A Framework and Model for Parking Decisions

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ABSTRACT

Parking choice search and availability is one of the most challenging symptoms resulting from the global urbanization and motorization growth. This paper presents an overall parking choice and search behavior framework, composed of three time-space phases: pre-trip static decision, en-route passive search, and in-area search strategy adaptation. The empirical part of the paper focuses on the first phase, and develops a parking choice model based on pooled stated and revealed preference data sources. A special web-based survey was designed to model the choice of parking type (on-street vs. off-street parking). The model estimation results show that the parking location choice is affected by the parking cost, search time and walking time to the destination, the facility type (on or off-street) and characteristics of the decision-maker with significant trade-offs among these factors. The parking model was applied to a case study to illustrate its capabilities in evaluating various policy measures. Specifically, the effect of a change in the demand for on- and off-street parking with respect to the parking pricing policy and the value of searching time for various parking durations were evaluated.

Keywords: parking behavior, discrete choice; parking search; on-street parking; off-street parking;

INTRODUCTION

Finding a parking spot in urban centers is increasingly a difficult task as drivers spend substantial time cruising for a vacant space. Shoup *(1)* reviewed several studies that on average estimated that vehicles cruising for parking amount to 30% of the total traffic in these areas. The slow moving vehicles searching for a vacant parking space affect other vehicles and can add to the congestion already prevalent in many urban centers. Parking search also contributes to increased pollution and higher fuel consumption. It may also lead to an increased risk of car crashes. This problem is likely to worsen with the continued growth in urbanization and motorization.

The significant disutility associated with parking search makes it a useful tool for urban transportation planners and managers *(2)*. A wide range of technology-based and policy tools that address parking are used in order to control and manage both transportation demand *(3)* and supply *(4)*. Parking-related measures include setting the number of available parking spots and their spatial distribution, setting parking prices, limiting parking durations, and development of free park and ride facilities around the city center. The implementation of these measures affects not only traveler's mode choice *(5)*, but also other travel decisions, such as destination, time of day, and may even lead to change or cancelation of various activities *(4)*. A successful design and implementation of such policies depends on the ability to understand and to predict their implications on travelers' behavior. Therefore, a wide range of studies have focused on the identification of the role of various parking attributes affecting drivers' choices. One of the methods that have been used in this context is the application of individual-level disaggregate travel-behavior models. The development of such models commonly includes administration of surveys in order to collect data regarding individuals' travel preferences. The collected data is then used to identify the influencing variables that will be incorporated in the model. Parking choice models and parking attributes may also be used as components in broader transportation models. For example, activity-based models include various sub-models that may take into account the outcome of the parking model.

Different parking choice models have been proposed in the literature. They can be classified with respect to the modeling approach, decision type, number of decisions that are modeled, and the data collection method (i.e., stated preference versus revealed preferences). The majority of the parking models address travel mode choice and parking characteristics *(6-8)* rather than choice between parking alternatives. In addition, most of the previous work considered parking choice as a standalone decision rather than a component in a broader behavioral framework. The following paragraphs summarize selected parking type choice models studied.

Van der Goot *(9)* estimated a multinomial logit (MNL) model for the choice among 22 parking alternatives that included illegal parking, off-street multi-storey parking, on street parking lot and off-street parking lot. The dataset was based on a revealed preference (RP) survey among drivers in the center of Haarlem, The Netherlands. The results showed the importance of walking time from parking stall to the destination, and inherent preference to off-street parking.

Axhausen et al. *(10)* estimated an MNL model for the choice among three parking types: illegal parking, on-street parking and off-street parking. The alternatives were described by their access time, search time, egress time and parking cost. The dataset for the model estimation consisted of a sample of 466 participants in a stated preference (SP) survey in Karlsruhe, Germany. The study emphasized the importance of distinguishing between different groups of individuals when setting a parking policy.

Tekmono and Hokao *(6)* estimated an MNL model for the choice between on-street parking, off-street parking lot, and off-street multi-storey parking facility. The model was estimated based on an RP survey among 528 drivers parking in the center of Surabaya, Indonesia. According to the model results, the choice among parking types was related to parking search and queue time, walking time, and parking cost.

Golias et al. *(11)* estimated a binary logit model for the choice between on-street and off-street parking. The model was estimated based on 3,451 observations from 317 drivers, who participated in an SP survey that was administered in the center of Piraeus, Greece. A basic, though expected, finding of this research is that parking cost has the most important impact on the choice of parking alternatives; as cheaper the parking alternative is, the more attractive it becomes.

Hess and Polak *(8)* estimated a random coefficients logit model for the choice among five parking types: free on-street, charged on-street, charged off-street, multi-storey parking facility and illegal parking. The model was based on 1,335 observations from a sample of 298 respondents in a SP survey conducted during 1989 in Birmingham, Sutton, Coldfield and Coventry, UK. The model estimation results revealed differences in the coefficients of the explanatory variables by location and trip purpose and established the existence of random taste heterogeneity.

