A meta-model of vehicle ownership choice parameters

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Abstract This paper builds a meta-model of vehicle ownership choice parameters to predict how their values might vary across extended periods as a function of macroeconomic variables. Multinomial logit models of vehicle ownership are estimated from repeated cross-sectional data between 1971 and 1996 for large urban centers in Ontario. Three specifications are tested: a varying constants (VC) model where the alternative specific constants are allowed to vary each year; a varying scales (VS) model where the scale parameter varies instead; and a varying scales and constants model. The estimated parameters are then regressed on macroeconomic variables (e.g., employment rate, gas prices, etc.). The regressions yield good fit and statistically significant results, suggesting that changes in the macroeconomic environment influence household decision making over time, and that macroeconomic information could potentially help predict how model parameters evolve. This implies that the common assumption of holding parameters constant across forecast horizons could potentially be relaxed. Furthermore, using a separate validation dataset, the predictive power of the VC and VS models outperform conventional approaches providing further evidence that pooling data from multiple periods could also produce more robust models.

Keywords Meta-model · Temporal transferability · Vehicle ownership modeling · Joint context estimation · Travel demand forecasting

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Introduction

In forecasting travel demand, the prevailing practice is to estimate disaggregate travel demand models using the most recent travel survey data available for a particular urban region. Once the parameters have been estimated, the model is used to project future transportation demand with the inherent assumption that the parameters remain constant over the forecast horizon. However, despite recent significant modeling advancements in travel behavior theory, there are two broad issues that require further consideration regarding existing travel demand forecasting practices.

First, it is not uncommon to see demand studies that project over periods of up to 30 years into the future. US Federal statutes, for example, require Metropolitan Planning Organizations to prepare long-range plans with horizons of 20–30 years (NCHRP 2012). It is therefore questionable whether the assumption of the parameters holding constant would remain valid; i.e., these models may not be transferable over such extended periods. If this assumption does not hold, then there would be significant errors in the predicted behavior due to the differences between the estimated model parameters and their true future values.

Second, current best practices in travel demand forecasting place a strong focus on using the most recently available data, especially for areas that have high growth (NCHRP 2012). While using up-to-date data is clearly important, this often leads to ignoring older datasets and the models estimated from them, which could potentially be an illuminating source of information. For instance, retrospectively examining how travel behavior has changed temporally could provide valuable insights, such as how age and gender differences have become less important indicators of vehicle ownership (Sanko et al. 2009). More importantly, pooling data together from different time periods has also been demonstrated to enhance a model’s explanatory power (Badoe and Miller 1998).

Objectives

This paper addresses these two concerns by building a meta-model of how the parameters of disaggregate travel demand models vary over time as a function of macroeconomic explanatory variables. The authors illustrate this meta-model approach by focusing on modeling the evolution of alternative specific constants (ASCs) and scale parameters. In order to test this hypothesis, multinomial logit (MNL) models of vehicle ownership are estimated from repeated cross-sectional data between 1971 and 1996 that are representative of large urban centers in Ontario. Three specifications are tested that allow only constants, only the scales, and both the constants and constants to vary in the estimation. The estimated ASCs and scale parameters are then regressed on macroeconomic variables (e.g., employment rate, gas prices, etc.) to see whether the evolution of the estimated parameter values could be explained by the regressors.

Since the parameters are direct manifestations of peoples’ preferences, which in turn are influenced by the macro environment, how these parameters evolve over time should reflect how macro conditions have influenced household vehicle ownership decisions. If the temporal variations of the parameters could be explained by other explanatory variables, then the issues raised earlier could be addressed through the following. First, it would be possible to predict how the parameters themselves might vary across the forecast horizon, which would relax the requirement of having the parameters hold constant over this period. Second, such an approach would make more efficient use of available data collected in the past to potentially build more robust models. These two assertions are tested by comparing the performances of the models above with conventional approaches.
Scope

This paper uses vehicle ownership to demonstrate the proposed methodology. Vehicle ownership is an important determinant of travel behavior, and it is intrinsically linked with household trip generation rates and mode choice. In addition, household structure, socioeconomic characteristics and accessibility are known to influence car ownership decisions (Potoglou and Kanaroglou 2008). These three broad factors change over time and are affected by macroeconomic conditions (e.g., a population’s income levels are inherently tied to the employment rate), and the changes of these explanatory variables could affect preferences (e.g., higher real incomes could shift the preferences—the betas—towards more automobiles). As such, household vehicle ownership serves as a good example of how preferences might vary over time due to the macro environment.

The paper focuses on explaining the evolution of the ASCs and scale parameters. The constants capture the average effect on utility of all unobserved factors (they are the mean of the error terms) and play a role similar to the constant in a regression model (Train 2009). The scale represents the level of uncertainty associated with how the observed factors affect utility levels by acting as the weights associated with the observable and unobservable terms in the utility function (Bhat et al. 2000). That is, as the scale parameter increases, the choice becomes more deterministic. Hence, any changes brought about by the macro environment not directly captured by the other parameters in the model could potentially be revealed by how the ASCs and scale parameters vary over time.

It is noted that the ASCs and scales do not directly explain the evolution of peoples’ preferences (e.g., ASC estimates are sensitive to model specification as well as to the market share evolution of the alternatives). Furthermore, the paper also does not account for any temporal change specific to the parameters associated with each explanatory variable. However, the purpose of the paper is to present a framework in which the temporal evolution of the parameters could be systematically captured via other macro variables that also change with time. Focusing on the ASCs and scales best demonstrates this objective for three reasons.

First, the ASCs capture the average effect of all unobserved factors, while the scale represents the level of uncertainty with the estimates. As such, any global factors that affect the estimates temporally are likely to be captured to a significant degree by the ASCs and scales. Second, the ASCs and scales are naturally defined when the MNL—the model used in this paper—is specified, which allows generalizing the results without having to worry about model specification. Finally, considering only the ASCs and scales scopes the analysis down to a manageable problem and clearly demonstrates the value of the work, in contrast with trying to draw conclusions from how each of the many explanatory variables change over time.

