatory variables	Description
Main travel mode of the trip chain (D)	Walk and cycling (reference) Private car Public transport
Average link speed (C) (trip chain distance/travel time)	Average link speed for private car mode Average link speed for public transport mode
<i>Weather characteristics</i>	
Universal thermal climate index (C)	UTCI in spring ^b UTCI in summer UTCI in autumn UTCI in winter
Precipitation (D)	No precipitation (reference) Drizzle: precipitation < 1 mm Rain: precipitation ≥ 1 mm
Visibility (D)	Visible distance up to 1 km Visible distance over 1 km (reference)
Snow covered (D)	Ground without snow covered (reference) Ground with snow covered
<i>Land use characteristics</i>	
Population density (C)	Population density of the municipality (100 residences per km ²)
Commuters in (C)	The number of gainfully employed who live in other municipalities while working at the given municipality (per 100,000 employees)
Commuters out (C)	The number of gainfully employed who live at the given municipality while working at other municipalities (per 100,000 employees)
Car possession (C)	The number of cars registered per 1000 residences in the municipality

Note C in the parenthesis denotes it is a continuous variable while D in the parenthesis denotes it is a dummy variable

^a 65 is the official retirement age of Swedish people

^b Spring includes March, April and May. Summer includes June, July and August. Autumn includes September, October and November. Winter includes December, January and February

while non-work activities are more influenced by the weather changes. Thus, in order to better understand the influences of weather on trip chaining behaviour, three models were established based on the classification of the main purpose of the trip chain, which are: subsistence, routine, and discretionary. The model estimation results are shown in Table 5.

Model estimation results

Variable effects

As shown in Table 5, females tend to chain more trips in subsistence and routine trip chains than male travellers. This echoes a previous study (McGuckin and Murakami 1999)

Table 5 Estimation results for subsistence/routine/discretionary trip chains

Explanatory variables	Subsistence trip chains		Routine trip chains		Discretionary trip chains	
	Estimates	T value	Estimates	T value	Estimates	T value
Intercept	0	fixed	0	fixed	0	fixed
<i>Individual socio-demographics</i>						
Male	Ref	–	Ref	–	Ref	–
Female	0.108	1.900	0.198	2.795	0.076	1.423
Age < 25	–0.669	–6.822	–0.128	–0.900	0.172	1.754
Age 26–40	Ref	–	Ref	–	Ref	–
Age 41–64	–0.190	–2.572	–0.108	–0.954	–0.258	–2.991
Age > 65	–0.559	–2.202	–0.298	–2.298	–0.294	–3.035
Physical disability	0.082	0.528	0.180	1.040	–0.010	–0.064
<i>Household characteristics</i>						
Household member > 3	–0.089	–1.080	0.028	0.242	–0.093	–0.993
Single family no child	–0.211	–1.894	0.071	0.665	0.264	3.261
Single family child 0–6 old	0.579	2.382	0.424	1.738	0.429	1.471
Single family child 7–18 old	0.158	1.037	0.385	1.839	0.092	0.571
Partnered family no child	Ref	–	Ref	–	Ref	–
Partnered family child 0–6 old	0.507	4.861	–0.013	–0.085	0.136	1.173
Partnered family child 7–18 old	0.186	1.959	0.040	0.304	0.157	1.505
Low income (<150,000 SEK)	Ref	–	Ref	–	Ref	–
Medium income (150,000 to 400,000 SEK)	–0.037	–0.344	0.295	2.883	0.179	2.268
High income (>400,000 SEK)	0.064	0.790	0.366	3.717	0.284	3.850
Number of cars in household	0.099	2.460	0.006	0.112	–0.121	–3.077
<i>Trip chain characteristics</i>						
Departure at morning peak	–0.310	–5.812	0.184	1.984	–0.198	–2.310
Departure at afternoon peak	–0.099	–1.319	–0.424	–4.838	–0.219	–3.705
Main mode is walk and cycling	Ref	–	Ref	–	Ref	–
Main mode is private car	2.705	22.53	1.577	15.89	2.861	27.90
Main mode is public transport	1.488	11.31	1.213	6.494	2.430	18.54
Average link speed for car mode	–0.050	–54.73	–0.044	–16.18	–0.040	–16.31
Average link speed for public transport mode	–0.053	–9.65	–0.036	–3.937	–0.029	–4.204
<i>Land use characteristics</i>						
Population density	0.010	2.146	–0.002	–0.236	–0.021	–2.711
Commuters in municipality	0.015	0.656	0.064	2.264	0.050	2.322
Commuters out municipality	0.088	1.301	–0.042	–0.528	0.017	0.277
Municipality car ownership	0.027	3.015	0.004	0.409	0.001	0.052
<i>Weather characteristics</i>						
UTCL_spring	0.006	0.991	–0.011	–1.361	0.0002	0.027
UTCL_summer	–0.005	–0.943	–0.029	–5.069	–0.004	–0.861
UTCL_autumn	0.014	1.927	–0.015	–1.718	–0.018	–2.72
UTCL_winter	0.002	0.425	–0.003	–0.415	0.0005	0.092
No rain	Ref	–	Ref	–	Ref	–