The aim of this paper is twofold: to develop a general framework for a parking behavioral model that describes the entire parking choice and search process. The second aim is to develop a model for the pre-trip parking location choice component of the proposed framework. This model is formulated and estimated using a combination of stated and revealed preference data.

CONCEPTUAL FRAMEWORK

The proposed parking behavior framework is presented in Figure 1. It consists of several decisions that the driver makes in choosing and searching for parking. These decisions are linked to spatial and temporal characteristics. More precisely, it is assumed that there are three distinct travel related phases in the parking search process:

Pre-Trip – The first phase includes driver's parking decisions and considerations that are made prior to the actual trip. The pre-trip decisions establish the initial intentions the driver has. These include choice of the parking type, parking facility or on-street search area and route choice.

En-route – This phase occurs when the driver is on its way to the destination using the route chosen pre-trip. As the driver approaches the destination, he passes a search awareness point *(12)*. This point, which may be defined by a walking distance to the destination, is where the search for parking begins. From this point on, the driver passively searches for parking until reaching the search area or the parking facility chosen pre-trip. The passive search is a general scan of the streets the driver passes through as he continues on his route towards the destination. In this scan, if the driver identifies an available parking space, he will evaluate it against the alternative to give it up and continue towards the destination.

In Search Area - The third phase is initiated as the driver enters the search area. The search area is defined as the area in which the driver reduces the travel speed while scanning for a vacant space near the destination. If a parking space is not found, the driver chooses one of several possible parking strategies. Relevant strategies include parking illegally, driving to another parking facility or an alternative search area, continuing to search for parking in the same area and thus choosing the next segment on the search route, or waiting at the parking lot entrance or in the street for a parking space to vacate. The decision on parking strategy is dynamically made and could be revised by the driver during the search.

