A multiple discrete continuous model of time use that accommodates non-additively separable utility functions along with time and monetary budget constraints

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ABSTRACT

This paper proposes a multiple discrete continuous (MDC) choice modelling framework with the following features for analyzing individuals' time use decisions: (a) accommodates non-additively separable (NAS) utility functions with respect to time allocation across different non-work activities, (b) considers both time and money constraints by integrating the two constraints into a single economic constraint, and (c) allows corner solutions for (i.e., non-participation in) discretionary, non-work activities. The proposed framework is applied to analyze weekly time use of employed individuals in Netherlands using a data set derived from the Time use and Consumption survey of the Longitudinal Internet Studies for the Social Sciences (LISS) panel. The empirical results of the proposed model are compared to those from two simpler models – (a) a model that ignores the monetary budget constraint but employs the NAS utility function and (b) a model that considers both time and money budget constraints but uses a simpler, additively separable utility function. The results suggest that considering both time and money constraints, when combined with the NAS utility function, facilitates in capturing rich substitution patterns in time allocation to non-work activities, in addition to revealing demographic heterogeneity in satiation effects. Further, the proposed model offers a superior goodness of fit when compared to that from the simpler models that ignore either the monetary constraint or the NAS utility function. Finally, the model results provide important policy insights for reducing demographic inequities in time allocation among employed individuals.

Keywords: complementarity and substitution patterns, non-additive separable utility, multiple budget constraints, multiple discrete continuous (MDC) decisions, time allocation

1. INTRODUCTION

Understanding and modeling individuals' time allocation is essential for understanding travel behavior, because individuals' travel choices are inextricably linked to their time use (Kitamura 1984; Pas and Harvey, 1997; Bhat and Koppelman, 1999; Jara-Díaz, 2007). A variety of methods have been used in the literature for time use analysis. These methods have benefited from advances in microeconomic theories of consumer behavior (Becker, 1965; DeSerpa, 1971; Evans, 1972; Jara-Díaz and Guerra, 2003; Jara-Díaz et al., 2008) and econometric advances in formulating and estimating models of time use.

In the context of econometric modeling methods for time use, significant progress has been made over the past two decades; see Jara-Díaz and Rosales-Salas (2017) for a recent review of time use models. Notable among these developments is the use of multiple discrete-continuous (MDC) choice models for analyzing time use patterns. Specifically, the MDCEV class of models proposed by Bhat (2005, 2008) offers a random utility maximization (RUM)-based econometric framework to simultaneously analyze time allocation to multiple activities while allowing corner solutions typical to time use data and important behaviors such as diminishing marginal utility with increasing consumption. These models, based on a translated constant elasticity of substitution (CES) utility function and a log-extreme value error term, have a tractable likelihood expression that makes it easy to estimate the model parameters. Thanks to the ease of estimation and the methods developed to apply these models for forecasting and welfare analysis (Pinjari and Bhat, 2011; Lloyd Smith, 2018), the MDCEV class of models and its variants have been applied to analyze time use in many different geographical contexts (Kapur and Bhat, 2007; Spissu et al., 2009; Chikaraishi et al., 2010; Wang and Li, 2011; Calastri et al., 2017a; Calastri et al., 2017b).

It is worth noting here that the RUM based MDC choice models have been advanced in a variety of directions. These include, for example, (a) exploration of stochastic distributional assumptions other than the convenient IID Gumbel distributions (Pinjari, 2011; Bhat et al., 2013); (b) exploration of alternative utility functional forms, including non-additively separable forms (Vasquez-lavin and Hanemann, 2008; Bhat et al., 2015; Bhat, 2018), (c) incorporation of multiple linear budget constraints (Satomura et al., 2011; Castro et al., 2012; Enam and Konduri, 2017), and (d) joint modeling of MDC choice data with a variety of other types of endogenous variable data (Bhat et al., 2016; Enam et al., 2017). Among all these developments, two specific directions that are germane to time use modelling – (1) models with non-additively separable utility forms for allowing rich substitution and complementarity

patterns in time use and (2) models with multiple budget constraints to simultaneously accommodate time and monetary budgets – are discussed in detail next.

1.1. MDC Choice Models with NAS Utility Functions

Interestingly, almost all time use studies involving MDC choice models so far have employed additively separable (AS) utility forms. AS utility forms combined with the weak separability assumption (Deaton and Muellbauer, 1980) essentially imply that the time use choice alternatives are only imperfect substitutes of each other. This is because the marginal utility of time-allocation to an activity does not depend on the time allocated to other activities (Pollak and Wales, 1992). This precludes the possibility of complementarity in time use, where an increase in time-allocation to one activity can lead to an increase in time-allocation to another activity. For example, it is likely that spending more time in out-of-home social recreational activities can lead to a greater time in eat out activities as well. Further, due to severe time and/or monetary constraints, allocation of time to one discretionary activity might involve substitution of time for another activity. Such strong substitution effects are not allowed by models with AS utility functions. To address such dependencies across time-allocation to different activities within an AS utility framework, previous studies employed correlations in the stochastic distributions of the utility functions; for example, through multivariate extreme value distributions (Pinjari and Bhat, 2010; Pinjari, 2011), multivariate normal distributions (Bhat et al., 2013), or through mixed MDCEV formulations with error components (Calastri et al., 2020). While accommodating positive correlations among AS sub-utility functions is one way to account for dependencies in time use, one cannot be sure if the correlation among sub-utility functions is due to common unobserved heterogeneity or due to complementarity in time-allocation. Besides, use of multivariate extreme value distributions does not allow the possibility of strong substitution of time allocation across choice alternatives because negative correlations are not feasible. Therefore, it is preferable to allow for substitution and complementarity in consumption explicitly in the utility functions via NAS utility forms that allow the marginal utility of time allocation to an activity to be dependent on time allocation to other activities.

To be sure, several MDC modeling studies account for complementarity in consumption directly through NAS utility forms with interaction terms between utility contributions from different activities. These include, for example, direct utility models by Vasquez-Lavin and Hanemann (2008), Lee and Allenby (2009), Lee et al. (2010), Bhat et al. (2015) and the indirect utility models by Gentzkow (2007), Song and Chintagunta (2007) and

Mehta (2007); also see a review paper on models of complementarity choices by Berry et al., (2014). However, none of these studies focus on time use analysis; except a very recent working paper by Palma and Hess (2020). Besides, all these studies consider a single linear budget constraint only.

1.2. Time Use Models that Consider both Time and Money Constraints

The economic literature on time use modeling has long employed both time and money budget constraints, albeit without corner solutions in consumption. For example, in his seminal work, Becker (1965) defines a theoretical framework in which the utility function is maximized subject to a money constraint and time availability. In his formulation, the time constraint is defined by the sum of consumption time and time assigned to work, whilst the monetary constraint is defined by the sum of non-work income and work income. Consequently, the time constraint collapses into the monetary constraint using a monetary value of time. Nevertheless, time and money may not be always freely exchangeable (to be collapsed into a single constraint) and therefore it might become necessary to consider the two constraints separately from each other (see, for example, DeSerpa, 1971; Evans, 1972; Gronau, 1986). To address this issue, various studies (Jara-Díaz and Guerra, 2003; Jara-Díaz, et al., 2008; Konduri et al., 2011; Jara-Díaz and Astroza, 2013; Jara-Díaz et al., 2016) develop modeling methods to accommodate multiple linear constraints with additive utility functional forms. Some of these studies also incorporate other important aspects such as goods consumption (along with time allocation) as an argument of the utility function and also consider technical constraints relating time and goods (DeSerpa, 1971; Jara-Díaz et al., 2016). However, most of these studies do not consider corner solutions in that the possibility of not allocating time to some discretionary activities is not incorporated in their models.

The first MDC model of time use with both time and monetary budget constraints and the possibility of corner solutions was formulated by Castro et al. (2012). By bringing the time and money budget constraints into an MDC modelling framework, their formulation starts to bridge the gaps between econometric formulations of time use and microeconomic models of time use. This formulation was later extended by Astroza et al. (2017) to consider goods consumption along with time use as determinants of consumer's utility function while also considering technical constraints such as minimum values for optimal time use and goods consumption variables. These studies, however, employ AS utility functions that do not allow complementarity and rich substitution patterns in time use.

1.3 Current Research

In view of the above discussion, the aim of this paper is to develop a MDC modeling framework of individuals' time allocation that can: (a) accommodate non-additive preferences allowing for complementarity and substitution effects, (b) consider both time and money constraints governing time allocation, and (c) allow for corner solutions. To do so, we employ a non-additively separable (NAS) utility function of Bhat et al. (2015) along with Becker's approach (1965) of integrating the time and money constraints into a single economic constraint called the full income constraint. Of course, collapsing both the time and money constraints into a single full income constraint assumes that the two resources (time and money) are exchangeable with each other. While there is value in keeping the two constraints separate, integrating them into a single constraint circumvents the modeling complexities associated with considering multiple budget constraints in MDC models with NAS utility forms. Specifically, the presence of separate constraints will lead to additional dimensions in the open integral of the likelihood function and increases the computational burden. This, when combined with the fact that the NAS utility forms used in the literature preclude a compact expression for the determinant of the Jacobian matrix makes such as model computationally cumbersome.[1] Also, as discussed later, our approach to collapse the two constraints into a single constraint along with the NAS utility form is better than a simpler model with a single time constraint or another simpler model that assumes an additively separable utility form while combining the two constraints into a single constraint.