Table 5 continued

Explanatory variables	Subsistence trip chains		Routine trip chains		Discretionary trip chains	
	Estimates	T value	Estimates	T value	Estimates	T value
Precipitation < 1 mm	-0.037	-0.581	-0.026	-0.295	-0.046	-0.677
Precipitation ≥ 1 mm	0.062	0.851	-0.178	-1.793	-0.014	-0.174
Visible distance ≤ 1 km	-0.112	-1.863	-0.076	-0.956	0.031	0.478
Ground with snow	1.125	4.889	0.809	3.107	0.787	3.602
<i>Estimated standard error</i>						
Individual level	0.982	18.36	1.274	18.98	1.093	18.10
Trip chain level	1	Fixed	1	Fixed	1	Fixed
<i>Thresholds</i>						
μ_1	2.953	7.291	-1.185	-2.384	0.663	1.643
μ_2	4.209	10.249	2.529	5.050	3.272	7.916
μ_3	5.042	12.089	3.541	6.984	4.220	10.057
μ_4	5.579	13.170	4.254	8.277	4.908	11.520
<i>Model fit</i>						
Number of observations	7154		3661		5317	
Number of individuals	3871		2888		3990	
Log-likelihood at zero	-11186.4		-6265.3		-11243.4	
Log-likelihood at final	-3803.7		-3227.2		-4682.4	
Log-likelihood of model without panel	-3915.2		-3463.0		-4816.0	

Note estimates in the bold values are significant at 10 % level

which found that females tend to make more complex trip chains than males. However, no gender difference can be found in terms of leisure trip chaining. In comparison to adult travellers (age 26–40), young travellers (age < 25) chain fewer trips in subsistence trip chains but more trips in discretionary trip chains, which also corresponds to a previous study (Ye et al. 2007). However, no significant difference was found between young travellers and adult travellers in terms of routine. Old adult travellers (age 41–64) have simpler subsistence and discretionary trip chaining than adult travellers. Elderly people (age ≥ 65) have simpler trip chaining than adult travellers in all types of trip chains. Presumably, elderly people have limited physical travel ability, which hinders them from doing complex trip chaining. In addition, the elderly people are also likely to have more flexible time–space constraints and thus do not need to conduct several errands in one trip chain (Andrews et al. 2012). Surprisingly, physical disability shows no significant impact on trip chaining behaviour. One plausible reason for this could be the well-established social welfare system in Sweden that provides home services for those physically disabled persons.

In terms of household characteristics, travellers from households with more than three members show no significant difference in the trip chaining pattern compared to those from households with no more than three members. Travellers from single families without children have more complex discretionary trip chains but simpler subsistence trip chains compared with travellers from partnered families without children. Travellers from single families with young children have more complex subsistence and routine trip chains than

those from partnered families without children. Some children-related trips, such as picking up/dropping off children at kindergarten, are often chained in subsistence/routine trip chains, thus contributing to trip chaining complexity. As children grow older, the effect of children-related trips becomes weaker. These findings are in line with the results from Susilo and Avineri (2014). Moreover, the effect of having children tends to be stronger for travellers from single families than travellers from partnered families, as travellers from partnered families are more flexible in arranging children-related trips. Travellers from medium- and high-income families are more likely to have complex routine and discretionary trip chains than those from low-income families, which corresponds to previous studies (Golob and Hensher 2007; Noland and Thomas 2007), presumably because travellers from medium- and high-income families conceptually can afford more discretionary activities in commercial areas, such as eating out or luxury shopping; thus, they are more likely to do trip chaining in routine and discretionary trip chains. However, the difference between medium- and high-income groups is low. Moreover, household income level shows no explanatory power in subsistence trip chaining behaviour. The effects of the number of cars surprisingly do not correspond to the effects of household income level. More cars in a household indicate simpler discretionary trip chaining. A possible explanation could be that travellers from families with several cars do not need to share cars, and are thus more flexible in terms of trips chaining.

