Day-of-the-Week Models of Shopping Activity Patterns

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Most empirical studies that deal with activity analysis develop models of daily activity patterns in which the model is assumed to represent all of the days of the workweek. An alternative approach, in which activity pattern models are developed separately for each day of the workweek, is presented. The underlying assumption is that the appropriate basic time unit for analyzing some activity patterns is the week not the day. By applying this approach, a better representation of the behavior of individuals and improved models of activity patterns can be achieved. This hypothesis is tested by developing independent models of daily activity patterns for each day of the workweek and comparing them among themselves and with an average-day model of shopping behavior. The results vary systematically during the week and thus encourage the development of day-of-the-week models for analyzing activity and travel patterns. Furthermore, predictions based on average-day models were found to be biased when used in analyzing a specific day of the week.

Most empirical studies that deal with activity analysis develop models of daily activity patterns, in which the model is assumed to represent all of the days in the workweek. An alternative approach, in which activity pattern models are developed separately for each day of the workweek, is presented. The underlying assumption is that the appropriate basic time unit for analyzing some activity patterns is the week, rather than the day. By applying this approach, better representation of individuals' behavior and improved models of activity patterns can be achieved. The rationale for this approach is discussed in the following section.

BEHAVIORAL FRAMEWORK

Most of the current activity pattern models use the average day as the basic time unit for analyzing activity patterns. This approach requires certain assumptions, two of which have been examined and placed in doubt in this paper:

- An individual's daily activity is habitual; that is, it repeats from day to day *(1)*.
- If day-to-day variability does exist, it is random rather than systematic.

These assumptions appear to be an oversimplification and have been questioned in several studies *(2–5)*. Hanson and Huff *(2)*, for example, examined the day-to-day variability in behavior in Sweden by using trip diaries that covered 35 consecutive days. Their findings show that although daily behavior does have a certain degree of regularity, it is not repetitive. Moreover, even though the working men in the sample exhibit a considerable amount of regularity with respect to their working pattern, it becomes evident that they exhibit considerable day-to-day variability in their discretionary activities.

Prashker and Hirsh *(5)* collected weekly activity diaries in Israel in order to study the differences in daily activity patterns. Their analysis of the average household daily trip rate and the average household daily time for various activities by day of the week revealed three main periods in the week: (*a*) Sunday through Thursday, (*b*) Friday, and (*c*) Saturday. This pattern reflects the structure of business in Israel where Sunday through Thursday are the prime business days, Friday is a reduced-hours workday, and Saturday is the day of rest. Further, significant differences were manifested among the first 5 days of the week. For example, there was a significant reduction in shopping intensity on Tuesday and a similar reduction in personal business on Wednesday.

Whereas the studies just cited tried to identify day-to-day variability, Herz *(4)* attempted to find time cycles within which variability is systematic. To do so, he used daily activity records evenly spread throughout the year, collecting from each individual data for 1 day only. Using aggregate data, Herz found that, aside from the high variability that exists among individuals for the average day, there is a systematic, day-to-day variability, which can be explained by the weekly cycle.

These empirical works provide evidence that day-to-day variability does exist and that it has a strong systematic component. Theoretical works that describe human behavior *(6,7)* place great importance on temporal constraints, and these are also found in empirical work *(8)*. Most temporal constraints are derived from the opening times of institutions and firms. These constraints define the times within which the individual can perform out-of-home activities. As usually happens in an urban system, opening hours do not have a regular daily cycle. In Israel, for example, public health services are closed on Monday and Thursday afternoons; most commercial shops are closed on Tuesday afternoons; banks are closed on Wednesday afternoons; and most schools and working places, especially those involved in services, have different working times on different days. Finally, most institutions and firms in Israel are closed on Friday afternoons and all of them are closed all day Saturday.

Another aspect of the temporal dimension of an individual's activity pattern is his free time. Daily free time is limited, and because each activity needs time for its execution, one activity is performed at the expense of other activities, which have to be postponed to other days.

