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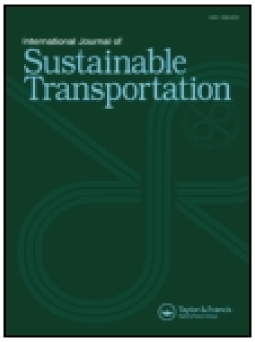
*Published in:*
International Journal of Sustainable Transportation

*Link to article, DOI:*
10.1080/15568318.2016.1163445

*Publication date:*
2016

*Document Version*
Publisher's PDF, also known as Version of record




Taylor & Francis
Taylor & Francis Group

International Journal of Sustainable Transportation

ISSN: 1556-8318 (Print) 1556-8334 (Online) Journal homepage: http://www.tandfonline.com/loi/ujst20

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**To cite this article:** Eva Valeri & Elisabetta Cherchi (2016) Does habitual behavior affect the choice of alternative fuel vehicles?, International Journal of Sustainable Transportation, 10:9, 825-835, DOI: 10.1080/15568318.2016.1163445

**To link to this article:** http://dx.doi.org/10.1080/15568318.2016.1163445



Accepted author version posted online: 20 Apr 2016.
Published online: 20 Apr 2016.

INTERNATIONAL JOURNAL OF SUSTAINABLE TRANSPORTATION
2016, VOL. 10, NO. 9, 825–835
http://dx.doi.org/10.1080/15568318.2016.1163445



# Does habitual behavior affect the choice of alternative fuel vehicles?

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**ABSTRACT**

Because of the recent improvements in the electrification process of cars, several types of alternative fuel vehicles are appearing in the car market. However, these new engine technologies are not easily penetrating the market around the world and the conventional ones are still the leaders. A vast literature has explored the reasons for such low market penetration, due mainly to car's features. Using a hybrid choice model approach, in this research we study if, and to which extent, habitual car use influences individual propensity to buy a specific type of engine technology. We found significant latent habitual effect on choices of type of car engine. This effect is important only for some of the car alternatives considered in the study. In particular, habitual car users prefer to buy a new car with liquefied petroleum gas and compressed natural gas types of engine technology instead of a conventional one. The importance of taking into account this latent construct is demonstrated also with the results of the simulated elasticity measures. In fact, the exclusion of latent habitual effect significantly underestimates the elasticity of diesel and hybrid cars and overestimates the elasticity of liquefied petroleum gas car.

**ARTICLE HISTORY**
Received 19 January 2015
Revised 1 March 2016
Accepted 4 March 2016

**KEYWORDS**
Alternative fuel vehicle; habitual behavior; hybrid choice model

## 1. Introduction

Car choice and use are certainly not new topics (e.g., Lave & Train, 1979; Manski & Sherman, 1980; Train, 1986). Because of the recent improvements in the electrification process of cars, new types of vehicles have appeared in the car market such as hybrid, plug-in, and battery electric vehicles (HEV, PHEV, and BEV), the well-known compressed natural gas vehicles (CNGV), and the liquefied petroleum gas vehicles (LPGV). All these cars are called alternative fuel vehicles (AFVs). Despite the worldwide interest in boosting the AFV market, these engine technologies are not easily penetrating the markets around the world (Potoglou & Kanaroglou, 2014).

A vast literature has studied the demand for AFVs and explored the reason for such low penetration. The majority of these studies (e.g., Bunch, Bradley, Golob, Kitamura, & Occhiuzzo, 1993; Batley, Knight, & Toner, 2004; Horne, Jaccard, & Tiedemann, 2005; Potoglou & Kanaroglou, 2007; Mabit & Fosgerau, 2011; Achtnicht, 2012; Daziano & Bolduc, 2013; Hackbarth & Madlener, 2013) analyzed the effect of car features (such as purchase price, driving range, fuel costs) and charging location (Batley et al., 2004; Bočkarjova, Rietveld, & Knockaert, 2013; Ito, Takeuchi, & Managi, 2013; Jensen, Cherchi, Mabit, & Ortúzar, 2014) on the AFV's demand. Some recent studies have also explored the role of individuals' attitudes, mainly toward environment sensitivity (Daziano & Chiew, 2012; Daziano & Bolduc, 2013; Jensen, Cherchi, & Mabit, 2013; Glerum, Stankovikj, Thémans, & Bierlaire, 2013) but also toward car features (Mabit & Fosgerau 2011), in their propensity to buy AFVs.

Although the characteristics of EVs and their recharging options play crucial roles in explaining their potential demand, some authors (Struben & Sterman, 2008; Shephard, Bonsall, & Harrison, 2012; Jensen et al., 2014) have recently shown that the diffusion effect can be one of the reasons behind the delay of EV market penetration. The diffusion effect refers to the time delay in adopting an innovative product because that an innovation is first adopted by a (usually initially small) segment of individuals, while the majority of the people delay their choice until the product will be widespread in the market. There are several reasons why the majority does not adopt the new product immediately: There is a vast literature in marketing that deals, for example, with the problem of brand loyalty (Erciş, Ünal, Candan, & Yıldırım, 2012; Vlachos & Lin, 2014; Carreira, Patrício, Natal Jorge, & Magee, 2014; Hoang-Tung, Kojima, & Kubota, 2014; Akamavi, Mohamed, Pellmann, & Xu, 2015), because individuals tend to prefer the product to which they are used to. In the same vein, several studies mainly in mode choice context have provided evidence that the probability of choosing new alternatives is often affected by inertia and habit. Indeed, habitual behavior effects can also be part of the reason for the resistance to AFVs. As with any new technology not yet spread into the market, there is uncertainty about how using an AFV could impact the individual's daily life. Jensen et al. (2014), for example, showed that individuals expressed concern about the ability to maintain their present mobility with an AFV and that this can favor the choice of a conventional vehicle over the AFV. It is then plausible to believe that inertia in buying a specific type of car (or type of engine) seems

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then to be related to the habit developed in terms of using the car. The scientific literature on habit/inertia is wide and embraces different disciplines, but to our knowledge the effect of habitual behavior on choice of AFV has never been studied. In transport literature, habit/inertia has been mainly measured by linking the current choice with the previous one (Bhat & Castelar, 2002; Srinivasan & Bhargavi, 2007; Cantillo, Ortúzar, & Williams, 2007; Yáñez, Cherchi, Heydecker, & Ortúzar, 2009; Yáñez, Raveau, & Ortúzar, 2010; Cherchi & Manca, 2011). This approach suffers from the well-known problem of the initial condition; i.e., the fact that habit/inertia does not affect the initial choice. The problem is more marked when panel data with very few waves are used, as they fail to capture the full effect of the accumulation of the individual experience that is at the basis of habitual behaviors. Interestingly, according to the psychological literature (Thøgersen, 2006; Carrus, Passafaro, & Bonnes, 2008) the frequency of past behavior is the best predictor of future behavior, but they assume the decision process does not involve the evaluation of the characteristics of each alternative, as in the economic theory. Recently, Cherchi, Meloni, and Ortúzar (2013) tested a new way to account for inertia that puts together both approaches. They assumed that inertia is revealed by past behavior, but recognized that past behavior is only an indicator of habitual behavior, with the true process behind the formation of habitual behavior being latent.