In terms of trip chain characteristics, subsistence trip chains during the morning peak hours, which usually refer to commuter trips (averaging 1.21 trips per chain), are simpler than those at non-peak hours (averaging 1.28 trips per chain), indicating morning congestion and time constraints limit commuters' options of achieving multiple errands during the morning peak hours. However, routine trip chains tend to be more complex when the departure time is in the morning peak hours, while they tend to be less complex when the departure time is in the afternoon peak hours. In terms of discretionary trip chaining, departure in the morning and afternoon peak hours correspond to simple trip chaining behaviour. Presumably, few discretionary activity spots, such as shopping malls, are open in the morning peak hours while most are closed during and after the afternoon peak hours, thus leaving fewer options for chaining discretionary activities. Compared to slow modes, trip chains with the main travel mode being car or public transport unsurprisingly have more trips per chain, which corresponds to the findings of previous studies (Ye et al. 2007; Schmöcker et al. 2010). The effects of "average link speed" were also included. "Average link speed" was defined as the total travel time of a trip chain in minutes divided by the trip chain distance in km. An increase in average link speed is associated with a decrease in the number of trips per chain, when the main mode of the trip chain is either by car or public transport. This is in line with Schmöcker et al. (2010), who showed a negative correlation between average link speed and trip chaining in home–home trip chains within 30 min of dwelling time. An increase of average link speed may indicate fewer percentages of slow modes used in the trip chains with the main mode being car or public transport, and a trip chain with a multimodal may often imply more than one activity/visit in this trip chain.

For land use characteristics, a denser population corresponds to an increase in the number of trips per subsistence trip chain, but a decrease in the number of trips per discretionary trip chain. Compared with the findings of Noland and Thomas (2007) and Farber et al. (2012) in the US, this finding indicates different population density effects on the trip chains with different main purposes, thus highlights the importance of segregating trip chains according to their different main purposes. Travellers in a municipality with more job positions, which refers to more commuters travelling in the municipality, have more complex routines and discretionary trip chains. This partially echoes a previous study

(Currie and Delbosc 2011) which showed that trip chains by cars in a central business district (CBD) were more complex than those outside a CBD.

In terms of weather impacts, the effects of UTCI are not consistent across seasons and trip chains of different purposes, which rejects the hypothesis of uniform effects of UTCI. For subsistence trip chains, an increase of UTCI corresponds to more trips chained in autumn, while the variations of UTCI show no significant influence on the number of trips in subsistence trip chains in the other three seasons. However, an increase of UTCI was associated with fewer numbers of trips in routine trip chains in summer and autumn. Similarly to routine trip chains, fewer numbers of trips in discretionary trip chains were found as UTCI increased, but only in autumn. The finding seems to contradict the common sense that more trips may be chained in routine and discretionary trip chains in warmer conditions, as the demand of routine and discretionary activities increases in warm weather conditions (Liu et al. 2014b). The results seem to show that the increased demand in warm conditions may not be chained in the existing routine and discretionary trip chains, but rather form new trip chains. Further sub-models, results not reported due to the space limitation, which apply to the sub-sample of season–mode combination, suggest that those increased demands in warm conditions are more substantial in trip chains with cars as the main mode than those with more main modes. Thus, the number of trips per trip chain may decrease even as the total number of trips per day increases. Rain (precipitation ≥ 1 mm) only negatively affects the trip chaining in routine trip chains, especially in trip chains with slow modes as the main modes. This can be due to the decreasing demand of routine and discretionary out-of-home activities in rain conditions (Liu et al. 2014a). Subsistence trip chains tend to be simpler in bad visibility situations compared to normal situations. However, no significant influences of bad visibility were found in routine and discretionary trip chaining. Travellers tend to do more trip chaining in all types of trip chains when the ground is covered with snow. This trend appears in trip chains with all modes. Trips that are connected with snow-related activities may contribute to the trip chaining behaviour. Moreover, as the “indirect cost” of travel increases due to snow (with the bus delays, the inconvenience of walking and cycling, etc.), separating errands into several trip chains becomes less attractive, which leads to the trip chaining decision.

The estimation results also indicate that the variations at the individual level are substantial after controlling for the observed individual characteristics and municipality land use characteristics. The variations due to unobserved attributes at the individual level are even larger than those in the trip chain level for routine and discretionary trip chains. By comparing the estimation results of the mixed ordered Probit model with panel data and the pooled ordered Probit model (results not shown in the paper), the difference between the corresponding estimates can reach 30 %. Several significant/insignificant variables in the pooled ordered Probit model become insignificant/significant. This result confirms that results from the one-level ordered Probit model which was used in most previous studies can be potentially biased, even with individual-level explanatory variables.

