Does the social context help with understanding and predicting the choice of activity type and duration? An application of the Multiple Discrete-Continuous Nested Extreme Value model to activity diary data

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Abstract

An understanding of activity choices and duration is a key requirement for better policy making, in transport and beyond. Previous studies have failed to make the important link with individuals' social context. In this paper, the Multiple Discrete-Continuous Nested Extreme Value (MDCNEV) model is applied to the choice of activity type and duration over the course of two days, using data from the Chilean city of Concepción. In common with other studies, heterogeneity across decision makers is accommodated in the model by analysing the impact of different socio-demographic, mobility and residential location variables on both the activity choice and the time allocation decision. In addition, different social network and social capital measures are found to be significantly correlated with the choice and duration of different activities, and we show how these relationships seem to differ from the effects of socio-demographic variables. Finally, we perform a forecasting exercise using the MDCNEV model, highlighting the differences in substitution patterns from a standard MDCEV model.

Keywords: MDCNEV; activity modelling; social networks; travel behaviour

1 Introduction

In recent years, activity-oriented approaches have gained considerable ground in the study of travel behaviour (Axhausen and Gärling, 1992). Travel demand is believed to be mainly a derived demand, directed at objectives such as going to work or performing

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recreational activities (Bhat et al., 2013; Ettema and Timmermans, 2003). The understanding of activity scheduling, which includes the decision of which specific activities to perform, with whom, for how long and using which transportation mode (Doherty et al., 2002; Gärling et al., 1998), can in turn lead to greater insights into the drivers of travel behaviour. Initial contributions to the literature treated the different dimensions of activity choice (such as type, timing and duration) separately, while in the last decade a growing amount of literature has highlighted the value of jointly investigating these aspects (Bowman and Ben-Akiva, 2001; Ettema et al., 2007).

The first econometric models accommodating both the discrete and continuous dimensions of choice were developed starting from the late 1950s by Tobin (1958), Heckman (1977), Dubin and McFadden (1984), Train (1986) and De Jong (1990). Starting by using a system of equations, each corresponding to one choice dimension (Bhat, 2001), Chandra Bhat and his co-authors gradually developed a more general and flexible framework to model the choice of multiple alternatives and a continuous amount associated with each of them, in the form of the Multiple Discrete-Continuous Extreme Value (MDCEV) model (Bhat, 2008). This model has been applied in several studies analysing activity choice and duration (e.g. Bhat, 2005; Bhat et al., 2006; Kapur and Bhat, 2007) and constitutes the state of the art in modelling multiple discrete-continuous choices. These studies concluded that socio-demographic characteristics of individuals and households, ownership and availability of mobility tools, accessibility and land use characteristics are significant determinants of the choice of the different activities. For example, Kapur and Bhat (2007) study weekend day activity engagement by participants in the 2004 American Time Use Survey. Their results show how low income households are more likely to perform in-home activities, such as in-home leisure or maintenance, a conclusion that reflects the financial constraints to performing the generally more expensive out-of-home activities. Individual socio-demographics also affect activity choice. Women are for example more likely to be involved in household maintenance, with the same applying to married as opposed to singlerespondents, while middle-age people (40-60) are found to be more likely to engage in arts and events. A limited number of studies applied the nested version of the model (MDCNEV) to study time allocation (Bernardo et al., 2015; Pinjari and Bhat, 2010b; Rajagopalan et al., 2009).

While most datasets collect information about respondents' socio-demographic characteristics alongside time use diaries, contextual information about the circumstances in which people make their choices is often not available. However, there is clear scope for a relationship between an individual's social environment and his/her travel and activity choices. We are careful here in not positing a specific directionality of this relationship at the outset. Indeed, if a relationship between a large social network and the choice of out-of-home recreation is found, then it may of course be tempting to infer that the person conducts many such activities as a result of having many friends, However, it is similarly possible that the person developed a large social network to facilitate him/her performing out-of-home recreational activities. While the challenges in terms of causality remain, it clearly still important to test for these effects in models to understand the relationship between the choices and the context in which they are made. This is one of the aims of the present paper. At the same time, it is also important to test for confounding between these contextual variables and other socio-demographic characteristics, another point we pay careful attention to.

The closest existing work has got to this issue has come in attempts to find an impact of the social dimension on leisure and social activities, specifically on their frequency (Carrasco and Miller, 2009) and duration (van den Berg et al., 2012), while some work has also jointly modelled several dimensions (Carrasco and Habib, 2009; Habib et al., 2008; Moore et al., 2013). These efforts showed the importance of considering the social dimension to explain engagement in social and leisure activities, highlighting the relevance of the cultural context examined (Kowald et al., 2013). One of the aims of the present work is to investigate the broader relations of the social dimension with time use going beyond just leisure and social activities, by looking at the time allocation for entire days.

The remainder of this paper is organised as follows. The next section describes the data used for our analysis, followed by a discussion of the modelling framework. We then present our application and the different models we estimated. After describing our results, we forecast with the MDCEV and the MDCNEV models and discuss the implications of including the social network variables for model performance and forecasting. We conclude by drawing policy considerations and suggesting directions for future work.

2 Data

2.1 Survey and data collection

The dataset used for our analysis was collected in 2012 within the *Communities in Concepción* project, which involved people from four neighbourhoods of the Chilean city of Concepción. Concepción is located approximately 500 km south of the capital Santiago and with its 1 million population it constitutes the second largest urban centre of the country. Two of the neighbourhoods (*Agüita de la Perdiz* and *La Virgen*) are close to the city centre, with the first one being a medium-high income neighbourhood, and the second being a medium-low income one. The other two (*S. Sabina* and *Lomas S. Sebastian*) are further away from the city. Medium-low income households mainly populate the first one, while the second one is home to medium-high income people. The specific sampling approach adapted for this study implies that there is not enough variability to control for accessibility, walkability and other measures normally used to describe the built environment characteristics.

The data were collected face-to-face in respondents' homes. Participants were initially asked to complete a detailed socio-demographic questionnaire, including questions about themselves, their family composition and their mobility and communication tool ownership. They were then asked to complete a 2-day activity diary by filling a grid with detailed information about the activities they have been engaged in during one recent weekday and one recent weekend day, and during which time slots these took place.

In addition to these more traditional components, respondents were asked to elicit their social network by completing a so-called "name generator". This technique, extensively used in the sociology (Campbell and Lee, 1991) and travel behaviour (Carrasco et al., 2008; Kowald et al., 2010; Pike, 2014) literature, consists of asking people to recall their entire social network or parts of it. Respondents are generally presented with a table in which each row represents a person in the network, and each column refers to the information to be provided for each member, such as type of relationship, time they have known him/her, frequency and mode of interaction. Different studies use different "prompts" to help people recall the relevant network, depending on the scope of the research. In this case, the instrument is based on Carrasco et al. (2008), and uses an *affective approach*, i.e. it asks respondents to report first the people that they are emotionally close to, and then separately list those they are "somewhat close to". Respondents were also asked to specify the network members who would receive or grant some form of support, whether emotional, monetary or help with mobility or search for employment.

2.2 Sample characteristics and data cleaning

The initial sample of 241 respondents was reduced to 235 during cleaning, leading to a final sample of 4,092 activities, i.e. an average of 8.71 per respondent per day. Table 1 reports the socio-demographic characteristics of respondents. The ranges for the level of education have been organised according to the impact of this factor on social status and employment opportunities. Basic schooling includes all the compulsory levels of education, up to high school, which correspond to the qualifications necessary to apply for post-secondary education. Technical school corresponds to a 3-4 year post-secondary degree which does not require undergraduate diplomas. The quota sampling applied was based on the latest available census information at the neighbourhood level, making the sample reasonably representative of each neighbourhood.

As we model the choice and duration of activities, the time use diary is the core part of the dataset for our analysis. We removed all the activities with unknown duration or missing description. In the case of reported activities exceeding 24 hours a day, we removed/shortened/reattributed the last activity(ies) reported. This was generally due to people including night activities that actually took place the following day.

People were allowed to freely describe the activities and we next had to reduce them to macro-categories used for the analysis, where we focussed on 12 categories, as listed in the first column of Table 2. Column 2 reports how many people choose each activity at least once; while column 3 shows the overall choice frequency, i.e. in how many separate occasions the activity is performed overall. The comparison between columns 3 and 5 (which contain the same information as 2 and 4, but in percentage terms) highlights that while everyone in the sample chooses the *Basic Needs* activity (which includes sleeping), the activity with the highest frequency is *Travel*. The last two columns show the overall number of hours spent by all people in the sample in the different activities, as well as the average only across those people who engage in a given activity.