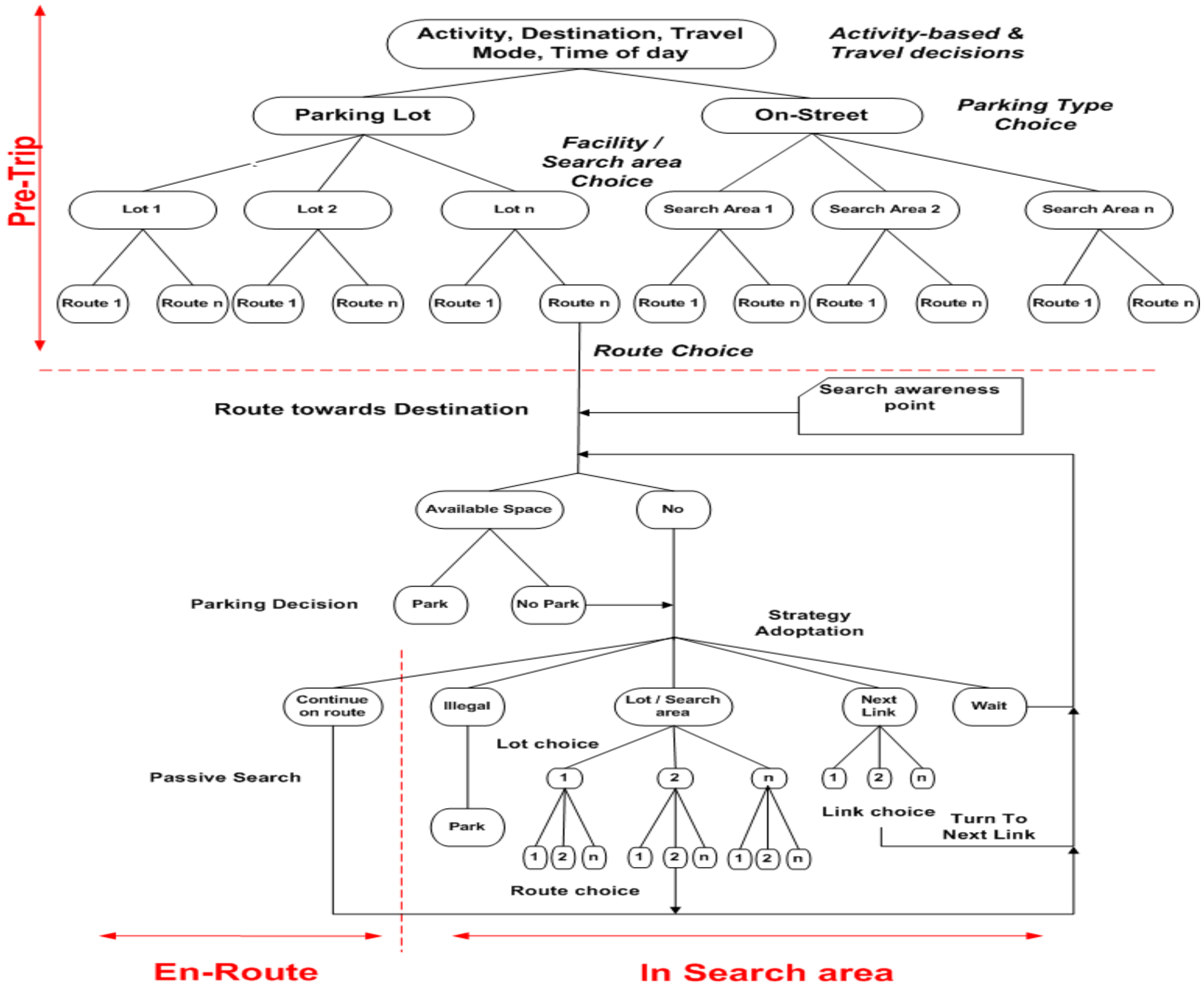

Figure 1. The conceptual framework for parking decisions

The various decisions that the drivers make depend on their own characteristics and on the attributes of the trip and the intended activity, such as the trip purpose and activity duration. Values for these variables may be input from an activity-based or traditional demand models.

The remainder of this paper focuses on the pre-trip phase of the parking behavior framework (i.e., choice of parking type and facility or search area), which functions as the basis to dynamic parking behavior en-route and in the search area.

DATA COLLECTION

A successful design and implementation of parking policies depends on the ability to predict their implications on travelers' behavior. For this purpose, an individual-level disaggregate parking behavior model was developed. The model development commonly involves administration of surveys in order to collect data regarding individuals' preferences.

The data collection in this study focused on parking in the Central Area of Tel-Aviv, Israel, which has severe parking problems for both residents and visitors. The Tel-Aviv metropolitan area has a population of 3.2 Million, with 0.4 Million in the city itself. It is the country's major economic center, especially in the business and finance sectors. The average household income in the city is 14% higher than the national average. The city center suffers an acute shortage of parking, with search time estimated at 20-25 minutes *(13)*.

Given the advantages and disadvantages of stated and RP data *(14)*, it was decided to estimate a model based on combined preference data. The combined approach allows to improve the efficiency of the estimation and to maintain higher validity of the results. The SP data is collected through a controlled experiment design. It is therefore feasible to collect a larger dataset with varying attribute levels that support estimation of trade-offs. At the same time the use of the RP data ensures that a high level of validity of the estimation results will be maintained.

Previous studies on parking behavior used mainly face-to-face interviews at the primary survey instrument, mainly because of the need to recall a specific part of the trip related to parking. In this study, data was collected using a web-based survey, which examined the parking habits and preferences of respondents. Web-based questionnaires are an efficient tool to collect preference information at a low cost. Data provided in internet surveys are at least as good in quality as those provided by traditional methods *(15)*.

In the RP part the respondents were first asked about their most frequent trip as drivers. The next questions referred to that trip and its parking characteristics such as trip origin, destination and purpose, parking search time, walking time to the destination, parking costs, parking duration and trip frequency. The respondents were also asked about alternative parking options they considered. If the most frequent trip did not involve parking search (e.g. when drivers have a designated parking space), the respondents were asked to report the most recent trip (within a month) in which they needed to search for parking. For respondents that reported that they did not search for parking, the RP part was skipped, and the respondent was presented with the SP part only.

The SP experiment included nine hypothetical choice situations with three parking alternatives for each respondent. The alternatives were composed of bundles of five parking attributes: parking duration, type (on-street or off-street), price, search time in case of on-street parking or waiting time in front of the entrance in case of off-street facility, and walk time to the destination. The number of attribute levels was set to three for each attribute, except parking type which has two levels.

The attribute levels used in the experiment were selected to allow a tradeoff between using values which make sense to the respondents and are close to their own experience (*14*), and taking into account the statistical preference for a wide range. For example, the average hourly parking price for on-street parking in Tel Aviv is 5.3 New Israeli Shekels (NIS, approximately \$1.5), and the average off-street hourly price is 12 NIS (≈\$3.4). These values were used as mid-points of their respective attribute levels. The midpoint values for the time variables in the survey were chosen in a similar way based on mid-values found in a pilot and in previous studies in the Tel Aviv Area. Table 1 shows the various attributes and their possible values in the experiment. Figure 2 shows an example choice scenario.

Table 1. Attributes and their levels in the choice experiment

Attribute	**Levels**	
	on-street	*off-street*
Price per hour (NIS) 3.5 NIS ≈ \$1	0 5 10	8 12 16
Searching time, on-street (minutes)	0 10 20	-- -- --
Waiting time, off-street (minutes)	-- -- --	0 5 10
Walking time (minutes)	0 10 15	0 10 15
Parking duration (hours)	1 3 5	1 3 5

The planned parking duration is 1 hour. Which alternative will you choose?

