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Abstract

Internet is capturing more and more of our time each day, and the increasing levels of engagement are mainly due to the use of social media. Time spent on social media is observed in the American Time Use Survey and recorded as leisure time on Personal Computer (PC). In this paper, we extend the traditional analysis of leisure activity participation by including leisure activities that require the use of a PC. We study the substitution effects with both in-home and out-of-home leisure activities and the time budget allocated to each of them. The modeling framework that includes both discrete alternatives and continuous decision variables allow for full correlation across the utility of the alternatives that are all of leisure type and the regressions that model the time allocated to each activity. Results show that there is little substitution effect between leisure with PC and the relative time spent on it, with in-home and out-of-home leisure episodes. Households with more children and full-time workers are more likely to engage in in-home and PC related leisure activities (especially during weekends). Increments in the travel time of social trips result in significant reductions in leisure time during weekdays.

Keywords: Discrete-continuous choice model; social media; leisure activity; activity-travel pattern; time use

1. Introduction

Social media platforms and online communities continue global expansion in recent years. In 2016, with a global population of 7.4 billion, 3.419 billion are internet users, of which 2.3 billion use social media (Wearesocial, 2016). Overall, it is estimated that two third of online adults are using social media platforms. The high penetration rate of social media is changing how individuals communicate and interact. By analyzing social media and its use, researchers are trying to understand people's thinking, communication patterns, health, beliefs, prejudices, group behaviors, which is relevant in social science and related disciplines. At the same time, the growing use of social media is also expected to modify travel patterns both indirectly, by changing activity needs and time spent at home or out-of-home, and directly, by modifying the perception and the utility of the time spent traveling, during which the use of social media is becoming ubiquitous. It is therefore also important to transportation researchers understanding the influences of social media on the time allocated to activities and ultimately on travel behavior.

Most previous studies in transportation focused on the influence of information communication technology (ICT) usage on working activity and commute trips (Wang and Law, 2007; Ben-Elia et al., 2014). Other studies turned their attention to the effects of internet usage on individual's attitudes towards time usage and involvement in other physical activities such as discretionary trips (Ferrell, 2005; Veenhof, 2006; Farag et al., 2006; Carrasco and Miller, 2009). However, limited studies have empirically investigated social media involvement, its effects on leisure activity participation, and the relative time use.

In this study, we propose an integrated econometric framework that accounts for the effects that internet usage for leisure and relaxing, which contains a major component of social media involvement, has on activity-travel patterns, including social and commute trips. The joint model proposed captures the potential correlation across activity involvement choices, the location where this activity takes place and time usage decisions associated to each chosen activity. A number of studies have shown that time-space constraints play an important role in shaping people's activity patterns (Pendyala, 2002; Yamamoto et al., 2004; Kitamura et al., 2006), and that time use affects individual's daily schedule (Bhat and Koppelman, 1999). Neglecting the correlation among spatial and temporal decisions may result in the inability of the modeling framework to accurately capture and reflect individual activity and time use patterns in our increasingly digitized world. It is the purpose of the study to identify the appropriate data for this problem, to formulate the model that account for both discrete (leisure participation and location) and continuous decisions (time spent on social media) and to quantify the impacts that the involvement on social media has on travel behavior.

The remaining of this paper is organized as follows. In Section 2 we present a brief review of recent studies on activity-travel patterns, impact of ICT usage on travel demand modeling and discrete-continuous models. In Section 3, we describe the data used for this study, which has been extracted from the most recent wave of the American Time Use Survey (ATUS 2013) available at the time of the analysis. Following that, we introduce the model framework for activity choices and time usage decisions (Section 4). In Section 5 and 6, the integrated model is estimated and then applied to study complementarities or substitutions effects in the context of social media involvement and travel behavior. Finally, Section 7 presents concluding remarks and future research directions.

2. Previous studies

Activity involvement and time use analysis are important components of activity choice modeling. A large number of studies investigated the factors that affect individual's activity involvement and travel patterns. In this context, socio-demographic characteristics, individual and family schedules, spatial and temporal constraints are found to significantly influence activity participation and travel behavior (McNally et al., 2007; Kemperman and Timmermans, 2008). Several other studies revealed that individual's activity location choices, which are constrained by space and time, are always associated with daily travel patterns and activity schedules (Bhat and Gossen, 2004; Bhat and Lockwood, 2004; Lin and Wang, 2015). The location choice problem between in-home and out-of-home is particularly important for discretionary activities. Related studies showed that activity attributes have a greater impact on the activity location than socio-demographics based on their marginal effects and that the characteristics of activities conducted prior and directly following the individual activity have a significant impact on its location choice. Also, longer work duration and commuting time could lead to lower participation in short, temporally and personally flexible out-of-home discretionary activities (Akar et al., 2011; Akar et al., 2012).

Internet usage, other than physical activities, is expected to increase the spatial and temporal flexibility of everyday activities (Schwanen and Kwan, 2008). Since the 90s, researchers in transportation have attempted to disentangle the effects of ICTs on travel patterns (e.g. Hamer et al., 1991; Pendyala et al., 1991; Balepur et al., 1998). Their work indicated that the effects of teleworking and of other online activities on personal travel are balanced or outweighed by new trip generation (Handy and Mokhtarian 1996, Mokhtarian, 1991, 1997, 1998; Mokhtarian et al., 1995, Mokhtarian and Salomon, 1997). More recently, researchers began to pay attention to the impacts of ICTs on the involvement in other physical activities, such as shopping, leisure, and social activities. Complementarity and substitution are the most common effects found to be associated with internet use. Mokhtarian et al. (2006) explored the potential impacts of internet use on leisure trips. This study indicated that internet use enables relocation of time to other activities by replacing traditional leisure activity with ICT-based counterparts.

