EVOLUTION OF ADULTS’ WEEKDAY TIME USE PATTERNS FROM 1992 TO 2010: A CANADIAN PERSPECTIVE

Anae Sobhani
PhD Student
Department of Civil Engineering and Applied Mechanics
McGill University
Ph: 647 894 2613, Fax: 514 398 7361
Email: anae.sobhani@mail.mcgill.ca

Naveen Eluru*
Assistant Professor
Department of Civil Engineering and Applied Mechanics
McGill University
Ph: 514 398 6823, Fax: 514 398 7361
Email: naveen.eluru@mcgill.ca

Abdul R. Pinjari
Department of Civil and Environmental Engineering
University of South Florida
4202 E. Fowler Ave., Tampa, Fl 33620
Ph: 813-974- 9671, Fax: 813-974-2957
Email: apinjari@eng.usf.edu

*corresponding author

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ABSTRACT
This paper examines the weekday time use patterns of Canadians aged 20 years or older using pseudo-panel analysis of four waves of data from General Social Survey (GSS) compiled for the years 1992, 1998, 2005 and 2010. The study contributes to activity pattern literature by estimating the Scaled Multiple Discrete Continuous Extreme Value model (MDCEV) model for non-workers and workers with a comprehensive set of activity purposes. The analysis allows us to examine the influence of individual socio-demographics (such as person age, gender, employment status) and household socio-demographics (such as household structure). Further, observed and unobserved effects of the year of data collection are also explicitly considered in our analysis enabling us to examine trends in activity participation across the years while controlling for various attributes. The results provide evidence that our proposed approach provides an appropriate framework to study activity participation decision process evolution in time. Further, we undertake a trend analysis and illustrate how baseline utility for various activity purposes changes for various demographic groups across the years.

Keywords: Activity-travel behavior, Canadian weekday activity participation, General Social Survey, multiple discrete continuous extreme value model
1. INTRODUCTION

Activity-based models focus on the activity-travel decisions of individuals, along with the spatial, temporal, and social contexts of activity episode participation (1). The analysis of activity participation decisions involves answering the which, where, when, how and with whom questions related to activity participation. In other words, the emphasis is on determining which activities will be pursued, where each of these activities will be undertaken, at what time is the activity supposed to start, how will the individual arrive at the location (if out of home), how long will the activity last and with whom is the activity pursued. The answers to these questions have a significant impact on the resulting transportation infrastructure usage. Hence, it is not surprising that travel demand modellers have started developing representation frameworks to model activity participation in an attempt to answer the above questions accurately. In fact, the travel demand forecasting community has seen a paradigm shift from an aggregate statistical four step model towards a disaggregate behavior oriented activity based model. The activity-based modeling framework recognizes the fundamental role of activity participation as a precursor to travel i.e. the activity based approaches have shifted the primary focus of attention from trips to activities. The shift has resulted in increased attention on the individuals’ activity participation decisions. It is no surprise that there have been many studies examining activity patterns (2, 3).

These earlier research efforts offer useful insights on the role of individual and household socio-demographics, employment characteristics, land use and urban form on activity participation decision processes. Typically, these research efforts employ cross-sectional databases of daily activity participation. These cross sectional databases while providing a detailed representation of activity participation decisions are not appropriate to examine evolution of activity participation decision processes in time. Towards this purpose, longitudinal databases that track individual level activity participation decisions across multiple years are likely to be more informative by allowing us to capture the influence of life cycle changes, technology, land use, perceptions on transit usage and changing social and cultural trends. Unfortunately, compiling such activity time use is prohibitively expensive and provide many challenges associated with respondent fatigue and retention (4,5,6).

1.1. Study Motivation

The current study is motivated from the need to address this data availability challenge. Specifically, we develop activity pattern analysis frameworks employing cross sectional databases compiled over multiple time points. The availability of multiple cross sectional datasets for different years provides a useful compromise between a single year cross sectional dataset and a truly longitudinal dataset compiled across multiple years. Though the multiple waves are not compiled based on the same set of individuals, they still provide data from multiple time points allowing us to examine the impact of technology, altering perceptions of road and transit infrastructure, and changing social and cultural trends across the population on activity participation. For instance, we could examine if the increased participation of women in the labor force has really influenced the amount of time women spend in child care over the last twenty years. The examination is a first step towards understanding the evolution of activity participation. The approach of pooling multiple waves of data from different sets of individuals is referred to as a pseudo-panel approach to data analysis. A number of research efforts in the
transportation community have adopted this approach (see (7)) for an application on travel
demand forecasting and (8) and (9) for studies on vehicle ownership)