The rest of the paper is organized as follows. A brief literature review of vehicle ownership modeling is first provided, focusing on models that employ disaggregate choice approaches. In addition, the transferability and updating methods for disaggregate choice models are also reviewed to help establish the research context. Afterwards, the paper elaborates on the proposed methodology and details the structure of each of the choice models presented. This is followed by a description of the data sources used to estimate the models, which are 19 years of cross-sectional data between 1971 and 1996 for urban areas in Ontario. Then, the estimation results for both the vehicle ownership models and the subsequent parameter regressions are presented and discussed. The performance of the proposed methodology is then compared against conventional practices by evaluating their
fit and predictive capabilities using a separate validation dataset from 1997 to 2009. A conclusion follows that summarizes the main contributions of this paper.

**Literature review**

**Vehicle ownership**

There is quite a large literature on vehicle ownership modeling. For Canadian cities, Mohammadian and Miller (2003) present a dynamic model of household vehicle transactions for the Greater Toronto Area, while a more recent vehicle ownership study has been conducted by Potoglou and Kanaroglou (2008) who model car ownership in Hamilton, Ontario with a MNL formulation. Their model attributes include socioeconomic and demographic characteristics of the household (e.g., household income and size), the type of dwelling, land use and accessibility measures (e.g., mixed density indicators), and other travel related variables (e.g., home-to-work distance).

Other vehicle ownership studies are summarized by Potoglou and Kanaroglou who review modeling efforts since 1990. Some of the applied formulations in their review include ordered probit (Kim and Kim 2004; Chu 2002), OL (Bhat and Pulugurta 1998), MNL (Ryan and Han 1999; Purvis 1994; Bhat and Pulugurta 1998), and linear regression (Prevedouros and Schofer 1992). Similar to Potoglou and Kanaroglou, these works use socioeconomic and demographic attributes as well as dwelling type, land use patterns and other accessibility indicators as the explanatory variables of the discrete choice models.

While the works mentioned focus on modeling the household’s vehicle ownership decision, Sanko et al. (2009) conduct a temporal analysis of household vehicle ownership in Nagoya for the years 1981, 1991 and 2001. The authors use a bivariate ordered probit model that include accessibility indicators and household related information to examine how vehicle ownership has been influenced by these factors over two decades. They identify that age and gender differences have become less important indicators of car ownership over time due to increasing motorization. The authors point out that using explanatory variables which bring some information on economic conditions could improve model transferability, which is a concept discussed in the next subsection.

**Model transferability and updating**

The transferability of disaggregate choice models has been widely studied in the travel demand literature, notably by Koppelman and Wilmot (1982). Transferability can be classified in two dimensions. In spatial transferability, a model developed for one spatial area is applied to another; in temporal transferability, a model estimated using data collected at one point in time is applied to a different period. Model transferability is appealing, primarily due to the reductions in cost, time and data requirements they provide (Ben-Akiva 1979). Readers interested in transferability are referred to Fox and Hess (2010) for a thorough review.

In temporal transferability, a key issue is whether the model parameters remain constant over time. This is particularly important when the underlying spatial context changes. For instance, Forsey et al. (2013) examined the transferability of work trip mode choice models in a rapidly growing suburban area. They find that transferred models perform quite well, and argue the need for disaggregate choice models that are capable of addressing the systematic effects of land use and transportation changes over time.
There are a number of updating methods available that could be used to improve the performance of the transfer models being applied. In all cases, it involves updating some or all of the parameters of a model estimated from one context (the estimation context) so it could be applied to another (the application context). Updating methods generally fall under: Transfer Scaling (Gunn et al. 1985; Koppelman et al. 1985); Bayesian Updating (Atherton and Ben-Akiva 1976); Combined Transfer Estimation (Ben-Akiva et al. 1995); and Joint Context Estimation (JCE) (Badoe and Miller 1995; Ben-Akiva and Morikawa 1990).

JCE involves estimating a model simultaneously using both the estimation and application context data. Badoe and Miller (1995) demonstrated that JCE provides a flexible and efficient method for testing parameter stability over time. JCE was also found to be equivalent to or superior to other updating procedures among those tested. Given these points, JCE is adopted for use in this study. Note that this procedure could be generalized for using different data sources altogether, notably in estimating models that contain both revealed and stated preference data (Ben-Akiva and Morikawa 1990).

Temporal evolution of parameters

Many past works have applied the updating methods listed above, and a general conclusion is that updating models improve transferability. However, Badoe and Miller (1998) suggest that these updating methods are limited as they are not able to explain the inter-contextual transfer biases as a systematic function of variables that characterize the contexts of interests. Rather, updating methods are only corrective means to account for the observed transfer biases, given information on the application context. They argue that achieving intrinsically transferable choice models requires that the contextual factors be explicitly incorporated into the models themselves to allow credible prediction of how travelers’ preferences may vary across different contexts.

However, studies that attempt to explain the contextual variations of parameters are sparse. Elmi et al. (1999) examine the transferability of trip distribution models for the Greater Toronto Area and suggest that sensitivities to travel time have declined over a 32 year period due to the increasing spatial spread of the Toronto region. Fox and Hess (2010) point out that this spatial-related hypothesis might provide an approach for forecasting how model parameters may change over time. Sanko and Morikawa (2010) study the contextual factors that affect the temporal transferability of updated mode choice constants. They regressed the differences in the updated ASCs from two time periods and find that regional characteristics, inertia in behavior, and level of service changes can explain these differences. They conclude that understanding how the ASCs change could improve transferability.

Methodology

Overview

The proposed methodology attempts to explain the inter-contextual transfer biases as a function of macroeconomic variables. Unlike past works, multiple time periods are considered. The research employs a MNL to model household auto ownership levels (0, 1, 2, 3 or more vehicles) and follows the JCE approach by estimating the model using data from 1971 to 1996, with different specifications that allow for the ASCs, the scales or both to
vary across the survey years. Afterwards, the estimated ASCs and scales are then regressed on macroeconomic variables to test whether a relationship exists between the parameter variations and changes in the macro environment. If a relationship does exist, then the parameters themselves could be forecasted into the future when these models are applied. This meta-model approach is compared against conventional practices by evaluating their performance on a separate application dataset from 1997 to 2009.

