Discrete Choice Models with Dynamic Effects: Estimation and Application in Activity-Based Travel Demand Framework

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Abstract

Most of the travel demand models in practice are estimated on a single-year cross-sectional data, which makes the model inherently static. This means that the underlying assumption in the model application for future years is that individual's behavior will remain constant over time and the changes will be entirely driven by the explanatory variables such as socio-economic characteristics, land-use, and transportation Level of Service (LOS). However, this assumption is not necessarily true. Individual's perception of different travel conditions and, thus, their travel behavior may also vary over time.

The paper illustrated how the model attributes which are dynamic over a period of time can be incorporated in a travel demand model in practice. The existing approach in practice is usually the aggregated calibration approach. In aggregate calibration approach, the core disaggregate model is estimated in a purely cross-sectional fashion (based on the latest available survey). Subsequently the model is calibrated for the base year and if needed re-calibrated to the future market share that has to be established externally. The model might benefit from adjustment of the corresponding constants for future years to reflect better the observed tendencies. However, this approach requires multiple scenarios to test. The approach described in this paper is a disaggregated approach where time trends were explicitly included in the estimated model as explanatory variables. The performances of these two approaches were compared with real data and concluded that two independent and different techniques proved to be in agreement at the aggregate level.

Keywords: dynamic discrete choice, multiple year cross-sectional data, auto ownership

Objective and Motivation

Most of the travel demand models in practice are estimated on a single-year cross-sectional data, which makes the model inherently static. This means that the underlying assumption in the model application for future years is that an individual's behavior will remain constant over time and the changes in travel behavior will be entirely driven by the changes in explanatory variables such as socio-economic characteristics, land-use, and transportation Level of Service (LOS). However, this assumption is not necessarily true. An individual's perception of different travel conditions and, thus, their travel behavior may also vary over time. Moreover, there are several sub-models of travel demand model which are very dynamic in nature, such as the share of telecommuters. The proportion of telecommuters and those who work from home permanently (that had been almost negligible until 2000s) has grown significantly over the past 10 years due to improvements in communication and computer technologies. This share is expected to continue growing in future years [1, 2, 3]. Travel models are developed with an eye towards application for future years and, thus, it is very important to incorporate the dynamics of travel attributes in travel demand models to make travel forecasting more realistic.

One of the traditional approaches to handle the dynamics of travel attributes in a model application for future scenarios is an aggregate calibration approach. In this approach, the travel model is estimated for the base year but then it is calibrated to match the aggregate shares of the travel attributes for the future year obtained from an independent source (or sub-model). This approach is highly reliant on the availability of calibration targets for future years and adds an additional calibration step in the implementation of the travel model for future years that is also conceivable to be implemented according to multiple scenarios. For example, given that today approximately 5% of workers work from home and this share is growing, it is possible to form 10% and 15% work-from-home scenarios for the year 2030 and calibrate the travel model to replicate the corresponding target for each scenario. In practical terms, this approach may be preferred since it has the necessary transparency and calls for an active involvement of the practitioners in the forecast. But, this somewhat arbitrary recalibration of the model for future years does not affect the behavioral richness of the originally estimated model since all variables and corresponding coefficients are preserved except for the most generic global calibration constants added to the model. Thus, individual's perception to different variable remains constants in this approach.

Due to the need of better understanding of dynamics of travel, there has been an increasing focus on collecting multi-day surveys. This will help in understanding dynamic responses beyond the traditional cross-sectional analysis. Multi-day surveys can help in understanding the dynamic aspects of daily travel. For example, it can help in locating usual shopping places for individual, which will help in modeling the activity location of shopping trips. This will be a big step towards improving the location choice models for daily activities. But, these multi-day surveys do not see variations in long-term attributes such as work location, telecommuting frequency, work from home, auto ownership, *etc*. and, thus, they do not help in understanding dynamic aspects of long-term travel attributes. A longitudinal dataset collected over multiple years for the same set of households is likely to be more informative to understand the dynamics of long-term travel attributes [4]. Such data is very expensive to collect and is often bound to a small sample size [5].