	Alternative 1	Alternative 2	Alternative 3
Parking type	On-street (5 NIS/hr)	Off-street (16 NIS/hr)	Off-street (8 NIS/hr)
Overall parking price (NIS)	5	16	8
On-street Parking search time (min.)	10		
Off-street parking entry queue time (min.)		0	10
Walking time to destination (min.)	15	0	10

Figure 2. Example scenario in the stated preference questionnaire

The choice scenarios were constructed from a $3^4 \times 2$ full factorial design resulting in 162 alternatives. In order to reduce the number of choice combinations, an orthogonal fractional factorial design was applied resulting in 27 alternatives was used *(16)*. In addition, the efficient design approach *(17)* was adopted to generate the combinations of three alternatives in each choice set and rule out dominant choice situations. The 27 choice sets in the final design were too many for respondents to evaluate. Therefore, they were blocked into three balanced sets of nine choice sets. Respondents were randomly assigned to blocks and then presented with the nine SP choice sets within this block. This number is reasonable and consistent with recommendations in the SP experiments literature *(18)*. The order of the questions within a block was randomized for every respondent.

The last part of the survey solicited demographic and socioeconomic information regarding age, marital status, household size, number of children, auto ownership, number of weekly driving hours, and income.

The survey was conducted during the months of July and August 2010. It was advertised via an e-mail message containing a web link directing to the questionnaire. In addition, 500 colored postcard-size leaflets were distributed among residents of the center of Tel Aviv. To encourage response to the survey, respondents were entered to a draw of 20 electronic parking payment devices (worth about $40 each). The resulting sample consisted of observations from 165 respondents that completed the SP part, of which included 112 respondents also completed the RP part. The combined dataset included a total of 1597 observations.

MODEL FORMULATION

Following random utility theory, the utility of an alternative is specified by:

$$U_{in} = X_{in}\beta_i + v_{in} \tag{1}$$

Where, U_{in} is the utility of alternative i to individual n; X_{in} is a vector of attributes; β_i are the corresponding parameters; v_{in} are random error terms.

The preference data consisted of up to ten observations for each respondent (one RP and nine SP). Therefore, the the MNL assumption that the error terms are independently and identically distributed (IID), which implies no correlation between observations and alternatives is not realistic. Instead, it can be assumed that the error component of the utility are independent across respondents but not within the choice situations for the same individual *(19)*. Neglecting these correlations may cause serious estimation errors *(20)*. In order to capture a variety of heterogeneity sources among individuals, a more flexible mixed logit error structure model was adopted. The error term is decomposed into two parts which are mutually independent: an individual specific error term, which is independent across respondents, but does not vary across the observations of the same individual; and a generic error term, which is independent across both individuals and choice scenarios. The resulting utility formulation is given by:

$$U_{int} = X_{int}\beta + \eta_n + \varepsilon_{int} \tag{2}$$

Where the error term ε_{int} is an IID Gumbel random variable. η_n is the individual specific random term. The individual effect is assumed to be normally distributed. The resulting choice probabilities, conditional η_n are given by:

$$P(y_{in} = 1|\eta_n) = \frac{e^{\mu(X_{in}+\eta_n)}}{\sum_{j\epsilon C_n} e^{\mu\left(X_{jn}+\eta_n\right)}} \tag{3}$$

Where, C_n is the choice set considered by individual n. y_{in} is a choice indicator (equal to 1 if alternative i is chosen, and 0 otherwise). μ is a scale parameter.

The motivation for combined RP-SP model estimation is the potential to gain in the accuracy of parameter estimates and in avoiding biases inherent in SP responses. The combined estimation consists of maximizing the joint likelihood function. The RP and SP formulations for an individual n can be stated as follows:

$$p\left(y_{int}^{SP}\right)|\eta_n = \frac{e^{\mu^{SP}(\beta X_{int}+\gamma Z_{int}+\eta_n)}}{\sum_j e^{\mu^{SP}\left(\beta X_{jnt}+\gamma Z_{jnt}+\eta_n\right)}} \tag{4}$$

$$p(y_{int}^{RP})|\eta_n = \frac{e^{\mu^{RP}(\beta X_{int}+\propto W_{int}+\eta_n)}}{\sum_j e^{\mu^{RP}\left(\beta X_{jnt}+\propto W_{jnt}+\eta_n\right)}} \tag{5}$$

Where, $\propto$, β and γ are vectors of unknown coefficients. X, Y and Z are vectors of explanatory variables that are common to the RP and SP data, and specific to RP and to SP, respectively. μ_{int}^{SP} and μ_{int}^{RP} are the scale parameters of the error terms for the SP and RP data, respectively.