More recently, Pas and Koppelman *(9)* studied multiday activity patterns using the 1973 Reading Activity Diary Survey. In this study, daily activity patterns were characterized by (*a*) the number of stops in the pattern; (*b*) the stops' purposes (subsistence, maintenance, or leisure); and (*c*) the time of day of the stops (morning or afternoon, peak or off-peak). Using this broad description of activity pattern, five daily patterns were identified for employed persons during the workweek. The study could not reject the null hypothesis that daily pattern selection is independent of the day of the week because of the small sample used. However, some spe-

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cific differences among days do exist. These researchers also showed that empirical results were consistent with the hypothesis that daily activity pattern is the outcome of a two-stage process: (*a*) selection of a multiday pattern and (*b*) selection of a daily pattern based on the multiday pattern.

In this paper is studied the day-to-day variability in the patterns of a single activity—shopping. The main hypothesis is that shopping behavior is dependent on the day of the week and that systematic day-to-day variability in shopping patterns does exist because of systematic variation in the temporal constraints set. This hypothesis is tested by developing models of daily shopping patterns for (*a*) each day of the week and (*b*) an "average" day of the week. The models are then compared in order to find any systematic day-to-day variability in shopping behavior.

The daily models developed in this paper do not include dynamic effect (i.e., they are estimated independently of the individual's behavior on any other day of the week). However, it may be assumed that a single maintenance activity that does not have to be performed every day on a regular basis will be executed only when the need for it exceeds some threshold value. Thus current shopping behavior may be interrelated with past activity patterns as well as with current-day characteristics and with future activity plans. Such an approach is used by Hirsh et al. *(10)*.

DESCRIPTION OF MODEL

During weekdays in Israel (Sunday to Friday) most stores are open from 8:00 a.m. to 1:00 p.m. and from 4:00 p.m. to 7:00 p.m. Some of the big department stores, however, are open continuously from 8:00 a.m. to 7:00 p.m. On Tuesday most stores close at 3:00 p.m. or 4:00 p.m. to comply with a municipal law, although the big department stores do not obey the law and remain open continuously until 7:00 p.m. On Friday most stores are open continuously and their closing time varies between 2:00 p.m. and 7:00 p.m. In this paper the daily shopping pattern assumed to be available for each individual during a weekday is one of the following: (*a*) to not shop that day, (*b*) to shop starting in the morning period (8:00 a.m. to 1:00 p.m.), or (*c*) to shop starting in the afternoon period (after 1:00 p.m.). The alternative of shopping in both periods is not considered separately because of the small number of individuals (only eight) who chose it. This alternative is included in the second one (i.e., starting to shop during the morning period).

The econometric models are based on utility-maximizing principles to describe the individuals' choices among the alternatives. For convenience, it was assumed that the distribution of the error term in the utility function of the daily shopping pattern is in accordance with the assumptions used by the logit-type models. Thus, because the choice set of each individual in each day contains more than two alternatives, the first statistical test examined the feasibility of applying the multinomial logit (MNL) model by testing the independence of irrelevant alternatives (IIA) assumption. In this case it is reasonable to asume that the individual considers the two alternatives of participation (morning or afternoon) to be more closely related than the alternative of not participating. The test is described in detail in Hirsh *(11)*, and it involved calibrating the MNL with all subsets of the alternatives. The IIA test showed that the trinomial structure has to be rejected and replaced by a hierarchical structure, shown in Figure 1, in which the individual first decides whether to shop on that day and then, given a decision to shop, chooses between morning and afternoon. For this structure, a nested logit model was adopted as follows:

$$P(s,d) = P(s) \times P(d|s) \tag{1}$$

where

$P(s,d)$ = the joint probability of selecting a daily shopping behavior,
$P(s)$ = the marginal probability that the individual will choose to shop on that day, and
$P(d|s)$ = the conditional probability of selecting shopping schedule d.