This paper uses a MNL of vehicle ownership as opposed to an OL due to three theoretical advantages. First, an unordered representation is consistent with global utility maximization, while an ordered formulation (i.e., OL) is not (Bhat and Pulugurta 1998). Second, MNL is more flexible in representing the effects of the explanatory variables, which could reveal nonlinearities between the covariates and auto ownership levels. This is advantageous when examining the temporal variations of the parameters to show how their effects might have evolved over time. Finally, the ASCs of the MNL aid in the interpretation of the regression results, as they capture all the unobserved factors that affect the vehicle ownership choice and reflect the alternatives’ market shares. On the other hand, there is no clear interpretation of the cutoff points for the OL. Note that this paper focuses on accounting for the evolution of parameters over the forecast horizon. That is, the proposed method, and more importantly the intended contributions, holds regardless of whether OL or ML is used.

Specification

Three specifications of the joint context estimation are put forward.

1. A varying constants (VC) model where the ASCs are allowed to vary each year. This model pools all the data together in a single estimation procedure and contains dummy variables for each of the ASCs for every year. The utility of alternative \( i \) for individual \( q \) across \( k \) attributes is specified as

\[
V_{iq}^t = \mu_i + \sum_k \beta_{ik} X_{ikq}^t
\]  

where \( \mu_i^t \) refers to the ASC for \( i \) at period \( t \), \( \beta_{ik} \) are the estimated parameters for each attribute \( k \), and \( X_{ikq}^t \) are the associated attributes for that alternative.

2. A varying scales (VS) model where the data is again pooled together, but this time allowing the scale parameter to vary for each survey year instead. Utility is specified as

\[
V_{iq}^t = \lambda^t \left( \mu_i + \sum_k \beta_{ik} X_{ikq}^t \right)
\]  

where \( \lambda^t \) is the scaling parameter for period \( t \). Note that for identification purposes, the base year’s scale (\( \lambda^1 \)) is set to 1.

3. A varying scales and constants (VSC) model where both the scales and ASCs associated with each year are simultaneously estimated with the pooled data

\[
V_{iq}^t = \lambda^t \left( \mu_i^t + \sum_k \beta_{ik} X_{ikq}^t \right)
\]  

The formulation above follows from Badoe and Miller (1995) who separate \( X_{iq} \) into context-specific variables and those that are common to both periods. For the model
proposed, the yearly ASCs and scales are context-specific while all other parameters remain common across the 19 years. For the three specifications, the log-likelihood function is

\[
\ln(L) = \sum_{t=1}^{T} \sum_{q=1}^{N_t} y_{tq}^{i} \left( z_{tq}^{i} + \sum_{k} \beta_{jk} X_{tq}^{ik} - \ln \left( \sum_{j} \exp \left( z_{tq}^{j} + \sum_{k} \beta_{jk} X_{tq}^{jk} \right) \right) \right)
\]

where \( T \) is total number of periods, \( N_t \) is the number of households for period \( t \), and \( y_{tq}^{i} \) is an indicator variable which is 1 if individual \( q \) chooses alternative \( i \) during period \( t \). Note that for the VC model, \( z_{tq}^{i} = 1 \forall t \), while for the VS model, \( \mu_{tq}^{i} = \mu_{vt} \). These three specifications test whether any temporal variations in the estimated parameters could be (solely) explained by the ASCs or the scale parameters. After the ASCs and scale parameters from the VC, VS and VSC models have been estimated, linear regression is used to explain the variations of these parameters over time. Examples of the macroeconomic regressors include employment rates, gas prices, as well as the yearly variations of these variables.

Estimation and evaluation

MNL estimation is conducted using BIOGEME (Bierlaire 2003, 2009). The estimation package has a specific module that allows the scale parameter to be estimated for different groups, which in this case represents the periods. Regressions are carried out using the MASS package in R (Ripley et al. 2012). In particular, the stepAIC algorithm is employed to conduct stepwise regression with the Akaike Information Criterion (AIC) as the measure of fit.

After the VC, VS and VSC models have been estimated, their ability to predict vehicle ownership levels for future time periods (1997–2009) are compared against conventional approaches. Three benchmark models are used where each is estimated using the 1992, 1994 and 1996 data. These benchmark model represent modern practices, which is to take (only) the most current available data. In the evaluation, two cases are tested:

- using the estimated regression parameters, the future values of the VC, VS and VSC parameters (ASCs and scales) are predicted from 1997 to 2009, and these projected parameters are used in the evaluation exercise;
- the final estimated parameters of the VC, VS and VSC models (i.e., the 1996 ASCs and scales) are held constant across the evaluation period.

Note that the estimated parameters for the benchmark models are held constant across the entire forecast horizon. In evaluating the models, two measures of performance are used:

- the log-likelihood values for when the models are applied against the validation data;
- the mean absolute error (MAE) aggregate test statistic, defined as

\[
MAE_t = \frac{1}{N_t} \sum_{i} \left| \hat{N}_t^{i} - N_t^{i} \right|
\]

where \( \hat{N}_t^{i} \) is the predicted number of households that have a vehicle ownership level \( i \), and \( N_t^{i} \) is the actual count. \( \hat{N}_t^{i} \) is calculated using the sample enumeration approach:

\[
\hat{N}_t^{i} = \sum_{q} \hat{P}_{tq}^{i}
\]

where \( \hat{P}_{tq}^{i} \) are the probabilities of vehicle ownership.

Predictive measures, such as the MAE, have been used in the literature to assess transferability (Fox and Hess 2010). Furthermore, the evaluation metrics above are chosen
to be consistent with Badoe and Miller (1995, 1998), which has served as the foundation work for this research. Note that $MAE^g$ and $N^g_i$ can be segmented by group $g$ if market segments are of interest in the study.