The data pooling of different respondents across multiple waves offers unique
methodological challenges. The proposed methodology should recognize the differences across
multiple time points adequately. Specifically, the choice process for the respondents in a
particular year might be influenced by various observed and unobserved attributes ((10), pp. 37-
75). For example, if there is a significant spike in households with multiple employed individuals
(from say 1995 to 2005), the pattern of activity participation might alter substantially across
these two databases. This is an instance of how observed attributes affect activity participation
decision process. The traditional outcome based models can accommodate such transitions
reasonably through appropriate model specification (number of workers in a household variable
or spouse is employed variable). However, say we are interested in measuring the impact of
growing environmental consciousness between 2000 and 2010; we might observe the influence
of these variations on vehicle usage for discretionary activity participation. This is the case of an
unobserved variable (as it will be very hard to define exogenous variable of this type) specific to
the study time period on the decision process. The accommodation of such unobserved effects
becomes crucial in the analysis process. In our study, we propose and implement a framework in
the context of activity participation framework that simultaneously accommodates for the
influence of observed and unobserved attributes on the activity participation framework across
multiple time points. The proposed modeling approach is employed to study the type of activity
pursued, the associated duration of the activity and the activity location (characterized as in-
home and out-of-home).

The approach employed in our study takes the form of a scaled multiple discrete
continuous extreme value (SMDCEV) model that builds on the advantages of the traditional
MDCEV model (11). The MDCEV model, based on random utility framework, provides an
analytically tractable approach to study multiple discrete choice decisions. The model is
particularly appealing for activity participation as it allows for the possibility of multiple activity
participation while simultaneously modeling the impact of satiation in determining the associated
duration of activity participation. The MDCEV framework has been extensively employed to
undertake a host of activity participation studies (see for example (12), (2), (13), (14) and (3)).
The focus of our research is to employ the SMDCEV model to undertake a comprehensive
examination of adults’ activity participation decisions in Canada using data from cross sectional
datasets over the last 20 years. The focus of the analysis is on examining the influence of
individual and household socio-demographics on activity participation decisions employing time
use supplements of the Canadian General Social Survey (GSS) compiled for the years 1992,
1998, 2005 and 2010. The results provide evidence that our proposed approach provides an
appropriate framework to study activity participation decision process evolution in time.

The reminder of the paper is organized as follows. Section 2 presents a brief review of
earlier research and positions the current study in context. In Section 3, the econometric
methodology employed in this paper is briefly described. Section 4 elaborates on data assembly
procedures and sample characteristics for non-workers and workers. In Section 5, the estimation
results of the Scaled MDCEV model are presented in the context of non-workers’ weekday
activity participation decisions. Finally, Section 6 concludes the paper.
2. EARLIER STUDIES AND CURRENT STUDY IN CONTEXT

2.1. Background

The transportation community has examined the various dimensions of activity participation in substantial detail over the past three decades. The studies employ a host of methods including descriptive analysis, linear regression, duration models, discrete choice models (ordered and unordered regimes), discrete continuous models and multiple discrete-continuous models. To undertake an exhaustive literature review is beyond the scope of our study. Hence we restrict ourselves to providing an overview of existing literature in this field.

Most of the earlier research efforts focused on a particular dimension of activity participation – activity type choice, duration of the activity, company type, travel mode, activity distance, and time period choice. For instance, some studies examine specific activity purposes including discretionary activity (1), maintenance activity (15), shopping activity participation (16), physical activity (17), child care (18), volunteering and community activities (19, 20). A number of studies have also focused on joint modeling of activity purpose and accompaniment type without examining time-use participation (15, 21-23). Some of these studies focus on intra-household interactions (for instance, see (21), (15) and (23)). Of course, individuals are not required to limit their choice of accompaniment to only household members; significant activity episode participation can be found in the company of wider social network beyond the household (for example, see (3), (13-14), (22), (24-28)). With the advent of modelling approaches that allow for multiple discrete continuous choice contexts studies that consider activity type, accompaniment type, and time of day choices while explicitly focusing on time-use participation as a continuous component of analysis were implemented (3, 14, 24-26, 29).