Marginal effects

Although the above-mentioned variable effects show the trends of different factors that influence the trip chaining behaviour in trip chains of different main purposes, those variable effects do not directly present the magnitude of those variable effects on the expected changes to the number of trips per chain. More importantly, it would also be interesting to see whether the inclusion of weather variables affects the interpretation of the

Table 6 Comparison of the marginal effects in the models with and without weather variables

Marginal effects	Subsistence trip chains		Routine trip chains		Discretionary trip chains	
	With weather	Without weather	With weather	Without weather	With weather	Without weather
<i>Individual socio-demographics</i>						
Female						
Age < 25	0.029 (1.90)	0.046 (2.92)	0.076 (2.81)	0.07 (2.61)	0.031 (1.43)	0.032 (1.45)
Age 26–40	-0.179 (-6.90)	-0.154 (-5.90)	-0.049 (-0.90)	-0.05 (-0.94)	0.071 (1.76)	0.074 (1.82)
	Ref	Ref	Ref	Ref	Ref	Ref
Age 41–64	-	-	-	-	-	-
Age > 65	-0.051 (-2.59)	-0.026 (-1.32)	-0.041 (-0.95)	-0.047 (-1.09)	-0.107 (-3.00)	-0.110 (-3.08)
Physical disability	-0.150 (-2.20)	-0.342 (-4.31)	-0.114 (-2.30)	-0.1 (-2.29)	-0.122 (-3.04)	-0.118 (-2.94)
	0.022 (0.53)	-0.002 (-0.06)	0.069 (1.04)	0.078 (1.17)	-0.004 (-0.06)	-0.001 (-0.002)
<i>Household characteristics</i>						
Household member > 3	-0.024 (-1.08)	-0.015 (-0.77)	0.011 (0.24)	0.025 (0.56)	-0.039 (-0.99)	-0.035 (-0.91)
Single family no child	-0.056 (-1.89)	-0.023 (-0.75)	0.027 (0.67)	0.026 (0.63)	0.109 (3.28)	0.107 (3.19)
Single family child 0–6 old	0.155 (2.38)	0.232 (3.53)	0.163 (1.74)	0.182 (1.89)	0.178 (1.47)	0.173 (1.43)
Single family child 7–18 old	0.042 (1.04)	0.028 (0.67)	0.148 (1.84)	0.157 (1.95)	0.038 (0.57)	0.040 (0.61)
Partnered family no child	Ref	Ref	Ref	Ref	Ref	Ref
Partnered family child 0–6 old	-	-	-	-	-	-
Partnered family child 7–18 old	0.136 (4.85)	0.153 (5.57)	-0.005 (-0.09)	-0.009 (-0.16)	0.057 (1.17)	0.051 (1.07)
Low income (<150,000 SEK)	0.050 (1.96)	0.038 (1.58)	0.016 (0.30)	0.010 (0.20)	0.065 (1.51)	0.061 (1.41)
	Ref	Ref	Ref	Ref	Ref	Ref
Medium income (150,000 to 400,000 SEK)	-	-	-	-	-	-
High income (> 400,000 SEK)	-0.010 (-0.34)	0.015 (0.53)	0.113 (2.89)	0.105 (2.66)	0.074 (2.27)	0.065 (1.99)
Number of cars in household	0.017 (0.79)	0.049 (2.26)	0.148 (3.73)	0.134 (3.53)	0.118 (3.87)	0.113 (3.73)
<i>Trip chain characteristics</i>	0.027 (2.46)	0.030 (2.74)	0.002 (0.11)	0.003 (0.15)	-0.050 (-3.09)	-0.051 (-3.13)
Departure at morning peak	-0.083 (5.82)	-0.079 (-5.75)	0.071 (1.98)	0.079 (2.21)	-0.082 (-2.32)	-0.079 (-2.22)
Departure at afternoon peak	-0.027 (1.32)	-0.028 (-1.39)	-0.163 (-4.87)	-0.168 (-5.01)	-0.091 (-3.73)	-0.090 (-3.70)