The probability, conditional on the individual specific term, that an individual n makes the sequence of nine SP choices and a single RP observation is the product of the individual probabilities:

$$p(Y_n|\eta_n) = \prod_{t=1}^{T=9} p\left(y_{int}^{SP}\middle|\,\eta_n\right) \times p(y_{in}^{RP}|\eta_n) \tag{6}$$

Where, $Y_n = [y_{n1}^{SP}, \dots, y_{n1}^{SP}, y_n^{RP}]$ is the vector of choices made by individual n.

The unconditional probability of the sequence of choices is given by:

$$p(Y_n) = \int p(Y_n | \eta) f(\eta)\, d\eta \tag{7}$$

Where, $\eta \sim N(0, \sigma^2)$.

Finally, the log-likelihood function is given by:

$$LL = \sum_{n=1}^{N} log\, p(Y_n) \tag{8}$$

RESULTS

Sample Characteristics

In the RP data, 40% of the respondents reported on their frequent trip, 53% referred to the last trip and only 7% indicated that they did not search for parking at all during the last month (and so, did not provide an RP observation). 48% of the reported trips were for work/education purpose. 52% of the respondents were students and 44% were employed. Thus, students are over-represented in the sample. There may be several reasons for that. First, young adults, and students in particular, constitute a large proportion of the population in the Tel-Aviv city center with 33% of the adults being 29 years old or younger *(13)*. Second, drivers with employer parking or other designated parking that do not need to search for parking were not included in the sample. Designated parking is often available to employees in the area, but not to other travelers. Finally, the use of a web-based survey may have resulted in over-representation of technologically-affluent populations. The potential bias introduced by the over-representation of students in the sample is handled by introducing interaction variables of the student status with various parking attributes in the model. In the reported trips, 53% of the drivers drove alone, 30% traveled with a single passenger and 17% had two or more passengers. 72% of the respondents indicated that they use the car as their main transportation mode, 15% use public transportation, 4% use motorcycle or bicycle and 3% walk. Most of the respondents drive their car more than 2 hours a week (79%). The high share of respondents who indicated car as their main transportation mode, in addition to the data of the car usage was important confirmation of the intended target population. In terms of parking types, 60% of the respondents reported parking on-street, 27% parked off-street and 13% had reserved parking. The average parking duration was 3:22 hours. The average parking price was 5 NIS (~$1.4). 83% of the respondents paid up to 10 NIS (~$2.8). 44% of the respondents spent less than 5 minutes searching for parking, 34% spent between 5 and 10 minutes searching for parking, and the remaining 22% searched for more than 10 minutes. In off-street parking, the average waiting time in front of the parking facility was 1:38 minutes. 68% of the respondents walked for less than 5 minutes from the parking space to their destination, 26% walked between 5 and 10 minutes and the remaining 6% walked more than 10 minutes.

Finally, 58% of the respondents indicated that the decision about parking type was made after arriving at the destination area and 63% decided about the parking location at the destination area. 30% and 16% made the decision type and location decisions, respectively, pre-trip. 12% and 21% made these decisions en-route, respectively.

Model estimation

Three models were estimated for the parking choice: (1) an MNL model using the RP data, (2) a panel model using the SP data, and (3) a joint RP-SP panel model using all available data. Table 2 presents the estimation results for the three models and the definitions of the variables included in them.

Table 2. Model Estimation results

Variable	Description	(1) RP model estimates (t-stats)	(2) SP model estimates (t-stat)	(3) RP-SP model estimates (t-stat)
InVehTime	Waiting time + Search time (minutes)	-0.0836 (-2.20)	-0.0868 (-10.61)	-0.0880 (-10.80)
PricePerHr	Overall parking price / Parking duration (NIS)	-0.0707 (-1.12)	-0.121 (-7.18)	-0.122 (-7.33)
PriceSqr	Squared overall parking price (NIS^2)	-0.000397 (-0.83)	-0.0011 (-12.88)	-0.00111 (-12.96)
PriceAlone	Price per hr. × Drive alone Dummy	-0.131 (-1.59)	--	-0.168 (-1.02)
RP-Type	Dummy for off-street parking type (RP)	-1.31 (-2.51)	--	-1.42 (-2.29)
SP-Type	Dummy for off-street parking type (SP)	--	0.745 (3.18)	0.643 (2.85)
SP-RP Choice	RP on-street parking type dummy × SP off-street parking type dummy	--	-0.488 (-1.90)	-0.345 (-1.33)
Walk	Walking time to the destination (minutes)	-0.144 (-2.35)	-0.0913 (-5.09)	-0.0970 (-5.53)
No-Walk	Dummy for a short walking time (≤ 1 minute).	-0.568 (-0.42)	0.451 (2.19)	0.390 (1.93)
TypeOld	Interaction: old age (50 <) × parking type dummy	1.31 (2.03)	-0.0263 (-0.08)	--
Student - Price	Interaction: student dummy × overall parking price	-0.0270 (-0.94)	-0.0154 (-2.38)	-0.0156 (-2.42)
SIGMA	STD (σ) value for the normal distributed error term($\eta \sim N(0, \sigma^2)$)	--	1.16 (9.04)	-1.15 (-9.00)
MU	SP-RP scale parameter (μ)	--	--	0.556 (2.63)
Number of observations		112	1485	1597
Number of cases		112	165	204
Number of parameters		9	10	12
L(0)		-77.632	-1631.439	-1709.072
L(β)		-56.001	-1281.379	-1342.004
McFadden $\bar{\boldsymbol{\rho}}^2$		0.163	0.208	0.208

