Investment in Mobility by Car as an Explanatory Variable for Market Segmentation

Shlomo Bekhor, Technion–Israel Institute of Technology, Haifa
Alon Elgar, Mevo-Hazait, Har Adar, Israel.

Abstract

According to the traditional approach, when estimating changes in transportation policies, the household income level (in all its forms) is perceived as the proper explanatory variable for modeling population transportation preferences. However, it is acknowledged that accurate information about this variable is difficult to gather. In contrast, information about household car characteristics is relatively simple to collect. This article presents the hypothesis that a lifestyle variable, such as investment in mobility by car (IMC), is a viable parameter for estimating household members' behavioral tendencies toward transportation, from both practical and conceptual reasons.

This research proposes a simple methodology to infer the IMC using existing data sources, and presents mode choice model estimation results using the IMC both as an explanatory variable and as a segmentation variable. The segmentation of the population in three IMC categories (low, middle, and high) yielded significantly different models of the preference systems for the three segments. These findings show that IMC is a viable variable for market segmentation.

Introduction

It is generally acknowledged that market segmentation is crucial to the modeling process. Disaggregate mode choice models have a particularly vast literature in which the population is segmented in various ways. Examples of different market segmentation approaches in mode choice modeling can be found in Dehghani and Talvitie (1980), Pas and Huber (1992), and more recently Outwater et al. (2004).

This article focuses on the independent variables commonly used in the mode choice modeling process and on the relevance of the variables used for market segmentation. In particular, we consider household variables such as income level and auto ownership. An example of the use of these variables for market segmentation in mode choice modeling can be found in Dehghani and Talvitie (1980).

The motivation for this article is that the number of cars in a household, usually used in travel forecasting methods, is in our opinion too general for market segmentation. A combination of number of cars per household and income level could yield a better indicator. However, data on household income is acknowledged in the literature as problematic to collect. In contrast, data on car characteristics is relatively easy to collect. This enables us to categorize each household according to an estimation of its investment in car mobility. The investment in car mobility is defined as the total market value of the cars in each household. In this article, we explore the possibilities of using this variable for market segmentation.

Determining which type of parameter is preferable for market segmentation can be examined from a practical or from a conceptual aspect. From a practical aspect, we suggest that the investment in mobility by car (IMC) parameter is preferable to income in its different forms, while from the conceptual point of view, it is at least as good as income. While we would have preferred to present a quantitative evaluation of the two parameters, we have to rely on secondhand databases (almost all transportation surveys conducted in Israel did not collect information about household income level), and thus limit our discussion to a qualitative evaluation.

Practical Considerations

In most household travel surveys, it is customary to obtain information about household income. However, we found evidence in the literature about surveys that neither collected nor used this information. For example, Badoe and Miller (1998) used data collected from the very extensive 1986 Transportation Tomorrow Survey (TTS) for the Greater Toronto Area (GTA). This survey, documented in detail in Data Management Group (1990), included a telephone interview of 4 percent of all households in the area (about 67,000 households) and contained information on household variables, but not household income.

Most travel surveys conducted in Israel, including the National Travel Habits Survey (NTHS) of 1996/7 (Central Bureau of Statistics 1997), which also served as a database for this research, do not include questions about income level. In fact, very few household trip surveys conducted in Israel include data about the income level of respondents. Attempts to use the income variable in modeling estimation were not successful (Taskir 1995).

We believe that this absence of information is not an omission by neglect, but a result of the surveyors' awareness of the unreliability of answers given by respondents to questions involving income. Furthermore, some of the surveyors were concerned that respondents would consider questions about income an illegitimate invasion of privacy, and this would have a damaging effect on the reliability of their answers to the entire questionnaire.

In contrast to the lack of information about income and its inherent unreliability, available surveys in Israel include information about cars possessed by each household. This information enables us to estimate average household investment in mobility by car. Respondents do not have any particular reservations about providing information about the cars they use, simply because it is an obvious fact. The information about car characteristics is also collected in many household surveys found in the literature. For example, the 2001 U.S. NHTS (2004) included information about car make, model, and production year.

Conceptual Considerations

Income level is a physical factor that defines the envelope of the household possibilities to allocate its resources. Salomon and Ben-Akiva (1983) pointed out that "the concept of lifestyle is becoming a major differentiating trait between population groups, substituting for economic and social classes." We do accept the general definition of the lifestyle suggested by the authors, namely that "the lifestyle is defined as a pattern of behavior under constrained resources." The authors showed in their study that lifestyle groups account for taste variations better than other schemes.