The objective of this article is to analyze if habitual behavior developed using the current vehicles can help in explaining the reasons why individuals deciding between conventional vehicles (CV) and AFVs do have a preference (not justified by the vehicle's characteristics) for the CV. In particular, we analyze individual habit (or propensity) toward the purchase of a certain engine type of car, investigating if and how habitual behavior of respondents influences their hypothetical purchase car choices. Following Cherchi et al. (2013), we model the habit effect in discrete choices as a latent variable, while usual or past behavior related mainly to the car use is revealed by three indicators: (1) the frequency of car trips per week, (2) the car as the main transport mode, and (3) the self-evaluated level of expertise with cars. We apply the model to a set of stated choice data collected in Italy.

Compared with other Western European countries, although new AFVs have entered the market, Italy appears to be lagging behind in market penetration, though it has high levels of air and noise pollution and a strong economic dependence from oil imports. CVs, including gasoline and diesel cars (respectively, GVs and DVs), still play important roles. Only CNGVs and LPGVs have recently gained relevant market shares in some regions of Italy. The other engine technologies still have very small market shares. The increasing number of AFVs available on the market, the high rate of car use, and the high number of cars owned by the Italian families (42% own two or more cars, mainly CVs; ISTAT, 2004) suggest that investigating the habit of using a car and its influence in the individual decision process of car choice is particularly relevant.

The article is organized as follows: We discuss data collection and methodology respectively in Sections 2 and 3, while the model results, elasticity measures, and car choice probabilities are addressed in Section 4. Finally, we assess the results, providing preliminary policy implications in Section 5 along with the conclusions.

## 2. Data collection

The data used in this study were collected to analyze the structure of individual preferences for different types of AFVs in Italy. The questionnaire included a stated preference (SP) exercise among seven types of cars (GV, DV, CNGV, LPGV, HEV, BEV [owned battery], BEV [leased battery]) and several other questions regarding (1) socioeconomic characteristics of the respondent (gender, level of education, current employment, family size, net yearly household income); (2) characteristics of the cars owned and used by the respondent's family such as number, age, and type of car engine technologies, availability of a private car garage, and mobility habits of interviewees (for instance, transport mode mainly used); and (3) a self-evaluated level of expertise about cars (on a 7-point Likert scale).

Face-to-face interviews were administered in three cities in Italy with different sizes and availabilities of refueling stations (Trieste, Bologna, and Pesaro). A total of four trained interviewers randomly administered 121 interviews in the first semester of 2013.[1]

An example of a SP task and further details of the survey are reported by Valeri and Danielis (2015). The SP includes five attributes that describe car alternatives: purchase price, expressed in Euros (€); annual operating cost (gasoline, insurance, tax, maintenance), expressed in Euros (€); acceleration, expressed in seconds needed to go from 0 to 100 km/h; range expressed in kilometres (km); and refueling distance, expressed as the distance required to get the closest refueling or recharging station (km). Attributes were pivoted around a status quo (SQ) value, and varied as follows: (i) purchase price: –20%, SQ, +20%, +40%; (ii) annual operating cost: –20%, SQ[2], +20%; (iii) range: SQ, +20%, +40%; (iv) acceleration: SQ, –10%, –20%; (v) refueling distance: gasoline, diesel, and hybrid (1, 5, and 10 km), CNGV and LPGV (5, 20, and 50 km), and BEVs (0, 5, and 10 km). Twelve choice tasks were randomly assigned to each respondent. Each interview lasted about 45 min.

An efficient design strategy was used to create the SP experimental design. All designs were built using NGENE 1.1.2 software (ChoiceMetrics, 2011). A fractional factorial design was used in the pilot, which allows us to estimate the priors, while efficient designs were used for the final experiment. The $D$ error was used as the measure of efficiency (Huber & Zwerina, 1996; Bliemer & Rose, 2010, 2011) and calculated as $D_z - \text{error} = \det(\Omega_1(X, \beta))^{1/H}$ where $H$ is the number of parameters to be estimated, $X$is the experimental design, and $\beta$ is the vector of parameter values (a priori), which can be equal to zero for those attributes whose prior is unknown. In the efficient design, coefficients are generic across alternatives.

## 3. Methodology

The methodology used to analyze the effect of habitual behavior in the car choice is a hybrid choice model (HCM), where we assume

[1]Only 121 interviews could be collected due to time and budget constraints. Although the sample size is admittedly small, we decided not to carry out other interviews in 2012 and to devote more resources for 2014 and 2015 as new AFVs will enter in the Italian car market and the social knowledge increases.

[2]The SQ values for all alternatives are calculated by Rusich and Danielis (2013).

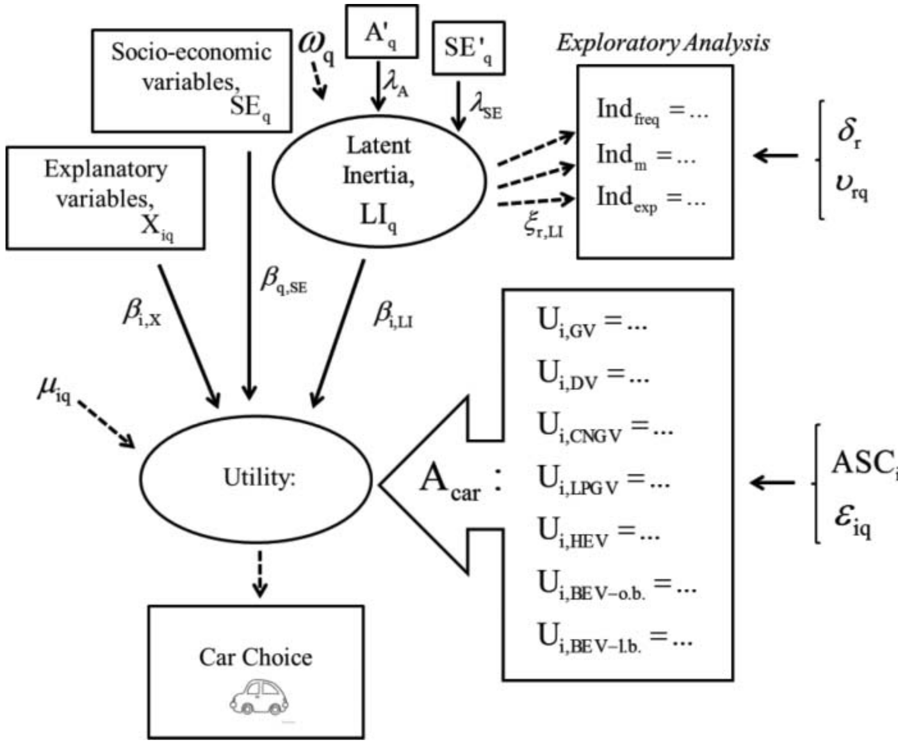


**Figure 1.** Theoretical framework of the latent inertia (LI) in the car choice.

that the habitual behavior is latent and is revealed by the daily usage of the current car.[3] A graphical summary is shown in *Figure 1*.