Model 1 – RP model: The model includes attributes of the various alternatives and socio-demographic interaction variables. Consistent with previous parking and modal choice studies and with economic theory, the coefficients of the hourly price (PricePerHr) and the price squared (PriceSqr) variables are both negative. However, relatively low value of the PriceSqr coefficient may suggest that drivers mainly consider the hourly parking price and give less attention to the total price. The coefficients of the In-Vehicle and Walk time variables are both significant and negative, as expected. No-Walk is a dummy variable for parking alternatives that involve little or no walking at all (under 1 minute). The coefficient of this variable is insignificant, and contrary to expectations, negative. This may be explained by the small number of RP observations with short walking times. Interestingly, the coefficient of the off-street Type dummy variable is significantly negative, meaning that drivers prefer on-street parking, ceteris paribus. For drivers over 50 years old, this effect is offset by the positive coefficient of the interaction variable TypeOld. StudentPrice and PriceAlone represent additional price sensitivities concerning students and drivers traveling alone.

Model 2 – SP model: The additional parameter SIGMA is the standard deviation of the normally distributed individual-specific error term η. It should be noted that, unlike the RP model, in this model, all parameters are statistically significant, and have the expected sign, with the exception of the coefficient of the TypeOld variable. While most parameter estimates align well with those obtained in the RP model, this is not the case for coefficient of the off-street type dummy variable. This parameter is now positive and significant. The variable SP-RPChoice aims to capture any justification biases. It refers to the parking type preference of drivers that reported parking on-street in the RP survey. The significant negative coefficient of this parameter indicates a consistent off-street type aversion by these respondents. The parameter of the No-Walk dummy variable is now significant and positive, which implies that drivers prefer parking alternatives that do not involve walking. Another interesting result is the additional price sensitivity of student, which is captured by the coefficient of the StudentPrice interaction variable. The student status may serve here as a proxy for low income.

Model 3 – joint RP-SP model: The signs of the coefficients of the off-street Type variables (RP-Type and SP-Type) in models 1 and 2 were opposite. For this reason, in the joint model, the Type parameter was separately estimated for the two data sources. In this way the SP and RP data are pooled by allowing difference between data sources in the Type parameter. The coefficients of the No-Walk and typeOld variables were also opposite in the two models. However, the No-Walk parameter was not significant in the RP data was low, and so its parameter was estimated jointly for the two data sets. The resulting parameter value is positive and significant. The typeOld interaction parameter was not significant in the model and therefore omitted from the final model. The parameter of the SP-RPChoice variable in the SP utility specification was kept in the model despite its relatively low t-stat (-1.33) due to its importance in capturing justification bias. The relative scale parameter MU equals 0.556. This implies that the variance of the utilities is substantially smaller in the SP data compared to the RP. The likelihood ratio test statistic for testing the joint RP-SP model against the two separate models is given by: -2(-1342.004 – (-1281.379 + (-56.001))] = 9.3 with seven degrees of freedom. Hence, the pooled model cannot be rejected at 0.05 level of significance based on test statistic value which is lower than the critical value $\chi^2_{7,0.05} = 14.07$.

The ratio between out-of-vehicle (walk) time and in-vehicle (search or wait) time in the pooled model equals to 1.1. This ratio is higher than the values reported in *(8)* and *(10)*, which are in the range of 0.8 to 1. However, it is much lower than values of time commonly found in the transportation literature, which are in the range between 1.5 and 2.5 *(21)*,. The difference may be explained by the fact that drivers are more time sensitive with respect to the parking search than to other parts of the trip. The parking search is carried out in proximity to the destination, and may be perceived as a distinct task and not part of the trip itself. The dummy variable No-Walk represents very short walking times from the parking space to the destination (under one minute). The positive sign of its coefficient suggests that drivers have additional preference towards parking alternatives with no walking time to destination.

Two parking type coefficients were estimated in the model for the two data sources: RP-Type and SP-Type. The estimation results revealed and opposite signs for the two parameters. Both are statistically significant. The difference in the estimates may be explained by the fact that respondents acted differently with respect to parking type attribute in the RP and SP parts of the survey. Off-street parking is generally more expansive, but involves less in-vehicle time compared to on-street parking. Thus, in the hypothetical SP scenarios in which no actual costs were incurred and no time was spent, respondents preferred the off-street alternatives. In contrast, the RP data, which represents respondents' actual behaviors, demonstrated a preference towards on-street parking alternatives. This result is similar to that found in *(6)*, which also found preference to on-street parking. In contrast, in *(8)* drivers tended to prefer off-street parking.