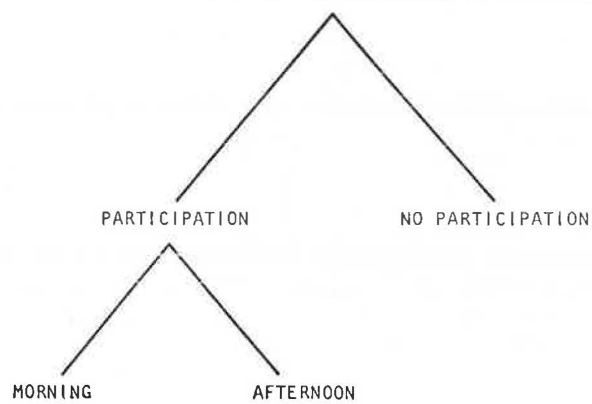

FIGURE 1 Hierarchy of the daily decision-making process.

This structure means that two types of models have to be estimated for each day. The first is a conditional logit model of choice of shopping schedule in the form of

$$P(d|s) = \exp(V_{ds} + V_d)/\sum_t \exp(V_{ts} + V_t) \tag{2}$$

where V_d is the systematic components of the individual's scheduling utility function, which vary only across *d*, and V_{ds} is the systematic components of the individual's scheduling utility function, which vary across *d* and *s*.

In the second stage, a binary logit model of shopping activity participation is estimated in the form of

$$P(s) = \exp(V_s + \tau I_s)/[1 + \exp(V_s + \tau I_s)] \tag{3}$$

where the inclusive utility of shopping is

$$I_s = \ln \sum_t \exp(V_{ts} + V_t) \tag{4}$$

in which τ is the coefficient of the inclusive utility (or log sum variable) and V_s is an additional systematic utility component of the shopping activity that is indepenent of the schedule.

Data were collected in 1983 from 567 individuals, aged 18 and older, in the form of weekly diaries. These individuals, members of 288 households in Israel, included 528 male and female household heads. Using the structure just described, two kinds of models were estimated:

- Day-of-the-week models that assume that an individual's utility function may vary from day to day. The models also assume independence of activity patterns executed on different days of the week.

- The "average-day" model that assumes independence between different days and a constant utility function throughout the week.

Because the average-day models assume independence among days, repeated observations of an individual may be treated as independent. In this case each individual was observed for 6 consecutive days. Using this data set, the average-day models can be estimated in several ways. First, data for only 1 day, selected randomly, can be used for each individual. Second, using all of the days, an average day for each individual can be calculated using the averages of all the relevant attributes. Third, all of the available information may be used if each day is treated as an independent observation. The latter option was selected for the following reasons. First, because the data have already been collected, this option retains the maximum amount of information. Second, because models that use all the observations have been estimated, the day-of-the week models are actually calibrated using subsets of this data. This property makes it possible to compare the two models using some statistical tests that apply to estimation with subsets of the data.

By using this approach, two variants of the average-day models were estimated: one that used data from the first 5 days of the week (Sunday through Thursday) and another that used the first 6 days of the week (Sunday through Friday). These models were estimated because Friday in Israel has significantly different temporal constraints than do the other days. Therefore, although the conventional models developed earlier did not distinguish among the days, this type of estimation made it possible to identify the effect of inclusion of a significantly different day in the average-day group.

At this point it should be noted that neither the day-of-the-week nor the average-day models consider interdependence among days. The average-day model assumes independence of observations, and the day-of-the-week models assume independence of the various models. However, it may be found that a certain degree of dependence does exist among activity patterns executed by the same individual on different days of the week. The neglect of this type of dependency in the models results in a specification error, which may bias the estimates of the maximum likelihood parameters. However, it is assumed that these effects are similar in the average-day and the day-of-the-week models, and hence the comparison of the models is not affected.

ESTIMATION RESULTS

General

Discussion of estimation results will be confined to the main topic of the paper: day-of-the-week models versus average-day models. The two model types will be compared on the basis of statistical t-tests and interpretation of parameters. Both the daily models and the average-day model have been calibrated using an identical specification, as can be seen in Tables 1–4. Tables 1 and 2 give the estimation results for the conditional and the marginal day-of-the-week models, and Tables 3 and 4 give the corresponding results for the average-day models. (The insignificant attributes are retained in the tables in order to allow the statistical comparisons that require identical specification.)