Socio-demographic factor	***Ranges***	***Frequency***	***Percentage***
Gender	Female	147	63%
	Male	88	37%
Age	<26	31	13%
	26-40	84	36%
	40-60	83	35%
	Over 60	37	16%
Education	Basic Schooling	89	38%
	Technical School	23	10%
	University Drop-Out	25	11%
	University Degree	97	41%
Employment Status	Student	25	11%
	Employee	101	43%
	Graduate Job	63	27%
	Homemaker	33	14%
	Retired	13	6%
Relationship Status	Lives with partner (Married)	134	57%
	Single	101	43%
Children	No children	123	52%
	1 child	61	26%
	2 or more child	33	14%
Household Income	<400.000 CLP	81	34%
	400,000-2,000,000 CLP	80	34%
	>2,000,000 CLP	40	17%
Driving Licence	Has Licence	113	48%
	Does not have a licence	122	52%

Table 1: Socio-demographic characteristics of the sample

It is important to remember that the activities are performed over two days, one weekday and one weekend day. This explains figures such as the overall 8.3 hours spent working, or the high duration for *Basic Needs*, corresponding to sleeping, eating and simply staying at home. The 11 activities other than *Basic Needs* are "non-essential", explaining why only some people perform them. While the meaning of the different activities in Table 2 is generally self-evident, some clarifications are required. *Family* can be thought of as "time to support/attend family members in non-essential activities": this does not include obligatory activities such as washing or dressing children, or having in-home meals, but does include activities such as helping children with their homework or playing with them. *Household Obligations* includes cleaning/tiding up, taking care of pets, performing ordinary maintenance at home. Recreation activities were divided depending on whether they were performed at home or out of home, while *Services* include errands, such as going to the bank, the doctor or the hairdresser. *Social* activities are visits to/from friends and relatives and other activities specifically aimed at social interaction. *Travel* constitutes a single activity. This is one of the possible approaches that can be adopted, and it is particularly suitable in our case as it allows us to observe the impact of sociodemographic characteristics on activity choice and duration, as well

Activities	*N. people who choose it*	*% of total sample*	*Overall choice frequency*	*% of all activities*	*Overall time spent (hrs)*	*Average time spent by those who choose it (hrs)*
Drop off-Pick Up	43	18%	78	2%	25.6	0.6
Family	43	19%	63	2%	178.5	4.1
Household Obligations	85	36%	183	4%	661.6	7.2
In-home Recreation	39	17%	98	2%	198.2	5.1
Out-of-home Recreation	85	36%	66	2%	191.5	2.3
Services	58	25%	71	2%	118.1	2.0
Social	164	70%	379	9%	932.6	5.7
Shopping	94	40%	141	3%	115.0	1.2
Study	52	22%	103	3%	263.7	5.1
Travel	226	96%	1601	39%	781.7	3.5
Work	138	59%	234	6%	1147.4	8.3
Basic needs (eat, sleep, stay home)	235	100%	1075	26%	6716.2	28.6

Table 2: Frequency and duration of activities in the sample

as the correlations with social network measures. Alternative approaches are of course possible, such as adding this time to the out-of-home activity at destination. As evident from the third column of Table 2, nearly everyone travels, as each out-of-home activity implies going to the destination and back.

3 Model specification

3.1 Modelling framework

The family of MDCEV models initially developed by Bhat (2005) and subsequently extended in different directions (Bhat, 2008; Castro et al., 2012; Pinjari and Bhat, 2010b) represents the state of the art in modelling multiple discrete-continuous choices. Travel behaviour has been the main field of application of this modelling framework, for example in the study of the choice of vehicle type and mileage (Bhat and Sen, 2006), vacation-related decisions (Pinjari and Sivaraman, 2013) and to type and duration of activities (Bhat, 2005; Kapur and Bhat, 2007). The model used in the present application is the Multiple Discrete Continuous Nested Extreme Value (MDCNEV) model, proposed by

Pinjari and Bhat (2010b) as an extension of the Multiple Discrete Continuous Extreme Value (MDCEV) model.

The model is derived coherently with the random utility maximisation theory, but relaxes the mutual exclusivity assumption inherent in traditional choice models. The additive but non-linear formulation of the utility function guarantees that the consumption of one good does not affect the utility of the others and that these goods are substitutes.

Both the MDCEV and the MDCNEV models are based on a direct utility function $U(x)$ that agents maximise by consuming a vector x of non-negative quantities of each of the K goods, $x = (x_1, \dots, x_K)$. The choice of total consumption amounts is subject to a budget constraint $xp = E$, where E is the budget, and p is the vector of prices. The vector x generally includes a unit-priced outside good to represent expenditure on a good that is always consumed by all the individuals in the sample. In our case, this represents the time spent on *Basic Needs*.

The utility formulation, introduced by Bhat (2008) is given by:

$$U(x) = \frac{1}{\alpha_1}\psi_1 {x_1}^{\alpha_1} + \sum_{k=2}^{K} \frac{\gamma_k}{\alpha_k}\psi_k \left(\left(\frac{x_k}{\gamma_k} + 1 \right)^{\alpha_k} - 1 \right), \tag{1}$$

so that $U(x)$ is quasi-concave, increasing and continuously differentiable with respect to x and ψ. ψ_k is the baseline utility of good k, i.e. the marginal utility of the good at zero consumption. It is a function of observed characteristics of the decision maker and of good k, z_k, which also includes a constant representing the generic preference for good k.

The parameters γ_k and α_k relate to good k. The γ_k parameters are translation parameters that allow for corner solutions. They also affect satiation as a higher γ_k implies that more consumption of the corresponding x_k is needed to reach saturation. The α_k parameter is solely associated with the satiation effect.

Further details about the role of the different parameters and the implications for the model structure can be found in Bhat (2008).

The probability that an individual chooses a specific vector of consumption amounts $\langle {x_1}^*, {x_2}^*, \dots, {x_M}^*, 0, \dots, 0 \rangle$, where M of the K goods are consumed, is given by:

$$\begin{aligned} &P({x_1}^*, {x_2}^*, \dots, {x_M}^*, 0, \dots, 0) \\ =&\frac{1}{p_1}\frac{1}{\sigma^{M-1}} \left(\prod_{m=1}^{M} f_m \right) \left(\sum_{m=1}^{M} \frac{p_m}{f_m} \right) \left(\frac{\prod_{m=1}^{M} e^{V_i/\sigma}}{\left(\sum_{k=1}^{K} e^{V_k/\sigma} \right)^M} \right), \end{aligned} \tag{2}$$

where σ is an estimated scale parameter and where $f_m = \frac{1-\alpha_m}{{x_m}^* + \gamma_m}$.

The MDCEV probability formulation above is obtained when assuming an i.i.d. extreme value distribution for the stochastic part of utility. This assumption of an absence of correlation can however be unrealistic in many settings, just as in a discrete choice context. Pinjari and Bhat (2010b) introduce the nested version of MDCEV, MDCNEV. They solve the expenditure allocation problem through the Kuhn-Tucker conditions by assuming that the unobserved part of utility of the different activities has a joint extreme value distribution given by:

$$F(\varepsilon_1, \varepsilon_2, .., \varepsilon_K) = exp\left[-\sum_{s=1}^{S_K}\left(\sum_{i \in s^{th} nest} exp\left(-\frac{\varepsilon_i}{\theta_s}\right)\right)^{\theta_s}\right], \tag{3}$$

where s represents one of the S_K nests that the K alternatives belong to, where $S_K < K$, i.e. at least some of the alternatives are nested together. The role of θ_s is that of a (dis)similarity parameter, i.e. a measure of the correlation between the stochastic components of the alternatives within a nest, with $0 < \theta_s \leq 1$. The MDCNEV model core parameters are the same as the MDCEV model except for the (dis)similarity parameters θ, where, if $\theta_s = 1 \, \forall s$, the nested model collapses to the non-nested one (or indeed if $S_K = K$).

Following Pinjari and Bhat (2010b), we can let $1, 2, \ldots, S_M$ be the nests that contain the M chosen options and $q_1, q_2, \ldots, q_{S_M}$ be the number of chosen alternatives in each of the S_M nests, so that $q_1 + q_2 + \ldots + q_{S_M} = M$. Assuming the distribution of the random components specified in Equation 3 above, the probability expression for the MDCNEV model can be written as follows:

$$\begin{aligned}
&P({x_1}^*, {x_2}^*, \ldots, {x_M}^*, 0, \ldots, 0) \\
&= |J| \frac{\prod\limits_{i \in \text{chosen alts}} e^{\frac{V_i}{\theta_i}}}{\prod\limits_{s=1}^{S_M}\left(\sum\limits_{i \in s^{th} nest} e^{\frac{V_i}{\theta_s}}\right)^{q_s}} \\
&\cdot \sum_{r_1=1}^{q_1} \cdots \sum_{r_s=1}^{q_s} \cdots \sum_{r_{S_M}=1}^{q_{S_M}} \left\{ \prod_{s=1}^{S_M} \left[\frac{\left(\sum\limits_{i \in s^{th} nest} e^{\frac{V_i}{\theta_s}}\right)^{\theta_s}}{\sum\limits_{s=1}^{S_k}\left\{\left(\sum\limits_{i \in s^{th} nest} e^{\frac{V_i}{\theta_s}}\right)^{\theta_s}\right\}} \right]^{q_s - r_s + 1} \left(\prod_{s=1}^{S_M} sum(X_r s)\right) \left(\sum_{s=1}^{S_M} (q_s - r_s + 1) - 1\right)! \right\},
\end{aligned} \tag{4}$$

where $sum(X_{rs})$ is the sum of the elements of a row matrix X_{rs}. A detailed description of the derivation of the probability expression above and the meaning of its different components is provided in Pinjari and Bhat (2010b).

3.2 Implementation for our time use data

In the present application of the model, people make a multiple discrete choice by choosing which activities to perform, and a continuous one by selecting the time allocated to each. As mentioned above, we need to make assumptions about the budget and specify the model including socio-demographic and social network characteristics in the utility and satiation from the different activities. Furthermore, an appropriate nesting structure needs to be implemented.

3.2.1 Budget

As mentioned in Subsection 3.1, utility is maximised subject to a budget constraint. In our case, the budget is defined as the total time available in the two days, i.e. $T = 48$ hours, and we consider only the time cost for each activity, so that the budget takes the form below:

$$\sum_{k=1}^{K} t_k = T, \quad t_1 > 0, \quad t_k \geq 0 \quad \forall k \quad (k = 2, \ldots, K), \tag{5}$$

where activity 1 is *Basic needs*, i.e. the *outside good* in our model (cf. Bhat, 2008).