The aim of this paper is to formulate a robust and behaviorally appealing approach to handle dynamics of travel model, instead of relying on traditional aggregate calibration approach, without using longitudinal dataset. Thus, a part of the motivation of this paper is to address the data availability issues to capture the dynamics of travel behavior.

Modeling Approach

The fundamental idea of the model formulated in this paper was to include the time trend variables in the disaggregate estimation of long-term models. The inclusion of such trend variables is possible when cross-sectional datasets of multiple years are available. Thus, this approach is more data-driven than aggregate calibration approach and requires disaggregate data points for multiple years. Even though a longitudinal dataset is ideal for long-term choices evolution model, the model development using several cross-sectional datasets still helps in understanding and distinguishing the impacts of varying demographics and urban environment variables (as well as other cross-sectional variables) from long-term trends that reflect the changing travel attributes. This paper shows possible formulations of such models with dynamic effects which can be estimated and applied easily in travel demand models in practice. This method can be eventually applied in combination with an aggregate calibration for future year, although the hope is that the need for aggregate controls for future years will be mitigated by the dynamic effects embedded in the disaggregate model in the first place. Using multiple year cross-sectional data is a practical compromise between a longitudinal data and single year cross-sectional data.

This paper takes an example of auto ownership model to illustrate how the dynamic long-term models can be estimated and applied. The growing in the aggregate auto ownership level in the western countries, such as the US, has been more or less saturated over the past years [6]. However, in many European and Asian countries, there has been a substantial increase in the auto ownership level in past few decades and the existing car ownership levels are still far from saturation [7, 8]. Similar trends were observed for the Jerusalem, Israel, metropolitan area, where the household auto ownership increased drastically in past 15 years differentially for 3 major population sectors in Jerusalem, see Figure 1. There was quite a strong tendency for a growing number of cars for the secular Jewish and Arab sectors while number of cars for the ultra-Orthodox Jewish population did not grow that substantially and remained very low. The tendency of increase in household auto ownership in Jerusalem is expected to continue for next few decades. Auto ownership model is one of the most important components of travel demand models. Household auto ownership strongly affects the activity participation. A household with more cars is likely to participate in more activities as potentially more activities are accessible by autos [9, 10]. Also, household car ownership directly affects the trip mode choice as driving modes will be unavailable for households without any cars. Thus, it is absolutely necessary to incorporate this auto ownership evolution in travel demand model for Jerusalem to address the expected changes in travel behavior in the future. Even though the dynamic auto ownership model may not be required in Western countries such as the US, a similar methodology can be used for other travel attributes that exhibit dynamic trends such as frequency of telecommuting or work from home.