The proposed empirical model is applied to the Time Use and Consumption survey obtained from the Longitudinal Internet Studies for the social Sciences (LISS) panel to analyze employed individuals' weekly time allocation to work and various non-work activities as a function of individual socio-economic characteristics. In doing so, both time and money budget constraints are considered while maximizing a NAS utility function of time allocation. This study is perhaps among the first applications of MDC choice models with NAS utility form for time use analysis; even with a single, time budget constraint. Besides, the proposed model also considers monetary budget constraint along with time constraint. In addition, we compare empirical results from the proposed model with those from two simpler models – one that

[1] That is, due to the absence of a compact expression for the determinant of the Jacobian, one will have to compute each and every element of the Jacobian matrix and then compute the determinant separately for each and every individual in the data at every realization of the simulated errors at every iteration during the estimation process. This precludes the use of compact matrix computations that enable fast computation of the likelihood functions and makes the parameter estimation a computationally cumbersome task. Future research should consider deriving alternate model structures with multiple constraints and NAS utility forms and/or computationally efficient approaches to estimate the parameters of such models.

ignores the monetary constraint but uses the NAS utility function and the other that employs both time and money budgets but with an AS utility function – to understand the importance of accommodating NAS utility form along with both time and monetary budgets.

The rest of this article is structured as follows. The next section describes the data used for the empirical application. Section three formulates the proposed model in addition to presenting two simpler models that are special cases of the proposed model. Section four presents and discusses the model estimation results and a comparison of the proposed model with other simpler models that ignore either a non-additive utility form or multiple resource constraints. The final section reports conclusions and some insights for future work.

2. DATA

The data used in this paper comes from the Longitudinal Internet Studies for the social Sciences (LISS) panel. The LISS panel, whose first wave was launched in 2008, is a representative sample of Dutch households drawn from the national population register. This monthly survey comprises a variety of smaller surveys which concentrate on different aspects related to individuals' lifestyles, such as, health, religion and ethnicity, work and schooling, and family and household. Among such surveys is the Time Use and Consumption survey which investigates individuals' time allocation and expenditure behavior. The first wave of this survey was commenced in January 2009 while the last wave was commenced in July 2017. In this paper, the empirical analysis utilizes data from the third wave of the study (October 2012). Specifically, the survey collected information on: (a) the time allocated by respondents to thirteen activities (including work) for seven days before the survey date, and (b) their average monthly expenses (in Euros) in 30 expenditure categories, for twelve months before the survey date (see Cherchye et al., 2012 for details on the survey and the data collected). In addition to the time use and expenditure data, the survey included questions on socio-economic characteristics of the consumers such as age, gender, household size, level of education, and income.

2.1 Data preparation and description

The third wave of the Time Use and Consumption study of the LISS panel included a random sample of 6,874 Dutch households, of which 20.5 percent did not fill up the survey and 2.3 percent sent back incomplete surveys. Of the remaining sample of 5463 households, we limited our analysis to single-worker households. Further, we focused on only those people who: (a) worked for at least one hour in the week before the survey, and (b) who reported some monetary

expense in at least one of the 30 expenditure categories in 12 months before the survey. Based on these criteria, the number of eligible respondents was 1531.

Next, following Astroza et al. (2017), a data cleaning and preparation process was performed to obtain the final data set. First, we excluded those individuals who reported average sleeping of less than four hours a day. Second, people who reported unrealistically large time allocations to different activities were removed from the sample (assuming those as reporting errors). Third, we excluded those workers who expended less than two euros per week, together with those people whose hourly wage was lower than three euros per hour. The overall number of observations removed from the research sample was 392, leaving a final estimation sample of 1139 individuals.

Recall from the survey description that there is a difference in the time horizon of measurement of time allocation to activities and monetary expenditures. Time use data was collocated for a week, while expenditure data was collected for a monthly timeframe. Therefore, to synthesize expenditure information to a weekly timeframe (same as that of time use information), the monthly expenditure variables were divided by four. The survey collected information on the individual's net monthly income also. Hereafter, for brevity, we will refer to net income as the income. To be consistent with the weekly timeframe, the monthly income was divided by four. The resulting weekly income was used in conjunction with the weekly time (hours) spent at work to compute the individual's hourly wage rate.

The final estimation data set consists of 1139 respondents, whose sociodemographic makeup is provided in Table 1. As can be observed, a majority of the respondents are male. The age distribution shows a skew toward older age groups. Further, a majority of them have at least graduate education, are first generation Dutch, live in an urban area, and live in their own houses. Clearly, perhaps because it represents single-worker households, the sample is more representative of affluent and urban residents who are male and live in their own houses. In the context of income, the individuals' average weekly income is approximately 543€ and the average hourly wage rate stands at 17€.

Table 1 about here

The following seven non-work activity categories were used for time use analysis:

(1) Personal care: eating, visiting the hairdresser, washing, dressing, etc.

(2) Leisure: reading, sport activities, cycling, travelling, going out, etc.

(3) Household chores: cleaning, shopping, gardening, odd jobs, etc.

(4) Activities with children: reading, taking child to see doctor, taking child to school, etc.

(5) Education: day or evening courses, language courses, professional courses, etc.

(6) Assisting friends and relatives: This activity type combines three similar activities reported in the data – (a) helping friends, (b) helping relatives and family members (other than children), and (c) helping parents; with washing, dressing, seeing the doctor, administrative chores, etc. and

(7) Administrative chores and family finances.

Because the expenditure categories available in the LISS panel were not directly associated with the above non-work activities employed in the analysis, we needed to match the expenses to the corresponding activities to have a one-to-one relation. The five non-work activities that were considered to incur monetary expenditures are the following: (a) personal care, (b) leisure, (c) household chores, (d) activities with children, and (e) education.

As in Astroza et al. (2017), two activities, (a) assisting friends and relatives and (b) administrative chores and family finances were assumed to not incur monetary expenditures. Table 2 presents the descriptive statistics of activity participation, time-allocation and expenditures in each of these activities.

Table 2 about here

As can be observed from the table, all individuals participate in personal care. Therefore, this activity is treated as an essential outside good in the model formulation; see the next section. Leisure activities (99.70 percent) and household chores (98.00 percent) have the next highest activity participation rates. On the contrary, activities with children and education have lower weekly participation rates. The average time devoted to leisure per week, for those who participated in that activity, is 32.10 hours (around 4.50 hours/day) followed by activities with children (11.90 hours) and household chores (10.00 hours). With respect to expenditures, activities with children are associated with the highest average value (57.21 euros/week), whereas education incurred the least expenses.

3. MODELING FRAMEWORK

In this section, we formulate the random utility maximization (RUM) framework to analyze individuals' time use decisions based on a NAS utility form proposed by Bhat et al. (2015) combined with the full income constraint approach to integrate the time constraint and money constraint into one single economic constraint. Specifically, Section 3.1 outlines the model

structure and Section 3.2 derives the likelihood expression for the model. As will be discussed later, we employ normally distributed stochastic distributions for the random utility terms. Given the use of the NAS utility form, a full income constraint (that combines both time and monetary constraints into a single constraint), and normally distributed stochastic terms, the proposed model is labeled the *full income constraint non-additively separable multiple discrete continuous probit* (FIC-NAS-MDCP) model. In addition to this model, we formulate two simpler models – one that uses an AS utility function with the full income constraint (i.e., a FIC-AS-MDCP model) and another that uses the NAS utility function but with only the time constraint (TC) and ignores the monetary constraint (i.e., a TC-NAS-MDCP model). We present these simpler model formulations and their corresponding likelihood functions in Section 3.3.