Badoe and Miller (1998) proposed a systematic approach to study variations in mode choice behavior. The methodology used was based on the Automatic Interaction Detector (AID) developed by Sonquist et al. (1971), the merits of which were emphasized by Hensher (1976). The authors found that the single most important variable for explaining differences in workers' mode choice behavior was the number of household vehicles. The authors classified this variable as "a socioeconomic factor." We are inclined to define it as a lifestyle variable, even though it is influenced by the socioeconomic status of the household. The number of cars is also an indicator of the household preferences for allocation of its resources between transportation and other uses.

We adopt the notion of lifestyle discussed by Salomon and Ben-Akiva (1983) as a preferable concept for selecting explanatory variables to market segmentation in travel demand modeling. However, we do expect that lifestyle variables that are directly related to transportation behavior, such as the number of vehicles and investment in mobility by car, would be more closely connected to the individual preference system than other lifestyle elements, such as household formation, participation in labor force, orientation toward leisure, and so on.

The assertion that the number of household vehicles is a lifestyle variable supports the claim by Salomon and Ben-Akiva (1983) mentioned above. In addition, the AID application proposed by Badoe and Miller for segmentation and classification is useful for a given set of variables. However, even the best classification system cannot identify and classify variables that are not defined as such. The number of cars in the household itself is not enough to identify lifestyle, as it does not distinguish between different levels of investment by the household in those cars. These levels of investment are believed to be highly correlated with the household preferences concerning choices of transportation alternatives. Therefore, we propose to use another lifestyle variable, complementary to the number of household vehicles, namely IMC.

Our hypothesis is that the behavior presented by the revealed action of IMC is significantly more closely related to population preferences concerning the use of alternative modes of transportation than income level alone. IMC is a behavioral phenomenon that demonstrates the outcome of the choices made by the household concerning its mobility.

The IMC variable could be formulated as a function of the following variables: income level, family size, age and gender composition, transit accessibility measures, consumption patterns, working patterns, and a preference function concerning the allocation of household resources among household uses.

Most of the above variables are easily observable, and data can be obtained from current practice surveys. However, the preference function concerning allocation of household resources cannot be obtained directly from existing surveys. Surveys generally provide information about the number cars in the household; however, data relating the decision to purchase a car at a given price and at a certain time is not collected. Therefore, at this stage, we limit the investigation to existing data sources, and propose a simple methodology to infer the IMC, presented in the next section.

Methodology

Data Preparation

The database used for model estimation is a subsample from the NTHS, carried out by the Israeli Central Bureau of Statistics in 1996–1997 on behalf of the Ministry of Transport. We confined this study to the Tel Aviv Metropolitan Area (about 1.7 million inhabitants in 1996), since we could reasonably attach a reliable level of service data only for this region.

The survey is a typical revealed preferences (RP) study. About 1 percent of the households were surveyed (5,917 households in the Tel Aviv area). Each person over the age of 14 kept a three-day diary. A total of 29,506 observations, corresponding to trips departing from home, were selected for the analysis. We purposely avoided chained trips, since for more than 95 percent of these cases the chosen mode was identical to the mode used in the trip departing from home.

Travel times for car and transit modes were imported from Emme/2 networks used for modeling a light rail transit project in the Tel Aviv Metropolitan area (Perlstein-Galit Company Ltd. 2001).

The survey collected additional information about the cars in the household. According to information in the questionnaire about the year of production and engine size, we calculated average market values for each car in the household. Table 1 presents average car values (December 1996 prices) according to the price booklet used for car insurance companies (Levi-Itzhak 1996).