With relation to the effects of e-commerce on shopping trips, it is difficult to reach a definitive consensus on the changes in travel behavior due to e-shopping. If, on one hand some studies found that the expansion of the e-commerce has contributed to the reduction of shopping trips, but only in a limited way (Mokhtarian, 2004; Weltervreden, 2007; Visser and Lanzendorf, 2004); on the other hand, some other studies found that e-shopping could induce even more physical shopping trips (Douma et al., 2004; Cao et al. 2010; Wilson et al., 2007; Farag, 2007).

The impact of internet use on business and personal travel has been explored by Wang and Law (2007). A positive effect of internet usage was found on the participation in out-of-home recreation and its associated travel activities. Robinson and Martin (2010) indicated that internet users seem to spend less time on other types of activity but have a higher frequency of social trips compared to non-users.

Existing papers more specifically dealing with the effect of social media usage on decisions related to travel and activity participation are more reviews or conceptual papers (Aguiléra et al., 2012; Dal Fiore et al., 2014) rather than empirical works, and the few latter are only partially covering the issue. Ben Elia et al. (2014) use data gathered in 2007, when social media usages were much lower, to investigate the relationships between use of ICT nomadic devices, activity, and travel. Le Vine et al. (2016) focus on the relationship between internet use and time spent traveling or in out-of-home activities. To the best of our knowledge, the most recent studies take a different perspective, since they rather assess the possibility of “harvesting transport-related information from social media” (Gal-Tzur et al., 2014) for example to better monitor traffic flows (D’Andrea et al., 2016), incidents (Zhang et al., 2015; Gu et al., 2016), service disruptions (Pender et al., 2014), transit performances (Dey et al., 2016), mode choice (Mondschein, 2015), O/D matrices (Lee et al., 2016) or activity locations (Hasan et al., 2014; Maghrebi et al., 2015). Works more specifically dealing with the impacts of social media on travel demand are limited to the study of route choice (Chen et al., 2015) or derived empirical rules from data streams rather than formal models (Gkiotsalitis et al., 2014). To sum up, previous knowledge in this area is still rather fragmented and more empirical work is needed in particular.

On a methodological viewpoint, most of the papers referenced so far are limited to the analysis of individuals’ activity participation and ignore the time associated with each activity, which is important for activity scheduling and for the definition of travel patterns. Indeed, jointly considering both categorical and metric endogenous variables is traditionally seen as rather challenging. However, models that accommodate discrete and continuous decisions have recently emerged in the activity-based analysis (Bhat, 2005; Habib et al., 2008; Habib et al., 2009; Srinivasan et al., 2006; Copperman et al., 2007). Discrete-continuous models enable researchers to capture the correlation that potentially exists between individual’s discrete and continuous choices. Bhat (2005) developed multiple discrete-continuous extreme value (MDCEV) models and applied them to model participation in discretionary activity and the duration of time investment. The model framework was then adopted to analyze children’s after school out-of-home activity-location engagement patterns and time allocations (Paleti et al. 2011). Pinjari and Bhat (2010) developed a multiple discrete-continuous nested extreme value (MDCNE) model to estimate non-worker activity time-use and scheduling behavior. However, the MDCEV type models are restricted by the assumption of fixed total time budget allocated to the considered activities. This limits the ability of the analyst to analyze change in time use due to changes in the independent variables included in the model formulation. Habib et al. (2008) developed a discrete-continuous model to estimate the relationship between social contexts, activity starting time and activity duration. A multinomial logit model is employed to capture “with whom” choices of social activities and a hazard model is adopted to capture related activity durations and starting time. This framework poses assumptions on the correlation structure that can be estimated between the discrete and the continuous dependent variables.

More recently, Liu et al. (2014) introduced a discrete-continuous modeling framework, which relaxed the constraints outlined in previous researches. A multinomial probit model is used to estimate discrete choices, and a regression is used to estimate the continuous decisions. Correlations across the discrete and the continuous parts are captured with a full variance-covariance matrix of the unobserved factors. The modeling framework was further extended by Liu and Cirillo (2015), which allows the specification of multiple regressions for each continuous component in the framework. This latter development will be adopted in this work to estimate joint models that describe leisure involvement (including social media), location (in home vs. out of home) and time spent on each of the considered activity types. Duration of different leisure activities could in fact have different determinants according to the kind of activity under consideration.

3. Data sources

The primary data source used in this analysis is extracted from the 2013 American Time Use Survey (ATUS).) (Bureau of Labor Statistics, 2014). The ATUS is designed and collected by the U.S. Bureau of Labor Statistics and contains detailed information on time use for each activity on which respondents have been involved the day before the interview. Activity related attributes include the start and end time of participation, activity type, and activity location; individual and household socioeconomic characteristics are also available in the dataset. Both in-home and out of home activities are reported, which makes ATUS particularly attractive for time use analysis and modeling.

In this study we are interested in leisure activity involvement, in the location where those activities take place and in the time spent for leisure. We distinguish between in-home and out of home leisure activities and between generic leisure activities and those involving the use of the computer. In particular, we refer to the ATUS category "*Computer use for leisure*"; this variable explicitly excludes games, listening to music, watching videos, e-mails, computer use for work and volunteer activities, which are included in different activity categories. Therefore, we argue that this activity category is mainly time spent online to use social media; a comparative study based on ATUS and a survey conducted by Nielsen supports our claim and concludes that "*the top leisure uses included in the ATUS variable are social networks, portals and search*".

(Greenstein and Tucker, 2015). So, social media usage seems reasonably well captured by this variable (Diana et al., 2016).