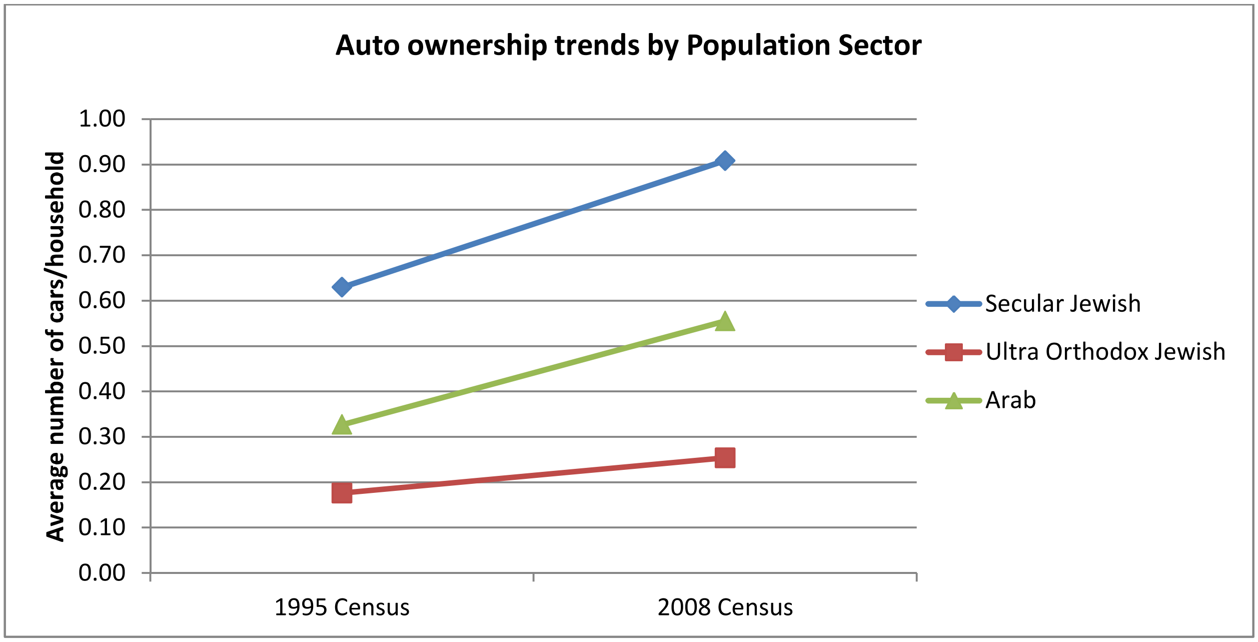

Figure 1: Auto ownership trends by Population Sector in Jerusalem

Data

The dataset for model development was created by pooling together independent cross-sectional datasets for multiple years with a different (randomly recruited) set of households for each year. Three independent household surveys conducted in 1996, 2010, and 2014/15 were used to estimate the current model. Table 1 shows the number of household records by population sectors for the three cross-sectional data.

Table 1: Number of households by Population Sector for three cross-sectional data

Year	Population sector			
	Arab	Ultra-Orthodox Jewish	Secular Jewish	Total
1996	128	310	1,651	2,089
2010	1,224	2,119	4,887	8,230
2014/15 (first wave)	167	262	657	1,086

The preliminary model estimation included only the first wave from 2014/15 survey. Since, this was an ongoing survey; the model estimation will be updated with the completion of more wave as more households will help us exploring richer behavioral trends. Nonetheless, the preliminary estimation showed promising insights on the dynamic aspects of auto ownership choice.

Model Structure

At the current stage of research, the choice model was specified as a simple multinomial logit model but including time trend components in the utility functions. Unlike a longitudinal dataset, which includes the observations from same household spanning over multiple years, each household record in the pooled dataset is independent due to randomly selected different set of households for multiple years. Thus, the current model structure doesn't need to account for the correlation across different household records. The focus of the research is on the analysis of dynamic trend components. The core model can be extended to incorporate possible nesting effects as well as random coefficients. The utility equation for auto ownership level *i* for year *t* can be written as follows:

$$U_{nit} = \beta_i X_{nt} + \gamma_i Y_{nt} f(t) \tag{1}$$

Where,

n represents the household ID,

X_{nt} and Y_{nt} are the explanatory variables for year "*t*" and household "*n*",

β_i and γ_i are the coefficients on explanatory variables X_{nt} and Y_{nt}, respectively, for i^{th} car ownership level,

$f(t)$ is the parameterized trend function

The alternatives in the auto ownership choice model were specified as follows:

1. 0 cars
2. 1 car
3. 2 cars
4. 3+ cars

It should be noted that choice process for the respondents in a particular year might be influenced by various observed and unobserved attributes [11]. In the auto ownership context, the differences in auto ownership levels across different years could be attributed to several reasons, such as changes in the average number of adults per household, changes in the proportion of high income households, changes in accessibilities *etc*. The model should be specified to incorporate such changes and, in general, control for the variation in the demographic and lifestyle variables that affect car ownership cross-sectionally. Thus, it is very important to ensure that the trend function is applied on <u>top</u> of a rich set of explanatory variables to control for the changes in demographic and accessibility variables. After accounting for the changes in demographics and accessibilities, trend function serves as a proxy for unobserved attributes that affected the auto ownership changes from one year to the other. Furthermore, rather than specifying these trend function as additive terms to the standard utility expressions, these trend functions were interacted with the demographic variables. This is essential to understand the potentially different long-term car ownership trends in different population markets. For example, as discussed earlier, different population sectors in Jerusalem have shown very different aggregate car-ownership growth tendencies for the last 15 years.