Table 1. Average Car Prices for Given Engine Size and Production Year[1]

	Engine Size					
Production Year	Up to 1000	1001–1300	1301–1600	1601–1800	1801–2000	2001 & More
Up to 1988	9.5	11.6	14.3	19.8	26.5	38.1
1989	17.6	18.5	27.2	40.2	56.0	72.1
1990	19.3	22.6	32.3	43.8	52.9	77.3
1991	21.8	27.3	37.8	45.1	54.9	75.7
1992	24.6	28.3	42.3	49.2	53.0	88.2
1993	29.1	31.7	45.9	58.8	72.7	98.2
1994	39.0	33.9	50.2	67.3	90.0	113.8
1995	-	38.9	60.8	73.1	93.6	115.7
1996	-	50.8	67.9	84.6	100.2	136.2
1997	-	57.9	78.6	98.5	101.1	187.0

1. December 1996 prices in thousands of NIS (U.S. $1 = 3.244 NIS).

Model Estimation

This article focuses on the methodological aspects of the population segmentation, rather than model structure and calibration. For this reason, we used the multinomial logit model with the same utility function for all models tested in this study. In this way, we kept the modeling estimation procedure constant throughout, and concentrated on different segments of the population. In addition, the same independent variables were used in all models.

The models were estimated according to two segmentation levels. First, the observations were separated according to car ownership and driver's license. Three models were estimated at this level:

- *Model A*: The first model was estimated with all the available households (29,506 observations).
- *Model B*: The second model was estimated for persons with a driver's license and living in households with at least one car (18,975 observations).
- *Model C*: The third model was estimated for the remaining observations (i.e., persons without a driver's license or living in households without a car; 10,531 observations).

The next segmentation level was formed by further dividing the 18,975 observations related to households with car and persons with a driver's license according to IMC. Three additional models were estimated:

- *Model D*: IMC up to 10,000 NIS (low investment; 3,094 observations);
- *Model E*: IMC between 10,000 and 60,000 NIS (middle range; 8,276 observations); and
- *Model F*: IMC higher than 60,000 NIS (high investment; 7,605 observations).

The thresholds for low, middle, and high IMC used in these models were defined by looking at the IMC distribution in the household sample, as shown in Figure 1. Since 1,834 (31%) of households in the sample do not possess a car, the IMC for these cases is 0. At the value of 10,000 NIS there is a sharp difference in the slope of the cumulative frequency, and for this reason this value was used as a reference for low IMC. There are similar differences around 30,000 and 60,000 NIS, but the 30,000 mark did not yield significant model estimation results. Figure 2 shows the household segmentation for the different models estimated.

Figure 1. Distribution of IMC in the Sample

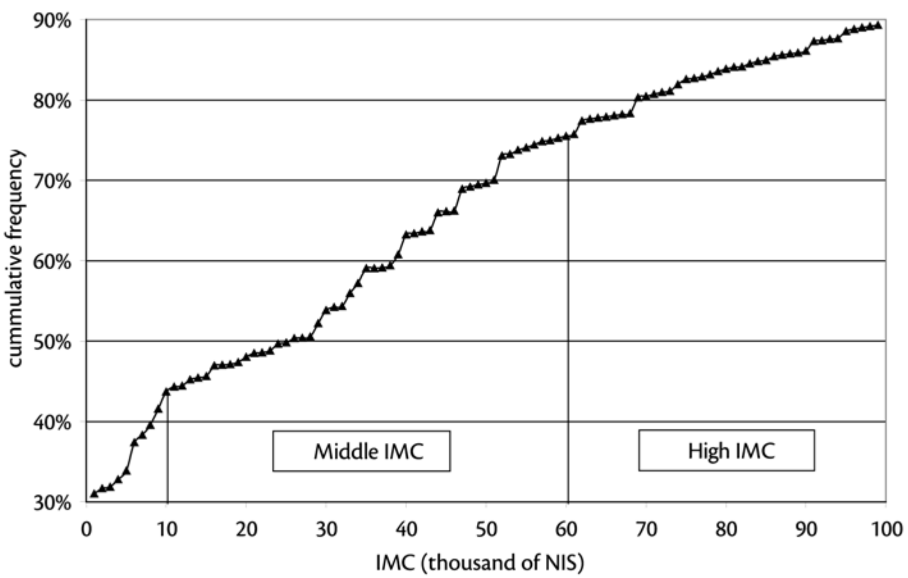
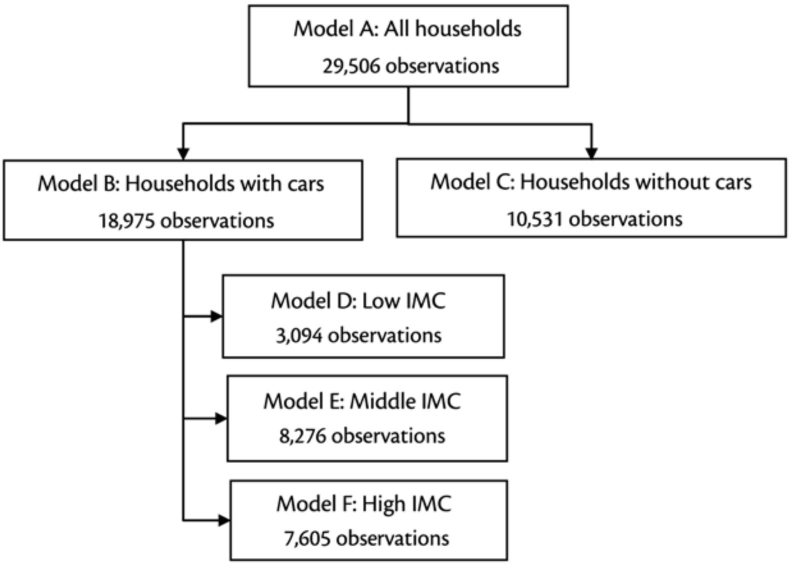