Traditionally, in discrete choice models, the individual is a rational decision maker who maximizes her or his own utility. Let be $U_{iqt}$ the utility that each individual $q$ associates to alternative $i$, in choice task $t$. Under the assumption that a latent habitual behavior affects the current choice, the utility can be written as

$$U_{iqt} = ASC_i + \boldsymbol{\beta}_{i,X} \cdot \mathbf{X}_{iqt} + \boldsymbol{\beta}_{q,SE} \cdot \mathbf{SE}_q + \beta_{i,LI} LI_q + \mu_{iq} + \varepsilon_{iqt} \quad (1)$$

where $\mathbf{SE}_q$ is a vector of individual background characteristics; $\mathbf{X}_{iqt}$ is the vector of car attributes, as included in the stated preference experiment; $LI_q$ is the latent variable that measures the habitual behavior of each individual $q$; $\boldsymbol{\beta}_{q,SE}$, $\boldsymbol{\beta}_{i,X}$ and $\boldsymbol{\beta}_{i,LI}$ are the sets of coefficients associated to the attributes; and $ASC_i$ are the typical alternative specific constants. The $\mu_{iq}$'s are random terms, normally distributed across individuals but fixed across choice sets to account for panel effects in the choice tasks. Following Walker, Ben-Akiva, and Bolduc (2007), the panel effect is specified in all the alternatives. Finally $\varepsilon_{iqt}$'s are the typical random terms distributed identical and independently extreme value type 1 (i.i.d. EV1).

The structural equation for the LI is specified as a linear function of observable alternatives (A) and respondent's socio-economic (SE) characteristics:

$$LI_q = \boldsymbol{\lambda}_{SE} \cdot \mathbf{SE}'_q + \boldsymbol{\lambda}_A \cdot \mathbf{A}'_q + \omega_q \quad (2)$$

where $\mathbf{SE}'_q$ is a vector of individual background characteristics that can be different from the vector included in the discrete choice model; $\boldsymbol{\lambda}_{SE}$ is a vector of coefficients associated with these characteristics; $\boldsymbol{\lambda}_A$ is a vector of coefficients associated with the observable alternatives characteristics ($\mathbf{A}$); and $\omega_q$ is a normal distributed error term with zero mean and standard deviation $\boldsymbol{\sigma_\omega}$.

In our specific case we define our LI as a function of the following characteristics[4]:

$$\{\mathbf{SE}; A\} = \{Education - Low_q, NumCarFamily_q, Unemployed_q; BusinessPurp - Car_q\}$$

As in the typical HCM theory, the measurement equation of the indicators is specified as

$$I_r = \delta_r + \zeta_{r,LI} \cdot LI_q + \upsilon_{rq} \quad (3)$$

where $\delta_r$ is a constant of the $r$th indicator, $\zeta_{r,LI}$ is the estimated effect of the LI on the $r$th indicator, and $\upsilon_{rq}$ is a random disturbance with a mean of zero and a standard deviation of $\sigma_I$.

Three indicators were used in our study to measure habitual behaviours. The first indicator, $Ind_{freq}$, measures the number of times (return car trips) each individual performs in a week. $Ind_{freq}$ is a continuous variable, and we assumed it is normally distributed.[5] Hence its structural equation is

[3] As pointed out by an anonymous referee, it is important to remember that investigating the impact of habitual behavior on the choice of the vehicle type does not necessarily reveal the specific attachment to some engine technology.

[4] The LI characteristics are defined as follows: *Education – Low* takes the value of 1 when the respondent has a primary education, 0 otherwise; '*NumCarFamily* is expressed with number of cars available in the respondent's family; *Unemployed* takes the value of 1 when the respondent is not employed, 0 otherwise; and *BusinessPurp – Car* takes the value of 1 when the car is mainly used for a business purpose, 0 otherwise.

[5] The weekly number of return car trips is not, strictly speaking, a continuous variable. As suggested by one reviewer a discrete distribution would be more precise that a continuous distribution.

$$f(Ind_{freq}) = \frac{1}{\sigma_{I_{freq}}}\phi\left(\frac{Ind_{freq,q} - \delta_r - \zeta_{r,LI}\cdot LI_q}{\sigma_{I_{freq}}}\right) \quad (4)$$

The second one, $Ind_{\text{m}}$, indicates the car as the most used transport mode among all the modes available (typically public transport, motorcycle, bike, etc.). The indicator is measured as a dummy variable (equal to 1 if the respondent does not use the car as the habitual transport mode for her or his trips, and 2 otherwise); hence its structural equation is a binary logit model as follows:

$$P(I_m = 1) = \frac{1}{1 + e^{[\delta_m + \zeta_{m,LI}\cdot LI_q)]}} \quad (5)$$

The third indicator, $Ind_{\text{exp}}$, is the self-evaluated level of expertise with cars. It is measured with four-point numerical scale, and hence its structural equation is an ordered logit model as follows:

$$P(Ind_{\exp} \leq 2) = \frac{1}{1 + e^{[\delta_{\exp} + \zeta_{\exp,LI}\cdot LI_q - \eta_1]}}$$
$$P(3 \leq Ind_{\exp} \leq 4) = \frac{1}{1 + e^{[\delta_{\exp} + \zeta_{\exp,LI}\cdot LI_q - \eta_2]}} - \frac{1}{1 + e^{[\delta_{\exp} + \zeta_{\exp,LI}\cdot LI_q - \eta_1]}}$$
$$P(Ind_{\exp} \geq 5) = 1 - \frac{1}{1 + e^{[\delta_{\exp} + \zeta_{\exp,LI}\cdot LI_q - \eta_2]}} \quad (6)$$

where $\eta$ are thresholds defined respectively as less than the second level (inexperienced), between third and fourth levels (relative expert), and between fifth and seventh levels (very expert). Moreover, for estimation purposes, we defined $\eta_1 = 0,\ \eta_2 = \eta_1 + \delta_1,\ \eta_3 = \eta_2 + \delta_2$.