The adopted parameterization of trend functions and subsequent analysis enable the model to be applied to future year scenarios. This is different from several prior attempts to capture dynamic effects by having year-specific dummies. A model with dummies specified for each year in the dataset may produce a better statistical fit as well as give insights regarding the past trends but it does not have an extrapolative power into future years.

Major Results

The estimated results for the dynamic auto ownership model are shown in Table 2. It can be seen that the model includes a rich set of household, individual, and transportation accessibility variables. The following section includes a discussion on the estimated coefficients.

Household Characteristics

Household sector: The constants in the model were completely segmented by population sector due to very significant differences in lifestyle across different population sectors (see [12] for more details on lifestyle differences across the population sectors). It can be observed that secular Jewish households tend to have higher car ownership. This was expected because secular Jewish households tend to exhibit similar characteristics as the households in most urban metropolitan areas in the Western world.

Number of workers: As expected, households with more workers tend to own more cars. This could be because workers tend to make trips to work frequently (weekday) and due to frequent travel, the need of car may be higher (see [13] for similar results).

Household size: Households with more members were found to own more number of cars. This could be because more members will create greater need to own a car and, thus, more likely to own cars. Similar results were found in [14].

Household income: Household income is one of the most important variables in auto ownership models. It dictates the purchasing power and, thus, the capability to purchase cars. As expected, higher income household were observed to own multiple cars (for similar results see 15).

Presence of children in household: Presence of children in household affects the need to own the car. Based on the model estimation, we can conclude that households with children were more likely to have high car ownership. Children affect the mobility of household because it may not be easy to take transit to engage in certain activities with children. Thus, it might increase the need to own multiple cars. For similar results, see [16].

Single family household: It was found that single family households were more likely to have higher car ownership. It could be because of the ease in finding parking for single family households. Several researchers have found a positive correlation between parking supply at home and car ownership (for example, see [17]). Thus, households in more parking spaces are more likely to have high car ownership.

Accessibility Measures

In addition to the usual household variables such as number of workers, presence of children, household size, household income, *etc*. individual auto dependency variables were included in the model estimation. The auto dependency was calculated as a function of "gain" in travel time to usual work/school location by auto mode when compared to transit mode. The higher value of auto dependency implies a greater need to own a car for regular commuting. The auto dependency at the household level is calculated as the sum of the auto dependencies of household members. Interestingly and contrary to the authors' experience with similar models for the US cities, the auto dependency was found to be insignificant for the Jerusalem metropolitan region. However, the aggregate zonal accessibilities to non-mandatory activities (representing potential non-commuting trips for shopping and other discretionary purposes) proved to be a significant determinant in explaining the car ownership level in a household in a way similar to the model developed for the US. Households located in areas with a better walk or transit accessibility had a logical propensity to have a lower car ownership level. Aggregate zonal accessibility measures are important variables in auto ownership models as these measures capture the supply side of decision making.

Trend Variable

The focus of this paper was to analyze how the dynamic trends in auto ownership can be captured in the model. In the model estimation, the trend variable was defined as the number of years elapsed after 1996. As mentioned earlier, trend variable should be added only after including a rich set of explanatory variables so that the effect of any change in demographic and accessibilities can be separated from trend effect. Both linear and polynomial functions of the trend variable were tested in order to capture possible saturation effects. The linear trend variable was found to be the most significant to explain the dynamics of auto ownership level.