Table 6 continued

Marginal effects	Subsistence trip chains		Routine trip chains		Discretionary trip chains	
	With weather	Without weather	With weather	Without weather	With weather	Without weather
Models with/without weather variables	Ref	Ref	Ref	Ref	Ref	Ref
Main mode is walk and cycling	-	-	-	-	-	-
Main mode is private car	0.556 (21.99)	0.572 (21.82)	0.606 (17.39)	0.613 (17.52)	1.186 (44.17)	1.189 (44.24)
Main mode is public transport	0.399 (11.70)	0.422 (12.14)	0.466 (6.66)	0.473 (6.70)	1.007 (21.74)	1.003 (21.66)
Average link speed for car mode	-0.013 (38.46)	-0.014 (-40.26)	-0.017 (-17.40)	-0.017 (-17.66)	-0.017 (-17.59)	-0.017 (-17.87)
Average link speed for public transport mode	-0.014 (10.06)	-0.015 (-10.17)	-0.014 (-3.97)	-0.014 (-4.01)	-0.012 (-4.24)	-0.012 (-4.22)
<i>Land use characteristics</i>						
Population density	0.003 (2.14)	0.003 (2.03)	-0.001 (-0.24)	0.0003 (0.047)	-0.009 (-2.72)	-0.009 (-2.92)
Commuters in municipality	0.004 (0.66)	0.006 (0.98)	0.025 (2.27)	0.026 (2.43)	0.021 (2.33)	0.024 (2.65)
Commuters out municipality	0.024 (1.30)	0.014 (0.75)	-0.016 (-0.53)	-0.032 (-1.05)	0.007 (0.28)	-0.005 (-0.19)
Municipality car ownership	0.007 (3.01)	0.006 (2.48)	0.002 (0.41)	0.001 (0.01)	0.0002 (0.05)	-0.001 (-0.17)
<i>Weather characteristics</i>						
UTCI_spring	0.002 (0.99)	-	-0.004 (-1.36)	-	0.0001 (0.03)	-
UTCI_summer	-0.001 (-0.94)	-	-0.011 (-5.10)	-	-0.002 (-0.86)	-
UTCI_autumn	0.004 (1.93)	-	-0.006 (-1.72)	-	-0.008 (-2.73)	-
UTCI_winter	0.001 (0.43)	-	-0.001 (-0.42)	-	0.0002 (0.09)	-
No rain	Ref	Ref	Ref	Ref	Ref	Ref
Precipitation < 1 mm	-	-	-	-	-	-
Precipitation ≥ 1 mm	-0.010 (-0.58)	-	-0.010 (-0.30)	-	-0.019 (-0.68)	-
Visible distance ≤ 1 km	0.017 (0.85)	-	-0.068 (-1.80)	-	-0.006 (-0.17)	-
Ground with snow	-0.030 (-1.86)	-	-0.029 (-0.96)	-	0.013 (0.48)	-
	0.301 (4.91)	-	0.310 (3.14)	-	0.326 (3.62)	-

Note estimates in the bold values are significant at 10 % level. Numbers in parenthesis are t values. The corresponding t-tests of the marginal effects are calculated through the delta method (Greene 2003)

other variables compared with a model without weather variables. Therefore, the marginal effect of each variable on the expected number of trips per chain for three types of trip chain is presented in Table 6. The marginal effect of variable i on the probability of observation (trip chain) k being in the n -th category of the number of trips per chain is calculated as:

$$M_{k,n}^i = \int_{-\infty}^{+\infty} -\hat{\beta}_i \left[\phi(\mu_n - X_k \hat{\beta} - \varepsilon_k) - \phi(\mu_{n-1} - X_k \hat{\beta} - \varepsilon_k) \right] \times \hat{\sigma}_k \phi(\varepsilon_k) d\varepsilon_k \quad (4)$$

where $w\hat{\beta}_i$ is the estimated parameter for variable i . The integral in Eq. (5) is evaluated with simulation techniques, which draw from the distribution of ε_k , $\phi(0, \hat{\sigma}_k)$, where $+$ is the estimated standard deviation of ε_k . Thus the marginal effect on the expected number of trips per chain for observation (trip chain) k is then:

$$E_k^i = \sum_{n=1}^5 M_{k,n}^i \times n \quad (5)$$

where E_k^i can be interpreted, in general, as the change of the expected number of trips per chain for observation k due to a one unit increase of variable i . For example, the first number in Table 6, 0.029, as the marginal effect of being female, means that increasing this variable by one unite (being female) would lead to an increase of the expected number of trips per subsistence trip chain by 0.029 trips, and its corresponding t test is 1.90. The marginal effects provide some insights. First, gender plays a stronger role in influencing trip chaining behaviour in routine trip chains than in subsistence and discretionary trip chains. Being elderly people, aged > 65, substantially changes the trip chaining behaviour compared with that change due to being in age groups other than the reference age group, aged 26–40. Second, family status, being single/partnered, or having/not having children influences subsistence trip chaining behaviour more substantially than family income. However, it is the other way around for routine and discretionary trip chaining behaviour. Third, mode choice plays vital roles in influencing trip chaining behaviour, especially for discretionary trip chains. The marginal effect of using a private car on discretionary trip chaining, 1.186, is twice as that for subsistence trip chaining, 0.556, and routine trip chaining, 0.606. This indicates a strong positive correlation between trip chaining and mode choice, as complex trip chains are more likely to be associated with car use. Thus, policies aimed at decreasing car share would also indirectly be accompanied by less trip chaining, especially in discretionary activities, which indicates less efficient trip scheduling. In terms of weather characteristics, snow-covered ground is the most important factor among the weather variables, and its marginal effects have even larger magnitudes than most individual and household social demographic variables. Additionally, the marginal effect of snow has a similar magnitude as the marginal effect of increasing 10,000 residences per km². It suggests a substantial increase of trip chaining complexity in snow-covered ground situations for all types of trip chains.