By combining "in home" and "out of home" with "use of computers" and "absence of use of computers" and also considering one versus multiple leisure activities, the resulting set of discrete choices over leisure activity types includes the following six alternatives:

1. No leisure activities (NL) on the day of the survey;
2. Pure in-home leisure activities that involve the use of the computer (LPC);
3. Pure in-home other (than computer use) leisure activities (LH);
4. Pure out-of-home leisure activities (LOH);
5. Multiple in-home leisure activities, of which some require the use of the computer (LH&LPC);
6. Multiple in-home and out-of-home leisure activities in which the computer is not in use (LH&LOH).

Table 1 Distribution of Leisure Activity

Category	Obs. (Weekdays)	Obs. (Weekends)
No leisure activity (NL)	543	519
Pure in-home computer use activities (LPC)	76	80
Pure in-home other leisure activities (LH)	3620	3773
Pure out-of-home leisure activities (LOH)	194	261
Multiple in-home leisure and computer use activities (LH&LPC)	523	502
Multiple in-home and out-of-home leisure activities (LH&LOH)	638	477

Each survey respondent, and the corresponding observation in the dataset can then be classified into one of the above six kinds of activity sequences. Table 1 provides the breakdown among activity sequences in the sample; a total of 5,612 observations are available for weekends, while 5,594 observations are available for weekdays. Household characteristics, land-use variables and time use information for each household, are the main variables extracted from the original dataset. Table 2 lists the basic statistics relative to the 2013 ATUS sample. We can observe that individuals with no leisure activity have the highest travel time to work, travel to social and entertainment activities and in average have more children. Individuals who use the computer for leisure activities have high income and spend also time on art and entertainment related activities. These trends are similar for weekdays and weekends. In average about 1.5 hours per day are spent on computer for leisure during weekdays and about 2.3 hours per day during weekends among observations who choose LPC. While average time spent on all leisure activity is about 3.1 hours per day during weekdays and about 3.8 hours per day during weekends among all observations.

Table 2 Data statistics

Variables		By activity types					
		NL	LPC	LH	LOH	LH& LPC	LH& LOH
Weekday:							
Gender (female = 1; otherwise = 0)		0.558	0.579	0.572	0.557	0.579	0.464
Metropolitan status (metropolitan = 1; otherwise = 0)		0.843	0.895	0.828	0.784	0.839	0.850
Working status (full time = 1; otherwise = 0)		0.628	0.553	0.404	0.603	0.333	0.600
No. of people in household		2.396	2.289	2.185	2.134	2.191	2.136
Age (years)		42.0	41.1	50.5	41.6	49.3	50.0
Household income ($)		77025	85903	61418	63961	72588	59232
No. of children in Household		1.1	1.1	0.8	0.7	0.7	0.7
Household type	1.Married,	56.2%	60.5%	51.8%	43.8%	55.8%	47.0%
	2. Unmarried,	20.6%	13.2%	17.2%	22.7%	14.0%	16.5%
	3.Single,	23.2%	26.3%	31.0%	33.0%	30.0%	36.6%
	4. Group	<1.00%	<1.00%	<1.00%	<1.00%	<1.00%	<1.00%
Travel time related to working (hrs.)		0.496	0.431	0.297	0.378	0.198	0.42
Travel time related to socializing and communicating (hrs.)		0.032	0.016	<0.010	0.012	<0.010	<0.010
Travel time related to arts and entertainment (hrs.)		0.104	0.103	0.069	0.161	0.057	0.088
Time spent on in-home leisure activity (hrs.)		NA	NA	4.204	NA	3.811	3.079
Time spent on in-home computer use for leisure activity (hrs.)		NA	1.500	NA	NA	1.475	NA
Time spent on out-of-home leisure activity (hrs.)		NA	NA	NA	1.842	NA	1.066
Weekends:							
Gender (female = 1; otherwise = 0)		0.636	0.625	0.542	0.563	0.540	0.503
Metropolitan status (metropolitan = 1; otherwise = 0)		0.834	0.825	0.818	0.820	0.849	0.832
Working status (full time = 1; otherwise = 0)		0.597	0.463	0.433	0.494	0.394	0.463
No. of people in household		2.370	2.288	2.203	2.241	2.191	2.140
Age (years)		44.3	41.0	50.0	44.4	48.5	45.0
Household income ($)		74030	81025	61709	65120	68533	57727

No. of children in Household		1.1	0.8	0.8	0.9	0.7	0.7
Household type	1.Married	53.0%	53.8%	52.3%	44.8%	54.7%	41.5%
	2. Unmarried	21.8%	18.8%	16.9%	22.2%	13.1%	22.9%
	3.Single	25.2%	27.5%	30.7%	33.0%	32.0%	35.6%
	4. Group	<1.00%	<1.00%	<1.00%	<1.00%	<1.00%	<1.00%
Travel time related to working (hrs.)		0.105	0.061	0.099	0.027	0.139	0.080
Travel time related to socializing and communicating (hrs.)		0.212	0.138	0.114	0.148	0.082	0.148
Time spent on in-home leisure activity (hrs.)		NA	NA	4.948	NA	4.511	3.334
Time spent on in-home computer use for leisure activity (hrs.)		NA	2.333	NA	NA	1.546	NA
Time spent on out-of-home leisure activity (hrs.)		NA	NA	NA	3.453	NA	1.929

4. Modeling framework

The econometric model system proposed captures the joint decisions of participation in leisure activity, where this activity takes place (in-home vs. out-of-home) if the leisure activity involves the use of the computer and the time spent on each of the leisure activity. The problem involves both discrete dependent variables (activity type) and continuous dependent variables (time use). A discrete-continuous model framework is adopted in the study to jointly estimate the leisure activity choice and the time spent on each leisure activity choice. An in house software coded in R language is used to estimate the integrated model with variance-covariance matrix.