3.1 Structure of the FIC-NAS-MDCP model

Consider the following NAS utility function that is maximized by an individual subject to two binding constraints:

$$U(\boldsymbol{x}) = \psi_1 \ln(x_1) + \sum_{k=2}^{K} \psi_k \gamma_k ln\left[\left(\frac{x_k}{\gamma_k}+1\right)\right] + \frac{1}{2}\sum_{k=2}^{K}\sum_{m\neq k \& m\neq 1} \theta_{km}\gamma_k\gamma_m \, ln\left[\left(\frac{x_k}{\gamma_k}+1\right)\right] ln\left[\left(\frac{x_m}{\gamma_m}+1\right)\right] \quad (1)$$

$$\text{s.t} \sum_{k=1}^{K} x_k p_k = E + \omega_{work} x_{work} \quad (2)$$

$$\text{s.t} \sum_{k=1}^{K} x_k g_k + x_{work} = T^* \quad (3)$$

In Equation (1), $U(\boldsymbol{x})$ is a quasi-concave, increasing and continuously differentiable utility function[2] with respect to the Kx1 time allocation vector $\boldsymbol{x}$ ($x_1 > 0$, while $x_k \geq 0$ for $k > 1$), and ψ_k ($k > 1$) and γ_k ($k > 1$) are parameters influencing the utility function. Specifically, ψ_k represents the baseline (marginal) utility of time spent at the point at which no alternatives have been chosen, whilst γ_k allows differential satiation effects across different activities. Note that the first alternative (i.e., *personal care; k=1*) is treated as an *essential outside good* because all individuals assign time to this activity. $U(\boldsymbol{x})$ is a valid utility function if ψ_k and γ_k are strictly greater than zero. To enforce these conditions, ψ_k and γ_k can be expressed as $\psi_k = \exp(z_k)$ and $\gamma_k = \exp(w_k)$. Additionally, such parameters are allowed to vary across respondents by writing $z_k = \boldsymbol{\beta}'\boldsymbol{z_k}$ and $w_k = \widetilde{\boldsymbol{\beta}}'\boldsymbol{w_k}$, where $\boldsymbol{z_k}$ and $\boldsymbol{w_k}$ are vectors of individual characteristics and of attributes related to the kth alternative (including alternative-specific constants) whilst $\boldsymbol{\beta}'$ and $\widetilde{\boldsymbol{\beta}}'$ are the corresponding vectors of parameters to be estimated. For

[2] To be precise, the functional form, due the non-additive terms in it, does not ensure global concavity and is not necessarily an increasing function at all possible parameter values and consumptions. However, due to the presence of an essential outside good whose utility function is concave and increasing (because its utility function does not interact with the utility terms of other goods), the overall function will be increasing and quasi-concave at optimal consumptions (i.e., optimal time allocations).

identification purposes, the alternative specific constant and the coefficients of all explanatory variables for the first alternative are normalized to zero. The θ_{km} parameters, as in Bhat et al. (2015), are the interaction effects that capture second order interactions and allow the marginal utility of a good k to depend on the consumption amounts of other goods m $(m \neq k)$. A positive interaction coefficient for an activity pair represents complementarity in time allocation between those two activities, whereas a negative interaction coefficient represents substitution. To facilitate the derivation of the Jacobian matrix, we assume that $\theta_{1m} = 0\ \forall m\ (m \neq 1)$. That is, the *essential outside good* does not interact with other choice alternatives. Besides, as mentioned in footnote 1, such a concave and increasing functional form for the essential outside good helps ensure that the overall utility function is increasing at optimal time allocations.

Equation (2) corresponds to the linear monetary budget constraint, wherein p_k is the monetary price of consuming unit time of a non-work activity k, E is the non-work income and $x_{work}\ \omega_{work}$ represents the salary income. The non-work income is defined as the difference between the income received from pensions, house properties, governmental support and others non-work related sources, and any fixed weekly expenditures such as mortgage, rent, utilities and commuting that do not depend on the participation or duration of non-work activities and work activity. The salary income is the product between the time allocated to work, x_{work}, and the person's wage rate, ω_{work}.

Equation (3) refers to the linear time budget constraint. In this equation, g_k is the time price of a non-work activity k and T^* is the total available time for all non-work activities and to work. It is worth noting here that T^* does not include the individuals' allocation of time to travelling and sleeping, as individuals' allocation of time to travelling and sleeping is not considered in this analysis.[3] Because the choice alternatives involved in the analysis themselves reflect time allocations, we set the time price in taking part in an activity k (i.e., g_k) to be equal to 1 $\forall k$ (see Castro et al., 2012). Note that whilst the hourly wage rate (i.e., ω_{work}) is exogenous to the framework proposed, the time allocated to work (x_{work}) is endogenous to the model. This is because, although time allotted to work does not enter the utility function (the model

[3] The reason for excluding these activities from the analysis is two-fold. First, the data set does not include information on individual's travel mode choice (but travel time depends on mode choice). Second, the absence of health information and sleep habits can potentially inflate the unobserved factors influencing the utility of sleep, leading one to unreliable conclusions on time allocation to sleep. Also, the activity type labelled "other", although present in the data, was excluded from the empirical analysis since it combines a variety of heterogeneous activities such as church attendance, attend funeral/wedding and several other activities. It would be difficult to find covariates that have an influence on time allocation to such heterogeneous activity type.

assumes that time allocated to work does not generate utility), it generates income which is expended in non-work activities. Since, x_{work} appears in the time budget constraint, the individual has to determine x_{work} as part of his/her utility maximization problem. An x_{work} value less than the optimal amount would lead to less income for non-work activities while a x_{work} value greater the than optimal amount would lead to less time available for non-work activities.

Using the above insight, in his notable work, Becker (1965) posits that an individual could potentially use the time s/he could devote to consumption (i.e., $\sum_{k=1}^{K} x_k$) to participate more in the labour market or vice versa. This allows the monetary and time budget constraints to be combined into a single constraint. That is, substituting $x_{work} = T^* - \sum_{k=1}^{K} x_k g_k$ into Equation (2) gives the following single economic constraint, which is also called the full income constraint:

$$\sum_{k=1}^{K} x_k \widetilde{p_k} = E + \omega_{work} T^* \tag{6}$$

where $\widetilde{p_k} = p_k + \omega_{work}$, $\omega_{work} > 0$ and $p_k \geq 0 \; \forall \; k, k = 1, \dots, K$

In the above equation, $\widetilde{p_k}$ is the full price of an activity k, which is equal to the sum of direct price p_k and indirect price ω_{work}, with the latter being the opportunity cost of not working. The right-hand side of Equation (6) can be interpreted as the sum of non-work income (i.e., E) and the income earned if all time were spent at work (i.e., $\omega_{work} T^*$). This maximum achievable income (i.e., $E + \omega_{work} T^*$) is then spent on non-work activities directly through expenditures on those activities (i.e. $x_k p_k$) and indirectly through the forgone income (i.e., $x_k \omega_{work}$). The latter can be interpreted as the income an individual could have earned by devoting x_k to work (i.e., the opportunity cost).

Using the above-discussed full income constraint that combines both time and monetary constraints into a single economic constraint, the individual's utility maximization problem can be re-written as follows:

$$U(\boldsymbol{x}) = \psi_1 \ln(x_1) + \sum_{k=2}^{K} \psi_k \gamma_k ln\left[\left(\frac{x_k}{\gamma_k} + 1\right)\right] + \frac{1}{2} \sum_{k=2}^{K} \sum_{m \neq k \& m \neq 1} \theta_{km} \gamma_k \gamma_m \, ln\left[\left(\frac{x_k}{\gamma_k} + 1\right)\right] ln\left[\left(\frac{x_m}{\gamma_m} + 1\right)\right]$$

$$\text{s.t. } \sum_{k=1}^{K} x_k \widetilde{p_k} = E + \omega_{work} T^* \tag{7}$$

To identify the optimal time allocations, we formulate the Lagrangian function and the Karush-Kuhn-Tucker (KKT) conditions for the utility maximization problem in Equation (7) as:

$$L = U(\boldsymbol{x}) + \lambda(E + \omega_{work} T^* - \sum_{k=1}^{K} x_k \widetilde{p_k}) \tag{8}$$

where λ is the Lagrange multiplier. The KKT conditions for optimal time allocations (x_k^*) are:

$$\frac{\psi_1}{x_1^*} - \lambda\widetilde{p_1} = 0, \qquad k = 1$$

$$\left(\frac{x_k^*}{\gamma_k} + 1\right)^{-1}\left[\psi_k + \sum_{m\neq k}^{K}\theta_{mk}\gamma_m \ln\left(\frac{x_m}{\gamma_k} + 1\right)\right] - \lambda\widetilde{p_k} = 0 \; if \; x_k^* > 0, \; k = 2, \dots, K$$

$$\left(\frac{x_k^*}{\gamma_k} + 1\right)^{-1}\left[\psi_k + \sum_{m\neq k}^{K}\theta_{mk}\gamma_m \ln\left(\frac{x_m}{\gamma_k} + 1\right)\right] - \lambda\widetilde{p_k} < 0 \; if \; x_k^* = 0, \; k = 2, \dots, K \tag{9}$$

The optimal time allocations satisfy the KKT conditions in Equation (9) and the full income constraint (Equation (6)). Since the first alternative (i.e., *personal care*) serves as the essential activity to which all individuals allocate a positive amount of time (consumers have to take part in at least one non-work activity), the expression for the Lagrange multiplier from the corresponding KKT condition is $\lambda = \frac{\psi_1}{x_1^* \widetilde{p_1}}$. By replacing this expression for λ in the KKT conditions for other activities, we can re-write the KKT conditions as below:

$$\left(\frac{x_k^*}{\gamma_k} + 1\right)^{-1}\frac{1}{\widetilde{p_k}}\left[\psi_k + \sum_{m\neq k}^{K}\theta_{mk}\gamma_m \ln\left(\frac{x_m}{\gamma_k} + 1\right)\right] = \frac{\psi_1}{x_1^* \widetilde{p_1}} \quad if \; x_k^* > 0, \; k = 2, \dots, K$$

$$\left(\frac{x_k^*}{\gamma_k} + 1\right)^{-1}\frac{1}{\widetilde{p_k}}\left[\psi_k + \sum_{m\neq k}^{K}\theta_{mk}\gamma_m \ln\left(\frac{x_m}{\gamma_k} + 1\right)\right] < \frac{\psi_1}{x_1^* \widetilde{p_1}} \quad if \; x_k^* = 0, \; k = 2, \dots, K \tag{10}$$

The above KKT conditions have an intuitive interpretation. For all non-work activities to which individuals assign a positive amount of time, the time spent is such that the full price-normalized marginal utilities are the same across activities at optimal time allocations (this represents the first set of KKT conditions in Equation (10)). For a non-work activity k ($k = 2, \dots, K$) to which no time is allocated, the full price-normalized marginal utility at the zero time allocation to that activity is less than the price-normalized marginal utility at the optimal time allocation of other activities (this refers to the second set of KKT conditions).