The research on activity participation is also influenced by the most significant issues of our times such as growing greenhouse gas emissions and wide spread prevalence of technology. The growing emphasis on the role of transport in mitigating the impacts of global warming has also encouraged researchers to study non-work activity mileage decisions (30) and impact of activity type and company type choice on vehicle usage (12). The increased access to information and communication technologies (ICT) and their influence on activity participation has also received wide recognition (11, 31, 32).

In general, findings from previous literature on activity participation indicate that females are more likely to pursue maintenance activities and family care (22, 18, 15, 23, 13). Younger individuals are more likely to pursue non-work activities with company, confirming the larger social networks of younger individuals (22). Individuals are more likely to pursue leisure activities in the company of friends and family (24). During weekdays, shopping episodes are more likely to be undertaken independently (15). Also, financial constraints dictate disinclination towards pursuing discretionary episodes (13). Studies on seniors have found that most seniors spend a large amount of time in passive leisure activities such as reading and watching TV (33).

2.2. The Current Research Effort

All the above studies highlighted in preceding section discuss the recent progress in understanding activity participation decisions. A number of studies reviewed earlier have employed cross-sectional datasets for analysis i.e. the research is purely based on a data collected at one point in time. To be sure, there have been some databases that consist of weekly activity participation data (34, 25). However, in terms of individual’s activity participation they are still a single weekly snapshot. The only study that has compiled longitudinal data for activity
participation decisions is the data compiled through the PROCESSUS Network from 2000
through 2008 in three waves. Unfortunately, the sample size of respondents in this data
collection effort was small to begin with (around 400 individuals) and the continued attrition of
respondents resulted in even smaller databases for waves 2 and 3. The small sample size makes it
hard to generalize the results from the analysis to the general population. Hence, the current
study contributes the first of its kind analysis, by evaluating time use patterns across the last 20
years using multiple waves of the GSS data. The American Time Use Survey (ATUS) Data is
another possible candidate for such analysis; however, the ATUS data is available only for the
last 10 years (since 2003).

There has been significant interest in studying activity participation decisions in United
States and Europe (see (24), and (3)); while in Canada this topic of research has received less
attention particularly from the multivariate modeling stand point. There have been a number of
studies exploring changes in time use patterns for workers (35), physical activity patterns (17),
child care (18), volunteer activity participation trends of immigrants (19, 20). However, all of
these studies in the Canadian context employ descriptive analysis or univariate analysis
approaches to examine differences in time-use (except for (21)) The GSS provides us with a
unique opportunity to undertake activity participation and time use research for Canadians using
data compiles detailed information on activity participation (including start time, end time,
location, with whom) for one household member interviewed. The data also compiles the
individual and household level socio-demographic information.

In summary, the current study contributes to literature in two ways. First, the study
stitches together multiple cross-sectional datasets to generate a pooled dataset that allows us to
study the evolution of activity participation using a scaled MDCEV mode framework. Second,
empirically, the study contributes to activity pattern literature by estimating the Scaled MDCEV
model for non-workers and workers with a comprehensive choice set of activity purposes. The
analysis will allow us to examine the influence of individual socio-demographics (such as person
age, gender, employment status) and household socio-demographics (such as household
structure). Further, observed and unobserved effects of the year of data collection are also
explicitly considered in our analysis enabling us to examine trends in activity participation across
the years while controlling for various attributes.

3. METHODOLOGY

3.1. Model Structure
In our model we extend the MDCEV model to formulate the SMDCEV model. For this purpose,
we provide a brief formulation of the MDCEV model and provide the formulation for SMDCEV.
Consider the following functional form for utility in our study, based on a generalized variant of
the translated CES utility function and with the consideration for no outside good:

\[
U(x) = \sum_{k=1}^{K} \gamma_k \exp(\beta'z_k + \varepsilon_k) \ln \left( \frac{x_k}{\gamma_k} + 1 \right)
\]  \hspace{1cm} (1)
where $U(x)$ is a quasi-concave, increasing, and continuously differentiable function with respect to the consumption quantity $(Kx1)$-vector $x$ ($x_k \geq 0$ for all $k$ alternatives), and $\psi_k$ ($= e^{exp(\beta'z_k)}$), $\gamma_k$ and $\alpha_k$ are parameters associated with alternative $k$. $\psi_k$ represents the baseline marginal utility, $z_k$ represents the vector of exogenous variables in the marginal utility, $\gamma_k$ enable corner solutions while simultaneously influencing satiation and $\alpha_k$ influences satiation only. Due to the similar role of $\gamma_k$ and $\alpha_k$ (in terms of allowing for satiation) it is very challenging to identify both $\gamma_k$ and $\alpha_k$ in empirical applications due to identification challenges (see (36) for an elaborate discussion on the issue). Usually, one chooses to estimate satiation using $\gamma_k$ or $\alpha_k$.

Depending on the chosen parameter for estimation the alternative utility structures are described as follows:

In the case where only the $\gamma_k$ parameters are estimated the utility simplifies to

$$U(x) = \sum_{k=1}^{K} \gamma_k e^{\beta'z_k + \varepsilon_k} \ln \left( \frac{x_k}{\gamma_k} + 1 \right)$$

(2)

Similarly, in the case of estimating only $\alpha_k$ the corresponding utility expression collapses to

$$U(x) = \sum_{k=1}^{K} \frac{1}{\alpha_k} e^{\beta'z_k + \varepsilon_k} \left( \left( x_k + 1 \right)^{\alpha_k} - 1 \right)$$

(3)

Following Bhat (2, 36), consider an extreme value distribution for $\varepsilon_k$ and assume that $\varepsilon_k$ is independent of $z_k$ ($k = 1, 2, \ldots, K$). The $\varepsilon_k$'s are also assumed to be independently distributed across alternatives with a scale parameter of $\sigma$. Let $V_k$ be defined as alternative utility. In that case, the value of $V_k$ according to the two profiles are as follows:

$\gamma$-profile

$$V_k = (\beta'z_k - \ln(\frac{x_k}{\gamma_k} + 1))$$

(4)

$\alpha$-profile

$$V_k = \beta'z_k + (\alpha_k - 1) \ln (x_k + 1)$$

(5)

Given the $V_k$ values for the two profiles, the probability that the individual $q$ ($q = 1, 2, \ldots, Q$) has a continuous vector $(\varepsilon^*_1, \ldots, \varepsilon^*_M)$ for the first $M$ of the $K$ goods ($M \geq 1$) under the scaled model is given as follows:

$$P(\varepsilon^*_1, \ldots, \varepsilon^*_M) = \frac{1}{\sigma^{M-1}} \left[ \prod_{i=1}^{M} c_i \right] \left[ \sum_{i=1}^{M} \prod_{j=1}^{i} c_j \right] \left[ \prod_{i=1}^{M} e^{\frac{V_i}{\sigma}} \right] \left[ \sum_{i=1}^{K} e^{\frac{V_i}{\sigma}} \right]^{M-1}$$

(6)

1 In our empirical context we found that the MDCEV model based on the $\gamma$-profile offered substantially better fit to compared to the MDCEV model with the $\alpha$-profile.
where \( c_i = \left( \frac{1 - a_i}{e_i + \gamma_i p_i} \right) \).

In the traditional MDCEV model the scale parameter \( \sigma \) is set to 1 for normalization. However, in our context, due to the inherent differences across the databases from four waves we can estimate the scale parameter provided we normalize \( \sigma \) for one wave. The \( \sigma \) is parameterized as \( \exp(\delta y) \) where \( y \) is the vector of three year indicator variables and \( \delta \) is the corresponding coefficient to be estimated. The \( \delta \) parameters are significant when they are different from 0 as that would imply that the scale parameter will be different from 1. In the event that all the \( \delta \) parameters are equal to 0, the Scaled MDCEV collapses to the traditional MDCEV.

It is important to recognize that the individual utility maximization is subject to the binding linear budget constraint that \( \sum_{i=1}^{K} e_i = E \) where \( E \) is the total continuous quantity. The analyst can supply the appropriate \( V_i \) values depending on the profile under consideration in the analysis. The model is programmed in GAUSS matrix programming language.