**Data**

The dataset used in the estimation comes from the Household Income, Facilities and Equipment (HIFE) microdata files provided by Statistics Canada (StatsCan2006). The HIFE data are household observations that provide information on the household’s socio-demographic characteristics, dwelling attributes and number of vehicles. A subset of the HIFE data is used, which are observations that pertain to large urban centers in Ontario. Table 1 shows some summary statistics for the dataset given in approximately 5 year intervals. Note that the household income levels are expressed in 1996 dollars. Furthermore, household with incomes below Statistics Canada’s defined low income cut-offs are excluded for simplicity (this avoids having to build separate models that segment the population).

Over the 25 year period, some observable trends include: the slight shift towards single detached dwellings; the decrease in household sizes which include the increase of single individual households as well as the decline of households with children and young adults; the shift away from rental tenure; a slight increase in average room size; the increase in households without earners, which is perhaps due to retirees or young adults moving away to college; the relatively small increase in average incomes over the 25 year period; and the increase in vehicle ownership levels.

It is important to note that HIFE is not a vehicle ownership survey. Hence, some likely important data such as information on parking availability as well as vehicle operations and capital costs are not provided. More importantly, there is also no information on accessibility indicators as the observations are not disaggregated spatially. As such, it was also not possible to supplement the dataset to add spatial or accessibility dimensions. However, HIFE does provide 19 years of consistent data which is a rich source to explore changing household preferences. Furthermore, it is assumed that household size and income are likely very strong predictors of vehicle ownership, making HIFE a suitable dataset for this study.

Aggregate macroeconomic data are also used in the regression section of the methodology. The potential regressors pertain to Canada or Ontario, and include the employment rate, various bank rates, the consumer price index, components of the gross domestic product, gas prices, as well as yearly changes of these factors. Note that the HIFE data needed to be transformed by aggregating some of the categorical values together, as well as discarding some potentially useful variables. This is required to ensure consistency between HIFE and the Survey of Household Spending (SHS) (StatsCan2012), which is the dataset used to evaluate the models for the years 1997–2009.

**Estimation results**

Estimated MNL parameters

A description of the MNL model parameters are found in Table 2. Note that the X’s identify the vehicle level choice (e.g., ROOM_1 is the ROOM parameter for households with 1 vehicle). Hence, except for the scale parameter, three of each of the parameters
listed in the table are estimated. They correspond to the “1”, “2” or “3 or more” vehicles, with “0” vehicles as the reference alternative. To allow unbiased comparisons across the different specifications, the same model has been applied to the VC, VS, VCS as well as the benchmark models.

Note that the explanatory variables in the final models need to be defined consistently for both the HIFE (estimation) and SHS (validation) datasets. This is required so that the resulting models can be tested appropriately using the SHS data. Although a less limiting factor, there was also an attempt to keep the model parsimonious. It is hoped that these steps help reduce the correlation among the systematic attributes and decrease the possibility of overfitting, which are important for predictive purposes.

The estimation results for the VC, VS, VSC and benchmark models (BM92, BM94 and BM96) are shown in Table 3 and Figs. 1, 2, 3 and 4. Table 3 only contains the values for the parameters that are common across all periods, while Figs. 1, 2, 3 and 4 display how the ASCs and scale parameters vary across the 19 year period along with their corresponding p values. It is important to note that the VC, VS and VSC models have been estimated using household income expressed in 1996 dollars. This was needed to
differentiate the scale parameter from inflation effects. Furthermore, the weights for each household observation were adjusted to provide equal weighting for all the survey years used.

Table 3 shows that the estimated values have relatively similar magnitudes across the different models. Their signs are also consistent with expectations. For instance, the household income parameters are all positive and increase with vehicle ownership levels. This means that households with higher incomes have a higher propensity to own more vehicles. The EARN2, FSD and ROOM parameters also follow this trend and logic. In addition, having two or more adults in the household (ADLT2) tends to increase vehicle ownership levels, while renting (RENT) and having a small bedroom (SBR) have the opposite effect. (Note that the ADLT2 parameter is positive for all models and vehicle ownership level except for ADLT2_1 in BM92, where the parameter is insignificant.)

The KID0 estimates are interesting since having no children aged between 0 and 17 in the household decreases the probability of having 1 or 2 vehicles, but increases the likelihood of owning 3 or more vehicles. This may be due to different household life stages. On one hand, having no children could be an indicator of households made up of young adults who likely cannot afford vehicles. On the other hand, this could also be a sign of retiring empty nesters that have probably accumulated a number of vehicles across their lifetimes.

Most of the parameter estimates across all the models are statistically significant, while some results (e.g., SBR) are only significant for the VC, VS and VSC models. It is plausible that the effects of these variables on vehicle ownership have declined since the early 1970s, hence their insignificance for the BM estimates. It is important to note that the authors kept the insignificant parameters in all the models as the same formulation needs to be applied for the VC, VS, VSC and the three BM models to reduce any bias in their comparisons. Furthermore, all the resulting parameters appear to be significant in at least one of the six models for the most part. For these reasons, as well as to keep the study simple and transparent, the paper did not consider the effects of removing particular variables.

Table 4 then summarizes some overall fit measures for the models. While these fit values should not be directly compared as the models are estimated from different datasets with varying numbers of observations, the fit measures seem to suggest that the models do not exhibit markedly different performances from each other.