3.2 Model estimation

We introduce stochasticity into the utility function $U(\boldsymbol{x})$ of Equation (1) through the baseline (marginal) utility as below:

$$\psi_1 = \exp(\epsilon_1)$$
$$\psi_k = \exp(\boldsymbol{\beta}'\boldsymbol{z_k})\exp(\epsilon_k) \tag{11}$$

where $\epsilon_k (k = 1, 2, \dots, K)$ are normal distributed random terms assumed to be independent and identically distributed (IID) across alternatives error term with a scale parameter of σ. The role of ϵ_k is to account for the idiosyncratic (unobserved) characteristics that impact the baseline (marginal) utility at a point at which no expenses have been made on any alternatives. Integrating the stochastic baseline (marginal) utility (Equation (11)) into the KKT conditions (Equation (10)) results in the following stochastic KKT conditions:

$$\left(\frac{x_k^*}{\gamma_k}+1\right)^{-1}\frac{1}{\widetilde{p_k}}\,\xi_k=\frac{\xi_1}{x_1^*\,\widetilde{p_1}}\quad if\ x_k^*>0,\ \ k=2,\dots,K$$

$$\left(\frac{x_k^*}{\gamma_k}+1\right)^{-1}\frac{1}{\widetilde{p_k}}\,\xi_k<\frac{\xi_1}{x_1^*\,\widetilde{p_1}}\quad if\ x_k^*=0,\ k=2,\dots,K \tag{12}$$

where $\xi_1=\exp(\epsilon_1), \xi_k=\exp(\boldsymbol{\beta}'\boldsymbol{z_k})\exp(\epsilon_k)+A_K$ and $A_K=\sum_{m\neq k}^{K}\theta_{mk}\gamma_m\ln\left(\frac{x_m}{\gamma_k}+1\right), (k=2,\dots,K)$

Let $w_k=\left(\frac{x_k^*}{\gamma_k}+1\right)^{-1}\frac{1}{\widetilde{p_k}}$, $w_1=(x_1^*\,\widetilde{p_1})^{-1}$, and let $\mathrm{B}_k(\xi_1)=\frac{w_1}{w_k}\xi_1-\ A_K$. Note that $\mathrm{B}_k(\xi_1)$ indicates that B_k is *a function of* ξ_1. Next, the KKT conditions may be written as follows:

$$\exp(\epsilon_k)=\frac{B_k(\xi_1)}{\exp(\boldsymbol{\beta}'\boldsymbol{z_k})}\ \ if\ x_k^*>0,\ k=2,\dots,K$$

$$\exp(\epsilon_k)<\frac{B_k(\xi_1)}{\exp(\boldsymbol{\beta}'\boldsymbol{z_k})}\ \ if\ x_k^*=0,\ k=2,\dots,K \tag{13}$$

Let $\zeta_k=exp(\epsilon_k)$ $(k=\ 1,2,\dots,K)$ be IID log-normal error terms[4] and let *g(.)* and *G(.)* denote the standard probability density and standard cumulative distribution functions, respectively[5]. Then, the likelihood that a consumer performs the first M of the K non-work activities and allocates the observed optimal times $(x_1^*,x_2^*,x_3^*,\dots,x_M^*)$ to those goods may be expressed as:

$$P(x_1^*,x_2^*,x_3^*,\dots,x_M^*,0,0,0,\dots,0)$$
$$=\int_{\zeta_1=0}^{\zeta_1=+\infty}|\boldsymbol{J}_m(\zeta_1)|\left\{\left[\prod_{m=1}^{M}\frac{1}{\sigma}g\left(\frac{1}{\sigma}\frac{B_m(\zeta_1)}{\exp(\boldsymbol{\beta}'\boldsymbol{z_m})}\right)\right]\right\}*\left\{\left[\prod_{j=M+1}^{K}G\left(\frac{1}{\sigma}\frac{B_j(\zeta_1)}{\exp(\boldsymbol{\beta}'\boldsymbol{z_j})}\right)\right]\right\}g(\zeta_1)\,\mathrm{d}\zeta_1 \tag{14}$$

where $|\boldsymbol{J}_m(\zeta_1)|$ is the determinant of the Jacobian matrix $\boldsymbol{J}_m(\zeta_1)$ whose elements $\boldsymbol{j}_{ih}(\zeta_1)$ can be written as follows $(i,h,=1,2,\dots M-1)$:

$$\boldsymbol{j}_{ih}(\zeta_1)\ =\frac{\partial}{\partial x_{h+1}^*}\left[\frac{B_{i+1}(\zeta_1)}{\exp\left(\boldsymbol{\beta}'\boldsymbol{z_{i+1}}\right)}\right]=\frac{1}{\exp(\boldsymbol{\beta}'\boldsymbol{z_{i+1}})}\left\{\frac{w_1}{w_{i+1}}\left[\zeta_1(\widetilde{p_{h+1}}L_1+\widetilde{p_{i+1}}L_{i+1}\tau_{ih})\right]-\widetilde{p_{h+1}}\theta_{i+1,h+1}w_{h+1}(1-\tau_{ih})\right\}$$

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[4] Note that $\xi_1=\zeta_1$, but $\xi_k=\exp(\boldsymbol{\beta}'\boldsymbol{z_k})\,\zeta_k+A_K$. Therefore, ζ_k is used to denote $exp(\epsilon_k)\ \forall k=1,2,\dots,K$.

[5] It is important to highlight that the proposed model can be potentially advanced to accommodate correlations among subsets of choice alternatives due to omitted variables (or unobserved factors) that have a common influence on the utility functions of different choice alternatives. Doing so, if the correlations are positive, can help avoid confounding of such common unobserved effects into complementarity effects (i.e., positive interaction parameters) between the utility functions of different alternatives. This is because positive dependency between the utility functions of choice alternatives can arise from error correlations and/or complementarity in consumption of those alternatives. Ignoring one can confound the parameter estimates of the other. However, incorporating error term correlations is not easy when NAS utility functions are employed in MDCP models. For example, it is common practice to accommodate error correlations assuming a multivariate normal distribution. This requires the analyst to convert the KKT conditions into an error-differenced form, where the conditions are written based on error differences (with respect to a base alternative). However, unlike in the case of the AS utility structure, the NAS utility structure used in this paper includes the A_K term in the KKT conditions (see Equation (13)), which makes it difficult to convert the KKT conditions into an error-differenced form. Another way to include error correlations is to employ error components in addition to an IID normal kernel, giving rise to a mixed MDCP framework. This approach is computationally very cumbersome because of two reasons. First, the dimensionality of integral in the likelihood function increases due to the error components. Second, the additional dimensions of integral come at a significant computational cost because of the absence of a compact expression for the Jacobian matrix appearing in the likelihood function. Specifically, the likelihood function involves the computation of each and every element of the Jacobian matrix to compute the determinant of the Jacobian separately at every realization of the simulated error terms for each and every individual at each iteration in the estimation process, while also ensuring that the term $\mathrm{B}_k(\xi_1)$ is not negative.

(15)

where $\tau_{ih} = 1$ if $i = h$ and $\tau_{ih} = 0$ if $i \neq h$, $L_k = \frac{1}{\widetilde{p_k}(x_k^* + \gamma_k)}$ $(k = 2, \dots, K)$ and $L_1 = \frac{1}{\widetilde{p_1} x_1^*}$

The likelihood in Equation (14) is a one-dimensional integral that can be computed using numerical quadrature techniques.