4.1 The Activity Choice Sub-model

Discrete choice analysis is adopted to model the choice of activity sequences. The discrete choice model forecasts the outcome of a categorical dependent variable Y_{DIS}. The six types of leisure activity sequences that were introduced in Section 3 thus constitute the discrete endogenous variable in the modeling framework. To each activity sequence i, i = 1 … 6, we associate a utility:

$$U_i = X_i^T \beta_i + \varepsilon_i, \tag{1}$$

where X_i are the socio-demographic attributes and activity related variables, β_i are the associated parameters to be estimated and ε_i are the error terms.

The decision maker is assumed to be rational and to choose the alternative with the highest utility. A multivariate probit model is adopted for the discrete problem, and therefore the error terms follow a multivariate normal distribution with full, unrestricted covariance matrix. The probit model is normalized to take into account the fact that the level and scale of the utility is irrelevant (Train, 2009).

The probability of choosing a given leisure activity sequence i can also be expressed in the way of difference:

$$\mathrm{P}(\mathrm{Y}_{DIS} = \mathrm{i}) = \int B(\widetilde{\mathrm{V}}_{i-j} + \tilde{\varepsilon}_{i-j} > 0, \forall j \neq i)\phi(\tilde{\varepsilon})d\tilde{\varepsilon}, \tag{2}$$

where $B()$ is a Boolean indicator of whether the statement in parentheses holds is, $\phi(\tilde{\varepsilon})$ is the density of the error term in difference formation (i.e. $\tilde{\varepsilon}_{i-j} = \varepsilon_i - \varepsilon_j$), $\widetilde{\mathrm{V}}_{i-j} = X_i^T\beta_i - X_j^T\beta_j$.

4.2 The Time Usage Sub-model

Regressions are used to estimate the time spent on leisure activities, which are classified into three groups according to the location where they take place and, for in-home activities, the use of computers. The model formulation therefore includes the following three continuous variables as dependent variables: (a) time spent on out-of-home leisure activity (LOH), (b) time spent on in-home leisure activity without computer use (LH), and (c) time spent on PC for leisure purpose (LPC). For example, if individual chooses multiple leisure activities (e.g. LH&LPC), two regressions are used to estimate the time usage on (b) LH and (c) LPC following Eqn. 5. The time spent on single leisure activity $\mathrm{s} \in \{\mathrm{LPC}, \mathrm{LH}, \mathrm{LOH}\}$, $Y_{reg,s}$, can be expressed as a linear combination of a vector of predictors $X_{reg,s}$ and error term $\epsilon_{reg,s}$:

$$Y_{REG,s} = X_{REG,s}^T\beta_{REG,s} + \varepsilon_{REG,s}, \varepsilon_{REG,s} \sim N\left(0, \sigma_{REG,s}^2\right). \tag{3}$$

Usually, regressions are solved by the Ordinary Least Squares (OLS) estimator (Weisberg, 2005). Alternatively, the problem can also be expressed in the form of a likelihood function to be maximized. The two methods are equivalent under the assumption that errors are normally distributed (McCulloch and Neuhaus, 2001, p.117).

For multi-leisure-activity participation, it can then be expressed by the generic equation:

$$Y_{REG,\eta} = X_{REG,\eta}^{T}\beta_{REG,\eta} + \varepsilon_{REG,\eta}, \varepsilon_{REG,\eta} \sim MVN\left(0, \Sigma_{REG,\eta}\right), \tag{4}$$

where $Y_{REG,\eta}$ is a set of observed time usages on given leisure activities subset $\eta \subseteq \{\mathrm{LPC}, \mathrm{LH}, \mathrm{LOH}\}$. The likelihood of observing $Y_{reg,\eta}$ is given by the normal density function:

$$P(Y_{REG,\eta}) = \phi(err|\mu, \sigma^2), \tag{5}$$

where *err*= $Y_{REG,\eta} - \hat{Y}_{REG,\eta}$. Correspondingly, the time usage of an individual on a single leisure activity *s* follows a normal distribution with zero mean and variance $\sigma_{REG,s}^2$. For those individuals who are involved in more than one leisure activity types, the time usage follows a multivariate normal distribution with variance:

$$\Sigma_{REG,\eta} = \begin{bmatrix} \sigma_{REG,1}^2 & \cdots & \sigma_{REG,1}, \sigma_{REG,n} \\ \vdots & \ddots & \vdots \\ \sigma_{REG,n}, \sigma_{REG,1} & \cdots & \sigma_{REG,n}^2 \end{bmatrix}. \tag{6}$$

4.3 The Integrated Discrete-Continuous Choice Model

The integrated discrete-continuous choice framework jointly models $Y_{REG,\eta}$ (Eqn. 5) and Y_{DIS} (Eqn. 2) in order to capture the correlation between discrete and continuous decision variables. Therefore, the integrated framework accounts for the following decisions:

- Discrete variable: choices of leisure activities participated by the individuals (NL, LH, LPC, LOH, LH&LPC, LH&LOH);
- Continuous variable: time spent on each participated activity (LH, LPC, LOH).

In particular, the model accounts for the correlation between leisure activity choices i and time spent on associated activity set η_i. Taking advantage of the fact that error terms of the regressions and the probit model follow normal distributions, the combination of error term from the two parts will follow a multivariate normal distribution.

$$(\tilde{\varepsilon}_{LH-NL}, \tilde{\varepsilon}_{LPC-NL}, \tilde{\varepsilon}_{LOH-NL}, \tilde{\varepsilon}_{LH\&LPC-NL}, \tilde{\varepsilon}_{LH\&LOH-NL}, \varepsilon_{REG,\eta}) \sim \mathrm{MVN}(0, \Sigma)$$

$\tilde{\varepsilon}_{LH-NL}, \tilde{\varepsilon}_{LPC-NL}, \tilde{\varepsilon}_{LOH-NL}, \tilde{\varepsilon}_{LH\&LPC-NL}, \tilde{\varepsilon}_{LH\&LOH-NL}$ represent error terms in difference of the probit model respective to NL activity. $\varepsilon_{REG,\eta}$ is a vector of error terms of regressions on given leisure activities subset $\eta \subseteq \{\text{LPC, LH, LOH}\}$.