The various attributes used in the models can be categorized under the following two classes: (*a*) those that may change during the week, such as the temporal constraints attributes or the individual's working pattern, and (*b*) those that do not change during the week (socioeconomic variables). The marginal participation mod-

TABLE 1 ESTIMATION RESULTS FOR THE CONDITIONAL DAILY SCHEDULING MODELS

Variable[a]	Sunday	Monday	Tuesday	Wednesday	Thursday	Friday
Dummy for afternoon participation	1.5	0.67	1.5	3.0	1.1	10.27
	(0.7)	(0.3)	(0.7)	(1.6)	(0.5)	(1.6)
Available time for shopping between	-0.01	-0.01	-0.01	-0.01	-0.01	-0.05
8:00 and 13:00	(3.3)	(3.7)	(3.8)	(3.7)	(4.4)	(2.8)
Available time for shopping between	0.01	0.007	0.004	0.006	0.02	-0.007
16:00 and 19:00	(2.1)	(1.5)	(0.9)	(1.1)	(3.1)	(0.5)
Dummy for male head of household	0.72	0.7	0.86	0.68	1.6	-0.05
	(1.5)	(1.3)	(1.5)	(1.4)	(2.8)	(0.07)
Dummy for private car present in house-	-1.7	-1.0	-1.0	-0.6	-0.17	0.6
hold	(2.1)	(1.8)	(1.9)	(1.1)	(0.3)	(0.5)
No. of children under 5	-0.83	0.33	0.25	0.27	-0.4	0.1
	(2.4)	(1.0)	(0.7)	(0.8)	(1.0)	(0.2)
Dummy for being at work on this day	0.9	0.27	-1.6	0.29	0.2	-13.2
	(0.7)	(0.3)	(1.4)	(0.3)	(0.2)	(2.4)
No. of work days in the week	-0.11	0.11	0.13	-0.2	-0.3	0.3
	(0.7)	(0.7)	(0.9)	(1.2)	(1.8)	(1.1)
Time in minutes from home to central	-0.01	0.01	0.02	-0.03	-0.004	-0.01
business district	(0.6)	(0.5)	(1.0)	(1.2)	(0.2)	(0.2)
Time in minutes from home to nearest	0.1	0.05	-0.1	0	-0.04	0.16
food store	(1.5)	(0.6)	(1.3)	(0)	(0.6)	(1.2)
No. of years of study	0.17	0.03	0.01	0.03	0.02	0.18
	(2.3)	(0.5)	(0.2)	(0.5)	(0.3)	(2.1)
Age	-0.07	-0.02	0.02	-0.03	0.002	0.01
	(3.3)	(1.2)	(0.8)	(1.3)	(0.1)	(0.4)
Dummy for households with male head	-0.22	0.41	-2.8	-1.3	-0.5	-0.74
only	(0.2)	0.3	(2.2)	(1.0)	(0.3)	(0.4)
Expected duration of shopping[b]	-0.009	-0.006	-0.02	0.02	0.02	-0.02
	(0.6)	(0.6)	(1.3)	(0.2)	(1.4)	(1.5)
No. of cases	211	213	173	206	205	207
$\mathcal{L}(0)$	-146.3	-147.6	-119.9	-142.8	-142.1	-143.5
$\mathcal{L}(\hat{\beta})$	-83.5	-86.6	-84.1	-95.5	-72.5	-48.2
ρ^2	0.43	0.41	0.30	0.33	0.49	0.66

Note: t-values are in parentheses.

[a]All variables are specific to the afternoon participation alternative except the variable of expected duration of shopping.

[b]This variable was estimated by linear regression for those who shop.