Figure 2. Segmentation Diagram



Since in this study we focus on the influence of IMC variable on mode choice, it is important to verify that transit service is available in all segments. For example, it may be possible that households with high IMC will be located in areas with poor transit service. At least for the data used in this analysis, no significant differences were found in the distribution of the main explanatory variables in each of the IMC groups. Table 2 shows the main statistics (mean and coefficient of variation) for each IMC group.

Apart from the IMC mean value, which is obviously different in each class, all other variables exhibit very similar mean and coefficient of variation values.

Results

Table 3 shows the results obtained from the initial segmentation procedure. The table contains the estimated coefficients and t-values for the first three models described. In addition, overall fit parameters and common level of service ratios are presented, such as values of time (VOT) and ratio between out-of-vehicle and in-vehicle transit times. The third model is related to observations without car

Table 2. Basic Statistics of the Main Explanatory Variables for Each IMC Group

Variable Description	IMC<10,000 NIS		10,000<IMC< 60,000 NIS		IMC>60,000 NIS	
	Mean	CV (%)	Mean	CV (%)	Mean	CV (%)
Number of transfers	1.3	39.9	1.3	40.8	1.3	40.7
Bus wait time (min)	7.6	66.1	7.8	63.9	8.3	64.2
Bus in-vehicle time (min)	24.1	76.7	25.5	78.1	27.3	75.7
Bus walk time (min)	5.8	88.5	5.8	88.3	6.7	89.2
Bus fare (NIS)1	6.0	53.8	6.2	55.8	6.5	55.6
Car in-vehicle time (min)	18.2	83.7	19.0	85.2	19.6	81.1
Car cost (NIS)1	7.7	62.8	7.9	63.1	8.0	61.5
Park cost (NIS)1	2.7	17.0	2.7	17.3	2.7	18.0
Park search time (min)	2.5	96.2	2.5	95.7	2.5	96.9
IMC (thousand NIS)1	6.2	37.0	36.6	34.6	104.0	36.3

1. December 1996 prices in NIS (U.S. $1 = 3.244 NIS).

available, and for this reason the IMC variable in these cases is not relevant for model estimation (since it is equal to 0).

Both IMC and a dummy variable that indicates households with two or more cars are quite significant in the first two models. Although the high t-values originate from the large sample size, we may infer that the IMC variable is not just a replacement for the auto ownership variable.

Table 4 presents the results for the segmentation according to IMC. The format of the table is identical to Table 3. Recall that the total number of observations in the three models of Table 4 sum up to the observations for households with car and persons with driver's license, as in the second model of Table 3. The car driver's market share in these cases is quite high, as expected, ranging from 71 percent in the lower third of the IMC to 82 percent in the higher third.

For the two extreme IMC ranges (low or high) the independent variable associated with IMC is not significant. However, in the middle range, the IMC variable is significant, perhaps indicating that at this range the influence of IMC is most pronounced.