The joint probability of activity choice and time usage can be derived as

$$\mathrm{P}(Y_{REG,\eta_i}, Y_{DIS}) = \mathrm{P}(Y_{REG,\eta_i})P(\,Y_{DIS}|Y_{REG,\eta_i}), \quad (7)$$

or

$$\mathrm{P}(Y_{REG,\eta_i}, Y_{DIS}) = \mathrm{P}(Y_{DIS})P(\,Y_{REG,\eta_i}|Y_{DIS}). \quad (8)$$

The likelihood of observing Y_{DIS} conditional on Y_{REG} can be

$$\widehat{\mathrm{P}}(Y_{DIS}|Y_{REG}) = \frac{1}{K}\sum_{k=1}^{K}\mathrm{B}(\widetilde{\mathrm{V}}_{ij} + \tilde{\varepsilon}_{ij}{}^{(k)} > 0, \forall j \neq y), \quad (9)$$

Where K is the number of simulations, $\tilde{\varepsilon}_{ij}{}^{(k)}$ is a draw from a multivariate normal with mean $\mu_{DIS|REG}$ and variance $\Sigma_{DIS|REG}$:

If $\begin{bmatrix} \tilde{\varepsilon}_{ij} \\ \varepsilon_{REG,\eta} \end{bmatrix} \sim MVN\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \Sigma_{DIS} & \Sigma_{REG,DIS} \\ \Sigma_{DIS,REG} & \Sigma_{REG,\eta_i} \end{bmatrix}\right)$,

then $\mu_{DIS|REG} = 0 + \frac{\Sigma_{DIS,REG}}{\Sigma_{DIS}}(err - 0), \Sigma_{DIS|REG} = \Sigma_{REG,\eta_i} - \frac{\Sigma_{DIS,REG}\Sigma_{REG,DIS}}{\Sigma_{DIS}})$ (10)

The Simulated Log Likelihood of the model is given by the following formula:

$$\mathrm{SLL}(\beta, \beta_{REG}, \Sigma, X, X_{REG}) = \sum_{n=1}^{N} \log(\frac{K_n^*}{K} \times \phi(Y_{n,REG}|X_{REG,\eta}^T\beta_{REG,\eta}, \varepsilon_{REG,\eta}))$$

where, N is the total number of observations in the data, K_n^* is the number of success in the probit simulation for the n^{th}observation. Simulation has been executed using 1000 pseudo Monte Carlo draws. Standard errors were calculated using Bootstrap re-sampling techniques.

5. Model estimation results

Results from the integrated discrete-continuous model are reported in Table 3 and Table 4, where we present model estimates for weekdays and weekend respectively. Individual and household socio-demographic variables, travel time to work and to social activities enter the final specifications of the estimated discrete-continuous models.

Table 3 Joint discrete-continuous model: estimation results of activity in weekdays (*t*-stats in parenthesis)

Variable	Activity Choice Sub-model LPC	LH	LOH	LH&LPC	LH&LOH
Alternative-Specific Constant	-1.769 *(-9.744)*	3.782 *(34.297)*	-1.627 *(-7.809)*	0.553 *(19.782)*	0.726 *(18.675)*
No. of children		-0.290 *(-4.803)*	-0.347 *(-4.137)*	-0.593 *(-4.441)*	-0.394 *(-5.082)*
Teen (age ≤18)		-2.163 *(-3.892)*	1.124 *(3.280)*		
Young (19≤ age ≤25)		-2.493 *(-3.585)*	1.532 *(3.526)*		
Adult (26≤ age ≤40)		-1.440 *(-4.500)*		-0.408 *(-2.757)*	-0.183 *(-5.048)*
Unmarried couple (dummy)				-0.166 *(-2.911)*	
Graduate or professional degree (dummy)	0.331 *(1.638)*	-1.042 *(-4.742)*			-1.203 *(-6.797)*
Full time worker (dummy)	-0.273 *(-1.811)*	-1.483 *(-14.158)*		-2.438 *(-14.458)*	

	Time Usage Sub-model Time on LPC	Time on LH	Time on LOH
Alternative-Specific Constant	1.481 *(19.558)*	4.515 *(21.552)*	2.586 *(12.241)*
Travel time related to socializing and communicating (hrs.)		-0.656 *(-6.227)*	
Travel time related to work (hrs.)	-0.158 *(-2.453)*	-0.696 *(-8.990)*	-0.264 *(-6.218)*
No. of children	-0.166 *(-3.424)*	-0.227 *(-6.051)*	-0.302 *(-3.728)*
Age		0.032 *(14.697)*	-0.029 *(-1.880)*
Full time worker (dummy)	-0.371 *(-1.007)*	-1.580 *(-14.506)*	0.111 *(-6.117)*
Household income		-0.008 *(-11.689)*	-0.002 *(-0.946)*
Log-likelihood (0)	-23755.88		
Log-likelihood (Final)	-18247.51		
R-squared	0.23		
Number of observations	5594		

Household income: scaled with 0.001.