4. **EMPIRICAL ANALYSIS**

4.1. **Data Source and Sample Formation**

The General Social Survey (GSS) program, established in 1985, conducts telephone surveys from a sample of households selected from the ten Canadian provinces. GSS is recognized for its regular collection of cross-sectional data that allows for trend analysis, and its capacity to compile data on emerging issues in Canada. The survey focused on Canadian time use patterns since 1986 in 5 waves approximately once every 5 years. In our analysis, we will employ data sources from 1992 to 2010. We have intentionally excluded the 1986 data because the format of data collection has been altered since 1992 and it is not feasible to compile the 1986 data in the same format as the remaining years. All four cycles include information on individual and household socio-demographics, daily activity attributes including in and out-of-home activity purposes, the day and month on which the activity is undertaken and accompanying person information for every activity. The task of assembling data across the various datasets required careful comparison across the activity categories.

The sample formation exercise involved a series of transformations on the original GSS time use datasets. **First**, the weekday activity level information (for non-work activity purposes) for in and out-of-home activities was compiled. To standardize the activity categories across the four waves, activity purposes were classified into six in-home and seven out-of-home categories (thirteen in total): 1) In-home household maintenance (includes in-home household maintenance and in-home meal), 2) In-home personal maintenance, 3) In-home child care, 4) In-home social, 5) In-home leisure (such as watching TV, playing game, personal hobby, leisure passive), 6) In-home physical activity, 7) Out-of-home household maintenance, 8) Out-of-home personal maintenance, 9) Out-of-home child care, 10) Out-of-home meal, 11) Out-of-home social, 12) Out-of-home leisure, and 13) Out-of-home physical activity. **Second**, the associated daily duration for each activity type was computed. **Third**, individual and household socio-demographics characteristics were appropriately appended to the person level activity database.
Fourth, the databases were split into two components based on whether the individual participated in work/school activity on the day; thus generating worker and non-worker profiles. Fifth, several screening and consistency checks were performed on the extracted samples, and records with missing or inconsistent data were eliminated. Finally, in each wave, 1500 individuals were chosen randomly from each year for worker and non-workers to obtain a sample of 6000 records each for workers and non-workers.

4.2. Time Use Descriptive Analysis

Tables 1 and 2 present individual’s daily activity average duration and participation percentage for each of the thirteen activity purposes in each data survey for non-workers and workers respectively. The average duration of participation in each activity category is determined as the mean of the total duration of participation of that specified activity across individuals who were involved in the activity. The reader would note that the percentages participation across different activities do not sum to 100%; because of multiple discreteness in the individual’s choice of activity purposes. Prior to undertaking multivariate model estimation, in the following sections, we briefly highlight the trends observed in non-worker and worker samples.

4.2.1. Non-Workers Time Use Descriptive Analysis

The GSS non-workers sample from 1992 to 2010 contains daily activity time use of 6000 individuals where 52% of them are aged 60 years and older, 65.2 % are female, 21.4 % are employed (individuals who did not participate in work activity), 25.5 % have an employed partner, 21.3 % of the individuals have at least one child and 20.6 % of them are single parents, 13.4 % of the sample have at least a bachelor degree and 30.5 % are separated/divorced.

The observation of non-work activity participation profiles (Table 1) clearly highlights that in-home leisure and in-home household maintenance activities are most commonly pursued. The duration of these activities has remained relatively stable across the 4 waves. We notice that the average duration spent on child care activities has increased considerably for non-workers while the number of individuals pursuing in child care activities has reduced. This could be an evidence for the emergence of smaller Canadian families (37). Further, we observe an increasing trend toward higher in-home leisure activity participation duration from 1992 through 2010. This could be explained due to enhanced technology availability (internet and TV) and growing older population in the households. Among activities other than child care, we observe that out-of-home leisure activity has the lowest participation rates.

4.2.2. Workers Descriptive Time Use Analysis

The GSS workers sample for analysis contains the weekday time use of 6000 individuals aged 20 years or older who participated in work/school related activities on the survey day. Descriptive analysis on this group shows that 92.7% of the respondents are aged less than 60 years, 49.6% of these individuals are female, 27.2% of the respondents have at least a bachelor degree, 45.8 % of the sample have an employed partner, 38.9% of the households in this category have at least one child and 17.2 % of them are single parents.

As you would expect, non-work activity participation profiles for workers indicate lower participation as well as smaller durations of non-work activity participation compared to non-workers. The most commonly pursued activity among workers is in-home leisure. Interestingly, workers are less likely to pursue in-home household maintenance and child care activities. The in-home and out-of-home leisure activity participation provides an interesting trend. We observe
that in 2010, the average in-home leisure duration has increased marginally while out-of-home leisure duration has reduced.