Table 3. Estimation Results—Initial Segmentation

Variable Description	**Model A** All Observations		**Model B** HH with Car and Persons with Driver's License		**Model C** HH without Car or Persons without Driver's License	
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Cd—constant	-1.312	-24.7	1.156	12.0		
Cp—constant	-1.487	-27.0	-0.607	-5.8	-0.706	-11.3
Bus—number of transfers	-0.300	-10.1	-0.284	-5.5	-0.316	-7.6
Bus—wait time (min)	-0.031	-8.4	-0.043	-6.0	-0.045	-9.6
Bus—in-vehicle time (min)	-0.016	-7.9	-0.016	-5.1	-0.024	-8.7
Bus—walk time (min)	-0.022	-5.0	-0.013	-1.7	-0.038	-6.5
Bus—fare (NIS)[1]	-0.169	-22.2	-0.131	-9.8	-0.205	-2.5
Cd—in-vehicle time (min)	-0.025	-7.5	-0.035	-6.8		
Cd—cost (NIS)[1]	-0.029	-3.2	-0.048	-3.6		
Cd—park cost (NIS)[1]	-0.003	-0.3	-0.030	-1.9		
Cd—park search time (min)	-0.012	-1.7	-0.031	-3.2		
Cp—in-vehicle time (min)	-0.030	-8.0	-0.030	-5.0	-0.008	-1.6
Cp—cost (NIS) [1]	-0.041	-4.2	-0.063	-3.9	-0.088	-7.4
Cd—IMC ('000 NIS) [1]	0.018	32.4	0.004	4.4		
Cp—IMC ('000 NIS) [1]	0.013	20.6	0.004	4.5		
Cd—dummy for 2+ cars in hh	0.931	19.5	0.930	12.8		
Cp—dummy for 2+ cars in hh	0.447	8.3	0.486	5.6		
Total number of observations	29506		18975		10531	
Bus riders	7932	27%	1826	10%	6106	58%
Car drivers	14784	50%	14784	78%		
Car passengers	6790	23%	2365	12%	4425	42%
Likelihood (0)	-32415.7		-20846.2		-7299.5	
Likelihood (Constants)	-30612.1		-12889.1		-7164.8	
Likelihood (Final)	-27034.5		-12169.9		-6715.4	
"Rho-Squared" w.r.t. 0	0.17		0.42		0.08	
"Rho-Squared" w.r.t. Const.	0.12		0.06		0.06	

[1] December 1996 prices in NIS (U.S. $1 = 3.244 NIS).

Table 4. Estimation Results—Segmentation by IMC

Variable Description	IMC<10,000 NIS		10,000<IMC< 60,000 NIS		IMC>60,000 NIS	
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Number of transfers	1.3	39.9	1.3	40.8	1.3	40.7
Cd—constant	1.141	5.1	1.206	7.3	0.880	3.8
Cp—constant	-0.333	-1.3	-0.788	-4.0	-0.911	-3.6
Bus—number of transfers	-0.297	-3.7	-0.267	-3.6	-0.218	-2.2
Bus—wait time (min)	-0.023	-1.7	-0.033	-3.2	-0.094	-5.6
Bus—in-vehicle time (min)	-0.022	-1.5	-0.022	-4.7	-0.015	-2.4
Bus—walk time (min)	-0.046	-2.7	-0.011	-1.0	-0.017	-1.1
Bus—fare (NIS)[1]	-0.075	-2.8	-0.118	-6.4	-0.217	-7.6
Cd—in-vehicle time (min)	-0.025	-2.3	-0.038	-5.2	-0.043	-4.2
Cd—cost (NIS)[1]	-0.036	-1.3	-0.048	-2.5	-0.044	-1.7
Cd—park cost (NIS)[1]	0.015	0.4	-0.048	-2.1	-0.026	-1.0
Cd—park search time (min)	-0.090	-3.9	-0.013	-0.9	-0.024	-1.5
Cp—in-vehicle time (min)	-0.014	-1.1	-0.030	-3.5	-0.044	-3.8
Cp—cost (NIS)[1]	-0.086	-2.5	-0.065	-2.8	-0.040	-1.4
Cd—IMC ('000 NIS)[1]	0.027	1.2	0.008	2.8	-0.009	-0.6
Cp—IMC ('000 NIS)[1]	-0.004	-0.2	0.014	3.8	0.005	0.3
Cd—dummy for 2+ cars in hh	0.633	1.9	0.771	8.0	1.237	10.6
Cp—dummy for 2+ cars in hh	0.300	0.7	0.392	3.4	0.718	5.2
Total number of observations	3094		8276		7605	
Bus riders	467	15%	905	11%	454	6%
Car drivers	2208	71%	6316	76%	6260	82%
Car passengers	419	14%	1055	13%	891	12%
Likelihood (0)	-3399.1		-9092.1		-8354.9	
Likelihood (Constants)	-2465.7		-5883.1		-4408.4	
Likelihood (Final)	-2355.0		-5629.7		-4142.4	
"Rho-Squared" w.r.t. 0	0.31		0.38		0.50	
"Rho-Squared" w.r.t. Const.	0.04		0.04		0.06	

[1] December 1996 prices in NIS (U.S. $1 = 3.244 NIS).