Our initial model included seven random variables to account for panel effect and one latent variable (LI) included as alternative specific in N-1 alternatives. This made the simultaneous estimation problematic. Raveau, Álvarez-Daziano, Yáñez, Bolduc, and Ortúzar (2010) and Raveneau, Yáñez, and Ortúzar (2010) studied the empirical performance of the sequential and simultaneous approaches, confirming that both resulted in estimators that were not statistically different. Although differences between simultaneous and sequential estimation are little, the simultaneous approach should still be preferred as estimation method for the hybrid discrete choice model. However, as discussed in two very recent papers by Bahamonde-Birke and Ortúzar (2014a, 2014b), its computational cost "can still be prohibitive[6] when models get more involved and in some cases sequential estimation can still be a potent alternative."[7] This is also our case and the reason why we chose to use the sequential estimation in this application.

[6] A Bayesian approach (Daziano & Bolduc, 2013) and a novel approach proposed by Bhat and Dubey (2014) allow simultaneous estimation with complex specifications. However, software is either not freely available or less tested than the maximum simulated methods.

[7] Bahamonde-Birke and Ortúzar (2014b, p. 9) have recently proposed a method to correct the bias due to the sequential estimation. However, they refer to the case of a multinomial logit model. We estimate instead a mixed logit with a full set of alternative specific panel correlation terms, which—being individual specific as the latent variables—can also account for this random effect, in a similar vein as the approach proposed by Ben-Akiva et al. (2002). Finally, Bahamonde-Birke and Ortúzar (2014b) note also that "correcting the estimators is particularly relevant when results are to be used to predict policy," which is not the case for our study.

## 4. Model results

### 4.1 *LI indicators: An exploratory analysis*

Before estimating the HCM, we performed an exploratory analysis to verify our a priori choice of the indicators for the LI. Using a principal component analysis (PCA), we found the first six factors explain the 65% of the overall variance in the data (MSA = 0.7). However, as shown in Table 1, in factor 1, which explains the 19% of the overall variance, we found our three variables with the highest and positive eigenvalues: (1) Car as the main transport mode (0.85), (2) frequency of car trips per week (0.74), and (3) the level of self-evaluated expertise with cars (0.36). All these indicators are related to the frequency of car use rather than on the intensity of car use that seems characterize the second factor.

Based on the PCA results, we selected the highest and positive eigenvalues of factor 1 (variables 8, 11, 14, and 15 in Table 1[8]) in order to perform a confirmatory factor analysis (CFA). Investigating a second-order relationship, it allowed us to verify if the data fit our hypothesized measurement model. In particular, we tested if the mentioned variables describe the latent construct of car habit. Based on the definition of a good model as reported, for instance, by Bentler (1990) and Kline (2005), it can be seen from Table 2 that our model fits the expected structure of the data. These observed variables are then related to the specified construct. All $t$ values indicate that the prescribed relationship between the variables and the latent factor is significant.

### 4.2 *Hybrid choice model*

This section describes the main results of the HCM. For reasons of space, we only present the best models and we leave out several specifications tested. In Table 3 we include (i) the LI variable model (model 1, LI only), (ii) the mixed logit model (model 2, ML), and (iii) the integrated latent variable and discrete choice model (model 3, HCM). The model estimated with only the latent habitual behavior was estimated using MIMIC,[9] and all the other models were estimated using PythonBiogeme (Bierlaire & Fetiarison, 2009).

The results from the LI variable model (model 1) show that latent habitual behaviour in our sample is positively affected by education, number of cars in the family, occupation, and the purpose of the most frequent car trips. In particular, individuals with low education and/or who are unemployed and/or have many cars in the family and who travel mainly for business seem to be more habitual in their behavior. At the same time, results from model 3 shows that the LI has different impacts across car alternatives. We found that individuals with a strong habit to use a car (any type of engine technology) have a preference for buying LPGVs and CNGVs instead of GVs and

[8] Even if the negative sign of variable 12 related to the frequency of walking or using a bike as the main transport mode appears to be a reasonable result, we do not consider this variable in the following CFA. On the contrary, we consider variable 15 in order to investigate the possible link of this SE variable with the LI; in fact, a positive result in the CFA might suggest us to test this variable to describe the LI, which is to be included in the HCM model (in addition, of course, to have an a priori on the importance and sign of this variable).

[9] MIMIC: Multiple Indicator Multiple Cause.

**Table 1.** Principal component analysis.

| No. | Factor pattern | Description | Coding | Factor 1 | Factor 2 | Factor 3 | Factor 4 | Factor 5 | Factor 6 |
|---|---|---|---|---|---|---|---|---|---|
| 1 | *NumCarGasoline* | Number of gasoline cars in the family | Number | 0.5950 | −0.6212 | 0.0340 | 0.1581 | 0.1026 | 0.1849 |
| 2 | *NumCarDiesel* | Number of diesel cars in the family | Number | −0.0586 | 0.5716 | −0.3983 | −0.1311 | 0.2120 | −0.0969 |
| 3 | *NumCar M-L-H* | Number of methane, LPG, and hybrid cars in the family | Dummy variable | −0.2390 | 0.1986 | −0.2404 | 0.5730 | −0.1811 | −0.1636 |
| 4 | *AgeCar* | Age of the oldest car in the family | Number | 0.3470 | −0.5640 | −0.0808 | 0.2828 | 0.0284 | 0.3443 |
| 5 | *Garage* | Garage ownership | Dummy variable | −0.1812 | 0.2832 | 0.5451 | −0.4279 | 0.1118 | 0.1823 |
| 6 | *Moto* | Number of moto in the family | Number | 0.2051 | 0.1237 | 0.4663 | 0.4969 | 0.3016 | −0.0861 |
| 7 | *Bike* | Number of bikes in the family | Number | 0.1395 | −0.1251 | 0.7322 | −0.2124 | −0.0646 | 0.0090 |
| 8 | *NumTrip-Car* | Frequency of car trips per week | Number | 0.7349 | 0.3090 | −0.1873 | −0.0164 | −0.0224 | −0.0419 |
| 9 | *KmCar* | Average distance for each car trip | km | −0.0822 | 0.3512 | −0.1140 | 0.2989 | 0.0625 | 0.4469 |
| 10 | *NumTrip400 km* | Number of car trips longer than 400 km per year | Number | 0.2313 | 0.4415 | −0.0374 | 0.1132 | −0.2664 | 0.5927 |
| 11 | *CarExpertise* | Self-evaluated level of expertise with cars | 7-point Likert scale | 0.3562 | 0.2586 | 0.1211 | −0.2759 | −0.3430 | 0.2457 |
| 12 | *Mode-Walking&Bike* | Walking and bike as the main transport modes | Dummy variable | −0.6051 | 0.0569 | 0.3435 | 0.3597 | −0.0677 | 0.1489 |
| 13 | *Mode-Moto* | Moto as the main transport modes | Dummy variable | −0.2278 | −0.4060 | −0.4453 | −0.3414 | −0.3732 | 0.1509 |
| 14 | *Mode-Car* | Car as the main transport mode | Dummy variable | 0.8516 | 0.1591 | −0.0427 | −0.0751 | 0.1988 | −0.1538 |
| 15 | *Business Purpose-Car* | Business as the main travel purpose for car trips | Dummy variable | 0.6790 | 0.1537 | 0.1160 | 0.1614 | −0.4069 | −0.2104 |
| 16 | *PurposeCar-Study* | Study as the main travel purpose for car trips | Dummy variable | 0.0665 | −0.0102 | −0.2139 | −0.1463 | 0.7821 | 0.2468 |