3.2.2 Profile specification

In our work, we do not investigate methods to estimate a complete specification and adopt one of the 3 suggested by Bhat (2008). In particular, we make use of the "γ-profile", where we estimate only the γ_k parameters for $k = 2, 3, \ldots, 12$ (as we are modelling the choice between 11 alternatives on top of the outside good) and α_1 for the outside good. All the model specifications that we estimated displayed an extremely small and insignificant value of α_1, where, with $\alpha_1 \rightarrow 0$, the utility form collapses to a log utility formulation (cf. Bhat, 2008) with:

$$U(t) = \psi_1 \ln(t_1) + \sum_{k=2}^{12} \gamma_k \psi_k \ln\left(\frac{t_k}{\gamma_k} + 1\right) \tag{6}$$

This formulation implies that direct utility increases with additional units of consumption in a logarithmic fashion, i.e. with diminishing returns. The only estimated parameters relating to satiation are the γ_k terms, which scale the consumption quantity of the *inside goods*.

3.2.3 Utility specification

Both socio-demographic and social network variables were included in the discrete part of the model through ψ_k, the alternative-specific baseline utility, where the majority of effects were included in the form of dummy variables. For example, age was divided into the ranges "less than 26", "26-40","40-60" and "Over 60", while, using different specifications, we also tested the effects of gender, level of education, marital status, number of children, type of job, driving licence holding, neighbourhood, and ownership of communication tools and income. The presence and number of children in the household was incorporated in the model using two dummy variables (one underage child and two or more), with those having no underage children used as the base. We also tried different specifications, for example directly including the number of children as well as having different dummy variables corresponding to the age of children in ranges, as suggested by Pinjari and Bhat (2010b).

In Chile, there is a strong correlation between the level of education and the type of job and consequently the level of income (Torche, 2005). Model specifications in which two or all these three variables were included clearly led to confounding effects, and it was therefore decided to retain only household income. This variable was included in three levels, with the lowest being less than 400,000 Chilean Pesos (CLP), i.e. approximately \$600, the medium level being between 400,001 and 2,000,000 CLP (i.e. between \$600 and \$3,000) and high income (used as a base in the model) corresponding to 2,000,001 CLP or more.

The survey also included information about the type of dwelling respondents lived in and its surroundings and information about their home arrangements, such as whether they rented or owned their home and how many people lived there. These variables were not found to significantly impact activity patterns. Information about the respondent's partner (where present) were also part of the questionnaire (e.g. type of job and residential and work location), but only the variable measuring whether the respondent lived with the partner (which in the present context is believed to be equivalent to being married) was found to have an effect, while the other variables were not significant.

As mentioned in Section 2, the survey also contained a *name generator* and a *name interpreter* where respondents ("egos") were asked to provide information about their personal social network members ("alters"). Several network measures can be computed from these tools and were used in our analysis.

One measure commonly used in the literature is the size of the social network, i.e. the number of people listed in the name generator. This was included in the model in a logarithmic specification (given the substantial variation across people) to test its relation with all the different activities. The information about the soical network also allowed us to compute measures related to network composition. For example, we computed the share of different types of contacts (immediate family, friends, colleagues) as well as shares of people in the network having certain characteristics which made them similar to the respondent, such as having the same age, job, sex or income. These latter measures are commonly defined as *homophily* and commonly used in studies focusing on social interactions (Axhausen and Kowald, 2015).

The availability of both the "ego's" and each "alter's" residential location allowed the definition of a variable representing the share of emotionally strong contacts who live close to the "ego". Different geographical measures were attempted and we eventually chose a 1 km distance, partly because of its highly intuitive meaning of easily walkable distance. This measure could have arguably generated some confounding effects with the number/share of alters constituting the immediate family, but we checked and the magnitude of the coefficients measuring the latter effect did not change when this new variable was introduced.

We also explored some *heterophily* effects, i.e. the effect of higher shares of contacts who are different from the "ego" in one dimension. These effects have not been widely explored in the literature, therefore we can try to interpret these results but only deeper analyses will help in their understanding and differentiation from spurious correlations.

In addition, the questionnaire included some questions about different types of *social capital*, i.e. resources that can be provided or granted from/to other people within the social network. Respondents were given a table where the first column listed different types of help and the other two columns had to be filled in with names of people granting or receiving each type to/from the respondent. Examples are "Mobility for work", "Advice with important problems" and "Taking care of children".

We will describe the significant coefficients of these variables in Section 4.

3.2.4 Parametrisation of γ_k

In addition to identifying the determinants of the discrete choice, we allow for socio-demographic interactions in the continuous part of the model, i.e. through the γ_k parameters. To ensure positivity of the γ_k in estimation, we write $\gamma_k = exp(\mu_k + {\delta_k}'\omega_k)$, where ω_k is a vector of individual characteristics. The baseline value for γ_k (i.e. for a respondent in the base socio-demographic categories) is thus given by e^{μ_k}, while e.g. $e^{\delta_{k,l}}$ is a positive multiplier (greater or smaller than 1) on this baseline value for a respondent who possesses the socio-demographic characteristic identified by the l^{th} element in ω_k. This socio-demographic parameterisation allows the level of satiation and the position of the activity-specific indifference curve to be dependent on the respondent's characteristics.

In our specific case, the vector of socio-demographic characteristics ω_k enters the expression as: $\omega_k = (\omega_k^{base} - \omega_k^{mean})/\omega_k^{mean}$, so that the meaning of the δ_k parameters is related to the deviation of the value of the variable for a specific respondent from the rest of the sample. A positive value of the shift increases the translation parameter for alternative k, and therefore implies less rapid satiation and higher time investment in activity k. Differently, negative values imply a decrease in the translation parameter and more rapid satiation from activity k.

All the variables described in Subsection 3.2.3 were also tested as determinants of the satiation dynamics for the different activities.

4 Results

4.1 Nesting structure

With 12 activities in our dataset, many thousands of different possible nesting structures arise. In our work, we tested over 30 different structures, making informed decisions on which ones merited empirical testing. A subsample of ten diverse nesting structures (including the best fitting and most behaviourally interesting ones) is reported in Table 3, where the nesting is applied to the base model (i.e. only including the baseline constants and translation parameters). For each of these models, we describe the activities belonging to each nest as well as the estimated nesting parameters, where brackets are used when the nesting terms are not significantly different from the base value of 1 at a significance level of 95%.

The different specifications are ordered by their goodness of fit, measured by the Log-Likelihood (LL). We also include the Bayesian Information Criteria (BIC) value used to compare the models with each other. The base non-nested model had a log-likelihood of $-3,832.80$ and BIC of $7,785.71$.

The nesting structure testing process was guided by grouping activities according to intuition and findings from existing literature, although in some cases (e.g. specifications 8 and 10, where *Work* is grouped with *Shopping* and *Travel*), non-intuitive groupings were attempted in order to detect additional relationships. Although specification 10 provided the best fit, we decided to adopt specification 9, as it is a more parsimonious and behaviourally sensible structure, while being only marginally worse in terms of fit. This final structure, which is also shown in Figure 1, includes a nest for in-home and one for out-of-home activities, with only *Family* not belonging to any nest. A reason for this lack of correlation could be that *Family* is a relatively broad category including activities which can take place at home or elsewhere.

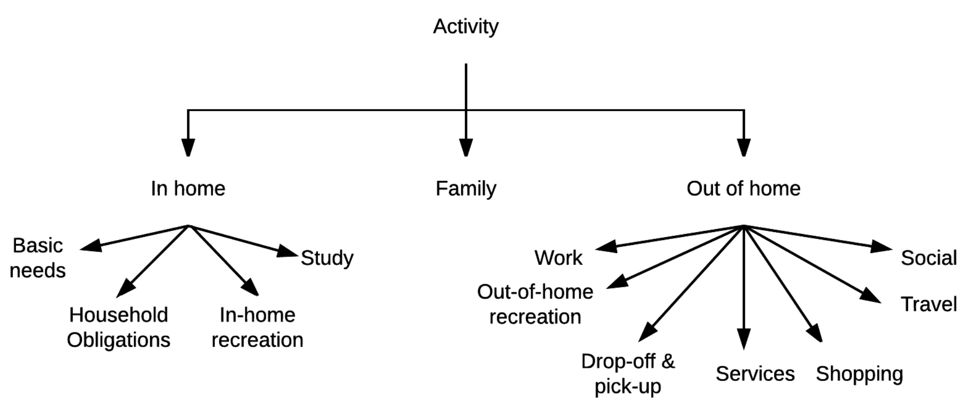

Figure 1: Final nesting structure

The θ_s parameters related to the two (non-degenerate) nests in Figure 1 have values of 0.4316 for the "In-home" nest and 0.7366 for the "Out-of-home" nest, with both being highly significantly different from 1 (cf. Table 6). These results suggest that there is a heightened correlation between the unobserved portion of utility of the activities in either nest, which is stronger in the first group of activities. Intuitively, it makes sense to find correlation between the activities we group together, as an individual may be more likely to reallocate time between different in home activities or different out of home activities than across the two categories. The different magnitude of the two nesting parameters suggests that the choice is more deterministic across the alternatives belonging to the first nest. This result is intuitive, in the sense that there are likely fewer unobserved factors affecting the in home activities as opposed to the out-of-home ones. Interestingly, we

