

Incentivizing alternative fuel vehicles: the influence of transport policies, attitudes and perceptions

Jose J. Soto^{1,2} · Victor Cantillo¹ · Julian Arellana¹

Published online: 16 March 2018

© Springer Science+Business Media, LLC, part of Springer Nature 2018

Abstract This paper aims to evaluate the influence of policies, attitudes and perceptions when incentivizing alternative fuel vehicles. The impact of possible policies such as gasoline taxes increases, purchase price subsidies, tax exemptions, and increases in fuel recharging station availability for alternative fuelled vehicles is evaluated using hybrid choice models. The models also allow assessing the sensitivity of latent variables (i.e., attitudes and perceptions) in the car purchase behaviour. The models are estimated using data from a stated choice survey collected in five Colombian cities. The latent variables are obtained from the rating of statements related to the transport system, environmental concern, vehicle preferences, and technology. The modelling approach includes regression between latent variables. Results show that environmental concern and the support for green transport policies have a positive influence on the intention to purchase alternative fuel vehicles. Meanwhile, people who reveal to be car-dependent prefer to buy standard fuelled vehicles. The analysis among cities shows similar trends in individual behaviour, although there are differences in attribute sensitivities. The policy scenario analysis revealed high sensitivity to capital cost and the need for extensive investments in refuelling stations for alternative fuel vehicles to become attractive. Nevertheless, all policies should not only be directed at infrastructure and vehicles but also be focused on user awareness and acceptance of the alternative fuel vehicles. The analysis suggests that in an environmentally conscious market, people prefer alternative fuels. However, if the transport policies support private transport, the market shares of alternative fuel vehicles will decrease.

✉ Victor Cantillo
victor.cantillo@uninorte.edu.co

Jose J. Soto
jsoto@utb.edu.co

Julian Arellana
jarellana@uninorte.edu.co

¹ Department of Civil and Environmental Engineering, Universidad del Norte, Km 5 Via a Puerto Colombia, Barranquilla, Colombia

² Faculty of Engineering, Universidad Tecnológica de Bolívar, Cartagena, Colombia

Keywords Alternative fuel vehicles · Hybrid choice model · Discrete choice · Latent variables

Introduction

The transport sector is responsible for about 23% of the world's CO₂ emissions. Moreover, global demand for transport is unlikely to decrease in the short term, given the growth of 80% in emissions for some means of transport during the 1990–2012 period (IEA 2014). Taking this into consideration, the use of alternative fuels to reduce vehicle emissions has become a major topic of discussion nowadays. However, it is quite hard to predict market success for alternative fuel vehicles because of the difficulty in forecasting the outcomes of policy measures that promote alternative fuels (Janssen et al. 2006).

International experience shows that market success of alternative fuel is not trivial. There are successful cases where the demand for alternative fuel vehicles has had a consistent rise. Such as the cases of compressed natural gas in Argentina (Yeh 2007; Janssen et al. 2006); compressed natural gas in Italy (Engerer and Horn 2010; DG MOVE 2015) and biofuels in Sweden (DG MOVE 2015).

Norway has the highest market share for electric vehicles, which is 23% (IEA 2016). Critical incentives to new car users are tax purchase price exemptions, road toll exemptions, bus lane access (Bjerkan et al. 2016), and increasing availability of charging stations (Mersky et al. 2016). However, bus lane access can be controversial because this can lead to a situation that could impede bus traffic (Myklebust 2013), a phenomenon that has already happened in the main cities. The Netherlands has the second highest market share for electric vehicles (10%), with incentives on registration and circulation taxes (IEA 2016).