**Table 2.** Confirmatory factor analysis.

| Variable | Estimate | Std. error | *t* value |
|---|---|---|---|
| *NumTrip-Car* | 0.7553 | 0.0518 | 14.5731 |
| *CarExpertise* | 0.3279 | 0.0763 | 4.2988 |
| *Mode-Car* | 0.8228 | 0.0501 | 16.4364 |
| *BusinessPurpose-Car* | 0.6185 | 0.058 | 10.6554 |
| Summary of fit statistics: | Our model | Statistics for a 'good' model | |
| $\chi^2$ | 4.9522 | | |
| $\chi^2/df$ | 2.5 | $<$ 3: good model | |
| $Pr > \chi^2$ | 0.0841 | $>$ 0.05 | |
| *SRMR* | 0.0298 | $<$ 0.05 | |
| *RMSEA* | 0.0916 | $<$ 0.05 good, 0.05–1.0 moderate, $>$1.0 bad | |
| *Bentler Comparative Fit Index* | 0.9818 | $\geq$ 0.95 | |

BEVs (owned battery). For the others fuel-type vehicles (DV, HEV, BEV [leased battery]), the effect was not significantly different from zero. Note that the latent variable is included only in the utility of the cars that the individuals declared were available in their family, except for BEV (owned battery).

Regarding the other attributes included in the discrete choice model, we note that all coefficients are significant and their signs are consistent with the microeconomic theory. Only acceleration time is not significant, as often found in the literature (e.g., Hoen & Geurs 2011). We found also that respondents have different sensitivities to the purchase price and range attributes by fuel/powertrain technology. In particular, the marginal utility of purchase price is much higher for the DV, GV, CNGV, HEV, and BEV (leased battery) alternatives than for the LPGV and, lastly, for alternative BEV (owned battery). Given this result, several tests were conducted to account for possible income effect. Following the approach proposed by Jara-Díaz and Videla (1989), strictly grounded on the microeconomic theory, we tested a square in the purchase price specification and specific purchase price coefficients for different income categories,[10] but we did not find strong evidence supporting the presence of income effect. As done by Jensen et al. (2013), we concluded that differences in purchase price marginal utilities can be due to specific car characteristics.

The range attribute also received particular attention. During the preliminary estimation process carried out in order to acquire knowledge of the data, we found different preferences between BEVs and non-BEVs, as expected with bigger value for the first ones. Since BEVs have generally a lower range than non-BEVs, we then used a piecewise linear function to test for nonlinear effect. Results indicated that the differences between BEVs and non-BEVs are not clearly attributable to nonlinear effect.

Several SE and characteristics of cars owned by the respondent's family[11] were also tested in the discrete choice part of models 2 and 3. However, the only SE significant were education and the ratio between the number of cars in a family and the number of members with driving licenses. Among the characteristics of car use, we found that individuals who use the car for long-distance trips (>400 km) have a positive preference for all alternatives except for the GV one. Finally, we mentioned that to test for empirical identification all ML models were estimated also with 10,000 draws.

### 4.3 *Elasticity measures and choice probability*

In this section we analyze the effect of accounting for LI in the elasticity and probability to choose different types of car. Using a Monte Carlo simulation approach, we simulated the choice probability over the sample and computed the average direct-point elasticity measures[12] for all significant attributes with both the ML and the HCM.[13]

[10]Income effects is a phenomenon by which a change in quantity demanded is due by a change in real income. Jara-Díaz and Videla (1989) showed that the presence of the income effect can be detected by using a specification that includes a squared cost parameter, because this allows ascertaining whether the indirect utility is, in general, a function of income.

[11]In particular, we considered gender, age of respondents, education level, current employment, number of family cars, number of family members with licenses, age of the oldest family car, and availability of a private garage.

[12]In choice modeling, the elasticity quantifies the extent to which the individual's choice probability of each alternative will change in response to the changes in the value of an attribute. In our case study, we simulate direct-point elasticities to measure the percentage change in the probability of choosing a specific car alternative in the choice set with regard to a given percentage change in an attribute (e.g., purchase price, range) of the same alternative. For further details see, e.g., Hensher et al. (2005, p. 371).

[13]As pointed out by an anonymous referee it might be interesting as future analysis to simulate elasticity measures and choice probabilities under specific scenarios, varying choice attributes according to potential policy measures, including cross-elasticity to further explore substitution effects between cars.

From the results reported in Table 4, we first note that the highest values of aggregate elasticity are for the monetary attributes (purchase price and annual operating cost), mainly related to the GV, BEV (leased battery), and CNGV alternatives. Negligible results are instead found for the refueling distance attribute, highlighting relative inelastic demand very close to zero[14] (except for the LPGV alternative that has a negative value ranging from –0.7 to –0.9). With reference to the range attribute, BEVs, LPGV, and HEV are relatively elastic with positive values over 1.2. We found interesting results when we compared the outcomes between the ML and the HCM in terms both of elasticity and choice probability. The M2 – M1 ($\eta_{ML} - \eta_{HCM}$) columns in Table 4 report the difference between the elasticity calculated with a ML and those simulated with the HCM. Positive (negative) values indicate underestimated (overestimated) elasticity measures due to the exclusion of the LI effect in the model. We found differences between specific alternatives mainly in the purchase price and operating cost attributes. In particular, the exclusion of the LI variables in the ML considerably affects the marginal utility of DV, LPGV, and HEV alternatives. Not taking into account the LI effect produces the following results: the elasticity measures of DV and HEV alternatives are significantly underestimated and the elasticity of the LPGV alternative is significantly overestimated. LPGV shows the major difference between the ML and the HCM also in term of choice probability. On this point, in fact, its average choice probability estimated in the ML is significantly underestimated (–20%). Looking at the overall results of the estimated probability, we found that the LI variables produced their effects not only in those alternatives in which the LI was included (GV, LPGV, BEV [owned battery]). In particular, the ML underestimates the probabilities of GV, LPGV, and BEV (owned battery) and also overestimates the probabilities of DV and HEV alternatives (that do not include LI variables). The estimated value of the BEV (leased battery) one is quite close to the estimated with HCM (0.8%) and no difference was found for the CNGV alternative.