5. MODEL RESULTS

5.1. Variable Specification
Several types of variables were considered in examining non-workers and workers time investment in each of the thirteen alternatives. The independent variables were classified into three categories: 1) household characteristics (household structure defined as single, couple, nuclear, single parent and household with more than 2 adults), 2) individual characteristics (gender, age (20 to 39 years old, 40 to 59 years old, and more than 60 years old), employment status, partner/spouse employment status, marital status (separated or divorced), and level of education (bachelor’s degree and more), and 3) year effect (1992 as a base). For the household and personal level variables besides estimating the impact on different activity alternatives, deviations from the general trend for the various years were evaluated through interaction variables (for example single * 1998, female * 2010) are also estimated.

For the continuous variables in the data, dummy variables for different ranges were tested. The dummy representation of continuous variables offered superior fit compared to the corresponding linear variables. Also, the model explicitly considers individual specific alternative availabilities based on household characteristics. For instance, individuals with no child in their household do not have the child care alternative as a possible activity type. The model specification process was guided by intuition, previous literature and statistical significance of the parameters.

5.2. Model Parameters
Two sets of models were estimated with the variables identified above for non-worker and worker samples: (1) MDCEV model and (2) Scaled MDCEV model. As mentioned in the model structure section, since it is challenging to identify both satiation parameters ($\alpha, \gamma$) we resorted to estimating the $\gamma$-profile for all activity purposes. The log-likelihood (parameter) measures for the two frameworks for non-worker samples are: MDCEV: -27627 (61) and SMDCEV: -27468 (71). The corresponding values for the worker samples are: MDCEV: -26565 (48) and SMDCEV: -26310 (76). The Log-likelihood ratio test for the two samples rejects the hypothesis that the two models are equivalent at any reasonable level of confidence. The comparison clearly highlights that the scaled model outperforms the traditional MDCEV model substantially for both non-workers and workers. Due to space concerns, we restrict ourselves to discussing the SMDCEV results of non-workers.

5.2.1. Non-Workers Model Results
Table 3 presents the parameter estimates corresponding to exogenous variables effecting attributes on the baseline and satiation utility specification for non-workers. Every column represents an activity purpose; while every row defines variables that have an effect on the activity purpose. Further, a ‘-’ entry associated with the influence of a variable for a particular activity purpose shows that the variable does not have a significant impact on the corresponding activity purpose utility. In the estimation process in-home household maintenance activity is considered the base alternative.
5.2.1.1 Individual Demographics
The individual demographic variables influencing non-workers’ activity participation decisions include gender, age, employment, partner employment, and marital status (separated/divorced). The gender variable impact indicates that male non-workers have a higher tendency to participate in all out-of-home activities (except child care) compared to females (see (17), (3), and (13) for similar results). Moreover, females are less likely to participate in in-home leisure activities (see (17) and (38)). This pattern of gender participation in activity purposes reiterates the traditional gender role that has been documented in a number of studies.

The age-related variables have a significant influence on non-worker activity participation. These variables are introduced as dummy variables (age 20-39 years, 40-59 years, and greater than 60 years old). The results indicate that young and middle-aged individuals (20-59 years) are more likely to participate in in-home social activities compared to older people. Further, young people (20-39 years) invest more time in in-home child care as well. Since this age group is the most likely child bearing age they are more likely to be involved in child care activities. The year effects relative to the age 20-39 variable indicates that the participation in personal maintenance for these individuals for 2005 and 2010 is lower than the other time periods. The change in the duration might be a result of modern attitudes to personal maintenance.

Individuals aged between 40-59 years are likely to pursue more in-home social activities. On the other hand, the results indicate that seniors (aged more than 60 years) have less inclination to pursue out-of-home household maintenance activities (see (33)). Given their physical condition, it is intuitive that the older individuals are disinclined to participate in household-related activities. Similar to younger individuals, the participation in personal maintenance is lower for older individuals. The advances in technology (particularly for personal medical equipment) might have allowed older individuals to spend lesser amount of time (compared to 1992 and 1998) on personal. Furthermore, divorced or separated non-workers are more willing to participate in in-home leisure activities. A possible explanation can be the likelihood of less fixed commitments compared to married individuals.