It is worth noting here that estimation issues may arise with the employed NAS utility function. Because the term B_k is defined as $\mathrm{B}_k = \frac{w_1}{w_k} \zeta_1 - A_K$, large values for positive interaction terms (embedded within A_K) may cause B_k to become negative causing estimation breakdowns since this term is included in both the probability density function and the cumulative distribution function of a log-normal distribution (see Equation (14)). To address this issue, we follow Bhat et al.'s (2015) heuristic where the interaction parameter values are adjusted at any iteration that the B_k became negative for any choice alternative for any individual in the estimation sample. Doing so helped us ensure that B_k was positive for all choice alternatives and for all individuals at every iteration of the estimation routine. Of course, by doing so, the parameter space may be somewhat restricted in that it may be difficult to fully capture complementarity effects when the interaction parameters are positive and large enough in magnitude that the corresponding B_k value becomes negative. Another aspect in this context is related to the influence of negative interaction parameters on the marginal utility function. As can be observed from Equation (10), it might appear that negative interaction parameters with large magnitudes would render the marginal utility at the optimal time allocation point (x_k^*) to be negative, which is inconsistent with the underlying microeconomic theory. However, this is not possible at optimal time allocations, because the model formulation has an outside good that has an increasing utility function and does not have any interaction effects. A utility maximizing individual would rather invest time on the outside good or other goods without interaction effects for a higher utility than allocate time for negative marginal utility.

3.3 Alternative model formulations

In addition to exploring the above-described model in which time and money constraints are integrated into a single *full income constraint* and the utility function is of the NAS form, we implemented two simpler models – one model employs an AS utility form instead of the NAS form but uses the full-income constraint (such a model is called the FIC-AS-MDCP model) and the other model employs the NAS form but ignores the monetary budget constraint (such a model is called the TC-NAS-MDCP model). Both these models are outlined below.

3.3.1 The FIC-AS-MDCP model

The first framework is a simpler version of the FIC-NAS-MDCP model that assumes additively separable preferences, called the FIC-AS-MDCP model:

$$U(\boldsymbol{x}) = \psi_1 \ln(x_1) + \sum_{k=2}^{K} \psi_k \gamma_k ln\left[\left(\frac{x_k}{\gamma_k} + 1\right)\right]$$

$$\text{s.t. } \sum_{k=1}^{K} x_k \widetilde{p_k} = E + \omega_{work} T^* \tag{16}$$

where ψ_1 and ψ_k are defined as in Equation (11)

The reader will note that in Equation (16) all interaction parameters are equal to zero and thus the marginal utility of a good k is independent of the consumption amounts of other goods. The stochastic KKT conditions for the FIC-AS-MDCP model can be written as follows:

$$\exp(\epsilon_k) = \frac{R_k(\xi_1)}{\exp(\boldsymbol{\beta}'\boldsymbol{z_k})} \;\; if \; x_k^* > 0, \; k = 2, \dots, K$$

$$\exp(\epsilon_k) < \frac{R_k(\xi_1)}{\exp(\boldsymbol{\beta}'\boldsymbol{z_k})} \;\; if \; x_k^* < 0, \; k = 2, \dots, K \tag{17}$$

where $\xi_1 = \exp(\epsilon_1)$, $R_k(\xi_1) = \frac{w_1}{w_k}\xi_1$, $w_k = \left(\frac{x_k^*}{\gamma_k} + 1\right)^{-1} \frac{1}{\widetilde{p_k}}$ and $w_1 = (x_1^* \widetilde{p_1})^{-1}$

Next, the likelihood that an individual takes part in the first M of the K non-work activities and observed time allocations for those M activities can be formulated as follows:

$$P(x_1^*, x_2^*, x_3^*, \dots, x_M^*, 0,0,0, \dots, 0)$$
$$= \int_{\zeta_1=0}^{\zeta_1=+\infty} |\boldsymbol{J}_m(\zeta_1)| \left\{\left[\prod_{m=1}^{M} \frac{1}{\sigma} g\left(\frac{1}{\sigma}\frac{R_m(\zeta_1)}{\exp(\boldsymbol{\beta}'\boldsymbol{z_m})}\right)\right]\right\} * \left\{\left[\prod_{j=M+1}^{K} G\left(\frac{1}{\sigma}\frac{R_j(\zeta_1)}{\exp(\boldsymbol{\beta}'\boldsymbol{z_j})}\right)\right]\right\} g(\zeta_1)\, \mathrm{d}\zeta_1 \tag{18}$$

where ζ_1, *g(.)*, and *G(.)* are defined as in the discussion after Equation (13). The elements $\boldsymbol{j}_{ih}(\zeta_1)$ of the Jacobian matrix $\boldsymbol{J}_m(\zeta_1)$ are given by:

$$\boldsymbol{j}_{ih}(\zeta_1) = \frac{\partial}{\partial x_{h+1}^*}\left[\frac{R_{i+1}(\zeta_1)}{\exp(\boldsymbol{\beta}'\boldsymbol{z_{i+1}})}\right] = \frac{1}{\exp(\boldsymbol{\beta}'\boldsymbol{z_{i+1}})}\left\{\frac{w_1}{w_{i+1}}\left[\zeta_1(\widetilde{p_{h+1}} L_1 + \widetilde{p_{i+1}} L_{i+1}\tau_{ih})\right] - \widetilde{p_{h+1}} w_{h+1}(1 - \tau_{ih})\right\} \tag{19}$$

where $\tau_{ih} = 1$ if $i = h$ and $\tau_{ih} = 0$ if $i \neq h$, $L_k = \frac{1}{\widetilde{p_k}(x_k^* + \gamma_k)}$ $(k = 2, \dots, K)$ and $L_1 = \frac{1}{\widetilde{p_1} x_1^*}$

3.3.2 The TC-NAS-MDCP model

The second framework assumes that an individual maximizes the NAS utility function in Equation (1) subject to only the time budget constraint (TC), named the TC-NAS-MDCP model:

$$U(\boldsymbol{x}) = \psi_1 \ln(x_1) + \sum_{k=2}^{K} \psi_k \gamma_k ln\left[\left(\frac{x_k}{\gamma_k} + 1\right)\right] + \frac{1}{2}\sum_{k=2}^{K}\sum_{m \neq k \& m \neq 1} \theta_{km}\gamma_k\gamma_m \, ln\left[\left(\frac{x_k}{\gamma_k} + 1\right)\right] ln\left[\left(\frac{x_m}{\gamma_m} + 1\right)\right]$$

$$\text{s.t. } \sum_{k=1}^{K} x_k g_k = \mathrm{T}^* \tag{20}$$

The implicit assumption of the above model is that all the non-work activities considered in the analysis are free of monetary costs. For identification, the scale parameter σ is fixed to one in the TC-NAS-MDCP model (Bhat, 2008)[3].

The stochastic KKT conditions for the TC-AS-MDCP model can expressed as below:

$$\exp(\epsilon_k) = \frac{B_k(\xi_1)}{\exp(\boldsymbol{\beta}'\boldsymbol{z_k})} \; if \; x_k^* > 0, \; k = 2, \dots, K$$

$$\exp(\epsilon_k) < \frac{B_k(\xi_1)}{\exp(\boldsymbol{\beta}'\boldsymbol{z_k})} \; if \; x_k^* < 0, \; k = 2, \dots, K \tag{21}$$

where $\xi_1 = \exp(\epsilon_1)$, $\mathrm{B}_k(\xi_1) = \frac{w_1}{w_k}\xi_1 - A_K$, $w_k = \left(\frac{x_k^*}{\gamma_k} + 1\right)^{-1} \frac{1}{\widetilde{p_k}}$, $w_1 = (x_1^* \widetilde{p_1})^{-1}$ and $A_K = \sum_{m \neq k}^{K} \theta_{mk}\gamma_m \ln\left(\frac{x_m}{\gamma_k} + 1\right), (k = 2, \dots, K)$

Then, the likelihood of an individual performing the first M of the K non-work activities and observed time allocations for those M activities can be written as follows:

$$P(x_1^*, x_2^*, x_3^*, \dots, x_M^*, 0,0,0, \dots, 0)$$
$$= \int_{\zeta_1=0}^{\zeta_1=+\infty} |\boldsymbol{J}_m(\zeta_1)| \left\{\left[\prod_{m=1}^{M} \frac{1}{\sigma} g\left(\frac{1}{\sigma}\frac{B_m(\zeta_1)}{\exp(\boldsymbol{\beta}'\boldsymbol{z_m})}\right)\right]\right\} * \left\{\left[\prod_{j=M+1}^{K} G\left(\frac{1}{\sigma}\frac{B_j(\zeta_1)}{\exp(\boldsymbol{\beta}'\boldsymbol{z_j})}\right)\right]\right\} g(\zeta_1)\, \mathrm{d}\zeta_1 \tag{22}$$

where ζ_1, *g(.)*, and *G(.)* are defined as in the discussion after Equation (13). The elements $\boldsymbol{j}_{ih}(\zeta_1)$ of the Jacobian matrix $\boldsymbol{J}_m(\zeta_1)$ are given by:

$$\boldsymbol{j}_{ih}(\zeta_1) = \frac{\partial}{\partial x_{h+1}^*}\left[\frac{B_{i+1}(\zeta_1)}{\exp(\boldsymbol{\beta}'\boldsymbol{z_{i+1}})}\right] = \frac{1}{\exp(\boldsymbol{\beta}'\boldsymbol{z_{i+1}})}\left\{\frac{w_1}{w_{i+1}}\left[\zeta_1(\widetilde{p_{h+1}}L_1 + \widetilde{p_{i+1}}L_{i+1}\tau_{ih})\right] - \widetilde{p_{h+1}}\theta_{i+1,h+1}w_{h+1}(1-\tau_{ih})\right\} \tag{23}$$

where $\tau_{ih} = 1$ if $i = h$ and $\tau_{ih} = 0$ if $i \neq h$, $L_k = \frac{1}{\widetilde{p_k}(x_k^* + \gamma_k)}$ $(k = 2, \dots, K)$ and $L_1 = \frac{1}{\widetilde{p_1}x_1^*}$

4. EMPIRICAL RESULTS

In this section, we first describe the estimation findings of the FIC-AS-MDCP model proposed in this study, after which we compare the results from all three model formulations. To arrive at the final empirical model, several specifications were explored using different sets of socio-demographic and economic variables. These variables include age, gender, type of dwelling (rented or own dwelling), household size, level of education (graduate or non-graduate), residence location (urban or non-urban area), and race (first generation Dutch or otherwise). A systematic approach was used to develop the empirical specification by including one variable at a time in the utility functions. The interaction parameters in the NAS utility models were explored after the empirical specification was finalized for the baseline utility and satiation parameters.