Table 4 Joint discrete-continuous model: estimation results (weekends) (*t*-stats in parenthesis)

	Activity Choice Sub-model				
Variable	LPC	LH	LOH	LH&LPC	LH&LOH
Alternative-Specific Constant	-1.713 *(-10.505)*	4.073 *(29.870)*	-1.244 *(-6.234)*	1.412 *(14.954)*	0.261 *(13.029)*
No. of children	-0.228 *(-2.827)*	0.148 *(-2.890)*	-0.584 *(-2.914)*	-0.419 *(-4.681)*	-1.007 *(-5.246)*
Teen (age ≤18)	0.844 *(4.101)*	-3.126 *(-4.375)*	2.751 *(6.535)*		2.414 *(2.483)*
Young (19≤ age ≤25)		-2.062 *(-7.447)*	0.746 *(2.609)*	-0.985 *(-1.974)*	
Adult (26≤ age ≤40)		-2.171 *(-8.436)*		-0.115 *(-3.397)*	-0.393 *(-3.397)*
Senior (41≤ age ≤65)		-0.687 *(-7.732)*			0.241 *(-4.200)*
Graduate or professional degree (dummy)	0.501 *(2.311)*	-1.085 *(-4.021)*			-1.705 *(-2.851)*
Full time worker (dummy)		-1.119 *(-4.579)*		-1.882 *(-7.304)*	-1.093 *(-2.261)*
Female (dummy)		-0.734 *(-4.778)*		-0.929 *(-4.326)*	-1.353 *(-4.813)*

	Time Usage Sub-model		
	Time on LPC	Time on LH	Time on LOH
Alternative-Specific Constant	1.293 *(9.821)*	4.137 *(23.352)*	2.235 *(20.466)*
Travel time related to socializing and communicating (hrs.)	-0.296 *(-1.984)*	-1.334 *(-10.229)*	-0.163 *(-1.139)*
Travel time related to work (hrs.)		-1.631 *(-8.505)*	-0.298 *(-5.190)*
Full time worker (dummy)	-0.297 *(-2.829)*	-0.475 *(-5.841)*	-0.147 *(-2.936)*
Female (dummy)	-0.236 *(-2.304)*		
No. of children	-0.331 *(-3.551)*	-0.368 *(-8.144)*	-0.230 *(-1.981)*
Age	-0.018 *(-2.040)*	0.031 *(10.752)*	
Teen (age ≤18)			1.173 *(2.559)*
Household income		-0.007 *(-8.139)*	
Log-likelihood (0)	-24101.30		
Log-likelihood (Final)	-20240.24		
R-squared	0.16		
Number of observations	5612		

Household income: scaled with 0.001.

Results obtained from the weekday model, attest that having a graduate or professional degree increases the probability of using social media, but being a full-time worker has an opposite effect, probably because of time constraints. In general, highly educated people with a demanding job tend not to be involved in leisure activities both in the home and out of the home. Teens and young adults are more likely to spend time outdoor for leisure. Having children significantly reduces the probability of being involved in leisure activities, which may be attributable to mobility constraints imposed by the presence of young children on the out-of-home activities of adults (see Scanzoni and Szinovacz, 1980); however, this variable was found to be not significant for leisure involving the use of a computer that is assumed to have a large portion of social media interaction. In addition to activity involvement, the integrated model provides insights on the amount of time spent on PC, at home, or out of home for leisure. It was found that increasing travel time to work reduces the time spent on social media; full-time working status and the fact to have children has similar effects on PC time for leisure. Travel time to social activities and to work, the number of children and income all have negative signs in the linear regressions used to model time use. A full-time job increases the time spent on leisure out of the home.

For weekend days, teens and professionals are highly involved in social media. People with more kids tend to have leisure at home, while teens and young adults still prefer outdoor activities. All other households and individual characteristics that are considered have negative impacts on leisure activity participation. It should be noted that gender, that was found to be not significant in the model for weekdays, turns out to be negative and significant also for social media involvement. Concerning time spent for leisure, all travel time-related variables are negative; in particular, individuals going out to socialize have less time to spend on the internet and on leisure activities in general. Teens consistently prefer out of home leisure activities, and income has a negative effect on leisure at home.

Table 5 Integrated discrete-continuous model: covariance of difference matrix

Covariance of difference matrix of weekdays

$$\hat{\Sigma} = \begin{array}{c|cccccccc} & LPC & LH & LOH & LH\&LPC & LH\&LOH & T_{LPC} & T_{LH} & T_{LOH} \\ \hline LPC & 2.00 & 0.36 & 1.34 & 0.25 & 0.41 & 0.01 & 0.14 & -0.44 \\ LH & 0.36 & 5.45 & -0.64 & 3.52 & 0.15 & -0.01 & 0.63 & 0.11 \\ LOH & 1.34 & -0.64 & 14.61 & -3.00 & -0.14 & 0.02 & -0.66 & -0.16 \\ LH\&LPC & 0.25 & 3.52 & -3.00 & 3.72 & 0.81 & -0.01 & 0.39 & -0.09 \\ LH\&LOH & 0.41 & 0.15 & -0.14 & 0.81 & 3.99 & 0.00 & -1.47 & -3.42 \\ T_{LPC} & 0.01 & -0.01 & 0.02 & -0.01 & 0.00 & 0.00 & 0.00 & 0.00 \\ T_{LH} & 0.14 & 0.63 & -0.66 & 0.39 & -1.47 & 0.00 & 4.27 & 0.66 \\ T_{LOH} & -0.44 & 0.11 & -0.16 & -0.09 & -0.34 & 0.00 & 0.66 & 1.20 \end{array}$$