<u>Household sector:</u> As discussed earlier, the changes in the auto ownership level in Jerusalem from 1995 to 2008 vary significantly by the household sector. Due to the differential changes in auto ownership growth rate by household sector, the trend variable was interacted with the household sector. It can be inferred from the estimated coefficients on the trend variable by population sector that the rate of increase in car ownership over time is highest for the Arab households and lowest of ultra-Orthodox Jewish households. In other words, Arab households are catching up with secular Jewish households and there might not be any differences in car ownership level between Arab and secular Jewish households in future years.

<u>Household income:</u> In addition to the interaction with population sector, the trend variable was interacted with several other demographic variables. The most significant interaction was found to be with the high income household indicator. The rate of increase in car ownership was found to be the lowest of the high income households reflecting the fact that most households in this category had the necessary number of cars already in 1996. Thus, their approach to car-ownership decisions has not changed much in the last 15 years and will probably remain similar in foreseeable future. It is different with low-income population in Jerusalem whose car-ownership attitude has been transforming over time and will probably continue to change in future. In the 1990s in Jerusalem, owning a car (and especially having more than one car in a household) was a luxury of higher income people. Today, cars

are more affordable to the general population and households do not have to belong to the higher income category to own multiple cars. It is expected that over a longer period of time (20-30 year into future) household income will stop playing a significant role in the car ownership decisions (as observed in the US today). However, given the current car ownership levels in Jerusalem for the short-term and mid-term forecasts it is important to connect the present and future in the most plausible way and reflect these differential trends by population sector and income group.

Table 2: Estimation results for auto ownership model

Variables	Number of cars							
	0		1		2		3+	
	Coeff	T-stat	Coeff	T-stat	Coeff	T-stat	Coeff	T-stat
Constants by population sector								
Arab			-1.405	-6.97	-5.496	-10.23	-9.368	-7.23
Ultra-Orthodox Jewish			-1.738	-11.05	-4.095	-14.00	-6.820	-12.69
Secular Jewish			-0.659	-6.27	-2.366	-12.37	-5.578	-18.12
Household Variables								
Number of workers			0.483	25.27	0.966	25.27	1.448	25.27
Household size			0.050	5.40	0.101	5.40	0.151	5.40
Household Income								
0-3,500 NIS			-1.787	-19.96	-3.573	-19.96	-5.360	-19.96
3,501-7,000 NIS			-0.817	-15.43	-1.633	-15.43	-2.450	-15.43
7,001-11,000 NIS (base)								
11,001-19,000 NIS			1.236	3.42	2.472	3.42	3.709	3.42
19,001+ NIS			2.004	5.37	4.008	5.37	6.012	5.37
Presence of children in household			0.065	1.42	0.129	1.42	0.194	1.42
Single family household (dwelling type)			0.414	5.50	0.827	5.50	1.241	5.50
Accessibility to non-mandatory activities from home location								
Log(1+walk accessibility)	0.033	2.43						
Log(1+transit accessibility)			-0.036	-5.38	-0.072	-5.38	-0.108	-5.38
Trend: Linear (year - 1996)								
Arab			0.171	11.64	0.305	8.24	0.415	4.62
Ultra-Orthodox Jewish			0.048	4.33	-0.008	-0.41	-0.067	-1.43
Secular Jewish			0.082	10.21	0.079	6.89	0.070	3.62
Linear trend × high income (11,0001+ NIS)			-0.035	-1.38	-0.069	-1.38	-0.163	-2.17

Performance Evaluation

This paper illustrated two approaches which can be used to handle the dynamics of certain travel attributes. A very important practical aspect is to compare the actual performance of these two approaches with real data and also evaluate the need for possible synthesis of both approaches. The performances of aggregate and disaggregate approaches to model auto ownership for Arab households in Jerusalem over the period 1996-2040 are shown, as an example, in Figure 2. The Arab households were chosen because of the strong observed and expected dynamics in car ownership for Arab population. The disaggregate model described below was applied for the synthetic population as part of the Activity-Based Model (ABM) application. The aggregate model was developed independently using longitudinal aggregate data and regression (and time series analysis) techniques without a consideration of a multitude of individual explanatory variables.