#	Nest 1	θ_1	Nest 2	θ_2	Nest 3	θ_3	Nest 4	θ_4	Non-nested activities	LL	BIC
1	*Solo activities* work, study	(0.9458)	*Social activities* family, OH recr., social	1	NA	NA	NA	NA	basic needs, IH recr., HH obligations shopping, travel	-3,832.45	7,795.92
2	*Discretionary* family, IH and OH recr., social	0.8893	*Compulsory activities* HH obligations, shopping, study, work	(0.9828)	NA	NA	NA	NA	basic needs. travel	-3,829.74	7,790.50
3	*Travel oriented* *drop off-pick up, travel*	(0.9999)	*Errands oriented* *shopping, services*	(0.9427)	*Leisure oriented* OH recr., social	0.8119	NA	NA	basic needs, HH obligations, IH recr., study, work	-3,829.16	7,794.80
4	*Home & Family* family, IH recr.	(0.9002)	*Work oriented* work, study	(1)	*Leisure oriented* OH recr., social	0.8203	NA	NA	drop off-pick up, HH obligations, service, shopping, travel	-3,828.22	7,792.93
5	*Home & Family* drop off-pick up, family	0.7875	*Errands oriented* shopping, services	(0.9437)	*Leisure oriented* OH recr., social	0.8217	NA	NA	basic needs, HH obligations, IH recr. travel, study, work	-3,824.58	7,785.65
6	*OH* drop off-pick up, OH recr., services, shopping, social, travel	0.6921	*IH* HH obligations, IH recr.	(0.994)	NA	NA	NA	NA	basic needs, IH recr., HH obligations shopping, travel	-3,812.55	7,756.13
7	*Personal and home* basic needs, HH obligations	0.5206	*Family oriented* drop off-pick up, family	0.7869	*Errands oriented* shopping, services travel	(0.9998)	*Leisure oriented* *OH recr.,* social	0.8303	IH recr., study, work	-3,812.37	7,766.69
8	*IH* basic needs, HH obligations, IH recr.	0.4726	*Family oriented* drop off-pick up, family	0.7876	*Shopping and work* shopping, work	(0.9995)	*Leisure oriented* OH recr., social	0.8267	services, study,travel	-3,802.41	7,746.77
9	*IH* basic needs, HH obligations, IH recr., study	0.4661	*OH* drop off-pick up, services, OH recr., shopping, social, travel, work	0.764	NA	NA	NA	NA	family	-3,792.77	7,716.57
10	*IH* basic needs, HH obligations, IH recr., study	0.4360	*Family oriented* drop off-pick up, family	0.7871	*Travel and work* travel, work	0.7637	*Leisure oriented* OH recr., social	0.8358	services, shopping	-3,787.21	7,716.37

Table 3: Sample of the attempted nesting specifications (nesting parameters shown in brackets when not significant)

find higher levels of correlation with respect to other applications of the same model to time use (Pinjari and Bhat, 2010b; Rajagopalan et al., 2009).

4.2 Overview of estimated models

The final specification of the MDCNEV model was obtained by starting off with a base model and progressively adding and combining variables on the basis of intuition, statistical significance and guidance from previous studies. All effects were tested as determinants of both the multiple discrete and continuous choice. The final specification was finally selected on the basis of better model fit and meaningfulness of the estimated effects, where it is worth noting that the differences in fit across different nesting structures remained largely unaffected by the inclusion of additional variables.

As stated above, one of the main objectives of the present work is to investigate the determinants of activity and travel behaviour and assess whether there is scope for confounding between social context and socio-demographic variables. To test for such confounding, we additionally estimated versions of the final model which included only the strictly socio-demographic effects and versions which include only the social context measures.

Table 4 reports measures of the goodness of fit for the base model (i.e. including only the baseline constants and satiation parameters), the two "partial" models discussed above and the full specification of the MDCEV and MDCNEV models. In all the specifications, the MDCNEV models present two extra estimated parameters, the θ for the two nests. The statistical tests reported in Table 4 show how adding socio-demographic and social context variables improves the base model, but also how the full specification provides a better fit than the two previous models, clearly suggesting that the socio-demographic and social network effects provide distinct insights into behaviour. We will return to the issue of potential confounding in Section 6, but for now focus on the results of the full specification. Finally, it is apparent that across all the different specifications, the introduction of the nesting structure results in a clear improvement in model fit.

4.3 MDCNEV model results

The results of the final specification of the MDCNEV model are presented in Tables 5 and 6, alongside the results for the full specification of the MDCEV model. In what follows, a detailed description of our preferred model, the full MDCNEV model specification, is given, followed by a comparison with the MDCEV model results.

4.3.1 Baseline constants

The first 11 lines in Table 5 report the baseline preference constant components of the utility of each alternative, where they enter through an exponential into ψ_k. The negative value of these constants highlights the preference for the base alternative *Basic needs* with respect to any other activity. In the base model, where interaction effects are not

		MDCEV	MDCNEV	LR-test (MDCNEV *vs* MDCEV)
Base specification	N. parameters	22	24	$80.1 \sim \chi^2_2$, $p < 10^{-17}$
	Log-Likelihood	-3,832.80	-3,792.77	
	AIC	7,709.61	7,633.54	
	BIC	7,785.72	7,716.57	
Socio-Demographics only	N. parameters	47	49	$109.6 \sim \chi^2_2$, $p < 10^{-23}$
	LL	-3,729.80	-3,675.02	
	AIC	7,536.80	7,444.05	
	BIC	7,699.41	7,7617.57	
	LR-test *vs* base	$206 \sim \chi^2_{25}$, $p < 10^{-29}$	$235.5 \sim \chi^2_{25}$, $p < 10^{-35}$	
Social Network only	N. parameters	42	44	$81.5 \sim \chi^2_2$, $p < 10^{-17}$
	LL	-3,742.913	-3,702.19	
	AIC	7,569.83	7,492.39	
	BIC	7,715.13	7,644.61	
	LR-test *vs* base	$179.8 \sim \chi^2_{20}$, $p < 10^{-26}$	$181.2 \sim \chi^2_{20}$, $p < 10^{-27}$	
Full specification	N. parameters	67	69	$90.8 \sim \chi^2_2$, $p < 10^{-19}$
	LL	-3,642.30	-3,596.88	
	AIC	7,418.61	7,331.77	
	BIC	7,650.40	7,570.48	
	LR-test *vs* base	$381 \sim \chi^2_{45}$, $p < 10^{-54}$	$391.8 \sim \chi^2_{45}$, $p < 10^{-56}$	
	LR-test *vs* socio	$175 \sim \chi^2_{20}$, $p < 10^{-26}$	$156.3 \sim \chi^2_{20}$, $p < 10^{-22}$	
	LR-test *vs* social	$201.2 \sim \chi^2_{25}$, $p < 10^{-28}$	$210.6 \sim \chi^2_{25}$, $p < 10^{-30}$	

Table 4: Comparison of goodness of fit measures

included, the values of these parameters are in line with the discrete choice, i.e. how many people in the sample ever choose the activity.

4.3.2 Impact of socio-demographics on the baseline utilities

Several socio-demographic characteristics significantly affect the utility of the choice alternatives.

The only significant effect of the *Sex* variable was found on *Household Obligations*, an activity that men are less likely to perform than women. This is an expected result, as gender imbalance in household activities is found in most cultural contexts (Lachance-Grzela and Bouchard, 2010; Ruppanner, 2008). Less utility is derived from *In-home recreation* when decision makers are between 40 and 60 years old with respect to the "Over 60s", while the youngest group is more likely to study and the 26-40 group is the one getting more utility from *Work*.

People who have one underage child are found to be more likely to work. Somewhat surprisingly, one underage child relates to reduced occasions for *Family* time, differently from the case of two or more children, needing more support and a higher rate of being picked up and dropped off.

According to our results, the lowest level of income is associated with higher likelihood of performing *Household Obligations* and *Family*-oriented activities. The latter effect was retained for its intuitive meaning despite the low statistical significance. These findings are entirely reasonable in light of the the fact that it is very common for medium and high income Chilean households to employ a housekeeper (Mora, 2006). Past studies (e.g. Bhat et al., 2006) argued that lower income household tend to be more likely to perform in-home activities due to the higher financial burden imposed by out-of-home recreation.

		Full Spec. MDCNEV		MDCEV		
	Activity	est	rob t-stat	est	rob t-stat	t-diff vs A
Baseline utility constants	Drop-off/Pick-up	-6.1329	-14.5	-7.0995	-14.17	-1.47
	Family	-5.7346	-16.44	-5.7456	-16.61	-0.02
	Household obligations	-3.2715	-16.06	-3.3285	-8.7	-0.13
	Out-of-home recreation	-4.0542	-25.71	-4.3559	-23.31	-1.23
	In-home recreation	-4.6827	-16.58	-6.4392	-11.97	**-2.89**
	Services	-4.1466	-34.41	-4.4725	-32.48	-1.78
	Social	-3.9735	-8.38	-4.4709	-7.92	-0.67
	Shopping	-3.4295	-15.22	-3.5271	-12.38	-0.27
	Study	-5.0538	-9.83	-7.2027	-6.72	-1.81
	Travel	-3.9229	-4.41	-4.5610	-4.45	-0.47
	Work	-3.8267	-30.12	-4.0182	-26.51	-0.97
Sex=male	Household obligations	-0.4083	-2.88	-0.8788	-3.16	-1.51
Age < 26	Study	0.4205	1.93	0.9125	2.07	1.00
Age 26-40	Work	0.4491	2.87	0.5267	2.8	0.32
Age 40-60	In-home recreation	-0.7471	-2.91	-1.7587	-3.22	-1.68
1 underage child	Family	-1.0412	-2.8	-1.0382	-2.83	0.01
	Work	0.7590	3.32	0.9679	3.51	0.58
2+ underage children	Drop-off/Pick-up	1.1407	3.17	1.4831	3.08	0.57
	Family	1.7703	4.56	1.7843	4.65	0.03
Low income	Drop-off/Pick-up	1.0297	3.83	1.3163	3.82	0.66
	Family	0.4098	1.34	0.4369	1.45	0.06
	Household obligations	0.4264	3.35	0.8123	3.31	1.40
Agüita de la Perdiz	In-home recreation	0.8625	3.05	1.8448	3.02	1.46
	Social	0.2589	1.61	0.4258	2.28	0.68
La Virgen	In-home recreation	1.0926	3.85	2.3797	4.18	**2.02**
Driving Licence	Drop-off/Pick-up	0.7128	2.43	0.9155	2.5	0.43
Internet Acess	Social	0.4019	1.92	0.6212	2.39	0.66
	Study	1.0547	2.19	2.2350	2.13	1.02
Lives with partner	Household obligations	0.3694	2.81	0.7755	3.05	1.42
	Shopping	0.4715	2.43	0.5955	2.42	0.40
Partner works	Drop-off/Pick-up	0.6484	2.04	0.8686	2.07	0.42
Social network size	Social	0.3039	1.85	0.4329	2.22	0.51
	Travel	1.4446	4.45	1.8634	4.87	0.83
Share of immediate family in the network	Household obligations	-1.0400	-2.96	-2.2341	-3.2	-1.53
Share of friends in the network	Household obligations	-0.8087	-2.85	-1.6903	-3.19	-1.47
Share of friends in the network	Shopping	-0.8578	-2.48	-1.1379	-2.55	-0.50
Social capital children X female	Drop-off/Pick-up	0.7740	2.83	1.0096	2.9	0.53
Social capital children X female	Study	0.3134	1.87	0.8541	2.51	1.43
Share of network in same age group (40-60)	Social	-0.6573	-2.31	-0.8342	-2.35	-0.39
Share of network with same work status (student)	Out-of-home recreation	1.2441	3.31	1.4771	3.09	0.38
Share of network with same work status (employed)	Work	1.4258	5.57	1.8881	6.84	1.23
Share of network employed when ego is student	Study	4.2603	4.13	7.3932	3.75	1.41
Share of close network members living within 1 km	Drop-off/Pick-up	-1.8379	-2.99	-2.2914	-3.01	-0.46
	Out-of-home recreation	-0.5204	-1.44	-0.6616	-1.42	-0.24
	In-home recreation	0.4135	1.47	1.0883	1.67	0.95
	Shopping	-0.8606	-2.39	-1.1000	-2.44	-0.41
	Travel	-1.4028	-2.28	-1.5739	-2.33	-0.19