a. *Covariance of difference matrix of weekend*

$$\hat{\Sigma} = \begin{array}{c|cccccccc} & LPC & LH & LOH & LH\&LPC & LH\&LOH & T_{LPC} & T_{LH} & T_{LOH} \\ \hline LPC & 2.00 & 0.98 & 1.79 & -1.74 & 0.01 & 0.19 & 0.04 & 0.09 \\ LH & 0.98 & 3.00 & -0.72 & -1.46 & -0.36 & 0.60 & 0.24 & -0.05 \\ LOH & 1.79 & -0.72 & 3.73 & -3.26 & 0.51 & -0.42 & -0.06 & -0.03 \\ LH\&LPC & -1.74 & -1.46 & -3.26 & 9.89 & 0.27 & 0.33 & -0.97 & -0.01 \\ LH\&LOH & 0.01 & -0.36 & 0.51 & 0.27 & 2.11 & -0.20 & -0.04 & -0.05 \\ T_{LPC} & 0.19 & 0.60 & -0.42 & 0.33 & -0.20 & 0.19 & 0.02 & 0.02 \\ T_{LH} & 0.04 & 0.24 & -0.06 & -0.97 & -0.04 & 0.02 & 3.46 & 0.12 \\ T_{LOH} & 0.09 & -0.05 & -0.06 & -0.01 & -0.05 & 0.02 & 0.12 & 1.65 \end{array}$$

b.

From the analysis of the results, it is possible to conclude that based on our sample and for weekends there is a substitution effect between travel time to social activities and time spent for leisure in the home, out of the home and on PC. With particular reference to the objective of this paper, it can be said that socializing outside the habitual domicile during the weekends reduces the need to communicate via social media. The same is not true for weekdays when temporal constraints prevent people from meeting in person relatives and friends. A long commute time reduces the time available for leisure, including the time for social media, especially during the weekdays. Moreover, the long commute time also has a stronger negative effects on in-home leisure activity participation and weaker effects on out-of-home activities during weekends. Activity involvements are also varies among different age groups (see Garikapati 2016, for similar results). Our study also confirms that highly educated people are more likely to be social media users, but in average they do not spend more time than the other population groups with their PC for leisure. The estimation results are also consistent with the findings of previous studies (see, Bhat and Misra 1999; Meloni et al. 2007; Kapur and Bhat 2007), in which similar effects of number of young children and travel time to work were found on in-home and out-of-home leisure activity participations. The covariance of difference matrices presented in Table 5 indicate that correlations are well captured by the model across activity participations ($LPC, LH, LOH, LH\&LPC, LH\&LOH$) and time usages ($T_{LPC}, T_{LH}, T_{LOH}$).

6. Model validation and application

For validation purposes, we re-estimated the model on 80% of the available observations in the dataset and then we applied the model estimates to predict the activity and duration choices of the remaining part of the survey sample. In Table 5 and Table 6, we report the actual relative frequencies of activity choices and time usages, the corresponding values predicted by the model together with the difference between observed and predicted values during both weekdays and weekends. The results show that both models do well in prediction for the discrete part (with errors less than 6% for weekdays and less than 5% for weekends). Concerning, the prediction of the activity duration, the overall error on time spent for leisure activity is about 9% for weekdays; we predict a total duration of leisure activities of about 3.62 hours instead of 3.35 hours. The bigger error on the duration of "time spent on LPC" is due the low number of observations available in the sample for this alternative. Also the bigger error for weekdays is probably due to the high variability in activity behavior over weekends.

Table 5 Discrete-continuous model: validation results of weekdays

		Actual	Predict	Difference
Activity choice frequencies	NL	10.11%	11.61%	1.50%
	LPC	0.89%	1.76%	0.86%
	LH	63.77%	69.56%	5.78%
	LOH	3.22%	2.23%	-0.99%
	LH&LPC	9.31%	3.33%	-5.98%
	LH&LOH	12.70%	11.52%	-1.18%
Time usage on activity choice	Time spent on LPC (hrs.)	1.68	1.22	-27.69%
	Time spent on LH (hrs.)	3.93	4.38	11.42%
	Time spent on LOH (hrs.)	1.15	0.97	-16.17%
	Average time usage on leisure activity (hrs.)	3.35	3.62	8.26%

Table 6 Discrete-continuous model: validation results of weekends

		Actual	Predict	Difference
Activity choice frequencies	NL	10.87%	13.26%	2.39%
	LPC	1.16%	2.37%	1.21%
	LH	67.11%	71.00%	3.88%
	LOH	4.55%	3.66%	-0.89%

	LH&LPC	8.56%	6.76%	-1.79%
	LH&LOH	7.75%	2.95%	-4.80%
Time usage on activity choice	Time spent on LPC (hrs.)	1.57	1.22	-22.22%
	Time spent on LH (hrs.)	4.36	5.28	21.22%
	Time spent on LOH (hrs.)	2.40	1.73	-27.94%
	Average time usage on leisure activity (hrs.)	3.86	4.39	13.86%

The models estimated have been also applied to test substitutions effects across different leisure activity types, the variation on the time budget allocated to each activity and the sensitivity to relevant socio-demographic variables. The most significant results are reported in Table 7. More in general terms and beyond the above mentioned substitution effects, we calculate small variations with few exceptions. A unit increase in the number of children produces a significant negative effect on leisure activity involvement; the number of individuals with no leisure activity increases by 33.7% during weekdays and by 17.4% during weekends. The same variable also reduces the average time spent on leisure activities. However, engagement in LPC and LH during weekdays would increase due to the increase in the number of children. More full-time workers (+ 10%) will increase engagement in LPC of about 4.6%. Interestingly, the time usage decisions in young, adult and senior groups are more sensitive to the changes in the travel time during weekdays, while the activity participation decisions are barely affected. Increasing travel time to social activities will decrease time spent on leisure, especially time spent on out of home leisure activities. Time on PC is the least affected by travel time to social activities. For example, when travel time to social activities increases by 25%, time spent on LPC will decrease 1.3% in the young group, 2.5% in adult group and 2.3% in the senior group. Under the same scenario, time spent on out-of-home leisure activity will decrease 5.5% in the young group, 9.6% in the adult group, and 10.5% in the senior group. However, the same choices during weekends are not sensitive the changes in both variables. The results also show that activity participation on leisure activities are barely influenced by the increment or decline of travel time to work. However, the variation in the time usage decisions indicates that travel time to work has different influence during weekends and weekdays. For example, when travel time to work increase 25%, time spent on in-home leisure activity will decrease 1% during weekend, and 0.5% during weekdays. While the same variation could reduce time spent on LPC by 0.5% during weekends and increase the time by 0.7% during weekdays.