Since the majority of the respondents were students, with relatively homogeneous characteristics, the effect of the socio-demographic variables was not expected to be significant. The only socio-demographic variable which was included in the final model is studentPrice. The variable captures the additional sensitivity of students to the overall parking price. Its coefficient is negative, which implies that students are more sensitive to parking price compared to other respondents.

MODEL APPLICATION

The estimated model was applied to a common parking choice scenario in order to investigate the potential sensitivities of parking choice in response to various changes in the parking attributes. Table 3 presents the parking scenario which was developed based on the RP survey data. The values of the parking attributes in the scenario were set according to their average values in the RP survey data.

The off-street share calculated based on the baseline scenario attributes values is 20%, while the on-street share is 80%. In order to investigate the effects of possible parking policies, changes were made in the attributes values of the baseline scenario. Each policy measure was represented as a change of a specific attribute (i.e., shift from the value that was set in the baseline scenario) while all other attributes values remain constant.

Table 3. Model application for a parking scenario

Attribute of parking	Parking A	Parking B
Type	*Off-Street*	*On-Street*
Hourly Price (NIS), $1=3.5NIS	*10*	*4*
Duration (hours)	*3*	*3*
Walking time to destination (min)	*2*	5
In-vehicle time (min)	*2*	10
Parking Utility	*-3.379*	*-2.01284*
Parking Share	*20%*	*80%*

Changes in parking pricing

Figure 3 shows the on-street and off-street parking shares as a function of the on-street hourly price.

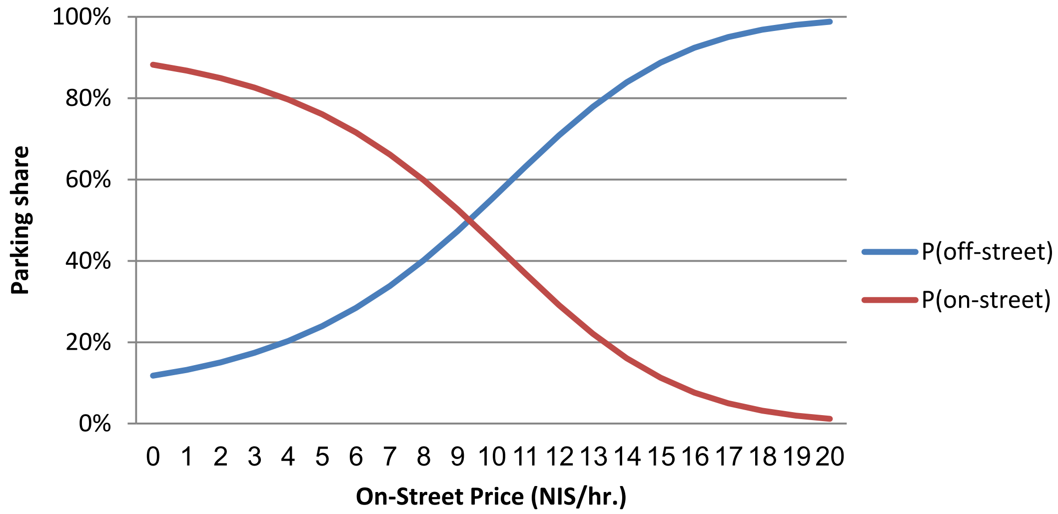

Figure 3. On-street and off-street shares as a function of the on-street parking price

The average on-street urban parking price in Israel is around 4.5 NIS/hr *(22)*. When this price level is applied to the on-street parking alternative in the scenario, the results indicate that the majority of the drivers (78%) prefer the on-street option. At this price, drivers will be willing to spend more in-vehicle time (10 min) and a longer walk to the destination (5 min) compared to the higher priced off-street alternative (off-street share of 22%).

Value of in-vehicle time

The value of parking search (in-vehicle) time can be estimated as *(23)*:

$$VOT = \frac{\frac{\partial U}{\partial InVehTime}}{\frac{\partial U}{\partial PricePerHr}} = \frac{\beta_{inVehTime}}{\beta_{pricePerHr}+2(\beta_{priceSqr}\times Duration^2\times PricePerHr)+\beta_{priceAlone}\times aloneDummy} \quad (9)$$

The value of search time was calculated based on the baseline scenario (parking price of 4 NIS/hr for 3 hours parking duration) and the model estimates. The resulting value equals to 18 NIS/hr for driving alone and 26.4 NIS/hr for driving with passengers. Figure 4 illustrates the monetary value of the search time as a function of the parking duration with respect to the on-street alternative in the baseline scenario. These values are somewhat lower than the average wage rate per hour in Israel, which is about 37 NIS/hr.