Table 5: MDCNEV and MDCEV results - Utility parameters

	Activity	Full Spec. MDCNEV est	rob t-stat	MDCEV est	rob t-stat	t-diff vs A
Satiation parameters						
Baseline gamma	Drop-off/Pick-up	0.3443	1.7	0.2306	1.12	-0.39
	Family	2.173	10.16	2.2297	10.35	0.19
	Household obligations	11.7755	53.86	4.0957	31.98	**-30.31**
	Out-of-home recreation	2.6369	18.12	1.8663	14.92	**-4.02**
	In-home recreation	7.9366	29.29	2.6165	12.56	**-15.57**
	Services	1.6599	9.52	1.1268	6.92	**-2.23**
	Social	2.6426	19.86	1.8293	16.14	**-4.65**
	Shopping	0.8574	6.33	0.5992	5.15	-1.45
	Study	5.774	23.69	1.8934	7.95	**-11.39**
	Travel	0.1695	0.55	0.1057	0.36	-0.15
	Work	5.8414	46.02	4.0355	38.25	**-10.94**
Shifts (log of baseline gamma)						
Age < 26	Social	0.0541	1.55	0.0529	1.45	-0.02
Age 26-40	Household obligations	-0.1689	-2.04	-0.1383	-1.69	0.26
1 underage child	Work	-0.1898	-2.92	-0.1852	-2.77	0.05
2 underage children	Study	-0.4857	-2.88	-0.6457	-2.68	-0.54
Agüita de la Perdiz	Household obligations	-0.2482	-4.06	-0.1958	-3.58	0.64
Network size	Travel	-1.3054	-4.45	-1.5622	-4.69	-0.58
Social capital travel	Travel	-0.1691	-1.94	-0.1959	-2.22	-0.22
Share of close network members living within 1 km	Shopping	0.2167	1.89	0.2115	1.88	-0.03
	Travel	0.2798	1.58	0.3108	1.67	0.12
Nesting parameters						
In home		0.4356	-12.36	-	-	-
Out of home		0.7382	-6.48	-	-	-

Table 6: MDCNEV and MDCEV results - Translation and nesting parameters

The effect of residential location was also tested, using the *Lomas S. Sebastian* neighbourhood (mid-high income, far from the centre) as a base. Living in the two neighbourhoods close to the city centre has a positive impact on *In-home recreation* with respect to people living further away from town. A potential explanation for this result is the existence of a large shopping centre close to the neighbourhoods located further away from downtown, which serves as an important recreational facility. Among these two, respondents in the mid-high income neighbourhood have a higher probability of performing social activities. There might be confounding effects as variables such as income and neighbourhood could measure the same effect. In this case, the residents of the richer and more central areas could also have the resources for more social activities taking place downtown.

As expected, having a driving licence increases the likelihood of *Pick-up/Drop-off*. We further find that internet access has a positive impact on *Social* activities: this is in line with the literature on social networks and travel activities, which has often suggested the presence of complementarities between access to communication technology and travel for social purposes (Schaap et al., 2016). Access to the internet also positively impacts the utility of *Study*, an intuitive effect when we think about how important this has become in the search for sources of information. In this case, we acknowledge that there is a potential inverse causality, as we cannot exclude that someone would get access to the internet because they want to study.

People who live with a partner (which in the present context coincides with being married) are more likely to perform *Household Obligations* and *Shopping*. This could be due to sharing household duties on a daily basis, while people who live alone or with the family of origin might not perform these activities in the two days of observation. Kapur and Bhat (2007) motivate the higher involvement of married individuals in household maintenance activities on the basis of increased household responsibility.

In addition, people whose partner works are more likely to *Pick-up/Drop-off* other people, suggesting that the duty is probably split or mainly performed by the non-working partner. In an attempt to gain further insights about these effects, different interactions were tested (for example with sex or partner/respondent being employed) but they did not yield significant results.

4.3.3 Correlation between social network variables and baseline utilities

Several of the measures computed using the *name generator* and *name interpreter* data are found to be significantly related to activity patterns. These results are also displayed in Table 5, just below the socio-demographic effects, where it is again important to stress that we cannot assess the directionality of the impact with certainty.

Social network size is related to performing *Social* activities as well as to *Travel*. We did not find a strong link between network composition and recreational or social activities, but we found that people with higher shares of immediate family members and friends tend to engage in *Household obligations* less than others. Having high shares of friends is correlated with lowered utility from *Shopping* as well. The latter result could be linked to the potential trade-offs between friendship maintenance and other activities.

In terms of *social capital* measures, the only form of help which showed a significant correlation with the choice of an activity was "Taking care of children", mainly meaning baby-sitting. We find that, in interaction with being female, those who receive help are more likely to engage in *Drop-off/Pick-up* activities and in *Studying*. The first effect may reflect the need to drop children off and then pick them up from the people who take care of them. We find the second effect to be an interesting finding, as it potentially shows the importance of social capital in providing an opportunity to mothers of young children to find time for improving their education. As mentioned before, it is difficult to interpret the directionality of these effects, as it is similarly plausible that mothers with children would decide to include in their network people who can help them taking care of their children so that they can perform other activities, such as studying.

We find a negative relation between belonging to the 40-60 age category and having a high share of contacts in the same age group and being less likely to perform *Social* activities. On possible interpretation is that people in this group meet their peers mainly in other contexts, such as work. Homophily in employment status is also explored and we find that students with many contacts who are themselves students are more likely to perform *Out-of-Home Recreation*, probably because students tend to gather in groups and it is easier for them to do so outside of their homes, although again the opposite directionality is also possible. We also find that workers whose networks have high shares of people in the job market are more likely to perform *Work* activities.

Only one of the *heterophily* effects we tested remained strongly significant in the final specification: there is a correlation between someone being a student but with high shares of employed people in the network, and being likely to perform study activities. This could be interpreted as a student with this social context being particularly driven to finish his/her studies and enter the job market (and consequently lifestyle) of most of his/her peers, but further investigations would be needed, as evidence on heterophily measures and their impacts on behaviour is not present in the literature.

A higher share of emotionally close "alters" living close to the "ego" is associated with a lower likelihood of *Drop-off/Pick-up*, *Shopping* and *Travel.* With a low level of statistical significance, but intuitively interesting, we also observe a negative relationship with *Out-of-Home Recreation* and a positive one with *In-Home Recreation.* A closely clustered network of family or close friends can indeed imply more activities to happen close to home or at these people's homes, instead of outside, or (considering the opposite direction of causality) that a person with a preference for more local activities tends to compose his/her network of "alters" who live close to him/her.

4.3.4 Translation (γ_k) parameters

As mentioned above, the translation parameters of the model are further parameterised as $\gamma_k = exp(\mu_k + {\delta_k}'\omega_k)$ to accommodate heterogeneity in satiation across decision-makers. Table 6 shows the values of e^{μ_k} (reported as "Baseline γ_k"), which represent the baseline satiation from alternative k; and the values of δ_k, i.e. the shifts from the base values of γ_k, which show the effects of specific socio-demographic characteristics and social network measures on the satiation from different activities (in terms of the shift to the log of the baseline γ_k). As explained in subsection 3.2.4, a positive value of the shift increases the translation parameter for alternative k and implies less rapid satiation and higher time investment in activity k, while negative values decrease the translation parameter and imply more rapid satiation.

The coefficients shown in Table 6 suggest that respondents younger than 26 year old get less satiated by *Social* activities with respect to over 60s, i.e. the base category. Despite the robust t-statistics being only 1.55, we decided to retain this result because of its highly intuitive interpretation. People aged 26 to 40 are more satiated by *Household Obligations*, i.e. they tend to spend less time in these than older people. We also find that having 1 and 2 or more underage children results in higher satiation from, respectively, *Work* and *Study*: this is in line with the common practice of parents with young children to reduce the work/study time to take care of them.

We find that living in *Agüita de la Perdiz* is related to lower duration of *Household*

Obligations, possibly due to the low complexity of these activities for low income groups.