Table 7 Sensitivity of activity and duration choices to changes in socio-demographics and travel times

	NL	LPC	LH	LOH	LH& LPC	LH& LOH	Time on LPC	Time on LH	Time on LOH	Average time spent on leisure
Whole sample										
Actual (weekdays)	542	75	3699	198	435	645	1.07	3.82	0.90	2.91
No. of children +1	33.7%	31.9%	0.7%	-6.8%	-33.9%	-10.9%	-14.0%	-5%	-34.2%	-6.2%
Fulltime worker +10%	3.4%	-0.2%	-0.8%	2.2%	-2.2%	2.4%	1.0%	-1.7%	0.9%	-1.5%
Actual (weekends)	605	87	3604	262	542	512	1.91	4.48	2.02	3.62
No. of children +1	17.4%	-16.2%	2.9%	-4.8%	-10.7%	-24.2%	-16.5%	-8.3%	-10.6%	-8.7%
Fulltime worker +10%	1.7%	4.6%	-0.1%	2.6%	-2.0%	-1.6%	-0.6%	-0.5%	-0.1%	-0.5%
Young										
Actual	30	11	127	13	23	55	1.91	3.87	0.98	2.80
Travel time to social +25%	-0.2%	-0.3%	-0.1%	0.8%	-0.3%	0.2%	-1.3%	-2.5%	-5.5%	-2.6%
Adult										
Actual (weekdays)	233	49	725	81	103	241	1.26	3.09	0.74	2.26
Travel time to social +25%	-0.1%	0.3%	0.0%	0.3%	-0.1%	0.1%	-2.4%	-4.9%	-9.6%	-4.9%
Travel time to work +25%	0.0%	0.5%	0.0%	-0.1%	0.1%	0.0%	-0.7%	-0.5%	-0.7%	-0.5%
Actual (weekends)	222	29	890	74	100	99	1.95	3.60	1.78	2.83
Travel time to social +25%	0.0%	0.2%	-0.1%	0.1%	0.1%	0.7%	-0.5%	-1.1%	-0.1%	-1.0%
Travel time to work +25%	0.1%	-0.1%	0.0%	-0.5%	-0.2%	0.1%	0.5%	-1.0%	-0.3%	-0.9%
Senior										
Actual (weekdays)	285	59	1312	149	175	485	1.42	3.43	0.73	2.62
Travel time to social +25%	0.0%	-0.3%	0.0%	-0.2%	0.1%	0.2%	-2.2%	-4.2%	-10.5%	-4.3%
Actual (weekends)	254	37	1601	106	237	225	1.84	4.42	1.94	3.56
Travel time to social +25%	0.2%	0.5%	0.0%	-0.1%	0.1%	-0.1%	0.0%	-0.9%	-0.2%	-0.8%

7. Conclusions

This paper proposed an econometric model that assesses the impact of internet usage for leisure and relaxing on activity-travel patterns, including social and commute trips. Internet usage for leisure can be considered as a proxy of social media involvement since activities such as listening to music or watching videos are excluded in our empirical setting. The framework further expands previous analyses that categorize leisure activities into in-home and out-of-home leisure activities, and explicitly models the time spent on each of the activity types considered. The analysis is based on data extracted from the American Time Use Survey and it has been separately performed for weekdays and weekends.

We found that in the U.S., an individual uses a computer for leisure about 1.5h on an average weekday and 2.33h per day on weekends, which makes the analysis particularly important in an activity-based travel analysis context. The empirical results provide valuable insights into the determinants of activity choice and time use decisions of individuals, such as household and individual demographics, and travel time to other activities. The presence of children in the households decreases the likelihood of being involved in leisure activities (including leisure on computer use) except for leisure at home during the weekends. In general, having children also negatively affects the time dedicated to leisure and relax. Individuals with graduate or professional degree are more likely to use the computer for leisure both on weekdays and weekends. Teens and young people are more likely to spend time outside the home for leisure. The time dedicated to leisure activities by young, adult and senior groups are sensitive to the changes in travel time to social activities during weekdays and weekends, except for time spent on out of home leisure during weekends.

The model has also been applied to study possible substitution effects within activities and trade-offs between socioeconomics characteristics and activity patterns. Results attest that the increase in the number of children will decrease participation in leisure activities and an increase in full-time workers will produce more leisure sequences involving the use of PC and social media. More time spent traveling to social activities will decrease participation to leisure activities during weekdays for adults and seniors.

A number of future research avenues are possible. Psychological effects and social interactions play an important role in individual’s schedule and activity decisions. Such variables can be included in this model framework to capture the influence of psychological and social changes in leisure activity involvement. Also, if data is available, it would be interesting to study the time spent on cell phone to access social media networks, as there is evidence that mobile connection has already overtaken fixed internet access (Chaffey, 2016).

Finally, the same model structure proposed can be applied to model the complete activity-travel pattern and the daily schedule. Mode and destination choice models should be included in the model structure to account for the accessibility to different out of home leisure activities by all the modes available to the individuals in the sample.

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