However, there are also cases where, despite a promising start, the demand for alternative fuel has slowed down, mainly because, these vehicles have encountered several barriers to their massification. For instance, the U.S. has experienced infrastructure development barriers (Melaina et al. 2017) because the users and media attention has skipped among various fuel vehicle technologies across the years (Melton et al. 2016). In the Chinese case, the relatively high price ratio between natural gas and gasoline is impeding further natural gas vehicle development (Wang et al. 2015). Similarly, the case of natural gas vehicles in Germany (von Rosenstiel et al. 2015) where there was a market failure for alternative fuels, despite tax incentives and investments. Nevertheless, knowing market conditions and individual preferences toward alternative fuels and their characteristics is crucial to define strategies to introduce these vehicles in the market successfully.

In the Colombian case, the gasoline-fuelled vehicles have an 81.9% market share, and the diesel-fuelled vehicles have 13.2% (however, most of the diesel vehicles are trucks for freight transport). Meanwhile, despite all of the recent efforts to promote alternative fuel vehicles with initiatives such as tax exemption and the encouraging of an electrical vehicles fleet for transport in the capital of the country, compressed natural gas only has a 4.9% market share. Across the country, electric and hybrid vehicles have not achieved a significant market share to appear in the statistics.

Improvement in competition refers to the continuous progress in engine efficiency to achieve lower emissions and the decline of conventional fuel prices over time, which makes the process of replacing traditional fuel a hard task. Also, according to Romm (2006), the six most common barriers to the widespread use of alternative fuel vehicles are a high first

cost for an alternative fuel vehicle, limited range, safety and liability concerns, high fueling costs, lack of fuel stations, and improvements in the competition. Due to evidence of changes in attitudes and perceptions after real-life experience with alternative fuel vehicles (Jensen et al. 2014), policies to promote the use of alternative fuels in the vehicle market must be well planned.

Much of the research has focused on evaluating the effect of subsidies on the purchase price, showing a substantial impact on the market share of these new technologies and a lower share for conventional fuel vehicles (Horne et al. 2005; Daziano and Bolduc 2013). Gasoline taxes to disincentive the traditional fuels have also been studied, but the results seem to indicate that carbon taxes alone would have a limited effect on people's purchase intentions (Ewing and Sarigollu 1998), as can be seen by the slight decrease in market shares even with a high tax. The increase of recharging infrastructure is another policy analysed to overcome the adoption barriers. However, the necessary investment in the refueling network seems to be huge in comparison to the market share augmentation (Achtnicht et al. 2012; Daziano and Bolduc 2013; Hackbarth and Madlener 2013).

Also, some scenarios have been evaluated that enhance the major drawbacks of alternative fuel vehicles: an increase in the range of electric cars and a decreased battery recharging time (Ewing and Sarigollu 1998; Mabit and Fosgerau 2011; Hackbarth and Madlener 2013; Tanaka et al. 2014), showing a remarkable increase in demand for electric vehicles. Results from analysing non-monetary incentives like free parking areas and access to HOV lanes indicate that free parking is not significant for respondents, even in limited parking areas, if the parking charges are low (Potoglou and Kanaroglou 2007). Similarly, if the trips are short, the time saved with the access to HOV lanes is not significant (Ewing and Sarigollu 1998).

One isolated policy in itself is not going to achieve a substantial change in consumers. Also, the necessary effort is enormous because market shares are not going to rise easily. Therefore, a combination of different policies may help lead to the adoption of alternative fuel vehicles, but they need to be adequately studied. Nevertheless, there are cases of conversion programs where the respondents would have adopted the alternative fuels (converting the vehicle from gas to compressed natural gas) even if they do not have incentives to do so (Saldarriaga-Isaza and Vergara 2009).

The use of hybrid choice models to evaluate policy scenarios opens a new horizon in the field of qualitative improvements that have been unexplored (Daziano and Chiew 2012). Daziano and Bolduc (2013) estimate a scenario where the environmental concern of the population increased to its mean value through a marketing campaign. However, the policy analysis and scenario evaluation using discrete choice models is an open issue. Some problems can be addressed when forecasting with hybrid choice models, such as endogeneity respect behaviour, presence of cross-sectional data, measured only at one point in time (Chorus and Kroesen 2014; Vij and Walker 2016), not knowing the factor scale when forecasting, and the establishment of an acceptable variation range for the measure evaluation.