The impact of employment variable indicates that employed individuals, who did not go to work on the survey day, are more likely to pursue a number of in-home and out-of-home activities. Specifically, they are likely to pursue out-of-home household and personal maintenance, meals and leisure activities and in-home personal maintenance and social activities compared to unemployed individuals (see (39), (40) and (13) for similar results). The result might be an indication that workers on their day off prefer to be involved in recreational activities with their family. Non-workers with employed partner are more likely to participate in out-of-home child care while at the same time are less likely to pursue in-home social and leisure activities. It is possible that because their partners might have a busier inflexible schedule they have to be more involved in taking care of their children; reducing the available time for participation in in-home recreational activities.

5.2.1.2 Household Demographics
Household structure variable (single, couple, nuclear, single parent and more than 2 adults) has a significant influence on activity participation decisions.

Single member households are more likely to pursue in-home social activities as they have fewer commitments and more available time to socialize. However, couples and families with at least one child are less likely to pursue in-home personal maintenance. In other words, larger families and most importantly households with children have a significant negative impact
on participating in in-home personal maintenance activities as these people might be busy taking
care of their families and therefore have less time to spend on their own. Moreover, as expected,
nuclear families spend less time in meal out activity.

5.2.1.3 Year Effect and Scaled Parameters
The year indicator variables account for overall difference to baseline utility across the years.
These variables are similar to constant variables and account for intrinsic preferences in the
sample. If unaccounted, these effects might manifest as differences in variable impacts
erroneously.

The Scaled MDCEV model allows the scale parameters to be different across different
years while considering 1992 as a base year (i.e. scale parameter of 1). In the current empirical
context for non-workers, the estimated scaled coefficients for the year 1998, 2005 and 2010 are
0.65, 0.73 and 0.69 respectively. The parameter estimates of the Scaled MDCEV model reveal
the presence of substantial differences in the scale parameters of the random utility components
across different years. Ignoring the presence of such differences would result in biased model
estimates.

5.2.1.4 Base Line Preference Constant
The estimated baseline preference constants and their t-statistics are presented in the last row of
the top panel of Table 3. As mentioned before, in-home household maintenance is considered as
a base alternative. These constants do not have any substantive interpretation and capture the
generic tendencies to pursue each types of activity.

5.2.1.5 Satiation Parameters
As evident, values of $\gamma_k$ closer to zero imply higher satiation effects (i.e., lower consumptions)
in activity $k$ (36). The non-workers satiation parameters are represented in bottom panel of Table
3. Based on the parameter estimates, out-of-home leisure activities are associated with low
satiation (hence high durations) compared to all other activities. Moreover, between in-home
activities, personal and household maintenance are associated with the highest satiation level
(low duration). Also, within out-of-home activities, same patterns can be seen for the personal
maintenance and child care activities. Further, we notice that younger and older people have
significant negative effects on the satiation parameters specific to in-home household
maintenance and leisure activities.

5.3. Activity Baseline Utility Profiles in 1992 to 2010
The estimates presented in Table 3 provide an indication of how various variables influence
activity participation. However, to obtain a picture of the trend differences across the years the
estimates presented are not adequate. We illustrate how baseline utility for various activity
purposes for different demographic groups across the years has varied by plotting the changes in
baseline utility. Towards this end, we consider a synthetic profile of a non-worker and worker.
Specifically, the individual is assumed to be a educated (bachelor’s degree and more) employed
female, aged 20 to 39 years old living with her employed partner without children (couple). In
the analysis process the defined variables (level of education, labor force status, gender, age,
family structure and partner labor force status) are changed each time, and the out-of-home
activities’ baseline utility values for the new synthetic person for the 4 waves are plotted for
workers and non-workers separately. The baseline utility value for each activity purpose is
computed by considering the effect of scaled parameters for the years 1998, 2005 and 2010. The results of these exercises are presented in Figure 1.

Figures 1 (a) and (b) illustrate the baseline utility profile changes due to gender for out-of-home activities for non-workers and workers respectively. It is interesting to note that the baseline utility for males is consistently higher (or equal) for all alternatives across the four waves. The differences in utility have reduced over the years particularly from 1998. For non-workers these differences are much wider while for workers there are differences for meal, leisure and social activities.