Larger social networks are associated with reduced duration of *Travel*. A possible interpretation of this effect could be related to the need to reduce travel time to be able to gain interaction time with more people. The coefficient measuring the impact of social capital received for travelling on travel duration could suggest that interacting with many people implies travelling with them in a less costly and more efficient way. The opposite directionality is also plausible, i.e. people could choose to include in their network people who can offer them lifts or lend them transport tools so that their travel activities can be quicker.

Having a higher share of important people living no further than 1 km away from the ego is related to higher duration of *Shopping* activities, and (weakly significant) higher duration of *Travel*, potentially indicating that they conduct these activities jointly with people living close to them.

4.3.5 Impact of variables on both the discrete and the continuous choice

As shown above, the effect of the independent variables on the discrete and continuous part of the model can be isolated by including them, respectively, only in the utility specifications (i.e, as elements of the z_k vector in $\psi(z_k, \varepsilon_k)$, only in the specification of the translation parameters (i.e. as ω_k in $\gamma_k = exp(\mu_k + {\delta_k}'\omega_k)$), or in both. Interesting behavioural insights can be gained from the cases in which a specific effect is significant in both parts of the model for a given activity. For example, the likelihood of working is positively affected by having one underage child, but the duration of this activity is lower than in the case of people without young children. This could suggest that having one child is associated with the need to provide for him/her, but not worth one parent exiting the job market for childcare. At the same time, it is reasonable that people with a small child would either work part-time, or simply work less than people without children. This is a strategy recognised in sociological studies, e.g. Moen and Sweet (2003).

4.4 Comparison of MDCNEV and MDCEV results

Tables 5 and 6 report the model estimates and robust t-ratios. For the MDCEV model, we also display the t-statistics for the difference between this model's estimates and the corresponding one in the full specification of the MDCNEV, with significant differences shown in bold.

We observe that the main differences lie in the baseline constants for the different alternatives and in the baseline γ parameters. In addition, we can observe that while the sign of coefficients is same in the two models, both the *Baseline constants* and most interaction effects are smaller in magnitude in the MDCNEV with respect to the MDCEV. This can be explained by noting that the utility of alternatives belonging to one of the nests is divided by the respective θ_s in the probability expression, so all these coefficients are expected to be smaller, except in the case of *Family* activities, which does not belong to any nest. At the same time, we observe a larger magnitude of the γ_k

parameters in the nested model. This can be understood by looking at the expression for the product-specific marginal indirect utility for the "γ-profile" (cfr. Bhat (2008)):

$$V_k = \beta' z_k - \ln\left(\frac{x_k^*}{\gamma_k} + 1\right) - \ln p_k, \quad (k \geq 2), \quad V_1 = (\alpha_1 - 1)\ln(x_1^*). \tag{7}$$

As V_k is negative in our case, if the components of the β vector are smaller, a compensation mechanism to leave the scale between x_k and z_k unaltered is needed. We thus observe values of the baseline γ_k which are higher than in the MDCEV model as they compensate for the scaled-down β parameters.

5 Model forecasting

Nested model structures, whether discrete choice or discrete-continuous, allow for correlations between individual alternatives. While the impacts of this correlation will manifest themselves in improvements in fit over non-nested models, and potential differences in other model parameters, the key benefit will be in changes to the substitution patterns between alternatives.

5.1 Approximating draws from a GEV distribution

For the standard MDCEV model, a simple and efficient forecasting algorithm exists (cf. Pinjari and Bhat, 2010a). This algorithm relies on the analyst producing draws from the underlying error structure, a process that is easy for the MDCEV model, which relies on type I extreme value draws, but substantially more complex for the MDCNEV model, which relies on generalised extreme value (GEV) draws (cf. Equation 3). Complex approaches to do so have been suggested by McFadden (1999) and Bhat (2009). We instead rely on a simpler approximation, as follows:

1. Compute the approximate correlations for each nest s as $1 - {\theta_s}^2$, and define an overall correlation matrix Ω.
2. Create (for each respondent) an Rx12 matrix with distribution $N(0, \Omega)$, where R is a number of draws chosen by the analyst. The correlation structure within this D_N matrix is easily created using a Cholesky factorisation.
3. Apply the inverse normal CDF transformation $D_U = F^{-1}(D_N)$ to transform the normally distributed draws into uniform draws.
4. Apply the transformation $D_E = -log(-log(D_U))$ to transform the uniform draws into extreme value draws.

We have shown in a number of tests that the approximation described above works correctly, as the resulting draws have a mean of around 0.577... (Euler's constant) and a standard deviation of about $\sqrt{\pi^2/6}$ (coherent with the extreme value distribution) and the approximate correlation structure implied by $1 - {\theta_s}^2$, i.e. Ω. In our forecasting runs, we use $1,000$ draws per individual.

5.2 Forecasting scenarios

We performed 3 different forecasting exercises, each time changing an attribute that was affecting an activity belonging to a different nest. This is a purely illustrative process, so the assumptions made are rather arbitrary. In the first scenario, we made the assumption that everybody in the sample would behave as if they were women, where gender only affects the utility of *Household Obligations*, an activity contained in nest 1. A similar reasoning was applied in the second scenario, where it was assumed that nobody in the sample has a partner who works, where this variable only affects the utility of *Drop-off/Pick-up*, an activity contained in nest 2. As there was no single socio-demographic effect that exclusively affects *Family* activities, we decided to simply set to zero the coefficient measuring the impact of having low household income on this specific activity. This equates to testing the impact of making *Family* time as (un)attractive to low income people as others.

5.3 Forecasting results

The results of this process are summarised in Table 7, where we regroup the activities by nest. For each scenario, we report the average number of hours spent by respondents in the different activities. We show the "true" values from the sample, followed by the "base scenario", i.e. the consumption context reproduced by the algorithm that is used as a starting point, to which the forecasting routine is subsequently applied. This first step shows that time allocation is reproduced quite accurately by the algorithm both in the MDCEV and in the MDCNEV models. This provides a validation of the model.

We then show the forecasted average time allocation for each activity as well as the percentage change from the base scenario. As expected, in all the three scenarios we see a change in the "affected" activity (the sign of which depends on the sign of the model coefficient) that is compensated by a change of the opposite sign of the time invested in other activities. The impact of the nesting structure is clear to see. In the first scenario, for example, we see that, in the MDCNEV model, the increase in time allocated to *Household Obligation* is compensated by a reduction in all other activities, but the reduction is larger in time invested other in-home activities. A corresponding pattern is observed in Scenario 2. Finally, in Scenario 3, we do not observe major differences between the MDCEV and the MDCNEV forecasting scenarios, as in this case *Family* is nested on its own. These results show that the nesting structure matters in forecasting and its impact on time reallocation is in line with expectations.

Scenario 1: everybody behaves as if they were women

Nest	Activity	*Sample*	MDCEV *Base scenario*	MDCEV *Forecast*	MDCEV *change*	MDCNEV *Base scenario*	MDCNEV *Forecast*	MDCNEV *change*
1	*Basic needs*	*28.6*	*26.55*	*26.21*	*-1.26%*	*26.09*	*25.74*	*-1.34%*
1	**Household obligations**	**2.6**	**2.65**	**3.30**	**24.42%**	**2.68**	**3.23**	**20.41%**
1	*In home recreation*	*0.8*	*0.78*	*0.77*	*-1.61%*	*0.79*	*0.76*	*-3.45%*
1	*Study*	*1.1*	*1.12*	*1.11*	*-1.24%*	*1.10*	*1.07*	*-2.83%*
2	Drop off/Pick up	0.1	0.17	0.17	-1.58%	0.17	0.17	-0.75%
2	Out-of-home recreation	0.8	1.01	0.99	-1.79%	1.13	1.12	-0.75%
2	Services	0.5	0.65	0.64	-1.87%	0.72	0.71	-0.80%
2	Social	4.0	4.13	4.06	-1.64%	4.36	4.33	-0.76%
2	Shopping	0.5	0.77	0.75	-2.23%	0.78	0.77	-0.99%
2	Travel	3.3	4.35	4.28	-1.53%	3.97	3.94	-0.75%
2	Work	4.9	5.06	4.97	-1.74%	5.39	5.35	-0.83%
3	Family	0.8	0.76	0.75	-1.85%	0.82	0.82	-0.92%

Scenario 2: everybody behaves as if no one had a partner who works

NEST		*Sample*	MDCEV *Base scenario*	MDCEV *Forecast*	MDCEV *change*	nested MDCEV *Base scenario*	nested MDCEV *Forecast*	nested MDCEV *Forecast*
1	Basic needs (outside good)	28.6	26.55	26.58	0.14%	26.09	26.12	0.09%
1	Household obligations	2.6	2.65	2.66	0.22%	2.68	2.68	0.15%
1	In home recreation	0.8	0.78	0.79	0.15%	0.79	0.79	0.08%
1	Study	1.1	1.12	1.12	0.14%	1.10	1.10	0.08%
2	**Drop off/Pick up**	**0.1**	**0.17**	**0.09**	**-45.95%**	**0.17**	**0.10**	**-41.88%**
2	*Out-of-home recreation*	*0.8*	*1.01*	*1.01*	*0.20%*	*1.13*	*1.13*	*0.29%*
2	*Services*	*0.5*	*0.65*	*0.65*	*0.19%*	*0.72*	*0.72*	*0.33%*
2	*Social*	*4.0*	*4.13*	*4.14*	*0.19%*	*4.36*	*4.37*	*0.23%*
2	*Shopping*	*0.5*	*0.77*	*0.77*	*0.25%*	*0.78*	*0.78*	*0.32%*
2	*Travel*	*3.3*	*4.35*	*4.36*	*0.17%*	*3.97*	*3.98*	*0.20%*
2	*Work*	*4.9*	*5.06*	*5.07*	*0.21%*	*5.39*	*5.41*	*0.26%*
3	Family	0.8	0.76	0.77	0.33%	0.82	0.83	0.20%