In this research, hybrid models were used to study the preference for alternative-fuel vehicles and the impact on consumer behaviour under several policy scenarios. The paper examines the Colombian vehicle market, considering differences and similarities in preferences across cities. In the country, the vehicle ownership rate is about 83 cars per 1000 inhabitants, which is small when compared with high-income countries. However, the stock of vehicles has been growing at a 5% average per year during the last decade. The Colombian vehicle owners do not have a high purchasing power, and the vehicle cost is highly relevant in their choice, which restrains vehicle access to a specific population with higher income, which causes the purchase to be highly sensitive to the capital cost.

Besides, vehicle lifespan is longer than in other countries, making the use of cleaner fuels vital, despite their higher price.

This paper aims to analyse the peculiarity of the Colombian market, comparing differences in elasticities among cities and with other countries. Also, it evaluates the impacts of transport policies, attitudes and perceptions on the choice of alternative fuel vehicles. Even though the econometric approach is not the primary focus of the article, this paper tackles the influence of a latent factor on other latent factors, which remains as a novel aspect in the topic.

The organisation of the paper is as follows: “**Data**” section provides information about the data used; “**Model framework**” section shows the model framework. The estimated results are given and analysed in “**Results**” section. “**Policy evaluation**” section presents the analysis of policies and scenario simulations. Finally, “**Conclusions**” section is the concluding chapter.

Data

The data was collected from a survey conducted in 2013 among vehicle owners in the five most populous Colombian cities: Bogotá, Medellín, Cali, Barranquilla and Bucaramanga. These five cities cover more than 65% of the total vehicles in the country. The recruitment process consisted of interviewing people in workplaces, universities, shopping malls, and at home. The interview places were selected to cover the socioeconomic variability across the population. Within the sites, people were randomly selected.

The instrument was applied face to face by trained interviewers to randomly selected car owners who, by having the experience of owning a car, were expected to have a better understanding of a car purchase situation, by taking into account the variables presented, not only purchase price. The absence of non-car owners is a limitation of the study. However, this research only considers car owners to avoid the possible bias that can be produced because of limited knowledge regarding actual vehicle costs by non-owners. Second, in Colombia, most of the new vehicles are acquired by current vehicle owners. Most of the people buying a car for the very first time purchase a used car. The survey consisted of the following parts:

Part 1 Respondent’s socioeconomic information (sex, age, the number of household members, the number of vehicles in the family, occupation, education level, field of study).

Part 2 Current vehicle characteristics: fuel type, capital cost, type of vehicle, model year and engine size.

Part 3 Stated preference (SP) survey: the respondents were asked to purchase a vehicle in ten hypothetical situations.

Part 4 Perceptions Questionnaire: rating of some statements related to environmental care, car dependency, and government policies towards green transport.

Part 5 Additional information: average monthly income and socioeconomic status of the respondent. Socioeconomic status is a classification system used in Colombia that divides households into six class levels sorted in ascending order (from lower to higher) and primarily used for tax billing purposes. The respondents were also classified into three categories according to their income: high, medium and low.

In the SP survey (part 3), different hypothetical situations were generated for three types of vehicles: Small cars (S), Midsize-Large cars (M) and SUV's. For each individual, the SP survey applied was customised according to the type and purchase price of their current vehicle.

We performed a first pilot study with a sample size of 124 individuals to define attribute levels and test the understanding of the instrument. The estimation results of the models from the pilot test were used as priors to generate the design. Regarding the experimental design, an efficient block design, using MNL specification was coded in NGENE®. Table 1 shows the survey attributes and levels. The experimental design uses the standard gasoline-powered vehicle as a reference for the other types of fuels, with each having three attribute levels. The SP design was selected following the D-optimality criterion and assuming the MNL model, with 30 choice situations divided into three blocks.