Figure 1 (c) represents the utility profile of non-worker synthetic person based on the age variable (adult vs. senior). The activity profiles across the two groups are exactly the same except for out-of-home household maintenance. Seniors are less likely to pursue these activities compared with adults. Figure 1 (d) illustrates the effect of presence of a child on the household for workers. As expected, worker females with no children who live with their partners (couple) are more involved in out-of-home meal and physical activities compared to those who have at least one child and live with their partner (nuclear family). In other words, presence of a child decreases the propensity of participating in these two activities for female workers with the nuclear family.

Finally, Figures 1 (e) and (f) illustrate the influence of employment status on the out-of-home activity profiles for non-workers and workers over the past 20 years respectively. Employed females on their day off, prefer to be more involved in out-of-home household and personal maintenance, meals and leisure activities compared to unemployed females; while unemployed female workers (i.e. students) have less inclination to participate in meal out activity compared to employed female workers. The various baseline utilities presented in Figure 1, provide an illustration how the model estimates can be employed to examine the variation of utility across various demographic groups and across the years.

6. CONCLUSION

In our study, we develop activity pattern analysis frameworks employing cross sectional databases compiled over multiple time points. The availability of multiple cross sectional datasets for different years provides a useful compromise between a single year cross sectional dataset and a truly longitudinal dataset compiled across multiple years. The data pooling of different respondents across multiple waves offers unique methodological challenges. The proposed methodology should recognize the differences across multiple time points adequately. Specifically, the choice process for the respondents in a particular year might be influenced by various observed and unobserved attributes. Towards this end, we employ a scaled multiple discrete continuous extreme value (SMDCEV) model that builds on the advantages of the traditional MDCEV model.

The Scaled MDCEV model is estimated for non-workers and workers with a comprehensive choice set of activity purposes. The analysis will allow us to examine the influence of individual socio-demographics (such as person age, gender, employment status) and household socio-demographics (such as household structure). Further, observed and unobserved effects of the year of data collection are also explicitly considered in our analysis enabling us to examine trends in activity participation across the years while controlling for various attributes. Two sets of models were estimated for non-worker and worker samples: (1) MDCEV model and (2) Scaled MDCEV model. The comparison between these models clearly highlights that the scaled model outperforms the traditional MDCEV model substantially for both non-workers and
workers. The results provide evidence that our proposed approach provides an appropriate framework to study activity participation decision process evolution in time. The model estimates provide an indication of how various variables influence activity participation. However, to obtain a picture of the trend differences across the years the estimates presented are not adequate. We illustrate how baseline utility for various activity purposes for different demographic groups changes across the years by plotting the changes in baseline utility. These trends plotted indicate the applicability of the models developed to analyze individual activity participation profiles.

To be sure, the study is not without limitations. The lack of land-use and urban form data in the time use data reduces the versatility of the impacts that can be examined in our analysis. It is possible that in the presence of land-use and urban form data the impact of temporal trends might offer significant inputs for policy decisions.

7. ACKNOWLEDGEMENTS
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REFERENCES


7) Sanko, N. Travel Demand Forecasts Improved by Using Cross-Sectional Data from Multiple Time Points. Transportation, 2013, pp. 1-23.


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TABLE 2 GSS Sample’s Daily Activity Duration and Percentage Participation for Workers

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### TABLE 3 Effects of Exogenous Variables on Non-Workers’ Baseline Utility and Gamma Parameters in the Scaled MDCEV Model

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**Effects of Exogenous Variables on Gamma Profile Performance in the Scaled MDCEV**

| Age 20-39 | -0.28 | (-2.60) | -0.27 | (-2.58) | - | - | - | - | - | - | - | - | - | - | - |
| Age 60+   | -0.24 | (-2.61) | - | - | - | - | - | - | - | - | - | - | - | - | - | - |
| **Constants** | 4.10 | (34.88) | 2.98 | (43.29) | 4.39 | (32.28) | 5.05 | (59.16) | 4.56 | (51.26) | 4.18 | (23.73) | 4.18 | (55.51) | 3.85 | (35.72) | 4.11 | (15.77) | 4.40 | (39.16) | 5.12 | (35.85) | 5.34 | (33.79) | 4.72 | (44.55) |
Figure 1 Exogenous Variables Effect on Non-Worker’s and Worker’s Baseline Utility