Scenario 3: everybody behaves as if income level was high (impact on Family only)

NEST		*Sample*	MDCEV *Base scenario*	MDCEV *Forecast*	MDCEV *change*	nested MDCEV *Base scenario*	nested MDCEV *Forecast*	nested MDCEV *Forecast*
1	Basic needs (outside good)	28.6	26.55	26.59	0.18%	26.09	26.14	0.18%
1	Household obligations	2.6	2.65	2.66	0.40%	2.68	2.69	0.42%
1	In home recreation	0.8	0.78	0.79	0.28%	0.79	0.79	0.28%
1	Study	1.1	1.12	1.12	0.21%	1.10	1.11	0.22%
2	Drop off/Pick up	0.1	0.17	0.17	0.45%	0.17	0.17	0.38%
2	Out-of-home recreation	0.8	1.01	1.01	0.24%	1.13	1.13	0.22%
2	Services	0.5	0.65	0.65	0.27%	0.72	0.72	0.26%
2	Social	4.0	4.13	4.14	0.26%	4.36	4.37	0.27%
2	Shopping	0.5	0.77	0.77	0.27%	0.78	0.78	0.25%
2	Travel	3.3	4.35	4.36	0.21%	3.97	3.98	0.19%
2	Work	4.9	5.06	5.07	0.30%	5.39	5.41	0.31%
3	**Family**	**0.8**	**0.76**	**0.66**	**-13.81%**	**0.82**	**0.72**	**-13.05%**

Table 7: Forecasting scenarios results

6 Inclusion of social network variables

As stated above, one of the objectives of the present paper is to understand whether elements of the wider choice context, such as the social environment, are related to time allocation decisions.

As already mentioned in Section 4.2, we want to test the presence of confounding effects between socio-demographics and social network measures by estimating models which include socio-demographics and social network measures only. Detailed results of these models are shown in Table 8 and 9. In line with what we did in Tables 5 and 6, we also present the t-difference to compare the parameters of the "partial" models (B and C in the Tables) to the full MDCNEV specification (A) as well as between themselves. When we compare the parameter estimates of these "partial" models with those of the full MDCNEV specification, which includes both socio-demographics and social network measures, we find no statistically significant differences in the interactions effects. This suggests that there are no confounding effects between social network measures and socio-demographics. The only differences are in the activity-specific baseline constants and in the baseline γ_k parameters, as expected. This is due to the fact that the base categories of respondents are different in the two models.

As shown in Table 4, the improvement due to the inclusion of the social network variables is nearly as large as the one resulting from the socio-demographics. But it is important to acknowledge the potential presence of endogeneity, and for this reason we performed model forecasts excluding the social network variables from the model. The forecasted time allocation obtained by applying the model specification that does not include social network variables are shown in Table 10. There are no substantial differences between these forecasts and the ones shown in Table 7. This is consistent with the lack of differences in the socio-demographic parameters between the models, and provides further reassurance that there is little or no confounding between the social network and other variables included in the model.

7 Conclusions

The present paper has aimed to contribute to the existing literature on choice of activity type and duration.

We successfully apply the MDCNEV model, finding significant correlations between activities and showing the importance of accommodating the nesting structure. Moreover, we propose a simple and effective method to approximate draws from a GEV distribution and successfully perform forecasting with the MDCNEV model, showing how the time allocation changes according to the nesting structure.

In terms of behavioural insights, we confirm the significant effect of several socio-demographic characteristics on activity type and duration choice. We also show the existence of significant relationships between social network variables and the choice of different activities. This extends to activities such as studying, travelling and house-

		Full Spec. MDCNEV (A)		Only Socio-demographics - MDCNEV (B)			Only Social Network - MDCNEV (C)			
	Activity	est	rob t-stat	est	rob t-stat	t-diff vs A	est	rob t-stat	t-diff vs A	t-diff vs B
Baseline utility constants	Drop-off/Pick-up	-6.1329	-14.5	-6.3119	-15.79	-0.31	-4.378	-21.44	**3.74**	**4.31**
	Family	-5.7346	-16.44	-5.7283	-16.42	0.01	-4.8006	-29.97	**2.43**	**2.42**
	Household obligations	-3.2715	-16.06	-3.8634	-29.06	**-2.43**	-2.9687	-17.34	1.14	**4.13**
	Out-of-home recreation	-4.0542	-25.71	-4.1182	-33.71	-0.32	-4.083	-25.58	-0.13	0.18
	In-home recreation	-4.6827	-16.58	-4.5869	-16.66	0.24	-4.1659	-27.8	1.62	1.34
	Services	-4.1466	-34.41	-4.1656	-34.78	-0.11	-4.1711	-33.97	-0.14	-0.03
	Social	-3.9735	-8.38	-3.308	-16.19	1.29	-3.5566	-7.94	0.64	-0.50
	Shopping	-3.4295	-15.22	-4.0442	-24.79	**-2.21**	-3.0681	-18.05	1.28	**4.14**
	Study	-5.0538	-9.83	-5.0171	-10.14	0.05	-4.0307	-34.1	**1.94**	**1.94**
	Travel	-3.9229	-4.41	-1.1809	-5.05	**2.98**	-3.9115	-4.44	0.01	**-3.00**
	Work	-3.8267	-30.12	-3.5555	-30.61	1.58	-3.4869	-33.76	**2.08**	0.44
Sex=male	Household obligations	-0.4083	-2.88	-0.3723	-2.68	0.18	-	-	-	-
Age < 26	Study	0.4205	1.93	0.7091	3.85	1.01	-	-	-	-
Age 26-40	Work	0.4491	2.87	0.2273	1.42	-0.99	-	-	-	-
Age 40-60	In-home recreation	-0.7471	-2.91	-0.723	-2.88	0.07	-	-	-	-
1 underage child	Family	-1.0412	-2.8	-0.9904	-2.65	0.10	-	-	-	-
	Work	0.759	3.32	0.8092	3.68	0.16	-	-	-	-
2 underage children	Drop-off/Pick-up	1.1407	3.17	1.3097	3.85	0.34	-	-	-	-
	Family	1.7703	4.56	1.7248	4.45	-0.08	-	-	-	-
Low income	Drop-off/Pick-up	1.0297	3.83	0.6831	2.52	-0.91	-	-	-	-
	Family	0.4098	1.34	0.4197	1.37	0.02	-	-	-	-
	Household obligations	0.4264	3.35	0.4661	3.74	0.22	-	-	-	-
Agüita de la Perdiz	In-home recreation	0.8625	3.05	0.9479	3.35	0.21	-	-	-	-
	Social	0.2589	1.61	0.2467	1.53	-0.05	-	-	-	-
La Virgen	In-home recreation	1.0926	3.85	1.0763	3.75	-0.04	-	-	-	-
Driving Licence	Drop-off/Pick-up	0.7128	2.43	0.6433	2.35	-0.17	-	-	-	-
Internet Acess	Social	0.4019	1.92	0.3829	1.87	-0.06	-	-	-	-
	Study	1.0547	2.19	1.1192	2.34	0.10	-	-	-	-
Lives with partner	Household obligations	0.3694	2.81	0.3742	2.84	0.03	-	-	-	-
	Shopping	0.4715	2.43	0.6063	3.19	0.50	-	-	-	-
Partner works	Drop-off/Pick-up	0.6484	2.04	0.6864	2.18	0.08	-	-	-	-
Social network size	Social	0.3039	1.85	-	-	-	0.2943	1.7	-0.04	-
	Travel	1.4446	4.45	-	-	-	1.4437	4.64	0.00	-
Share of immediate family in the network	Household obligations	-1.04	-2.96	-	-	-	-1.0444	-2.96	-0.01	-
Share of friends in the network	Household obligations	-0.8087	-2.85	-	-	-	-1.0582	-3.57	-0.61	-
Share of friends in the network	Shopping	-0.8578	-2.48	-	-	-	-1.0733	-3.03	-0.44	-
Social capital children X female	Drop-off/Pick-up	0.774	2.83	-	-	-	0.9631	3.7	0.50	-
Social capital children X female	Study	0.3134	1.87	-	-	-	0.186	1.17	-0.55	-
Share of network in same age group (40-60)	Social	-0.6573	-2.31	-	-	-	-0.6767	-2.37	-0.05	-
Share of network with same work status (student)	Out-of-home recreation	1.2441	3.31	-	-	-	1.3752	3.62	0.25	-
Share of network with same work status (employed)	Work	1.4258	5.57	-	-	-	1.3274	5.05	-0.27	-
Share of network emplyed when ego is student	Study	4.2603	4.13	-	-	-	5.2369	6.6	0.75	-
Share of close network members living within 1 km	Drop-off/Pick-up	-1.8379	-2.99	-	-	-	-1.4174	-2.55	0.51	-
	Out-of-home recreation	-0.5204	-1.44	-	-	-	-0.5333	-1.44	-0.02	-
	In-home recreation	0.4135	1.47	-	-	-	0.3787	1.6	-0.09	-
	Shopping	-0.8606	-2.39	-	-	-	-0.9158	-2.5	-0.11	-
	Travel	-1.4028	-2.28	-	-	-	-1.3418	-2.2	0.07	-

Table 8: MDCNEV models with socio-demographics and social networks measures - Utility parameters