Furthermore, there are clear differences in the marginal effects between the model with weather variables and the model without weather variables. Such differences in the effects of individual and household social demographic variables are more substantial than those in the effects of trip chain and land use characteristic variables, especially for subsistence trip chains. It is also worth noting that the difference in the marginal effects can reach 50 % and even higher, e.g. the marginal effect of “Female” in the model with weather variables for subsistence trip chains is 0.029, while that number in the model without weather

variables is 0.046 (59 % higher). Overall, the results suggest that including weather in the model provides more accurate marginal effects, and thus provides more reliable interpretation.

Spatial distributions of utci effects

Previous studies have shown clear regional differences in terms of weather impacts on the number of trips travelled (e.g. Liu et al. 2014a, b), but few studies have explored the spatial heterogeneity of weather effects on trip chaining behaviour. Given that only a few studies have used a thermal index in weather–travel behaviour research, the exploration of spatial heterogeneity in the effects of a thermal index is limited. Thus, as an extension of the current analysis, a spatial expansion method is applied to assess the spatial heterogeneity of UTCI effects while the seasonal difference of UTCI effects is also considered. The spatial expansion method applies spatial-based variables to detect the systematic spatial trend on the given variable effect. In the transport field, the spatial expansion method has been used to explore spatial variations of the accessibility measure and the distance travelled (e.g. Morency et al. 2011; Farber et al. 2012).

In general, the spatial expansion method works on the principle of expanding the coefficients of a non-expanded model as functions of expansion variables, usually location- or social group-based variables, which are meant to capture variations at those levels. In this study, the coefficients of UTCI in the model shown in Table 4 are expanded as a function of the coordinates of a municipality and the corresponding land use characteristics.

$$\beta_{UTCI,i} = \alpha_{0,i} + \alpha_{1,i}x + \alpha_{2,i}y + \alpha_{3,i}xy + \alpha_{4,i}x^2 + \alpha_{5,i}y^2 + \alpha_{6,i}p_density + \alpha_{7,i}com_{in} + \alpha_{8,i}com_{out} + \alpha_{9,i}car \quad (6)$$

In Eq. (6), the coefficients of the UTCI variables were further developed by means of a second order polynomial expansion of the municipality coordinates and a linear combination of its land use variables. x and y refer to the longitude and latitude of a given municipality. $p_density$, com_{in} , com_{out} , and car refer to the municipality land use variables shown in Table 4. $\alpha_{n,i}$ refers to the corresponding coefficients being estimated, where i refers to the season index, and $i \in \{\text{spring, summer, autumn, winter}\}$. Such a spatial expansion of the coefficient indicates that the marginal effects of UTCI on the number of trips per trip chain are spatially distributed as a function of the land use characteristics and the geographical location. These spatially expanded coefficients can also be interpreted in essence as the interaction between the effects of thermal condition and spatial location. A coefficient with significant expansion components indicates that a specific geographical location/attribute affects the role of the thermal perception condition and leads to a contextual relationship between location variations.

The coefficients of UTCI for the model of routine trip chains are spatially expanded, as the corresponding non-expanded coefficients of summer and autumn are statistically significant and the corresponding marginal effects are considerable compared with those in the models of other trip chain categories. The estimation results showed that the spatially expanded coefficients of UTCI in spring and winter are all insignificant, as the corresponding non-expanded coefficients are insignificant (see Table 5). Thus, only the coefficients of UTCI in summer and autumn are chosen to be spatially expanded. The estimated

Table 7 The spatially expanded coefficients of the model for routine trip chains

Expanded UTCI coefficients	Routine trip chains	
	Estimates	<i>T</i> value
<i>UTCI for summer</i>		
Intercept	4.711	1.193
<i>x</i>	-4.659	-2.156
<i>y</i>	-0.342	-0.248
<i>xy</i>	0.759	2.520
<i>x</i> ²	-0.117	-0.627
<i>y</i> ²	-0.063	-0.496
Population density	-0.002	-1.061
Commuters in municipality	0.005	0.714
Commuters out municipality	-0.008	-0.490
Municipality car ownership	0.0004	0.112
<i>UTCI for Autumn</i>		
Intercept	-2.336	-0.275
<i>x</i>	0.812	0.263
<i>y</i>	0.594	0.197
<i>xy</i>	-0.237	-0.512
<i>x</i> ²	0.284	1.115
<i>y</i> ²	-0.021	-0.078
Population density	-0.001	-0.728
Commuters in municipality	0.022	2.282
Commuters out municipality	-0.073	-2.906
Municipality car ownership	-0.003	-1.149
<i>P</i> value of the likelihood ratio test	0.000	

Note estimates in the bold values are significant at 10 % level. The likelihood ratio test tests whether a spatially expanded model is superior to the corresponding non-expanded model

spatially expanded coefficients of the model for routine trip chains are then shown in Table 7.