A segmentation analysis based on the SE included in the LI variable is also reported in order to further explore the LI effect (Table 5). We considered two sample segments: people with a low education level and people who use their cars mainly for business purposes. We found differences in the absolute values of the simulated elasticity between the different sample's segments analyzed. For both segments, the results confirm that the exclusion of the LI mainly affect the elasticity of the demand for specific fuel-type vehicles with respect to particular attributes.

In particular, the most affected is the elasticity of the demand for DV, LPGV, and HEV alternatives with respect to purchase price and operating cost. However, further details can be added. For instance, the exclusion of the LI effect overestimates the elasticity of the CNGV alternative with respect to both monetary attributes, but only for people with a low education level. Moreover, for this segment we found two peculiarities: Only if the LI effect is not taken into account its purchase price elasticity is underestimated for the BEV (owned battery) alternative and is overestimated for the GV alternative with respect to their range elasticity. For respondents who use their cars mainly for business purposes, the LI effect in the simulated elasticity for the HEV alternative is still present but less strong if compared (in absolute values) with the low education level segment.

In terms of choice probability, the main differences between low educated people and the overall aggregated sample (Table 5 on the right-hand side) were found for the DV and HEV alternatives, while for the respondents who use their cars mainly for business purposes the main difference is only for the DV one.

## 5. Result assessments and conclusions

The existing literature on alternative fuel vehicles highlights the potential benefit of latent variables to capture significant effects that cannot be kept by observable variables in the choice models. However, adding latent variables (mainly environmental concerns) in the decision-making process improves the explanation of the phenomenon but still does not fully explain the low market penetration of these new technologies. In this article, we contribute to this literature by explicitly including the effect of habitual behavior to explain the choice preferences for both AFVs and CVs. In particular, we analyze individual habit (or propensity) toward the purchase of a new car, investigating if and to what extend habit of using a car affects the purchase of a new car with a specific type of engine. We model the effect of habitual behavior in discrete choices as a latent variable, while usual or past behavior related mainly to the car use is revealed by three indicators: (1) the frequency of car trips per week, (2) the car as the main transport mode, and (3) the self-evaluated level of expertise with cars. We apply the model to a set of stated choice data collected in Italy.

In line with other studies, we found that purchase price, annual operating cost, and the driving range are the most important attributes to elicit car choices. In particular, we found differences in preferences' sensitivity for the purchase price across alternatives and also a higher marginal utility for the BEVs range.

The novel result of our research is that we found a significant effect of latent habit in the choice of buying a new car. Interestingly, we found that habitual behavior is due to habit developed in using the current car and it shows a resistance to change the type of vehicle, due to impact (or probably the uncertainty of the impact) that the new engine technology has on everyday mobility. This impact is different across car alternatives. The results are not only related to the statistical fit of the model but might generate some preliminary policy implications. Usually, one of the topics in the car choice literature is the identification of which car alternative is the most preferred (see the work for the Italian car market done by Valeri and Danielis (2015) using the same database we used in this research). Considering the intensive rate of car use, the high number of cars owned by the Italian families, and the important role that the automotive sector has in Italy, we investigated if car use and expertise play a role in the process of buying a

[14]This means that the revenue gained by any increase in the refueling distance will more than make up for the loss of patronage the refueling distance increase will bring (Hensher et al., 2005, p. 391).

**Table 3.** Overview of the econometric results.

| | Model 1, LI only | | Model 2, ML | | Model 3, HCM | |
|---|---|---|---|---|---|---|
| Variable | Value | Robust *t*-test | Value | Robust *t*-test | Value | Robust *t*-test |
| ASCs | | | | | | |
| ASC BEV (leased battery) | | | −2.6 | −2.08 | −2.31 | −1.9 |
| ASC BEV (owned battery) | | | −4.46 | −3.56 | −3.65 | −2.86 |
| ASC LPGV | | | −4.42 | −3.5 | −4.48 | −3.48 |
| ASC CNGV | | | −0.42 | −0.56 | −0.50 | −0.67 |
| ASC DV | | | 0.53 | 0.67 | 0.48 | 0.58 |
| ASC HEV | | | −0.718 | −0.93 | −0.61 | −0.79 |
| Attributes (linear effects) | | | | | | |
| *Acceleration time* (s) | | | 0.012 | 0.49 | 0.014 | 0.57 |
| *Annual operating cost* (€1.000) | | | −1.73 | −9.57 | −1.75 | −9.71 |
| *PurchasePrice-BEV-owned battery* (€1.000) | | | −1.95 | −4.67 | −1.95 | −4.49 |
| *PurchasePrice-G* (€1.000) | | | −1.16 | −2.38 | −1.17 | −2.38 |
| *PurchasePrice-nonG-BEVleased battery* (€1.000) | | | −3.19 | −13.39 | −3.22 | −13.69 |
| *BEV Range* (1.000 km) | | | 8.11 | 2.49 | 8.13 | 2.57 |
| *non-BEV Range* (1.000 km) | | | 1.16 | 2.53 | 1.19 | 2.52 |
| *Refueling distance* (km) | | | −0.02 | −4.67 | −0.02 | −4.67 |
| Socioeconomic characteristics | | | | | | |
| *Education-High-DV* | | | −1.04 | −2.7 | −0.924 | −2.47 |
| *Education-Medium-DV* | | | −1.06 | −2.51 | −0.87 | −2.09 |
| *NumCarFamily/NumFamWithLicense* | | | 1.03 | 1.32 | 0.372 | 0.47 |
| *LongDistanceTrips* (> 400 km) | | | 0.27 | 2.44 | 0.293 | 2.46 |
| Latent habitual behavior (structural equation) | | | | | | |
| LI, GV | | | | | −0.59 | −1.99 |
| LI, LPGV | | | | | 1.36 | 3.04 |
| LI, CNGV | | | | | 1.39 | 2.19 |
| LI, BEV (owned battery) | | | | | −0.85 | −0.96 |
| LI_mean | 0.12 | 0.90 | | | | |
| Latent habitual behavior (measurement equations): | | | | | | |
| Socioeconomic variables | | | | | | |
| *Education-Low* | 0.73 | 2.17 | | | | |
| *NumCarFamily* | 0.18 | 3.05 | | | | |
| *PurposeCarUse-Business* | 0.941 | 3.31 | | | | |
| *Occupation-unemployed* | 0.194 | 0.79 | | | | |
| LI indicators | | | | | | |
| *Mean_habitual behaviour* | 0.12 | 0.9 | | | | |
| *Ind_Freq_mean* | −3.28 | −1.56 | | | | |
| *Ind_Freq_lambda* | 5.59 | 4.47 | | | | |
| *Ind_Freq_sigma* | 1.67 | 15.47 | | | | |
| *delta1* | 1.39 | 6.19 | | | | |
| *delta2* | 1.46 | 5.32 | | | | |
| *Ind_Mcar_mean* | 3.34 | 5.07 | | | | |
| *Ind_Mcar_lambda* | −3.24 | −3.21 | | | | |
| Panel correlation | | | | | | |
| SIGMA-BEV (leased battery) | | | 1.8 | 8.11 | 1.48 | 6.56 |
| SIGMA-BEV (owned battery) | | | −2.24 | −3.16 | −1.94 | −2.94 |
| SIGMA-GV | | | 1.9 | 4.07 | 2.16 | 5.14 |
| SIGMA-LPGV | | | 2.2 | 4.43 | 2.39 | 4.79 |
| SIGMA-CNGV | | | 0.779 | 3.69 | −0.814 | −3.9 |
| SIGMA-DV | | | 0.659 | 1.99 | 0.803 | 3.03 |
| SIGMA-HEV | | | 0.974 | 5.56 | 1.05 | 4.98 |
| Overall statistics | | | | | | |
| Number of draws | | | 250 | | 250 | |
| Sample size | 96 | | 1152 | | 1152 | |
| Init log-likelihood | −2874.463 | | −2241.688 | | −2225.212 | |
| Final log-likelihood | −496.954 | | −1523.184 | | −1509.422 | |
| Rho for the init. model | 0.827 | | 0.321 | | 0.322 | |
| Rho bar for the init. model | 0.823 | | 0.309 | | 0.309 | |