It can be concluded from Figure 2 that the disaggregate approach was able to capture a similar profile as that of aggregate approach. It is a remarkable result that two independent and different techniques proved to be in agreement at the aggregate level. However, the biggest advantage of having a disaggregate auto ownership model is that it has the ability to capture the impact of any unforeseen changes in demographics and land-use variables used as the explanatory variables, which would be very difficult to incorporate in aggregate calibration approach.

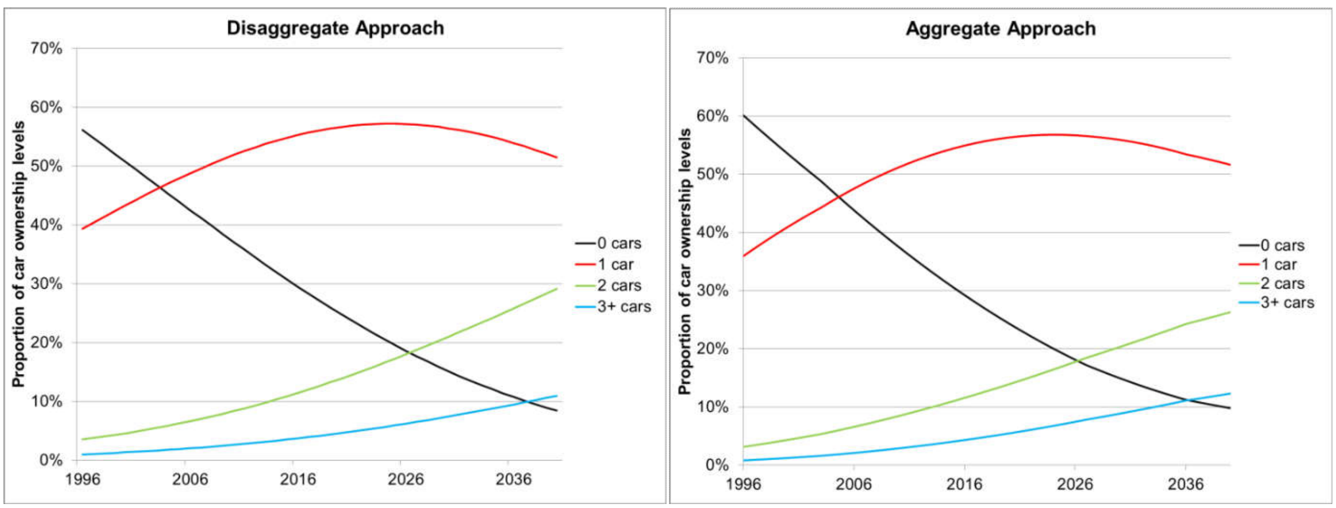

Figure 2: Performance evaluation of Arab car ownership prediction by disaggregate and aggregate approach

This approach should be used with caution when applied for a distant future. The trend functions are estimated using the observed data of multiple years. When the model is applied to future years, the trend function is extrapolated to the future year. The extrapolation could sometimes yield unreasonable results if the growth rate was very high for the observed years. See Figure 3 for an example. In this paper, the trend function was estimated using the data from 1996, 2010, 2014/15. Let's consider a hypothetical growth curve as shown in Figure 3. It can be seen that if when this growth rate is extrapolated to distant future years, the average car ownership goes as high as 1.5+ cars per households (which is an unreasonably high value). In such scenarios, an aggregate calibration may be required to restrict the growth after certain value (can be called as saturation level). The saturation level can be set based on the data from different regions. For example, the saturation level for car ownership in Jerusalem can be set to the average car ownership in high income households in developed countries.