The likelihood ratio test shows the spatially expanded model is superior to the non-expanded model as the *p* value is less than 0.01. In terms of the spatial trend of UTCI effects in summer, the coefficient of longitude *x* is significant and negative (-4.659). This indicates that travellers on the east coast of Sweden tend to have simpler routine trip chains than those on the west coast of Sweden when UTCI rises. The coefficient of the interaction effect *xy* is significant and positive (0.759). However, land use characteristics do not contribute to the spatial trend of the UTCI effect in summer. On the contrary, the land use characteristics affect the spatial trend of the UTCI effect in autumn instead of the location coordinates. The number of commuters travelling in/out of the municipality plays an important role in affecting the spatial trend in autumn. Municipalities with more commuters travelling in (CBD) have a higher UTCI effect, while municipalities with more commuters travelling out (residential areas) have a lower UTCI effect.

As stated above, those spatial trends of the UTCI effects differ between seasons. Plotting the spatial trends provides valuable insights into understanding the geographical variation of UTCI effects and demonstrates the differences of magnitude between municipalities of interest. In this paper, the marginal effects of UTCI on the expected values

of outcomes (the number of trips per routine trip chain) are plotted. The marginal effect of UTCI for travellers at municipality j having n trips per routine trip chain in season i is then the mean of the marginal effects for all observations which take place in season i in the given municipality j :

$$E_{j,i} = \frac{1}{N_{j,i}} \sum_{k \in N_{j,i}} E_k \tag{7}$$

where $N_{j,i}$ is the number of observations that belong to municipality j in season i . The value of $E_{j,i}$ can be interpreted as the change in the expected value of the outcome for travellers at municipality j having n trips per routine trip chain due to a 1 °C rise in the UTCI. Note that not all municipalities have observations (observed routine trip chains) in all seasons, and thus only marginal effects in the municipalities which have no less than five observations in a given season are plotted ($N_{j,i} \geq 5$). Only the marginal effects for summer and autumn are shown in Fig. 1, as the coefficients of UTCI in spring and winter are not spatially expanded. Three municipalities in Sweden—Stockholm, Gothenburg, and Malmö—and their adjacent municipalities are zoomed out.

As shown in Fig. 1, the marginal effects of UTCI on the expected number of trips per routine trip chain range from -0.045 trips to 0.040 trips in summer and autumn, while the non-expanded model yields the corresponding marginal effects as -0.011 and -0.006 for summer and autumn (see Table 6). Thus, the marginal effects of UTCI show a considerable inter-municipality variation. As the marginal effect of UTCI on the expected number of trips per routine trip chain is calculated with the spatially expanded coefficients, the

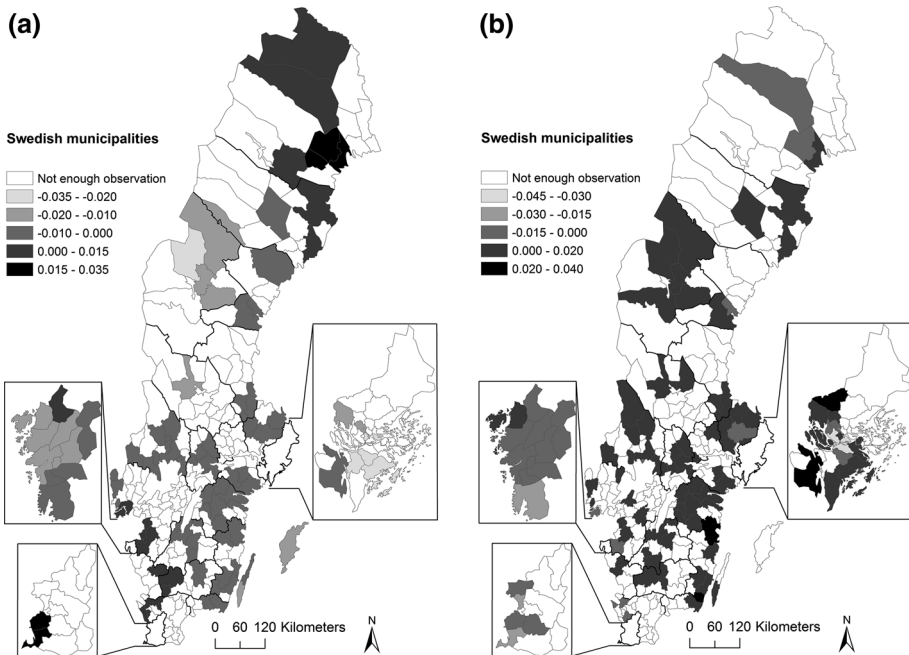


Fig. 1 The spatial distributions of the marginal effects of UTCI on the expected number of trips per routine trip chain. **a** Marginal effect in summer. **b** Marginal effect in autumn