TABLE 2 ESTIMATION RESULTS FOR THE MARGINAL MODELS OF PARTICIPATION IN SHOPPING ACTIVITY

Variable[a]	Sunday	Monday	Tuesday	Wednesday	Thursday	Friday
Dummy for no participation	1.37	2.5	1.8	0.5	3.4	1.5
	(1.4)	(2.5)	(1.8)	(0.4)	(2.9)	(1.0)
Available time for shopping between 8:00 and 13:00	-0.002	-0.002	-0.004	-0.002	-0.002	0
	(0.9)	(0.9)	(1.6)	(1.1)	(1.0)	(0)
Available time for shopping between 16:00 and 19:00	-0.005	-0.006	-0.003	-0.005	-0.001	0.001
	(2.1)	(2.1)	(1.6)	(2.7)	(2.8)	(0.3)
Dummy for male head of household	0.76	0.68	1.1	0.9	0.13	0.4
	(2.9)	(2.1)	(3.2)	(3.8)	(0.3)	(1.8)
Dummy for private car present in household	-0.003	-0.35	0.02	-0.13	0.3	-0.35
	(0.1)	(1.0)	(0.1)	(0.5)	(0.9)	(1.3)
No. of children under 5	-0.2	-0.22	-0.31	-0.1	-0.15	-0.22
	(0.9)	(1.1)	(1.8)	(0.6)	(0.8)	(1.3)
Dummy for being at work on this day	-0.04	-0.42	-1.2	0.12	-1.1	1.1
	(0.07)	(0.8)	(2.0)	(0.2)	(1.9)	(2.0)
No. of work days in the week	0.03	-0.04	0.06	-0.03	-0.04	-0.15
	(0.4)	(0.5)	(0.8)	(0.3)	(0.4)	(2.0)
Time in minutes from home to central business district	-0.007	-0.06	0	0.02	0.02	0.02
	(0.7)	(0.5)	(0)	(1.8)	(1.8)	(1.5)
Time in minutes from home to nearest food store	0.02	0.04	0.02	-0.04	0.02	0.06
	(0.5)	(1.2)	(0.4)	(1.1)	(0.6)	(1.5)
No. of years of study	-0.003	0.02	0.01	0.007	0.008	-0.06
	(0.1)	(0.7)	(0.3)	(0.2)	(0.3)	(1.8)
Age	-0.003	-0.02	-0.006	-0.01	-0.009	0.003
	(0.2)	(0.2)	(0.5)	(1.1)	(0.9)	(0.3)
Dummy for households with male head only	-0.93	-0.9	-1.9	-1.4	-0.6	-1.8
	(1.3)	(1.2)	(2.2)	(1.8)	(0.7)	(2.3)
Log sum of the scheduling conditional model	0.2	-0.07	0.23	0.4	-0.17	-0.8
	(0.6)	(0.2)	(0.7)	(1.0)	(0.7)	(2.4)
No. of cases	507	503	509	504	506	516
$\mathcal{L}(0)$	-351.4	-348.7	-352.8	-349.3	-350.7	-357.7
$\mathcal{L}(\beta)$	-316.8	-315.1	-302.5	-311.9	-314.9	-306.9
ρ^2	0.10	0.10	0.14	0.11	0.10	0.14

Note: t-values are in parentheses.

[a]All variables are specific to the alternative of no participation.

TABLE 3 ESTIMATION RESULTS FOR THE POOLED CONDITIONAL SCHEDULING MODELS

Variable[a]	5 Days Pooled	6 Days Pooled
Dummy for afternoon participation	0.5	-0.3
	(0.7)	(0.5)
Available time for shopping between 8:00 and 13:00	-0.01	-0.01
	(8.3)	(8.5)
Available time for shopping between 16:00 and 19:00	0.01	0.01
	(4.2)	(4.6)
Dummy for male head of household	0.8	0.5
	(4.0)	(3.2)
Dummy for private car present in household	-0.7	-0.6
	(3.1)	(3.2)
No. of children under 5	-0.1	-0.09
	(0.7)	(0.8)
Dummy for being at work on this day	-0.02	0.2
	(0.9)	(0.9)
No. of work days in the week	-0.01	0.01
	(0.7)	(0.8)
Time in minutes from home to central business district	0.002	0.003
	(0.3)	(0.4)
Time in minutes from home to nearest food store	-0.02	-0.003
	(0.7)	(0.4)
No. of years of study	0.05	0.04
	(2.0)	(2.0)
Age	-0.02	-0.006
	(2.0)	(1.0)
Dummy for households with male head only	-1.0	-0.9
	(2.1)	(2.1)
Expected duration of shopping[b]	-0.001	-0.004
	(0.1)	(1.0)
No. of cases	1,008	1,215
$\mathcal{L}(0)$	-698.7	-842.2
$\mathcal{L}(\beta)$	-510.4	-666.2
ρ^2	0.27	0.21

Note: t-values are in parentheses.