The following analysis is based on the values of time and bus penalties calculated for each of the models. VOT is computed respectively for each mode as the ratio between the in-vehicle time coefficient and the cost coefficient, and the bus penalties are computed by dividing the different out-of-vehicle time coefficients by the in-vehicle bus time coefficient. Table 5 presents the results.

Table 5. Values of Time* and Bus Penalties

	Model A	Model B	Model C	Model D	Model E	Model F
Cd—VOT (NIS/hr)	52.9	43.7		40.3	46.9	57.6
Cp—VOT (NIS/hr)	43.8	28.6	5.1	9.9	27.5	64.8
Bus—VOT (NIS/hr)	5.5	7.5	6.9	17.6	11.0	4.2
Bus walk time penalty	1.4	0.8	1.6	2.1	0.5	1.1
Bus wait time penalty	2.0	2.6	1.9	1.1	1.5	6.1
Bus transfer penalty	19.2	17.3	13.3	13.5	12.4	14.2

* December 1996 prices in NIS (U.S. $1 = 3.244 NIS).

As expected, car driver VOT is higher in all models than car passenger and bus VOT, with exception of model F, where VOT for car passenger is highest. The comparison across the models shows a general pattern; that is when car VOT increases (both for drivers and passengers), bus VOT decreases. Note also the low VOT for the segment without car (Model C). The last three models, corresponding to the segmentation according to IMC, exhibit a systematic pattern: VOT for car driver and car passenger increases with increasing VOT, and VOT for bus passenger decreases with increasing VOT.

The comparison of the bus penalties shows less consistent results. We expected significantly higher penalties for higher income populations. Since the walk time coefficients in all models segmented by IMC are not significant at the 90 percent level, it is not possible to draw conclusions for the walk time penalty. The wait time penalty can be compared, and the results show that this value is quite high for high IMC (model F), which is consistent with the high VOT found for this segment.

The transfer penalty was found quite similar for each of the models. We also found in the literature similar values for the transfer penalty. Lin et al. (1997) estimated an intermodal transfer penalty of 15 minutes for New York and New Jersey commute corridors, using RP and SP data for car and transit riders. In a study for work trips in Boston (Central Transportation Planning Staff 1997), the transfer penalty ranges from 12 to 15 minutes of in-vehicle time for urban mode choice modeling. In Israel, the planning agencies are also currently using 12 to 15 minutes of in-vehicle time in transit mode choice and assignment model implementations.

Summary and Conclusions

IMC as an independent variable in the logit model for estimation of the population choice parameters for modal split modeling was proposed in this article as a possible replacement to the income variable for both practical reasons and qualitative conceptual reasons. The ultimate test to verify the most suitable variable is a database that contains both IMC and income; the latter variable was not available in our database.

In the tests presented in this study, we found that segmentation of the population in three categories of IMC yielded significantly different models of the preference systems for the three populations. These findings suggest that the IMC is a viable variable for market segmentation.

The IMC parameter has limitations that need to be acknowledged. First, even if people tend to maintain certain standards of car ownership, they usually keep their cars for two to three years, sometimes even for four years or more. Automobile market value in Israel drops 8 to 20 percent per year (typically 15% per year). Thus, a typical household may be very easily classified 20 to 30 percent above or below the average IMC of the household; that is, the typical household might be classified at a lower or higher category of IMC than to which it actually belongs.

This limitation is inherent to the IMC variable and the proper way to deal with it, using the present data conditions, is to have the segments broad enough to allow the marginal crossover from one IMC category to another.

A more rigorous solution to this problem would be to estimate the average reference year for car possession in the household. This can be done in subsequent surveys by asking respondents how many years they kept their previous car, how many years they have had the present car, and how many years they intend to keep it. Such a procedure would enable the researcher to get a more reliable estimate about the true IMC of the household, and would thus allow for a more refined segmentation of the population.