In order to gain some preliminary insight on the transferability of these parameters, t-statistics are calculated to test for parameter equality with respect to the 1996 benchmark.
| Coefficient | BM92 Est. | BM92 p val | BM94 Est. | BM94 p val | BM96 Est. | BM96 p val | VC Est. | VC p val | VS Est. | VS p val | VSC Est. | VSC p val |
|-------------|-----------|------------|-----------|------------|-----------|------------|---------|----------|---------|-----------|---------|-----------|
| ADLT2_1     | -0.040    | 0.760      | 0.232     | 0.050      | 0.116     | 0.360      | 0.227   | 0.000    | 0.263   | 0.000     | 0.219   | 0.000     |
| ADLT2_2     | 0.836     | 0.000      | 1.050     | 0.000      | 1.400     | 0.000      | 1.140   | 0.000    | 1.330   | 0.000     | 1.120   | 0.000     |
| ADLT2_3     | 0.761     | 0.010      | 0.695     | 0.030      | 1.630     | 0.000      | 0.628   | 0.000    | 0.726   | 0.000     | 0.622   | 0.000     |
| EARN2_1     | 0.527     | 0.000      | 0.180     | 0.160      | 0.134     | 0.330      | 0.014   | 0.660    | 0.018   | 0.690     | 0.017   | 0.650     |
| EARN2_2     | 1.320     | 0.000      | 0.962     | 0.000      | 1.000     | 0.000      | 0.738   | 0.000    | 0.874   | 0.000     | 0.720   | 0.000     |
| EARN2_3     | 1.800     | 0.000      | 1.920     | 0.000      | 1.440     | 0.000      | 1.480   | 0.000    | 1.770   | 0.000     | 1.450   | 0.000     |
| FSD_1       | 0.028     | 0.850      | 0.489     | 0.000      | 0.422     | 0.010      | 0.482   | 0.000    | 0.561   | 0.000     | 0.469   | 0.000     |
| FSD_2       | 0.506     | 0.000      | 0.979     | 0.000      | 0.855     | 0.000      | 0.885   | 0.000    | 0.995   | 0.000     | 0.862   | 0.000     |
| FSD_3       | 0.706     | 0.000      | 1.010     | 0.000      | 1.040     | 0.000      | 1.070   | 0.000    | 1.220   | 0.000     | 1.050   | 0.000     |
| HHINC_1     | 0.011     | 0.003      | 0.003     | 0.002      | 0.016     | 0.000      | 0.012   | 0.000    | 0.015   | 0.000     | 0.012   | 0.000     |
| HHINC_2     | 0.012     | 0.003      | 0.007     | 0.002      | 0.021     | 0.000      | 0.021   | 0.000    | 0.025   | 0.000     | 0.021   | 0.000     |
| HHINC_3     | 0.016     | 0.003      | 0.011     | 0.002      | 0.026     | 0.000      | 0.027   | 0.000    | 0.033   | 0.000     | 0.027   | 0.000     |
| KID0_1      | -0.264    | 0.000      | -0.263    | 0.030      | -0.214    | 0.110      | -0.312  | 0.000    | -0.328  | 0.000     | -0.298  | 0.000     |
| KID0_2      | -0.385    | 0.010      | -0.246    | 0.050      | -0.254    | 0.070      | -0.312  | 0.000    | -0.236  | 0.000     | -0.297  | 0.000     |
| KID0_3      | 0.292     | 0.080      | 0.207     | 0.160      | 0.337     | 0.040      | 0.208   | 0.000    | 0.374   | 0.000     | 0.204   | 0.000     |
| RENT_1      | -0.633    | 0.000      | -0.624    | 0.000      | -0.530    | 0.000      | -0.355  | 0.000    | -0.403  | 0.000     | -0.338  | 0.000     |
| RENT_2      | -1.100    | 0.000      | -0.948    | 0.000      | -1.130    | 0.000      | -0.646  | 0.000    | -0.716  | 0.000     | -0.614  | 0.000     |
| RENT_3      | -1.740    | 0.000      | -1.170    | 0.000      | -1.360    | 0.000      | -0.698  | 0.000    | -0.768  | 0.000     | -0.662  | 0.000     |
| ROOM_1      | 0.123     | 0.000      | 0.282     | 0.000      | 0.180     | 0.000      | 0.169   | 0.000    | 0.211   | 0.000     | 0.167   | 0.000     |
| ROOM_2      | 0.373     | 0.000      | 0.457     | 0.000      | 0.338     | 0.000      | 0.359   | 0.000    | 0.471   | 0.000     | 0.350   | 0.000     |
| ROOM_3      | 0.430     | 0.000      | 0.745     | 0.000      | 0.494     | 0.000      | 0.509   | 0.000    | 0.652   | 0.000     | 0.497   | 0.000     |
| SBR_1       | -0.235    | 0.080      | 0.234     | 0.070      | -0.228    | 0.090      | -0.077  | 0.020    | -0.089  | 0.040     | -0.073  | 0.040     |
| SBR_2       | 0.174     | 0.370      | -0.563    | 0.010      | -0.185    | 0.370      | -0.275  | 0.000    | -0.301  | 0.000     | -0.269  | 0.000     |
| Coefficient | BM92 | BM94 | BM96 | VC  | VS  | VSC |
|-------------|------|------|------|-----|-----|-----|
|             | Est. | p val| Est. | p val| Est. | p val| Est. | p val| Est. | p val| Est. | p val|
| SBR_3       | -0.764 | 0.110 | -0.309 | 0.490 | -2.180 | 0.050 | -0.833 | 0.000 | -0.982 | 0.000 | -0.828 | 0.000 |
| ASC1        | 0.789 | 0.010 | -0.035 | 0.910 | 0.094 | 0.760 | -0.056 | 0.580 |
| ASC2        | -2.520 | 0.000 | -2.990 | 0.000 | -3.350 | 0.000 | -4.620 | 0.000 |
| ASC3        | -5.160 | 0.000 | -7.310 | 0.000 | -7.260 | 0.000 | -8.730 | 0.000 |
model (Table 5) (Galbraith and Hensher 1982). It is interesting to note that some parameters \((ADLT2_3, KID0_2, KID0_3)\) reject the null hypothesis of parameter equality across the VC, VS and VSC models but are transferable across the benchmark models. This may be due to the changing household sizes and family structures (shown in Table 1) which would be captured by the VC, VS and VSC models but not the BM’s.