Four technological alternatives were always presented within each choice scenario, taking into account that the diesel vehicle alternative was only presented to SUV's owners instead of the electric vehicle alternative which was available for the rest of the car users. They are standard gasoline vehicle (G), natural gas vehicle (NGV), hybrid electric vehicle (HEV), electric vehicle (EV) for small cars (S) and midsize-large cars (M) owners, and diesel vehicle (D) for SUV's.

The vehicle attributes considered in the experiment were based on focus groups and literature review. These attributes are:

- *Capital Cost* the purchase price of the vehicle.
- *Range* Number of kilometres travelled by the vehicle with a full charge of fuel.
- *Refuelling Cost* Total cost of refuelling.
- *Annual Tax* Public tax paid by the car owner in a year.
- *Fuel Availability* Presented as a ratio of 1 to X gasoline service stations. In the models, the variable was included as a proportion (range 0–1).

A total of 1065 valid questionnaires were collected out of 1200 issued. Since each respondent answered ten choice situations, 10,650 observations were used in the model estimation. Surveys not fully finished by respondents were considered as invalid responses, representing a non-response rate of 11%.

The survey also included a questionnaire of perception indicators in which respondents rated some statements on a 1–5 point Likert scale. The purpose was to evaluate the influence of underlying factors and allow the incorporation of latent factors that might affect the decision-making process.

Initially, some pairs of statements related to government policies were presented. The task consisted of expressing the degree of acceptance of those policies taking into account that if the respondent agrees with one, they disagree with the other. The pairs of statements were those indicated in Table 2. It should be noticed that a rating of 1 means a stronger preference for the left alternative, while a score of 5 means the opposite. It is important to clarify that statements regarding pro-environmental behaviour sometimes appeared as the left alternative while some other times as the right alternative. The reason to present the statements representing pro-environmental behaviour in different locations was to avoid position bias. The treatment given to these indicators is similar to a rating survey, where the ordinal logit defines preference probabilities between policies, rather than extrapolation.

In addition to those indicators, the respondents were also asked to evaluate some statements about environmental concerns and their propensity towards the use of cars and technologies

Table 1 SP design attributes and levels (expressed as percentage deviations from base values of standard gasoline-powered vehicles)

Vehicle type	Small cars				Midsize-large cars				SUV					
	G	NGV (%)	EV (%)	HEV (%)	G	NGV (%)	EV (%)	HEV (%)	G	NGV (%)	EV (%)	HEV (%)	D (%)	HEV (%)
Capital cost	100%	105	130	125	100%	105	125	115	100%	110	125	115	100	115
	\$USD 17,500	110	140	135	\$USD 27,500	115	135	125	\$USD 32,500	115	135	125	105	125
Range	100%	115	150	145	100%	120	145	135	100%	120	145	135	110	130
	320 km	45	40	120	380 km	40	40	120	400 km	45	40	120	110	125
Annual taxes	100%	55	45	130	100%	50	45	130	100%	50	45	130	120	140
	\$USD 325	65	55	150	380 km	60	55	150	400 km	55	55	150	130	150
Refuelling cost	100%	95	20	60	100%	95	20	50	100%	95	20	50	105	50
	\$USD 42	105	30	70	\$USD 750	105	30	60	\$USD 850	105	30	60	120	60
Fuel availability	100%	115	40	80	100%	115	40	80	100%	115	40	80	130	70
	\$USD 42	20	10	95	100%	15	10	80	100%	20	10	80	70	75
	\$USD 42	25	15	100	\$USD 60	20	15	90	\$USD 75	25	15	90	80	85
	\$USD 42	30	20	105	100%	25	20	100	100%	30	20	100	90	100
	\$USD 42	50	25	100	100%	50	25	100	100%	50	25	100	100	100
	\$USD 42	25	13	100	100%	25	13	100	100%	25	13	100	100	100