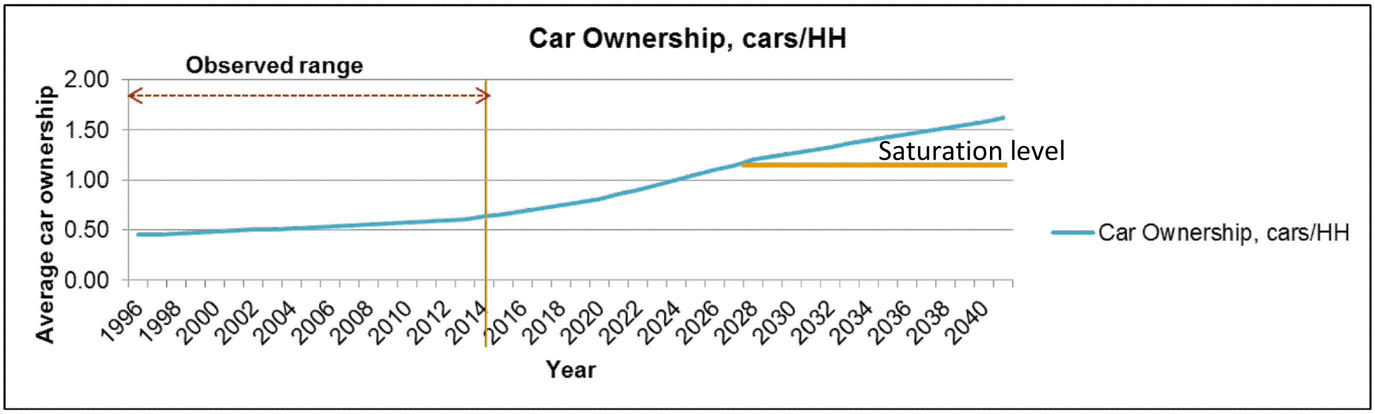

Figure 3: Illustration of issues with extrapolation of growth curves for long-term forecast

Conclusions

The paper illustrated how model attributes which are dynamic over a period of time can be incorporated in a travel demand model in practice. The existing approach in practice is usually the aggregate calibration approach. In this approach, the core disaggregate model is estimated in a purely cross-sectional fashion (based on the latest available survey). Subsequently the model is calibrated for the base year and if needed re-calibrated to the future market share that has to be established externally. This approach can take an advantage of an independent data source which can describe the market share evolution at an aggregate level. This is conceivable and practical for such model dimensions as usual work arrangements (telecommuting frequency and work from home, in particular), mobility attributes with such details as car type or transit pass holding, total regional VMT growth linked to the average commuting distance over time and tour/trip frequency, etc. In all this cases, the model might benefit from adjustment of the corresponding constants for future years to reflect better the observed tendencies. However, this approach requires multiple scenarios to test.

The approach described in this paper is a disaggregate approach where time trends were explicitly included in the estimated model as an explanatory variable. This approach requires more survey data with multiple years as data points. However, this approach does not require a true longitudinal survey which includes data collection for the same household over multiple years. In fact, the approach shown in this paper benefits from using pooled dataset from independent HTSs collected in different years. Using independent HTSs eliminates the correlation across multiple-year data points for the same household and, thus, a simple multinomial logit model structure can be used for capturing the main dynamic in auto ownership.

These two approaches were applied for Jerusalem region and their performance was compared to each other. It can be concluded that disaggregate approach was able to capture a similar profile as that of aggregate approach, with an ability to handle the impact of unforeseen changes in demographics for future year. However, the forecasts for future year should be used with cation as the extrapolation of the trend function may lead to unreasonable results. In such scenarios, aggregate controls might be required. Although, the hope is disaggregate model with trend variable will still be closer to the reality.

Even though a dynamic auto ownership model may not necessarily be of great importance in countries where the auto ownership levels have reached a saturation state, a similar methodology can be used to model other dynamic attributes, such as telecommuting, working from home, *etc*. which will help in making the travel models more realistic for the future year implementation.

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