[a]All variables are specific to the afternoon participation alternative except the variable of expected duration of shopping.

[b]This variable was estimated by linear regression for those who shop.

TABLE 4 ESTIMATION RESULTS FOR THE POOLED MARGINAL PARTICIPATION MODELS

Variable[a]	5 Days Pooled	6 Days Pooled
Dummy for afternoon participation	1.9	1.6
	(3.5)	(3.3)
Available time for shopping between 8:00 and 13:00	-0.003	-0.002
	(1.6)	(1.1)
Available time for shopping between 16:00 and 19:00	-0.003	-0.003
	(1.2)	(1.2)
Dummy for male head of household	0.9	0.7
	(5.0)	(4.6)
Dummy for private car present in household	-0.23	-0.15
	(1.4)	(1.0)
No. of children under 5	-0.17	-0.16
	(2.2)	(2.3)
Dummy for being at work on this day	-0.07	-0.02
	(0.3)	(0.08)
No. of work days in the week	-0.05	-0.01
	(0.8)	(0.4)
Time in minutes from home to central business district	-0.006	-0.003
	(1.1)	(0.7)
Time in minutes from home to nearest food store	0.01	0.01
	(0.9)	(1.1)
No. of years of study	0.02	0.009
	(1.3)	(0.6)
Age	-0.01	-0.008
	(2.5)	(1.9)
Dummy for households with male head only	-1.4	-1.3
	(3.7)	(3.8)
Log sum of the conditional scheduling model	0.44	0.2
	(1.5)	(0.6)
No. of cases	2,529	3,045
$\mathcal{L}(0)$	-1753	-2110
$\mathcal{L}(\beta)$	-1589	-1896
ρ^2	0.09	0.1

Note: t-values are in parentheses.

[a]All variables are specific to the alternative of no participation.

els also include a log sum variable, which represents the conditional scheduling model described in Equation 4.

In general, the following conclusions can be drawn from the estimation results. First, the results support the hypothesis that the scheduling choice for shopping can be distinguished from the participation choice. This is because the various attributes are found to have different effects on participation and scheduling decisions. This is especially true for the average-day model (Tables 3 and 4) where the free-time attributes are found to influence the scheduling choice but not the participation choice.

The results are less conclusive for the day-of-the-week models of activity patterns. The variables in the daily models (Tables 1 and 2) have different values on different days. However, with few exceptions, the 95 percent confidence interval for many estimates reveals that the null hypothesis, equality of coefficients across the days in the daily models or between the average-day and the daily models, cannot be rejected. Nevertheless, even if the estimated values of the single attributes do not exhibit significant differences across the days, the predicted behavior that results from the daily models can be significantly different from the behavior predicted by the average-day models. This aspect of policy analysis will be demonstrated later in the paper. In the following subsections some of the details of the estimation results are discussed further.

Temporal Constraints Attributes

The category of temporal constraints attributes includes the morning and the afternoon available shopping time for the individual. These attributes are calculated from the individual's reported working pattern and the opening hours of stores in Israel. These are the only attributes, in addition to the individual's working pattern, that change in value during the week. The morning and the afternoon free time are not combined in order to capture the effect of policies such as introducing flexible working hours, which may not change the total free time available to the individual but do change the morning and afternoon free time. Also, in this way the hypothesis that people are using the morning and the afternoon time differently can be tested.

The estimation results for the average-day model show that the free-time attributes are significant to the scheduling decision but not to the participation choice. The daily models, on the other hand, show that the afternoon free time is significant to the participation choice on days when most stores are open in the afternoon (Sunday, Monday, Wednesday, and Thursday). Also, the daily models show that the morning free time on Friday has different value than on the other days, an effect that the average-day models, by definition, cannot show.