	Activity	Full Spec. MDCNEV (A) est	Full Spec. MDCNEV (A) rob t-stat	Only Socio-demographics - MDCNEV (B) est	Only Socio-demographics - MDCNEV (B) rob t-stat	Only Socio-demographics - MDCNEV (B) t-diff vs A	Only Social Network - MDCNEV (C) est	Only Social Network - MDCNEV (C) rob t-stat	Only Social Network - MDCNEV (C) t-diff vs A	Only Social Network - MDCNEV (C) t-diff vs B
Satiation parameters										
Baseline gamma	Drop-off/Pick-up	0.3443	1.7	0.3739	1.87	0.10	0.4007	2	0.20	0.09
	Family	2.173	10.16	2.1788	10.2	0.02	2.3898	12.31	0.75	0.73
	Household obligations	11.7755	53.86	12.6928	56.49	**2.93**	12.4104	54.86	**2.02**	-0.89
	Out-of-home recreation	2.6369	18.12	2.7457	18.72	0.53	2.5759	17.86	-0.30	-0.83
	In-home recreation	7.9366	29.29	8.0376	29.79	0.26	8.9861	32.62	**2.72**	**2.46**
	Services	1.6599	9.52	1.6289	9.37	-0.13	1.6152	9.36	-0.18	-0.06
	Social	2.6426	19.86	2.7614	21.7	0.65	2.6797	20.63	0.20	-0.45
	Shopping	0.8574	6.33	0.8269	6.43	-0.16	0.8564	6.29	-0.01	0.16
	Study	5.774	23.69	7.0771	25.79	3.55	6.512	25.57	**2.09**	-1.51
	Travel	0.1695	0.55	0.2969	1.14	0.32	0.1627	0.53	-0.02	-0.33
	Work	5.8414	46.02	6.7449	54.92	**5.12**	6.1281	50.85	1.64	**-3.58**
Shifts (log of baseline gamma)										
Age < 26	Social	0.0541	1.55	0.0784	2.17	0.48	-	-	-	-
Age 26-40	Household obligations	-0.1689	-2.04	-0.1996	-2.32	-0.26	-	-	-	-
1 underage child	Work	-0.1898	-2.92	-0.1832	-2.9	0.07	-	-	-	-
2 underage children	Study	-0.4857	-2.88	-0.4919	-2.43	-0.02	-	-	-	-
Agüita de la Perdiz	Household obligations	-0.2482	-4.06	-0.2872	-4.59	-0.45	-	-	-	-
Network size	Travel	-1.3054	-4.45	-	-	-	-1.2717	-4.78	0.085	-
Social capital travel	Travel	-0.1691	-1.94	-	-	-	-0.1472	-1.67	0.177	-
Share of close network members living within 1 km	Shopping	0.2167	1.89	-	-	-	0.2177	1.9	0.01	-
	Travel	0.2798	1.58	-	-	-	0.2642	1.5	-0.06	-
Nesting parameters										
In home		0.4356	-12.36	0.4416	-11.75	0.12	0.4561	-11.32	0.31	0.21
Out of home		0.7382	-6.48	0.7497	-6.18	0.07	0.7538	-6.07	0.27	0.07

Table 9: MDCNEV models with socio-demographics and social networks measures - Translation and nesting parameters

Scenario 1: everybody behaves as if they were women

Nest	Activity	*Sample*	**MDCEV**			**MDCNEV**		
			Base scenario	*Forecast*	*change*	*Base scenario*	*Forecast*	*change*
1	*Basic needs*	*28.6*	*26.58*	*26.26*	*-1.21%*	*26.15*	*25.82*	*-1.25%*
1	**Household obligations**	**2.6**	**2.65**	**3.29**	**24.00%**	**2.67**	**3.19**	**19.52%**
1	*In home recreation*	*0.8*	*0.78*	*0.76*	*-1.64%*	*0.77*	*0.74*	*-3.43%*
1	*Study*	*1.1*	*1.12*	*1.10*	*-1.54%*	*1.13*	*1.09*	*-3.52%*
2	Drop off/Pick up	0.1	0.17	0.17	-2.01%	0.16	0.16	-0.84%
2	Out-of-home recreation	0.8	0.99	0.97	-1.86%	1.07	1.07	-0.72%
2	Services	0.5	0.65	0.64	-1.82%	0.69	0.69	-0.71%
2	Social	4.0	4.16	4.09	-1.64%	4.37	4.34	-0.72%
2	Shopping	0.5	0.76	0.74	-2.05%	0.74	0.74	-0.86%
2	Travel	3.3	4.31	4.25	-1.49%	3.97	3.95	-0.69%
2	Work	4.9	5.06	4.98	-1.75%	5.45	5.40	-0.77%
3	Family	0.8	0.76	0.75	-1.70%	0.83	0.82	-0.82%

Scenario 2: everybody behaves as if no one had a partner who works

Nest	Activity	*Sample*	**MDCEV**			**nested MDCEV**		
			Base scenario	*Forecast*	*change*	*Base scenario*	*Forecast*	*Forecast*
1	Basic needs	28.6	26.58	26.62	0.14%	26.15	26.17	0.09%
1	Household obligations	2.6	2.65	2.66	0.23%	2.67	2.67	0.14%
1	In home recreation	0.8	0.78	0.78	0.18%	0.77	0.77	0.09%
1	Study	1.1	1.12	1.12	0.11%	1.13	1.13	0.06%
2	**Drop off/Pick up**	**0.1**	**0.17**	**0.09**	**-46.66%**	**0.16**	**0.09**	**-43.34%**
2	*Out-of-home recreation*	*0.8*	*0.99*	*1.00*	*0.21%*	*1.07*	*1.08*	*0.32%*
2	*Services*	*0.5*	*0.65*	*0.65*	*0.19%*	*0.69*	*0.69*	*0.34%*
2	*Social*	*4.0*	*4.16*	*4.17*	*0.19%*	*4.37*	*4.39*	*0.24%*
2	*Shopping*	*0.5*	*0.76*	*0.76*	*0.25%*	*0.74*	*0.75*	*0.34%*
2	*Travel*	*3.3*	*4.31*	*4.32*	*0.17%*	*3.97*	*3.98*	*0.19%*
2	*Work*	*4.9*	*5.06*	*5.07*	*0.21%*	*5.45*	*5.46*	*0.27%*
3	Family	0.8	0.76	0.76	0.32%	0.83	0.83	0.20%

Scenario 3: everybody behaves as if income level was high (impact on Family only)

Nest	Activity	*Sample*	**MDCEV**			**nested MDCEV**		
			Base scenario	*Forecast*	*change*	*Base scenario*	*Forecast*	*Forecast*
1	Basic needs	28.6	26.58	26.63	0.18%	26.15	26.20	0.19%
1	Household obligations	2.6	2.65	2.66	0.39%	2.67	2.68	0.45%
1	In home recreation	0.8	0.78	0.78	0.28%	0.77	0.77	0.30%
1	Study	1.1	1.12	1.12	0.17%	1.13	1.13	0.19%
2	Drop off/Pick up	0.1	0.17	0.17	0.46%	0.16	0.16	0.42%
2	Out-of-home recreation	0.8	0.99	1.00	0.28%	1.07	1.08	0.28%
2	Services	0.5	0.65	0.65	0.27%	0.69	0.69	0.27%
2	Social	4.0	4.16	4.17	0.26%	4.37	4.39	0.29%
2	Shopping	0.5	0.76	0.76	0.28%	0.74	0.74	0.26%
2	Travel	3.3	4.31	4.32	0.22%	3.97	3.98	0.22%
3	**Family**	**0.8**	**0.76**	**0.66**	**-13.74%**	**0.83**	**0.71**	**-13.56%**
2	Work	4.9	5.06	5.08	0.27%	5.45	5.46	0.30%

Table 10: Forecasting scenarios results- excluding social network variables

hold obligations, while past studies mostly focused on effects related to the spheres of social activity and leisure. While we cannot give definitive interpretations about the directionality of the causal effects between social network variables and time use, we can conclude that people's personal social environment is related to the choice of which activities to perform and for how long. This calls for more work to better understand this relationship, including causality. Crucially, our limited testing has revealed no major confounding between the variables associated with the social network and other socio-demographic measures.

From a policy perspective, the use of a dataset that includes information about personal and social contexts and of a method that jointly estimates activity type choice and duration provides rich contextual information about activity and travel patterns. As a consequence, disparate aspects such as income, the presence of children, personal network composition, communication technology use, lifecycle, and social support can be combined in an integrated framework to understand people's time and spatial patterns. In this way, the results highlight not only the trade-offs between mandatory and non-mandatory activities, but also how income and neighbourhood affect opportunities and constraints according to contextual personal characteristics. This is potentially useful information to understand the specificities of transport-related social exclusion aspects.

In spite of the interesting overall picture that this study provided, the present study presents some limitations that leave scope for future research, going beyond the already mentioned issue of directionality.

As explained, we estimated a model including both the weekday and weekend activities, but it is important to acknowledge that important differences in patterns between the two types of days exist. The size of the dataset did not allow the estimation of separate models for weekday and weekend activities, while separating time spent in an activity into weekday and weekend time could lead to violations of the separate 24 hour budgets.

In addition, social networks and social capital data imply a number of potential sources of measurement error: first of all, tools such as name generators rely on respondents‘ ability to recall all the relevant members of their network. Moreover, social capital is measured by asking respondents to name the people who are relevant for some specific form of help. Correct completion of this part of the survey relies on the ability to recall relevant contacts and on the homogeneous understanding of the question across the sample. These issues lead to the consideration of alternative model specification, e.g. treatment of social measures as latent constructs instead of direct incorporation in the utility function. This could be particularly interesting as the dataset contains a large numbers of personality and well-being questions, which could allow us to link network characteristics and activity choice to underlying personality traits of the decision maker.

Finally, an important direction for future research would be the consideration of whether activities have been performed by respondents on their own or together with other people (family, friends). In the present context, segmentation on the basis of the party involved would have led to an excessive number of possible choice alternatives for the sample size, but this is indeed an interesting exercise to perform with suitable data.

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