While a few other parameters do not support the hypothesis of parameter equality, most of the others appear to be transferrable across the models. While these transferability results are not valid in general, they do support the notion of focusing only on the ASCs and scales for this paper. Although not the focus of this paper, other formal measures could...
be computed to evaluate the transferability of the automobile ownership models, including the Transferability Test Statistic (Atherton and Ben-Akiva 1976) and Transfer Index (Koppelman and Wilmot 1982). In addition, it is noted that conducting the formal tests on the entire dataset could lead to different results.

Figure 1 below depicts the estimated ASCs for the 1 vehicle alternative for both the VC and VSC models (lines) as well as their corresponding p values (bars) from 1971 to 1996. The results clearly suggest that the ASCs for the 1 vehicle alternative are not significant across the 19 years. This could mean that most of the factors that influence owning 1 vehicle have been captured by the model. Figures 2 and 3 illustrate the corresponding

Fig. 3 Estimated ASCs for the 3 or more vehicles alternative and corresponding p values. Note that all p values for the VC and VSC specifications are zero

Fig. 4 Estimated scale parameters for the VS and VSC models. Most of the VSC scale parameters are insignificant
results for the other two alternatives. The ASCs for the 2 or 3 or more vehicles alternatives are significant throughout the entire period. Except for slight variations in magnitude, the VC and VSC ASCs appear almost identical. Disregarding the erratic changes from year-to-year, the ASC2 and ASC3 for the VC and VSC models appear to be increasing with time. This is consistent with the gradual rise in motorization levels observed from the data.

The slight variations in the VC and VSC constants in Figs. 2 and 3 are most likely due to the VSC model accounting for the scale changes from year-to-year. Figure 4 shows the evolution of the scale parameters for the VS and VSC models over time with 1971 as the base year (set to 1). While their magnitudes are different, the scales appear to move together and exhibit a relatively stable ratio ($\ast 0.8$). Except for 1973, the scale parameters for the VS model are all statistically significant.

One important thing to note is the high $p$ values for the VSC scale parameters, which offer strong evidence that the scales are statistically insignificant across the entire 19 year period. This seems to imply that the temporal instability is captured by the ASCs, which render scales invariant over time. This also means that when the varying ASCs are added to this model, the estimates for the other model parameters become more transferable.

### Table 4  Summary measures of fit for the models

| Model | BM92 | BM94 | BM96 | VC | VS | VSC |
|-------|------|------|------|----|----|-----|
| No. of estimated parameters | 27 | 27 | 27 | 81 | 45 | 99 |
| No. of observations | 5,701 | 6,668 | 6,005 | 86,257 | 86,257 | 86,257 |
| Null log-likelihood | -8,326.07 | -8,326.07 | -8,326.07 | -84,026.3 | -84,026.3 | -84,026.3 |
| Final log-likelihood | -6,019.37 | -5,950.91 | -5,762.87 | -59,426.6 | -59,845.9 | -59,389.0 |
| Adjusted rho-squared | 0.274 | 0.282 | 0.305 | 0.292 | 0.287 | 0.292 |

### Table 5  T-statistics for testing parameter equality with respect to BM96 values

| Variable | BM92 | BM94 | VC | VS | VSC | Variable | BM92 | BM94 | VC | VS | VSC |
|----------|------|------|----|----|-----|----------|------|------|----|----|-----|
| ADLT2_1  | 0.85 | 0.67 | 0.85 | 1.1 | 0.78 | KID0_1   | 0.26 | 0.27 | 0.72 | 0.82 | 0.61 |
| ADLT2_2  | 2.22 | 1.42 | 1.35 | 0.35 | 1.39 | KID0_2   | 0.65 | 0.04 | 0.4  | 0.12 | 0.3  |
| ADLT2_3  | 1.62 | 1.74 | 2.25 | 1.97 | 2.23 | KID0_3   | 0.19 | 0.59 | 0.76 | 0.21 | 0.78 |
| EARN2_1  | 2    | 0.24 | 0.85 | 0.8  | 0.82 | RENT_1   | 0.57 | 0.54 | 1.35 | 0.95 | 1.45 |
| EARN2_2  | 1.52 | 0.19 | 1.72 | 0.8  | 1.79 | RENT_2   | 0.14 | 0.89 | 3.11 | 2.58 | 3.25 |
| EARN2_3  | 1.34 | 1.79 | 0.2  | 1.56 | 0.05 | RENT_3   | 1.11 | 0.59 | 2.65 | 2.31 | 2.76 |
| FSD_1    | 1.86 | 0.32 | 0.39 | 0.87 | 0.3  | ROOM_1   | 0.99 | 1.75 | 0.26 | 0.71 | 0.3  |
| FSD_2    | 1.56 | 0.56 | 0.18 | 0.82 | 0.04 | ROOM_2   | 0.55 | 1.88 | 0.46 | 2.71 | 0.25 |
| FSD_3    | 1.19 | 0.11 | 0.14 | 0.83 | 0.05 | ROOM_3   | 0.84 | 3.25 | 0.26 | 2.6  | 0.05 |
| HHINC_1  | 1.47 | 3.76 | 1.24 | 0.28 | 1.25 | SBR_1    | 0.04 | 2.52 | 1.11 | 1    | 1.13 |
| HHINC_2  | 2.56 | 4.1  | 0.24 | 1.27 | 0.26 | SBR_2    | 1.26 | 1.28 | 0.42 | 0.53 | 0.39 |
| HHINC_3  | 2.77 | 4.25 | 0.13 | 1.93 | 0.03 | SBR_3    | 1.18 | 1.57 | 1.22 | 1.08 | 1.22 |
| ASC1     | 1.6  | 0.31 | 0.47 |     |     | ASC2     | 1.66 | 0.74 | 3.18 |     |
| ASC2     | 2.85 | 0.07 | 2.29 |     |     | ASC3     |     |     |     |     |
Estimated regression parameters

The estimated MNL ASCs and scale parameters in Table 3 are then regressed on macroeconomic variables in an attempt to explain their inter-temporal transfer biases via a meta-model. Only the results from the VC and VS models are included in the regression because (1) the scale parameters for the VSC model turned out to be insignificant, and (2) the ASCs of the VSC were nearly identical to the VC values. The ASCs for the 1 vehicle alternative are also not included due to insignificance. The stepwise regression procedure yields gas prices (\(\text{gasPrice}\), \(d\text{GasPrice}\)), employment rate (\(\text{empRate}\), \(d\text{EmpRate}\)), the number of single detached starts (\(d\text{SingleDet}\)) and a temporal effect captured by \(\text{year}\) as significant regressors. The \(d\) before \(\text{GasPrice}\), \(\text{EmpRate}\) and \(\text{SingleDet}\) indicate a backward difference. For instance, \(dgas\) is the difference between this year’s and last year’s gasoline prices. Note that other explanatory variables (e.g., passenger vehicle price index) showed very good results but are excluded from the final regressions since forecasting their values may turn out challenging, thereby making them unsuitable for the application.