[3] Recent paper by Bhat (2018) suggests that one can estimate the scale parameter even when there is no price variation. In the current paper, however, we did not explore this possibility.

4.1 Baseline marginal utility parameters

The parameter estimates for the three econometric frameworks discussed in the previous section are presented in Table 3. As discussed in the methodological section, for identification purposes, one of the activities serves as base reference alternative in the baseline utility specification. In the current application, personal care activity is the base category. Recall that the personal care activity is also the essential good in which all individuals spent some time, whereas other non-work activities need not be undertaken by all individuals. Consistent with this observation, as can be noted from the table, all baseline alternative specific constants are negative indicating that individuals are more likely to participate in personal care compared to the other activities, *everything else being equal*. The coefficients of the gender dummy variable suggest that males are more likely than females to take part in all non-work activities other than household chores (see, for example, Lu and Pas, 1999), *ceteris paribus*. In this context, the finding that males are more likely to pursue leisure activities than females is in contrast with that reported by Born et al., (2014) in the context of weekday time use in a North American city. In the context of household chores, unlike the traditional gender roles typically reported in the literature (see, for example, Pas, 1984; Kitamura et al., 1996; Golob and McNally, 1998; Yamamoto and Kitamura, 1999; Meloni et al., 2007) that females are more likely to undertake such activities more than males, the difference between employed males and employed females is not statistically significant. This is presumably because the current analysis is for employed individuals only.

In the context of age, people in the 30-55 age group appear to be more likely to participate in activities with children (than those below 30 years or above 55 years). People between 45 and 55 years of age are associated with higher participation in household chores (see, for example, Jenkis and O'Leary 1995; Srinivasan and Athuru, 2005), assisting friends and relatives, and administrative chores and family finances relative to younger adults (age<=30), *ceteris paribus*. Individuals who are over 55 years old seem to take part less (than younger adults) in Leisure (see, for example, Calastri et al., 2017a). The latter finding is consistent with the results observed by several studies such as Habib et al. (2008), Chikaraishi et al. (2010), Kapur and Bhat (2007), Pinjari et al. (2016) and Hutchinson et al. (2019). Further, as expected, older people seem to be less likely than younger adults (age<=30) to take part in education activities. As the household size increases so does the likelihood of an individual devoting time to household chores, activities with children and administrative chores and family finances (this finding is also reported by Bhat et al., 2016 and Astroza et al., 2017).

Those who have completed graduate schools are associated with higher likelihood of undertaking education activities (see, for example, Astroza et al., 2017 and Astroza et al., 2018) but lower likelihood of allocating time to household chores, *ceteris paribus*, presumably because individuals who have a higher education level are more stimulated to continue learning and improving their abilities. The differences in activity participation between those living in urban areas and those in non-urban areas were not found to be statistically significant. On the other hand, individuals who are first generation Dutch are more likely to participate in leisure activities than others, *ceteris paribus*.

Table 3 about here

Now, we compare the interpretations of baseline utility parameters from the three different model structures. Overall, only a few differences were found between the three models in terms of the interpretations they offer on demographic variation in baseline utility parameters. These are discussed here. The TC-NAS-MDCP model did not yield statically significant gender differences in individuals' propensity to take part in activities with children. However, both the models that consider monetary constraints suggest that employed males are more likely (than females) to take part in activities with children. Further, the FIC-AS-MDCP model did not yield a significant difference between males and females in their likelihood of taking part in household chores, whereas the other two models that employ the NAS utility function yielded a marginally significant difference (the corresponding t-statistic is smaller than 1.65).

4.2 Satiation parameters

The satiation parameter estimates for the three econometric frameworks are presented in Table 4. The satiation parameters, along with the baseline utility parameters, influence the continuous quantity (time allocation) decision. A notable result is that individuals' demographic variables were not found to have a statistically significant influence on the satiation parameters of the TC-NAS-MDCP model. On the other hand, the other two models that combine monetary budget constraint with the time budget constraint yield significant variations in satiation parameters across different demographic segments. These results suggest that accommodating monetary budget constraint along with the time budget constraint helps in revealing demographic heterogeneity in the satiation parameters.

In the context of gender differences in time allocation, according to the proposed model, males tend to allocate more time to leisure and administrative activities but less time to activities with children, if they perform these activities, *ceteris paribus*, than females. Recall from the discussion in the context of baseline marginal utility parameters that males were found to be more likely than females to take part in activities with children. However, the satiation parameters suggest that males are likely to spend less time than females - if they participate in such activities. Such nuances are missing in the results of the TC-NAS-MDCP model that ignores the monetary budget constraint.

Table 4 about here

According to the proposed model, people with at least graduate-level education tend to spend less time in education, assisting friends and relatives, and administrative activities than those who are less educated (see, for example, Spissu et al., 2009). It is interesting to note that while people with higher education are more likely to take part in education activities (recall from discussion on baseline marginal utility parameters), they tend to spend less time doing so. This is presumably because people with higher education face greater time constraints. Again, such nuances are missing in the TC-NAS-MDCP model results. Finally, respondents who lived in urban areas devoted lower amount of time to household chores activities relative to those who live in non-urban areas, *ceteris paribus.*

4.3 Interaction parameters in the NAS utility function

The interaction parameter estimates in the NAS utility functions for the two NAS models are presented in Table 5. Note that the FIC-AS-MDCP model does not have interaction parameters as it employs an AS utility function. As can be observed from the parameter estimates in the both the NAS models, all the estimated interaction effects suggest substitution in time allocation between different pairs of activities. A plausible reason for this is due to tight time and/or budget constraints (i.e., limited availability of time and/or money) individuals are likely to trade-off the time they allocate between different activities. That is, due to limited availability of time and/or money, allocation of time to some of the activities might reduce the allocation of time to other activities; as opposed to individuals spending time on activities without regard to how much time they allocation to other activities.

Table 5 about here

Another interesting result is that the NAS utility form model that considers both time and money constraints reveals substitution effects between several pairs of activities. On the other hand, the NAS utility form model that considers only time constraint yields only one substitution parameter. An explanation for this difference is that the model that considers time and money constraints yields a greater number of substitution effects due to monetary trade-offs people might make in allocating time to different activities.

We now turn to the interaction effects in our preferred model, which considers the NAS utility form and both time and money constraints. The negative interaction effect between household chores and assisting friends & relatives suggests that people trade-off the time they allocate between these two activities. There are significant substitution patterns in the allocation of time to activities with children and education as well as between activities with children and administrative chores and family finances. A plausible explanation is that working parents are likely to renounce or reduce, at least temporarily, the time they devote to personal education activities to look after and enjoy time with children (see, for example, Kitamura et al., 1996; Yamamoto and Kitamura, 1999; Klerman and Leibowitz, 1999; Bianchi, 2000; Guryan et al., 2008; Bianchi, 2011). Regarding interaction parameters associated with education, substitution is found between the allocation of time to education and assisting friends & relatives, and between education and administrative chores & family finances. Similarly, substitution effects are found between education and leisure activities. Further, substitution effects are found between assisting friends & relatives and administrative chores & family finances, as well as between assisting friends & relatives and leisure.

4.4 Model fit

The Bayesian Information Criterion (BIC) and Akaike Information Criterion (AIC) values employed for evaluating the goodness of fit of the three modeling frameworks proposed in this study are reported in Table 6. As can be seen from the table, both the models that incorporate the full income constraint (i.e., combine both time and money budget constraints into a single constraint) perform much better than the TC-NAS-MDCP model that does not consider monetary constraint. Between the two models that consider full income constraint, the model that employs the NAS utility form outperform the one that employs a simpler AS utility form. Note that, given a common empirical variable specification in the utility functions, the FIC-NAS-MDCP model subsumes the FIC-AS-MDCP model a special case when all the interaction parameters in the former model are set to zero. Therefore, one can conduct a log-likelihood ratio (LLR) test to compare the two models. The LLR value between the two models is 477.54,

which is far greater than the critical chi square value for 8 degrees of freedom (for the 8 interaction parameters) at a p-value of as low as 0.001. Based on this one can reject the null hypothesis that the FIC-AS-MDCP model is the true model, in favor of the FIC-NAS-MDCP model.