*Notes*: All the generic SE tested in the discrete choice part of models 2 and 3 were included in all alternatives except for the GV alternative.

new car, with special attention to the AFVs. Moreover, we verified that the different types of engine technologies display dissimilar implications. The results show that respondents with a strong habit to use a car (any type of engine technology) have a preference for buying LPGVs and CNGVs instead of GVs and BEVs (owned battery). This might reveal green purchasing preferences. It is reasonable to infer that the negative effect of habitual behavior toward GVs might be probably due to economic motivations related to the car use/management, changes in public attitude toward AFVs, and/or to the influence of automotive advertisements. This is even true if the car is highly used, as happens in Italy. In particular, with reference to the economic/financial reasons, it is commonly accepted that the use of a GV implies having to deal with a high fossil fuel price for the refueling and high annual operating costs of the car. These aspects (especially the first one) are very important because of the intensive car use. On the other side, also (an increase of) the public environmental sensitivity to car-related

**Table 4.** Elasticity measures and choice probability.

| | Operating cost | | | Purchase price | | | Range | | | Refueling distance | | | Choice probability | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Cars | M1 HCM | M2 ML | M2-M1 $\Delta\eta_{ML} - \eta_{HCM}$ | M1 HCM | M2 ML | M2-M1 $\Delta\eta_{ML} - \eta_{HCM}$ | M1 HCM | M2 ML | M2-M1 $\Delta\eta_{ML} - \eta_{HCM}$ | M1 HCM | M2 ML | M2-M1 $\Delta\eta_{ML} - \eta_{HCM}$ | M1 HCM | M2 ML | M2-M1 $\Delta P_{ML} - P_{HCM}$ |
| GV | −3.697 | −3.881 | −0.184 | −4.037 | −4.278 | −0.241 | 0.791 | 0.834 | −0.043 | −0.088 | −0.092 | −0.004 | 13% | 8% | −5% |
| DV | −2.611 | −2.102 | 0.509 | −2.818 | −2.269 | 0.549 | 0.845 | 0.677 | 0.168 | −0.093 | −0.074 | 0.019 | 29% | 43% | 14% |
| BEV (leased battery) | −4.482 | −4.444 | 0.038 | −5.317 | −5.275 | 0.042 | 1.910 | 1.895 | 0.015 | −0.120 | −0.119 | −0.001 | 0.62% | 1.47% | 0.8% |
| BEV (owned battery) | −2.299 | −2.389 | −0.09 | −3.991 | −4.113 | −0.122 | 1.230 | 1.272 | −0.042 | −0.119 | −0.124 | −0.005 | 7% | 4% | −4% |
| LPGV | −3.563 | −4.452 | −0.889 | −1.810 | −2.258 | −0.448 | 1.205 | 1.511 | −0.306 | −0.689 | −0.867 | −0.178 | 22% | 2% | −20% |
| HEV | −3.104 | −2.630 | 0.474 | −3.752 | −3.249 | 0.503 | 1.172 | 0.985 | 0.187 | −0.040 | −0.037 | 0.003 | 16% | 29% | 13% |
| CNGV | −4.161 | −4.172 | −0.011 | −4.938 | −4.945 | −0.007 | 0.928 | 0.923 | 0.005 | −0.281 | −0.285 | −0.004 | 12% | 12% | 0% |

*Note*: $\Delta$ is the difference between the elasticity measures or probabilities calculated with the ML and those simulated with the HCM (M2 – M1).