Individual and Household Characteristics

The individual characteristics used in the models are the individual's age, education, status in the household, and working pattern. The household characteristics are car availability, number of children, and marital status of the head of household. All of the variables, except the individual's working pattern, remain constant during the week. These variables can also be classified under the following two categories: those that are more related to need for shopping (e.g., number of children) and those that are more related to the individual's ability to shop (e.g., accessibility or working pattern).

The estimation results support the hypothesis that the scheduling decision can be distinguished from the participation decision because some of the variables were found to be significant only to the participation model and others were significant to the scheduling model. However, the variables do perform differently in the average-day and in the daily models. In general, both the scheduling and the participation average-day models exhibit more significant socioeconomic variables than do their corresponding daily models. On the other hand, an individual's working pattern was not found to be significant in the average-day model, but the daily models show that these attributes can be significant to both the scheduling and the participation decisions on some days. The daily models were also able to capture a well-known phenomenon in Israel: Thursday afternoon is the major shopping time for male heads of households. The probable reason for this is that Thursday afternoon is the last opportunity working people (mostly male heads of households in 1982) have to shop for the weekend because stores are closed from Friday afternoon until Sunday morning.

Statistical Comparison

The discussion so far has been based on the interpretation of the models. As was mentioned previously, the average-day model and the day-specific models may be compared by using statistical tests. The average-day conditional scheduling model (Table 3) is calibrated using 1,008 observations from the first 5 days of the week or 1,215 observations from the first 6 days of the week. These are the sum of the observations used in the daily models (Table 1). Because the two model types have the same specification, the following statistic can be used to compare them:

$$-2\,(L_{MP} - \sum_{d} L_{Md}) \tag{5}$$

where L_{MP} and L_{Md} are the log-likelihood value (at convergence) for the (pooled) average-day model and for day d, respectively. The statistic is distributed chi-squared where the number of degrees of freedom is $(\sum_{d} M_d - M)$ where M is the number of parameters estimated in the pooled model and M_d is the number of parameters in the model for day d.

In this case, the values of this statistic for the daily scheduling models are 391.6 and 176.4 with 70 and 56 degrees of freedom for 6 and 5 days, respectively, which means that the daily scheduling models are significantly different from the average-day scheduling model. However, the null hypothesis of equality of coefficients between the daily and the average-day models cannot be rejected for the marginal participation models for both 5- and 6-day models.

Note also that the two average-day models (the 5- and 6-day models) can be compared. First, using the 95 percent confidence intervals, none of the parameter estimates in either the participation or the scheduling model exhibits significant difference between the 5- and the 6-day models. Also, the values of the statistic in Equation 5 for comparing the 5-day model plus Friday with the 6-day model are almost zero for both the participation and the scheduling models, which implies that there is no significant difference in the parameter estimates between the 5- and the 6-day models. However, given the value of ρ^2, it appears that the 6-day average model is inferior to the 5-day model. This means that the inclusion of a day with a specific temporal constraint system (i.e., Friday) in the calculation of an average model reduces the performance of the average model.

POLICY ANALYSIS

To further illustrate the difference between the two approaches, the average-day and the day-specific models were applied to predict the effect on shopping activity of shortening the workweek in Israel from 6 to 5 days (Sunday through Thursday) and adding 1 work hour to each of the 5 working days. This policy was simulated for 275 individuals in the sample who worked a 6-day week. The policy was reflected in the following attributes of the various models:

- Morning free time—on Friday, this free time is equal to 5 hr.
- Evening free time—Sunday through Thursday, this free time decreases by 1 hr.
- Number of working days in the week—reduced to 5 days.
- Being at work on a given day takes a value of zero on Friday.

Table 5 gives the prediction for the base situation and the effects of the hypothetical policy on weekly shopping behavior according to both approaches. From the table it can be seen that in the observed base situation Thursday is the major shopping day; on Friday and Tuesday there is a tendency to refrain from shopping especially during the afternoon period. On Sunday and Wednesday the shopping pattern is similar; Monday displays a slight increase in shopping, mainly during the afternoon.