The second problem with the IMC variable is related to the way the variable was calculated. The available database provided two types of information: car production year and vehicle engine size. This relatively limited information forced us to compute for each combination of these variables an average value for all vehicles belonging to the same category. However, there is a wide variation in the market value of different cars with the same production year and engine size. For example, for production year 1992 and engine size group of 1600 to 1800 cc, the weighted average of the market value for cars in this group in Israel was estimated at 49,200 NIS in 1996 prices (about U.S. $15,166). However, prices ranged from as low as 33,000 NIS to 80,000 NIS for the same combination of year and engine size.

This problem can be easily solved by adding a simple question in the survey about car make. This information is quite easy to obtain, since most drivers know the make of their car. For example, the 2001 U.S. NHTS (2004) included information about car make, which could be employed in the procedure suggested here.

Finally, the IMC parameter appears to have a rather wide variance when it is derived from questionnaires that have not been designed to minimize this variance. The variance can be minimized to make the IMC a much sharper tool for segmentation purposes.

Reduction of the variance as a result of the market cost of different car makes can be achieved very easily by adding a simple question. However, reduction of the variance due to the tendency of car owners to keep a car more than one year and the difference between car owners as regards the period of car possession calls for a more detailed inquiry. As already pointed out, it would be reasonable to add questions about how many years drivers kept previous cars, how long the present cars were in their possession, and how long they intended to keep these cars until the next car acquisition.

References

Badoe, D.A., and D. J. Miller. 1998. An automatic segmentation procedure for studying variations in mode choice behaviour. *Journal of Advanced Transportation* 32(2): 190–215.

Central Bureau of Statistics. 1997. *National travel habits survey* (in Hebrew). Report prepared for the Israeli Ministry of Transport.

Central Transportation Planning Staff. 1997. *Transfer penalties in urban mode choice modeling*. Report prepared for the Federal Transit Administration.

Data Management Group. 1990. *TTS version 3 data guide*. Joint Program in Transportation, University of Toronto.

Dehghani, Y., and A. Talvitie. 1980. Model specification, modal aggregation, and market segmentation in mode-choice models: Some empirical evidence. *Transportation Research Record* 775: 28–34.

Hensher, D. A. 1976. Market segmentation as a mechanism in allowing for variability of traveller behaviour. *Transportation* 5(3): 257–284.

Levi-Itzhak. 1996. *Car price tables* (in Hebrew). December 1996.

Lin, R., R. M. Pendyala, and S. Polzin. 1997. Assessment of intermodal transfer penalties using stated preference data. *Transportation Research Record* 1607. Washington, D. C. National Research Council, 74–80.

National Household Travel Survey User's Guide 2001. Available online at http://nhts.ornl.gov/2001/usersguide/index.shtml. Accessed July 2004.

Outwater, M. L., V. Modugula, S. Castleberry, and P. Bhatia. 2004. Market segmentation approach to mode choice and ferry ridership forecasting. *Transportation Research Record* 1872: 71–79.

Pas, E. I., and J. C. Huber. 1992. Market segmentation analysis of potential inter-city rail travelers. *Transportation* 19: 177–196.

Perlstein-Galit Company Ltd. 2001. *Travel demand forecasting model*. Report prepared for NTA—Mass Transit System for the Tel Aviv Metropolitan Area.

Salomon, I., and M. Ben-Akiva. 1983. The use of the life-style concept in travel demand models. *Environment & Planning A* 15(5): 623–638.

Sonquist, J. N., E. L. Baker, and J. N. Morgan. 1971. *Searching for structure*. Institute for Social Research, University of Michigan, Ann Arbor, MI.

Taskir Company Ltd. 1995. *Household survey in the Haifa metropolitan area* (in Hebrew). Report prepared for the Netivey Carmel Company.

About the Authors

Shlomo bekhor (*sbekhor@technion.ac.il*) is a senior lecturer in the Faculty of Civil and Environmental Engineering at the Technion—Israel Institute of Technology, Haifa, Israel. His main areas of interest include route choice modeling, network equilibrium models, and innovative transport systems.

Alon Elgar (*elgaralon@yahoo.com*) is an independent consultant. He previously worked as a senior planner (economist) in the Israel Ministry of Transport and the Jerusalem Municipality. His main areas of interest and activities are long-term spatial planning, planning methodology, and economic evaluation of transportation projects.