The results are summarized in Table 6. ASC2 and ASC3 are vectors of the ASCs from the VC model, while SCALE is a vector of scale parameters from the VS model. Both vectors have nineteen observations, one for each of the 19 years. In general, the regression results show relatively good fit (i.e., adjusted R-squared values). The F-statistics also suggests that the regressions are significant. As the parameter estimates are time-series like, Durbin-Watson test statistics are calculated for each model. The tests indicate that autocorrelation is not an issue and that the standard errors for the estimated regression parameters have not been underestimated.

Similar to the MNL results, the signs of the regression parameters could also be interpreted, at least for the ASCs. For instance, when \(dgas\) is positive, it means that gas prices have increased relative to last year. Hence, a negative parameter is expected for ASC2 and ASC3 as increasing gas prices should theoretically discourage vehicle ownership. Similarly, positive \(d\text{EmpRate}\) and \(d\text{Sing}\) parameter estimates agree with expectation since positive changes in employment levels and single detached starts are signs of a strong

| Coefficient | ASC2 | ASC3 | SCALE |
|-------------|------|------|-------|
|             | Est. | p val | Est. | p val | Est. | p val |
| intercept   | -76.550 | 0.000 | -116.0 | 0.000 | 1.536 | 0.000 |
| \(d\text{SingleDet}\) | 0.0002 | 0.078 | | | |
| \(\text{gasPrice}\) [cents/L] | -0.023 | 0.058 | -0.03 | 0.068 | -0.003 | 0.001 |
| \(d\text{GasPrice}\) [cents/L] | 0.037 | 0.000 | 0.055 | 7.70 | | |
| \(\text{year}\) | | | | | |
| \(\text{empRate}\) | 0.047 | 0.056 | | | |
| \(\text{dEmpRate}\) | 27.34 | 25.19 | 26.82 |
| F-statistic | 0.7454 | 0.80 | 0.731 |
| Adj. -R-squared | 1.6554 | 2.015 | 1.4934 |
| Durbin-Watson | 0.1281 | 0.38 | 0.0527 |
economy, which in turn pushes vehicle ownership levels higher. The positive year estimate shows increasing motorization levels over time.

Interpreting the scale parameter regression results is less transparent. The scale parameter sets the weights associated with the systematic portion of the utility. In a sense, it represents the level of uncertainty associated with how the observed factors affect utility levels. According to the results, as gas prices and the employment rate increase, the attributes included in the utility specification become less important in the decision. That

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**Fig. 5** Log-likelihood values for the VC, VS, VSC and BM models when the ASCs and scales are forecasted for 1997–2009

**Fig. 6** Log-likelihood values for the VC, VS, VSC and BM models when the ASCs and scales are held constant (i.e., 1996 values are used) for 1997–2009
is, it suggests that as costs and income levels change, it becomes slightly harder to predict vehicle ownership levels in the future with a model estimated with today’s data.

**Empirical application**

The proposed methodology is put to the test by comparing the fits and predictive performances of the VC and VS models to the benchmark models across a separate validation dataset from 1997 to 2009. Figures 5 and 6 illustrate the log-likelihood values to measure fits, while Figs. 7 and 8 display the mean absolute error (MAE) values to measure the models’ predictive capabilities. Figures 5 and 7 depict the scenario where the ASCs and scale parameters in Table 3 are forecasted across 1997–2009 using the estimated regression values found in Table 6 (the “Forecast Scenario”). For comparison, Figs. 6 and 8 portray the “Constant Scenario”, where the ASCs and scale parameters are held constant across the forecast horizon (i.e., the 1996 parameters are used throughout).

For the Forecast Scenario, the log-likelihood results suggest that the models exhibit relatively the same fit when applied to the validation dataset, with the VC/VS models performing slightly worse/better. When the ASCs are held constant, the VC model performs just as good as the other models, as shown in Fig. 6. Note that the log-likelihood values change each year due to the difference in sample sizes of the validation dataset—this is not necessarily because the fit has improved in certain years.

Despite having relatively similar fit to the benchmark models, the VS model in both scenarios significantly outperforms the benchmark models in the predictive tests using an MAE metric. As shown in Figs. 7 and 8, the MAEs for the VS model are much lower than the three BM models for both the Forecast and Constant scenarios. On the other hand, the VC model exhibits inconsistent performance compared to the others when the ASCs are forecasted, but it does display strong predictive promise when the 1996 ASCs are held constant throughout. The mediocre performance of the VC model in the Forecast Scenario can be attributed to a number of issues, most notably the relatively simple and atheoretic...
meta-model that has been used. Improving this model’s specification by using a richer dataset could potentially yield better performance.

Despite this, two interesting results follow from the figures. First, the VC and VS models outperform their BM counterparts in the predictive tests for the Constant Scenario. This suggests that applying a Joint Context Estimation approach using data from multiple periods could potentially make the estimated models more robust and accurate. These results agree with previous work (see Badoe and Miller 1995; Karasmaa 2007). Second, in both Figs. 7 and 8, the 1992 benchmark model does slightly better than the BM94 and BM96 models. This seems to suggest that even using the most up-to-date data may not guarantee the best performance in forecasting transportation demand. This also supports the notion of pooling data from different periods together to produce more robust forecasts.