interpretations of those spatially expanded coefficients are also applicable to the spatial distribution on the expected number of trips per routine trip chain. The expected number of trips per routine trip chain tends to increase by between 0.015 and 0.035 trips in northeast coast cities such as Luleå and Umeå when UTCI increases by 1 °C in summer, while that expected number tends to decrease by between 0.01 and 0.02 trips in Gothenburg and between 0.02 and 0.035 trips in southern municipalities close to Stockholm. In autumn, the marginal effect of UTCI in Stockholm is between -0.03 and -0.045 trips, but the marginal effect in its adjacent municipalities is between 0 and 0.02 trips. This reflects the spatial heterogeneity of UTCI effects due to the difference in land use characteristics. Similarly, the marginal effect of UTCI in Gothenburg is around -0.01 trips, but the marginal effect in its southern adjacent municipality, Kungälv, which is a major residential area near Gothenburg, is -0.04 trips, as the spatial trend for the marginal effect of UTCI in autumn is significantly lower in residential areas (-0.073 in Table 7).

Conclusions

Using the 2011 NTS datasets, this paper investigates the variability of trip chaining behaviour. The roles of an individual's social demographics, household characteristics, trip chain characteristics, weather characteristics, and land use characteristics were examined through panel mixed ordered Probit models, and trip chains of different main purposes were analysed accordingly. Instead of using directly measured weather variables, which were the case for most previous studies, a thermal index, UTCI, was used. Moreover, spatial heterogeneity, which has usually been ignored in previous studies, is also taken into account by using a spatial expansion method.

The effects of individual/household social demographics, trip chain characteristics, and land use characteristics found in this paper in general correspond to the findings from previous studies. Household structure (having children, single, or partnered) significantly influences the trip chaining pattern, especially in subsistence trip chains. Household income level strongly affects the trip chaining pattern in subsistence and routine trip chains. Population density is negatively associated with the number of trips per subsistence trip chain, but the opposite is true for discretionary trip chains.

In terms of weather effects, the effects of UTCI are not consistent across seasons and trip chains of different purposes. UTCI has a significant effect on the number of trips per trip chain, especially in autumn. Increasing UTCI is associated with an increasing number of trips chained in subsistence trip chains in autumn, while the opposite is true for routine and discretionary trip chains. Rain (precipitation ≥ 1 mm) only negatively affects routine trip chaining. Fewer numbers of trips are chained in subsistence trip chains in bad visibility situations compared with normal situations. Snow-covered ground is found to be the most influential factor affecting trip chaining behaviour. Travellers tend to do more trip chaining in all types of trip chains when the ground is covered with snow, which is also applicable to trip chains with all modes. These significant effects of weather variables suggest different trip chaining behaviour due to the change of weather and such differences are not unique over seasons and activity purposes. This has an important implication for transport policy, as traffic management efforts then must not only cope with the seasonal pattern of trip chaining behaviour, but also consider local weather. For instance, complex subsistence trip chaining behaviour is expected in a warm autumn, while single trip chains are more common for routine and leisure purposes in a warm autumn. Therefore, more congestion in

rush hour is expected during this period. Appropriate congestion mitigation measurements and car parking management need to be adjusted to cope with this change of trip chaining behaviour. More car trips with complex trip chains are also expected on snowy days; therefore, it is important to provide reliable road access to the main activity locations to cope with the increasing demand of these complex trip chains.

The results from spatial expansion present the spatial distributions of the marginal effects of UTCI on the expected number of trips per routine trip chain. Distinct spatial trends are observed in summer and autumn. Spatial location variables (latitude and longitude) are found to be significant in influencing the spatial trend of the UTCI effect in summer, while municipality-level land use characteristics show little explanatory power. However, it is the other way around in autumn. The marginal effects of UTCI on the expected number of trips per routine trip chain range from -0.045 trips to 0.040 trips in summer and autumn, which indicates substantial spatial variations. These findings also indicate that transport policies aimed at trip chaining behaviour must also be localised to incorporate the local climate.

It is worth noting that this study uses national-level data and the municipality-level land use information is only a rough proxy for accessibility. Although focusing on a relatively small area and using detailed land use information may help provide more accurate land use impacts and allow for a more advanced modelling approach—e.g. spatial dependency—such an analysis may not provide a comprehensive understanding of weather impacts due to the lack of weather variation given a specific geographical location. Moreover, using longitudinal data would also help better understand the variation of the trip chain complexity measure given the fact that activity travel behaviour evolves over time (Susilo and Kitamura 2008). Further segregating models by travel modes also yields more detailed variable effects, as those variable effects are not necessarily consistent across trip chains with different main modes. Finally, using subjective weather perception is appreciated, as it is the perceived weather condition rather than objective weather condition that is involved in the travel decision making process, and thus influences travel behaviour. This weather perception may not only be affected by thermal conditions but also by other psychological factors. These topics are plausible directions for future research.

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