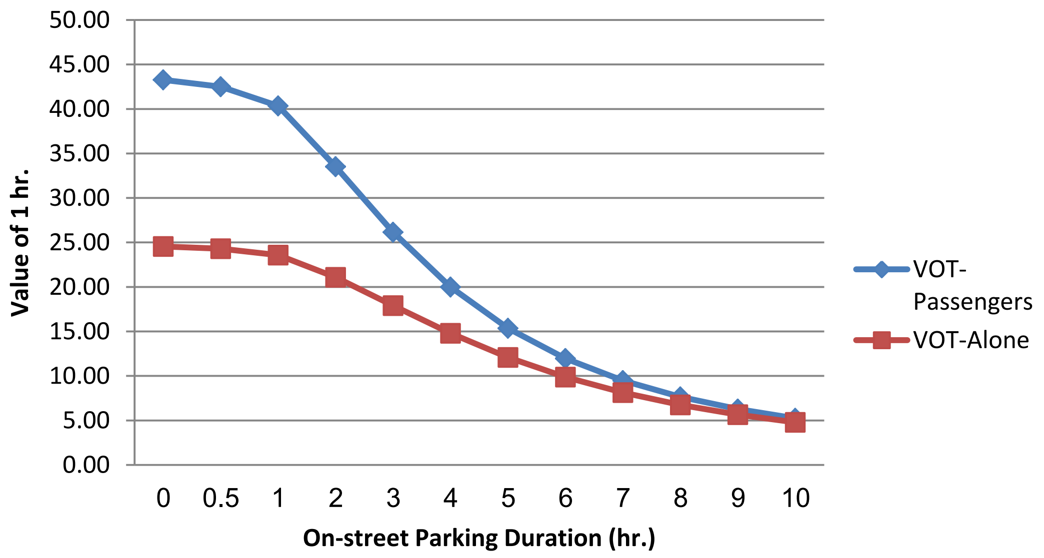

Figure 4. Value of search time vs. parking duration time

As Figure 4 shows, the value of search time decreases as the duration of the intended parking becomes longer. This result may indicate that the time drivers spend during the parking search becomes less distressing as parking duration becomes longer. In other words, drivers are willing to spend more time searching for parking if the duration of the activity is long. Another interesting result is that when drivers are alone their value of search time is lower compared to when driving with passengers. This result is reasonable since when driving alone the driver spends only his own time, whereas, when passengers are in the vehicle the time spent in searching is more valuable since the passengers also incur the time lost.

CONCLUSIONS

In this paper, a framework for the complete parking search process was conceptually specified. This framework provides important insights on parking related decisions that are made prior to the trip. Analysis of the survey results regarding parking decisions timing suggests that the majority of drivers make the final parking decision dynamically in proximity to the destination, thus supporting the proposed approach. Further research and exploration of the framework phases may provide an additional insight to the choice process and the relations between the different sub-decisions composing the search.

A model was specified and estimated for the pre-trip portion of this framework. The model estimation uses both RP and SP data. The joint RP-SP estimation process and the integration of heterogeneity component improved the results compared to estimation of two separate models.

The estimation results revealed interesting drivers' parking behavior patterns. As expected, the most dominant factor in parking related decisions is the price. The results suggest that drivers consider parking price factor in two manners: as an overall cost for the entire parking duration and as price paid per hour of parking. The in-vehicle time and walking time to the destination are also important variables. Their coefficients were almost identical, suggesting that in contrast to other transportation decisions, when in-vehicle time is dedicated to parking search, it is valued almost as highly as walking time. Another interesting result is the effect of passengers on drivers' value of time (searching or walking). The parking value of time is lower for drivers that drove alone compared to that of drivers that were travelling with passengers. Additional factors affecting parking choices are the parking type (on-street or off-street) and parking duration and student status.

The presented case study demonstrated the ability of the model to evaluate the effect on parking decisions of various parking policies and measures, such as changes in the parking pricing, and availability (that would affect search times), allowed parking durations, incentives and penalties on provision on employer provision of parking facilities and so on. In standalone, the parking model captures only the direct effects on parking choice. A more complete evaluation would involve embedding the parking choice model within wider urban transportation planning frameworks that would also capture the effects of parking attributes on activity locations and timing decisions and mode choices.

Furthermore, the estimation results presented in this paper address only the pre-trip parking choice model. The proposed parking behavior framework is more comprehensive and also addresses decisions made en-route and in the search phase close to the destination. Follow-up research attempts to address these aspects of parking behavior, and in particular the choice dynamics that stem from the view of parking behavior as a series of interrelated sub-decisions (e.g., search strategy adaptation, alternative evaluation, and route choice) made dynamically. This offers significant challenges in useful formulation of the models, developing data collection technologies and instruments and the subsequent estimation of the behavior models.

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