The average-day model fails to reproduce the base situation because it predicts an almost identical shopping pattern for the first 5 days of the week. On the other hand, the base situation prediction according to the day-of-the-week models is quite close to observed reality. These results suggest that, when applying a model to predict changes in base behavior that are due to exogenous changes implemented differentially by day of the week, the day-of-the-week model may be expected to be more accurate.

The data in Table 5 also indicate that the average-day model predicts that the major change Sunday through Thursday is a 30 percent reduction in shopping in the afternoon. Of those who stopped shopping in the afternoon, 25 percent will switch to shopping in the morning on that day. As for Friday, the model predicts only a 13 percent increase in the participation rate. Overall, the average-day model predicts a 9 percent weekly reduction in shopping due to the shortened workweek.

The day-of-the-week model predicts a 27 percent reduction in afternoon shopping Sunday through Thursday; only 5 percent of these people will switch to morning participation. On Friday, the model predicts an increase of 85 percent in the participation rate, which is 6.5 times more than the increase predicted by the average-day model. Overall, the day-of-the-week models predict a weekly reduction of only 5 percent in shopping, which is almost half the reduction predicted by the average-day approach.

Intuitively, expectations favor the predictions produced by the daily models. That is, a dramatic increase in shopping on Friday and a small overall change in the level of total shopping during the week are expected.

CONCLUSIONS

The hypothesis that the utility an individual derives from his daily shopping pattern is not constant during the week but depends on the specific day of the week and that the utility function therefore cannot be approximated by an average utility function is examined. This hypothesis was tested by developing models of daily shopping patterns for each day of the week and comparing them with a model based on average utility function. The main findings of the empirical work are listed next.

1. The estimation results support the distinction suggested between the decision to shop and the scheduling choice for shopping. The various attributes used in the models were found to have different effects on participation and scheduling decisions.
2. The models exhibit behavior that favors the assumption that the utility function of the shopping pattern does not have a constant value but varies by day of the week.
3. The changes in the utility function are similar to the changes in the temporal constraints set, but these changes are not fully compatible. For example, on Wednesday and Thursday an individ-

TABLE 5 EFFECTS OF SHORTENING THE WORKWEEK ON SHOPPING BEHAVIOR OF 275 INDIVIDUALS WHO WORK 6 DAYS A WEEK

	Sunday	Monday	Tuesday	Wednesday	Thursday	Friday
Base situation						
No participation	177	167	189	172	159	197
Morning participation	25	19	57	24	24	59
Afternoon participation	69	82	25	76	90	17
Base prediction, day-of-the-week models						
No participation	179	168	188	172	161	196
Morning participation	27	17	60	19	13	57
Afternoon participation	65	83	23	81	99	20
Policy effect, day-of-the-week models						
No participation	196	186	195	191	197	130
Morning participation	28	19	59	17	14	124
Afternoon participation	47	63	17	65	62	19
Base prediction, average-day model						
No participation	192	190	191	192	193	182
Morning participation	23	22	25	24	31	27
Afternoon participation	56	56	55	56	49	64
Policy effect, average-day model						
No participation	203	202	203	204	205	170
Morning participation	27	26	28	27	34	83
Afternoon participation	41	41	40	41	34	20

ual may be exposed to the same set of temporal constraints and still may exhibit different behavior.

4. Average-day models based on average utility are biased when applied in anayzing a specific day of the week. Thus, when a policy that influences the activity pattern of specific days has to be evaluated, the use of day-of-the-week models is suggested. The results of the policy analysis performed indicated that there are large differences among the effects predicted by each approach.

In conclusion, the empirical results show that the daily models can represent individual behavior better and thus suggest that day-of-the-week models should be used in activity and travel pattern analysis, especially when policies that affect activity patterns during different days of the week are to be evaluated. The policy analysis results can be highly influenced by the modeling approach used. It is proposed to develop the daily model further and to study activities other than shopping, which may have a different temporal cycle. Also, the daily activity pattern can include several activities; hence daily interaction between activities can be analyzed.

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