**Table 5.** Elasticity measures: SE segmentation analysis.

| Cars | M1 HCM | M2 ML Operating cost | M2 – M1 | M1 HCM | M2 ML Purchase price | M2 – M1 | M1 HCM | M2 ML Range | M2 – M1 | M1 HCM | M2 ML Refueling distance | M2 – M1 | M1 HCM | M2 ML Choice probability | M2 – M1 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Education–L | Education–L | Δ | Education–L | Education–L | Δ | Education–L | Education–L | Δ | Education–L | Education–L | Δ | Education–L | Education–L | $\Delta P_{ML} - P_{HCM}$ |
| GV | −4.24 | −4.14 | 0.10 | −4.33 | −4.50 | −0.17 | 0.85 | 0.87 | −0.02 | −0.09 | −0.09 | 0.00 | 0.08 | 0.05 | 0.03 |
| DV | −2.58 | −2.12 | 0.46 | −2.75 | −2.37 | 0.38 | 0.78 | 0.67 | 0.11 | −0.08 | −0.08 | 0.00 | 0.35 | 0.43 | −0.08 |
| BEV (leased battery) | −4.53 | −4.51 | 0.02 | −5.11 | −5.19 | −0.08 | 1.87 | 1.90 | −0.03 | −0.13 | −0.12 | 0.01 | 0.01 | 0.02 | −0.01 |
| BEV (owned battery) | −2.36 | −2.41 | −0.05 | −4.71 | −4.29 | 0.42 | 1.38 | 1.32 | 0.06 | −0.12 | −0.13 | −0.01 | 0.03 | 0.03 | 0.00 |
| LPGV | −3.28 | −4.36 | −1.08 | −1.65 | −2.20 | −0.55 | 1.13 | 1.49 | −0.36 | −0.66 | −0.86 | −0.20 | 0.25 | 0.02 | 0.23 |
| HEV | −3.48 | −2.71 | 0.77 | −4.28 | −3.24 | 1.04 | 1.28 | 1.01 | 0.27 | −0.05 | −0.04 | 0.01 | 0.09 | 0.29 | −0.19 |
| CNGV | −3.7 | −3.99 | −0.29 | −4.39 | −4.57 | −0.18 | 0.87 | 0.88 | −0.01 | −0.23 | −0.26 | −0.03 | 0.18 | 0.16 | −0.02 |
| Cars | PurpCar–Business | PurpCar–Business | Δ | PurpCar–Business | PurpCar–Business | Δ | PurpCar–Business | PurpCar–Business | Δ | PurpCar–Business | PurpCar–Business | Δ | PurpCar–Business | PurpCar–Business | $\Delta P_{ML} - P_{HCM}$ |
| GV | −3.74 | −3.85 | −0.11 | −4.03 | −4.23 | −0.20 | 0.81 | 0.83 | −0.02 | −0.1 | −0.09 | 0.01 | 0.11 | 0.09 | 0.02 |
| DV | −2.57 | −2.13 | 0.44 | −2.65 | −2.27 | 0.38 | 0.82 | 0.68 | 0.14 | −0.08 | −0.07 | 0.01 | 0.32 | 0.43 | −0.11 |
| BEV (leased battery) | −4.4 | −4.42 | −0.02 | −5.34 | −5.28 | 0.06 | 1.88 | 1.89 | −0.01 | −0.13 | −0.12 | 0.01 | 0.01 | 0.02 | −0.01 |
| BEV (owned battery) | −2.32 | −2.38 | −0.06 | −4.08 | −4.12 | −0.04 | 1.24 | 1.27 | −0.03 | −0.11 | −0.12 | −0.01 | 0.05 | 0.04 | 0.01 |
| LPGV | −3.49 | −4.45 | −0.96 | −1.78 | −2.26 | −0.48 | 1.18 | 1.51 | −0.33 | −0.67 | −0.87 | −0.20 | 0.24 | 0.02 | 0.22 |
| HEV | −3.1 | −2.64 | 0.46 | −3.93 | −3.30 | 0.63 | 1.17 | 0.99 | 0.18 | −0.05 | −0.04 | 0.01 | 0.16 | 0.29 | −0.13 |
| CNGV | −4.1 | −4.16 | −0.06 | −5.07 | −4.98 | 0.09 | 0.93 | 0.92 | 0.01 | −0.29 | −0.29 | 0.00 | 0.12 | 0.12 | 0.00 |

*Note*: Δ is the difference between the elasticity measures or probabilities calculated with the ML and those simulated with the HCM (M2 – M1).

issues might be preferable for a potential purchase of an AFV instead of a GV, influenced for instance by the increased low-emission car advertisements as occurred in the time period when the survey has been administered. The role of the environmental concern in determining green purchase behaviors could be an interesting aspect to be tested in the next survey. In fact, in the scientific literature there are many studies around the world focusing on public environmental sensitivity toward transport topic through willingness-to-pay estimates. However, based on these results, economic reasons seem generally to prevail over specific reasons that advantage GVs over AFVs (e.g., performance/acceleration, high density of the refueling station network). On the other hand, a habitual car usage (any type of engine technology) generates preferences for LPGVs and CNGVs. Also in this case, some hypotheses on the reasons are opposite to those proposed for the GVs (e.g., economic advantage and environment sensitivity). Despite the intensive car use and the considerable market share that GVs still have in the Italian market (33.33% in 2012[15]), these results are paradoxically heartening for policy makers. Anyone who already uses an AFV is inclined to potentially buy an AFV instead of a GV and those who use a GV probably will switch to an AFV option. These results might be useful also for authorities (such as the Transport Regulation Authority and the Competition Authority) in setting fuel/energy price and emission/air quality regulations and subsidies, for international companies, or for defining the relevant market (e.g., Valeri, 2013) to support the AFVs growth. Moreover, also car producers/manufactures and the other automotive industry actors, which in the Italian context play a considerable role, might capture some indications in order to direct their product development strategies. For them, especially the demand elasticity estimates are potentially useful. On this point, we found that not taking into account for LI under- or overestimates the demand elasticity. Its effect is different among alternatives (DV, LPGV, HEV), attributes (purchase price, operating cost), and individuals' SE characteristics. For instance, not accounting for LI significantly underestimates the elasticity of DV and HEV alternatives and overestimates the elasticity of the LPGV. This effect is significantly higher for individuals with a low education level and for those who use their cars mainly for business purposes. Purchase price and operating cost elasticities might be used by car producers to implement promotion expenditure and pricing strategies, including choice of regular prices and magnitude of discounts, maximizing their revenue and profits, and developing competitive strategy analysis.

This study is, to the best of our knowledge, the first attempt to study the effect of habitual behavior on the choice for AFVs and our results reinforce the importance of properly accounting for the latent habitual behavior in the discrete purchase choice of a new car. Several improvements are possible and desirable as future research. As first step, we hope to extend the analysis using a larger sample to confirm the findings and to better point out potential heterogeneity among groups of regions, cities, etc. We might also use the scores obtained for factor 1 in the PCA (Table 1) to calibrate the LI-only model and compare the results of the new HCM with those reported in Table 3.

[15]UNRAE (Unione Nazionale Rappresentanti Autoveicoli Esteri), http://www.unrae.it/files/AUTO%202013_53980ec250bd0.pdf, p. 22.

## Declaration of interest

The opinions expressed are those of the authors only and should not be considered as representative of the European Commission's official position.

## Funding

The first author thanks the European Social Fund of the Friuli Venezia Giulia region for funding in 2014 via the SHARM (Supporting Human Assets of Research and Mobility) Project "Market penetration scenarios for cars with different fuel technologies," in which both the University of Trieste and the Denmark Technical University, Department of Transport, are involved. We thank Prof. Romeo Danielis for use of the data collected through the research project "Un Electric Car Club for the Friuli Venezia Giulia," in which the first author was involved.

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