Table 6 about here

4.5 Discussion

4.5.1 Importance of the proposed model structure

The empirical analysis in this section can be used to make important inferences. First, accounting for both time and money constraints in the form of a full income constraint yields in notable improvement in the model fit (over the model that considers only a time budget constraint) as well as reveals important sociodemographic differences in the satiation effects in time allocation. Several nuances, particularly those related to sociodemographic heterogeneity in the satiation rates, are missing from the TC-NAS-MDCP model that ignores the money budget constraint. The latter approach models time use decisions as if the non-work activities were all free of monetary cost as well as the opportunity cost of not working. On the other hand, the full income constraint approach allows the accommodation of both the direct price of an activity and the corresponding opportunity cost of not working, which assists in improving the model fit as well as revealing greater demographic heterogeneity in the satiation rates in time allocation to different activities. Therefore, it is important to consider both time and money budget constraints when analyzing individual-level time use. While this has long been recognized, the previous literature on time use modeling has not done so while accounting for non-additive nature of utility functions. In this paper, we find that accommodating NAS utility functions improves the model fit as well as results in rich substitution patterns in time allocation to different activities. Since employed individuals' time is substantially constrained, both due to the time budget and due to the need to generate income to consume non-work activities, the NAS model that accounts for both time and money budget constraints results in significant substitution patterns between various pairs of activities. Therefore, ignoring the monetary constraint resulted in a model that revealed substitution between only a single pair of activities, whereas the proposed FIC-NAS-MDCP model revealed substitution between several more pairs of activities. In summary, this empirical analysis highlights the importance of considering both time and money budget constraints while also accounting for the NAS nature of utility functions in MDC models of time use.

4.5.2 Policy Implications

Important policy implications may be derived from this analysis. Recall from the discussion of the empirical results that employed males are more likely to take part in non-work activities such as leisure, education, and administrative chores and family finances than employed females. Furthermore, employed males are found to spend more time in leisure activities than employed females. They are also found to spend less time in activities with children than females. While statistically significant differences were not found between employed males and females in their time allocation to household chores, traditional gender roles and inequities in time allocation are still apparent. Considering that the data used for this analysis comprises employed individuals from single worker households, it appears that a woman who is the primary breadwinner of a household spends more time with children (than her male counterparts) but a man who is the primary breadwinner enjoys more time of leisure and education activities as well as gets to spend more time on administrative chore and family finances (than his female counterparts). It is worth noting here that several governments strive to reduce the amount of time women spend on childcare, with an aim of increasing their time spent in the labor market, promoting their career growth, and increasing their wellbeing. The fact that inequities continue to exist (Sullivan, 2019; Rubiano-Matulevich and Viollaz, 2019), even between employed women and employed men suggests that greater attention and continued policy efforts are needed to reduce the gender gap in time allocation patterns. To address such inequities, policies toward provision of affordable childcare programs for working women from single worker households, efforts to increase wage rates for women, and allocation of funds to reduce costs of education for women might help free up their time as well as monetary resources to enable them to undertake leisure and education activities. Doing so can help increase the wellbeing of women (through greater time allocation to leisure) and allow women to further their careers through increased education attainment. Such policies can also help women increase their time allocation to work as well as maintain a better balance between paid work and other, unpaid in-home activities such as childcare.

The empirical results suggest that individuals with higher education are more inclined to take part in education activities. Over time, this will likely result in a widening education gap within the population, with the possible implication that less educated individuals will be confined to low income jobs. Neoclassical human capital theory of labor markets (Becker, 1971) suggests that those with lower education and skill levels face worse labor market outcomes than those who invest more time to improving their knowledge base. Therefore, it is likely that low educated households will be confined to low income jobs and subsequently

suffer from social mobility issues that will amplify in the long run (Lucas, 2012). For example, Currie and Stanley (2007) observe that lower income people who reside in suburban and regional areas are likely to experience difficulties in participating in education (this results in vicious cycle where low education leads to low income which, in turn, adds to the inability to further education). Policies should therefore promote for more investment in education and learning *activities*, particularly for the less educated and for women as well as for those in living communities with poor access to educational institutions and learning facilities.

Another finding relevant to policy discussion is that older adults are less likely to undertake education activities compared to younger individuals. While it is likely that older people may have already attained the education needed for their work, the economic literature has extensively investigated how employee development contributes to a firm's performance (Becker, 1964; Collins, 1979; Mincer, 1974). Woods and De Menezes (1998) affirm that investing in employee training positively affects the workforce commitment toward the firm, resulting in a willingness to work harder (see also Whitener, 2001). Further, employees perceive that the company pays attention to their improvements and values their efforts (Lee and Bruvold, 2003). As such, employers could potentially introduce flexible work schedules to allow their employees to undertake education activities. This could help provide more time for older adults to upgrade their abilities and remain up-to-date, as they are likely to have less time for learning activities relative to their younger counterparts.

5. CONCLUSIONS

This paper proposes a multiple discrete-continuous (MDC) choice modeling framework that incorporates time and money constraints into a single economic constraint (i.e., the full income constraint approach) along with a non-additively separable (NAS) utility structure for assessing individuals' time use patterns. The proposed FIC-NAS-MDCP framework is applied to analyze weekly time use of employed individuals in Netherlands using a data set derived from the third wave of the Time use and Consumption survey of the Longitudinal Internet Studies for the Social Sciences (LISS) panel. The empirical results of the proposed model are compared to those from two simpler models – one that ignores the monetary budget constraint but employs the NAS utility function (TC-NAS-MDCP model) and the other that considers both time and money budget constraints but uses a simpler AS utility function (FIC-AS-MDCP model).

The proposed FIC-NAS-MDCP model outperforms both the simpler models in terms of model fit as well as the insights it offers on the time use patterns of employed individuals. Since the proposed model considers both time and money constraints in the form of a full

income constraint, it reveals important sociodemographic differences in the satiation effects in time allocation. The sociodemographic heterogeneity in the satiation rates were not revealed by the TC-NAS-MDCP model that ignores money budget constraints. These results suggest the importance of considering both time and money budget constraints when analyzing individual-level time use. Further, accommodating NAS utility functions improves the model fit as well as results in rich substitution patterns in time allocation to different pairs of activities. Specifically, since employed individuals' time is substantially constrained, both due to the time budget and due to the need to generate income to consume non-work activities, the NAS model that accounts for both time and money budget constraints results in significant substitution patterns between various pairs of activities. Ignoring the monetary constraint in an NAS utility model (i.e., the TC-NAS-MDCP model), however, did not reveal as many substitution effects as the model that considers both time and money constraints using the full-income constraint approach. These results suggest that the benefits of the NAS utility form are better harnessed using the full-income constraint than a single, time-constraint. In addition, the model results offer important policy insights for reducing demographic inequities in time allocation among employed individuals.

Various avenues can be explored in future research. For instance, it would be of interest to incorporate technical constraints into the proposed approach as to accommodate minimum consumption time for some activities (e.g., a minimum amount of time spent in personal care; see, for example, DeSerpa, 1971 and Astroza et al., 2017). DeSerpa (1971) and more recently Jara-Díaz and Guerra (2003) and Jara-Díaz et al. (2016) assert that both good consumption and time allocation decisions contribute to the utility an individual derives from participating in activities. As such, a second research avenue could involve the use of non-additively separable preferences where both consumption of goods and allocation of time generate utility. Third, it will be interesting to compare the (Becker's) approach in this paper of combining time and money constraints into a single full-income constraint with a model where both constraints are recognized separately. Doing so allows one to relax the assumption made in this paper that time and money are freely exchangeable resources, which might not be applicable for subsistence activities such as eating and sleeping. Such activities might need at least a minimum amount of time that individuals would not be willing to tradeoff with money. A fourth avenue for future research could be to combine a latent class model (see Kamakura and Russell, 1989) with multiple constraints and a NAS utility structure, where each class allows for different complementarity and substitution patterns and/or different constraints such as time constraint in one class, money constraint in the second class, and both constraints in the third

class. Fifth, it would be worthwhile to couple NAS utility forms and multiple resource constraints with flexible error covariance structures in the model framework. Doing so can potentially help the analyst disentangle two different sources of dependency among utility functions of different choice alternatives – error term correlations due to common omitted variables and interactions in the utility functions due to complementarity effects. Finally, it would be useful to explore alternate functional forms for the interactions terms in the NAS utility forms (see Pellegrini et al., 2019; Palma and Hess, 2020) as well as a linear utility structure for the outside good (Bhat, 2018).