**Conclusion**

**Conceptual framework**

The proposed methodology builds a meta-model of vehicle ownership choice parameters to predict how these parameters may vary across extended periods. The research attempts to explain the inter-period transfer biases as a function of macroeconomic variables which could help improve the model’s transferability. Furthermore, the approach makes more efficient use of available data to build more robust, reliable and accurate forecasting models.

The following summarizes the proposed meta-model methodology:

1. Pool data from multiple time periods together then build and estimate a model where some of the parameters are allowed to vary. This paper built automobile ownership models where the scales and ASCs varied while holding all other parameters constant. Note that consistency across the datasets is important.

Fig. 8 Mean absolute error values for the VC, VS, VSC and BM models when the ASCs and scales are held constant (i.e., 1996 values are used) for 1997–2009
2. Estimate a meta-model by regressing the parameters that are allowed to vary on variables that could possibly explain their evolution. The paper focused on macroeconomic variables (e.g., employment rates, gas prices, etc.).

3. Prepare the forecasting inputs to the travel demand model along with the inputs to the meta-model. Ideally, there would be consistency across these forecasting inputs (e.g., the same base assumptions are used to generate both sets of inputs).

4. Conduct the forecast where both the target variable (e.g., automobile ownership levels) and the varying parameters are projected. The meta-model is used in projecting the values of the latter.

Contributions

Some of the main conclusions of this research include:

1. Having both varying ASCs and scales in the VSC model results in insignificant scale parameters. Hence, it appears that the ASCs capture the inter-period transfer biases thereby reducing the statistical significance of the scales. This also indirectly makes the non-ASC parameters more transferable.

2. The VC and VS models outperform the benchmark models in the Constant Scenario. This provides strong evidence that pooling data from multiple periods and using a joint context estimation approach could enhance a model’s predictive power and produce more robust forecasts. Furthermore, the empirical results seem to suggest that using the most up-to-date data may not guarantee the best performance (the 1992 benchmark performed better than the 1996 model in the validation exercises). The authors do note that the more robust performance of the VC and VS models compared to that of the benchmarks could also be due to pooling the data (i.e., more observations) and not necessarily due to having more explanatory power.

3. Regressing the VC and VS estimated parameters on macroeconomic explanatory variables resulted in good model fit and statistically significant parameters. While it is acknowledged that correlation does not mean causation, the empirical results suggest that changes in the macroeconomic environment may help predict how the ASCs or scales vary over time.

Another contribution of this paper is the innovative use of readily available data collected for non-transportation purposes to conduct transferability studies over an extended period. Although previous works have examined model transferability over long periods, most use datasets taken at only a few (often two or three) periods in time. The HIFE and SHS data, on the other hand, together provide over 40 years of relatively consistent surveys.

The authors also recognize that even though the ASCs, scales or other parameters could be predicted in such a way to improve the performance of travel demand models, the proposed methodology would implicitly require the predictors themselves to be forecasted (for the application presented, forecasts of gas prices, employment levels, etc. would be needed). In this case however, the assumptions and models would be more consistent with each other. For instance, in forecast scenarios of high gas prices, both the parameters and inputs to the model might capture the effect of the increase in fuel prices on travel demand.
Future directions

While the initial results of this study appear promising, future work remains. First, although the VC model did not exhibit a strong performance in the Forecast Scenario for the fit and predictive tests, the statistically significant parameter regressions suggest that a relationship may exist between the ASCs and the explanatory variables. It is therefore plausible that the mediocre results may be due to the relatively simple model applied. One first step towards improvement could be to use a more comprehensive model with more covariates (albeit at the risk of overfitting). Alternatively, other specifications could also be tested. For instance, the explanatory variables could be categorized together (e.g., all attributes related to household structure) and the parameters for these variables to be allowed to vary over time.

The authors also acknowledge that the current sequential estimation procedure used can cause a loss in efficiency. A more sophisticated estimation procedure could also be conducted where the regression parameters are estimated simultaneously with the discrete choice model. This procedure would not be unlike estimating a discrete–continuous model. In any case, the authors note that regardless of whether the models are estimated sequentially or simultaneously, the proposed framework and contributions still hold.

While the research focuses on explaining the evolution of vehicle ownership choice parameters through macroeconomic variables, other explanatory variables could also be considered. In particular, it would be interesting to explore the spatial structure hypothesis of Elmi et al. (1999). Hence, the regressions could be re-run using transit ridership, accessibility, land use and other transportation related variables. Furthermore, while the work has focused on temporal transferability, the same conceptual framework could also possibly be explored in the context of spatial transferability. In this case, the study would test whether the variation of parameters across geographic areas could be explained by the differences in the attributes (e.g., regional economic conditions) of these areas.

Some of the estimated parameters across the VC, VS and VSC models are not transferable, and this could possibly be due to potential correlations among them. Future work could consider dropping the variables that support or do not support transferability, and seeing whether the corresponding results still hold. It is also possible to repeat the effort in a backcasting context where the models are estimated using the SHS data and evaluated using the HIFE data. Whether or not the results are symmetric to the ones obtained in this paper can yield potentially useful insights.

Although it is commonly accepted that short-term forecasts are likely to be more accurate than long-term ones, Figs. 7 and 8 seem to show no difference between the two. While the relative performances of the VC and VS models with respect to the BM models seem to be consistent, all the models do not exhibit any tendencies for improved performance in the short-term. This interesting result can warrant further empirical investigation.

While this work shows how surveys not specific to transportation could be a rich source of data, the lack of cost, spatial, accessibility and other important information poses significant limitations to the model. Hence, it would be interesting to test the proposed methodology on other datasets to see any improvement in the process, or if adding such variables cause the regressions to be insignificant. In particular, the Transportation Tomorrow Surveys (DMG 2012) which have been collected in 5-year intervals since 1986 for the Greater Toronto-Hamilton Area would be suitable for this purpose.
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