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TABLES

Table 1: Descriptive of demographic information of respondents (N = 1139) in the estimation data

	Frequency	Percentage
Gender		
Male	809	71.02
Female	330	28.97
Age		
<= 30 years old	103	9.04
30 – 45 years old	410	35.99
45 – 55 years old	342	30.02
55 years old or over	285	25.02
Presence of children in the household		
Yes	501	43.98
No	638	56.01
Single person household		
Yes	353	30.99
No	786	69.01
Level of education		
Graduate	832	73.05
Non-graduate	307	26.95
Race		
First generation Dutch	1025	89.99
Second or third generation Dutch	114	10.01
Type of residence		
Urban	1082	95.00
Non-urban	57	5.00
Type of dwelling		
Rent	330	28.97
Self-owned dwelling	809	71.03
Income (euros/week)	Mean = 542.47	St. dev. = 244.81
Wage (euros/hour)	Mean = 17.06	St. dev. = 19.65

Table 2: Descriptive of activity participation, time allocation, and expenditures in the estimation data

Activity	Participation rate (% of individuals participating in the activity)	Weekly time allocation to activities for those who participated in the corresponding activities (hours/week)		Weekly expenditure on activities for those who participated in the corresponding activities (euros/week)	
		Mean	**St.Dev.**	**Mean**	**St.Dev.**
Work	100.00%	38.0	12.0	-	-
Personal care	100.00%	8.4	5.3	51.54	63.92
Leisure	99.70%	32.1	15.75	10.26	14.98
Household chores	98.00%	9.95	7.37	11.04	16.11
Activities with children	36.10%	11.9	10.01	57.21	44.95
Education	24.90%	6.22	6.55	4.34	12.00
Assisting friends and relatives	54.70%	6.86	6.74	-	-
Administrative chores & family finances	89.10%	2.98	3.15	-	-
Number of observations			1139		

Table 3. Estimation Results: Baseline Utility Parameters ($\boldsymbol{\beta}$)

	FIC-NAS-MDCP		FIC-AS-MDCP		TC-NAS-MDCP	
	Parameter	t-stat	Parameter	t-stat	Parameter	t-stat
Baseline parameters ($\boldsymbol{\beta}$)						
Baseline Constants						
Household Chores	-0.28	-1.87	-0.41	-2.95	1.87	8.14
Activities with children	-2.73	-26.06	-2.82	-25.89	-4.22	-26.35
Leisure	-0.17	-1.07	-0.63	-6.67	1.78	4.15
Education	-1.09	-8.17	-1.76	-16.82	-2.10	-10.61
Assisting friends and relatives	-0.49	-3.74	-1.47	-26.60	-0.86	-6.81
Administrative chores and family finances	-0.71	-8.84	-0.83	-11.93	0.13	1.40
Gender: Male (Female is base)						
Household Chores	0.14	1.45	0.07	0.85	0.08	1.33
Activities with children	0.31	4.24	0.34	4.44	0.03	0.29
Leisure	0.16	2.77	0.32	3.59	0.44	7.37
Education	0.19	3.71	0.28	4.84	0.26	2.55
Assisting friends and relatives	0.22	5.22	0.32	6.46	0.29	3.68
Administrative chores and family finances	0.11	1.64	0.21	3.11	0.40	6.07
Age: 30-45 yrs (<=30 yrs. is base)						
Activities with children	0.53	6.93	0.55	7.07	1.21	10.00
Age: 45-55 yrs (<=30 yrs. is base)						
Household Chores	0.12	2.90	0.11	2.75	0.14	2.19
Activities with children	0.43	5.20	0.45	5.32	0.65	5.07
Education	-0.08	-1.56	-0.07	-1.19	-0.17	-1.58
Assisting friends and relatives	0.14	3.92	0.15	3.53	0.27	3.60
Administrative chores and family finances	0.11	2.57	0.13	3.11	0.22	3.23
Age:>55 yrs (<=30 yrs. is base)						
Leisure	-0.13	-3.27	-0.16	-4.16	-0.17	-2.71
Education	-0.16	-3.17	-0.22	-3.87	-0.37	-3.26
Dwelling type: Rented (own dwelling is base)						
Activities with children	0.09	1.04	0.09	1.04	0.14	1.05
Leisure	0.10	2.33	0.09	2.03	0.18	2.55
Education	0.13	2.50	0.14	2.30	0.24	2.16
Assisting friends and relatives	0.08	2.17	0.11	2.35	0.16	1.80
Household size						
Household Chores	0.04	2.85	0.04	2.79	0.02	0.89
Activities with children	0.42	14.87	0.43	14.83	0.77	16.54
Education	0.03	1.56	0.03	1.68	-	-
Assisting friends and relatives	0.01	0.75	0.04	2.75	-	-
Administrative chores and family finances	0.07	3.78	0.03	2.16	-	-
Education: Graduate (Non-graduate is base)						
Household Chores	-0.07	-2.06	-0.06	-1.81	-0.11	-1.93
Education	0.08	1.77	0.09	1.67	0.22	1.98
Type of residence: Urban (Non-urban is base)						
Household Chores	0.17	1.57	0.18	1.61	-0.07	-0.72
Education	0.07	1.19	0.08	1.25	0.13	0.90
Race: First generation Dutch						
Leisure	0.11	2.31	0.11	2.31	0.12	1.40

Table 4. Estimation Results: Satiation Parameters (γ_k)

	FIC-NAS-MDCP		FIC-AS-MDCP		TC-NAS-MDCP	
Satiation parameters (γ_k)	Parameter	t-stat	Parameter	t-stat	Parameter	t-stat
Constants						
Household Chores	1.92	6.29	2.06	7.11	0.49	4.76
Activities with children	3.49	8.58	3.62	10.74	5.73	10.82
Leisure	2.57	8.49	3.27	16.21	1.29	2.33
Education	2.69	8.27	3.76	10.85	7.89	7.54
Assisting friends and relatives	2.02	8.91	3.09	22.41	3.18	8.97
Administrative chores and family finances	0.82	4.11	1.01	5.62	0.56	12.25
Gender: Male (Female is base)						
Household Chores	0.09	0.55	0.16	1.08	-	-
Activities with children	-0.75	-3.22	-0.90	-3.83	-	-
Leisure	0.35	3.60	0.15	0.73	-	-
Administrative chores and family finances	0.45	3.11	0.36	2.45	-	-
Education: Graduate (Non-graduate is base)						
Education	-0.26	-1.33	-0.43	-1.19	-	-
Assisting friends and relatives	-0.24	-2.62	-0.29	-2.11	-	-
Administrative chores and family finances	-0.16	-1.55	-0.16	-1.56	-	-
Type of residence: Urban (Non-urban is base)						
Household Chores	-0.48	-2.01	-0.49	-2.02	-	-

Table 5. Estimation Results: Interaction Parameters ($\boldsymbol{\theta_{km}}$) of NAS Utility Functions and Scale Parameter (σ)

Activity type pairs with interaction parameters ($\boldsymbol{\theta_{km}}$)	**FIC-NAS-MDCP**		**FIC-AS-MDCP**		**TC-NAS-MDCP**	
	Parameter	t-stat	Parameter	t-stat	Parameter	t-stat
Household Chores – Activities with children	-	-	-	-	-	-
Household Chores – Leisure	-	-	-	-	-	-
Household Chores – Education	-	-	-	-	-	-
Household Chores – Assisting friends & relatives	$-16*10^{-2}$	-4.30	-	-	$-8*10^{-2}$	-2.41
Household Chores – Admin chores & family finances	-	-	-	-	-	-
Activities with children – Leisure	-	-	-	-	-	-
Activities with children – Education	$-5*10^{-3}$	-2.80	-	-	-	-
Activities with children – Assisting friends & relatives	-	-	-	-	-	-
Activities with children – Admin chores & family finances	$-9*10^{-3}$	-3.32	-	-	-	-
Leisure – Education	$-11*10^{-2}$	-3.19	-	-	-	-
Leisure – Assisting friends & relatives	$-16*10^{-2}$	-3.25	-	-	-	-
Leisure – Admin chores & family finances	-	-	-	-	-	-
Education – Assisting friends & relatives	$-9*10^{-3}$	-3.04	-	-	-	-
Education – Admin chores & family finances	$-6*10^{-3}$	-2.26	-	-	-	-
Assisting friends & relatives – Admin. chores & family finances	$-1*10^{-2}$	-3.82	-	-	-	-
Scale parameter (**σ**)	0.36	22.28	0.37	22.07	Fixed to 1	

Table 6. Model Fit Metrics

	FIC-NAS-MDCP	FIC-AS-MDCP	TC-NAS-MDCP
Number of observations	1139	1139	1139
Number of parameters	57	49	38
Log-likelihood at convergence	-13,484.63	-13,723.40	-16,271.93
Bayesian Information Criterion (BIC)	27,370.62	27,809.66	32,811.30
Akaike's Information Criterion (AIC)	27,083.46	27,562.80	32,619.86