Table 2 Support government policies indicators

Alternative 1		Alternative 2				
1. Invest in highways and road expansion for car transit	1	2	3	4	5	Invest in public transport, improving the BRT infrastructure
2. Parking charge in public areas	1	2	3	4	5	More public areas available for parking
3. Use sidewalks for parking and additional lanes	1	2	3	4	5	Use sidewalks for green areas, bike paths and pedestrians
4. Raise gasoline taxes to reduce use and emissions	1	2	3	4	5	No gasoline taxes for lower prices
5. Keep vehicle circulation free	1	2	3	4	5	Congestion charging
6. Invest public resources in public transport for a better service without raising prices	1	2	3	4	5	Invest public resources in gasoline subsidy for lower operational cost

Table 3 List of indicators and expected sign

Indicators	Expected sign
Support for green transport policies	
1. More public areas available for parking	–
2. No gasoline taxes to reduce prices	–
3. Congestion charging	+
Environmental concern	
4. Use sidewalks for green areas, bike paths and pedestrians	+
5. Air pollution does not affect my life	–
6. Industries must be asked for the use of recycled products	+
7. I would rather buy an environmentally friendly item even if they are more expensive	+
8. Environmental requirements are an obstacle to progress	–
Attitudes pro-technology	
9. I like top-notch technology	+
10. Most problems could be solved with technology	+
11. Technology does more harm than good	–
Attitudes pro-car use	
12. A car is vital in my life	+
13. When my car does not work, I will use public transport instead of a taxi	–
14. I use a vehicle for all my trips, even for short distances	+
15. Invest in public transport, improving the BRT infrastructure	–

using a Likert scale. Through a factorial analysis, some indicators were discarded. Table 3 presents the final structure considered for modelling purposes.

Most of the participants were men (see Table 4). This gender gap is expected, as men have 74% of driving licenses in Colombia. Also, most of the respondents are working people and students, and about 80% of the interviewees have a college education or higher. Regarding income classes, almost all of the respondents belong to middle or high-income classes. The former can be easily explained because in the country where the survey was applied, vehicles are not affordable for most low-income users and the small cars are the most popular. Table 5 show similar sample distributions across cities.

Table 4 shows that small cars and SUV's owners have a predisposition to choose conventional fuel vehicles. However, the hybrid electric vehicle achieves high acceptance rates among respondent's choices—about the same as natural gas. Electric cars were the least chosen vehicles (Table 5). This phenomenon could be explained by the lack of knowledge about the technology, or by the presence of habit or inertia effect (Cantillo et al. 2007; Valeri and Cherchi 2016). It is interesting the case of Bucaramanga, where most respondents chose the HEV option. Also, in Table 6, the percentages above 3 of each indicator responses per city are shown. There are some differences between cities, with relatively high standard deviations; however, the tendencies are, in general, the same despite some individual cases.

Model framework

The discrete choice approach based on the random utility theory was used. This theoretical framework postulates that individuals possess perfect information about the alternatives

Table 4 Respondents socioeconomic characteristics

Attribute	Total (%)	Bogotá (%)	Bucaramanga (%)	Medellín (%)	Cali (%)	Barranquilla (%)
Respondent information						
Gender						
Male	68.6	64.0	63.5	76.2	62.3	76.1
Female	31.4	36.0	36.5	23.8	37.7	23.9
Educational level						
Elementary	0.8	0.0	2.0	0.5	1.8	0.0
High-school	11.9	15.0	10.0	13.4	16.4	5.8
Technic	7.3	6.0	8.0	12.9	6.8	3.7
College	55.5	42.0	64.5	57.4	45.0	67.1
Graduate	24.4	37.0	15.5	15.8	30.0	23.5
Level of income						
Low	6.1	10.0	3.5	6.9	7.7	2.9
Medium	58.2	65.5	65.5	63.9	30.4	66.7
High	35.7	24.5	31.0	29.3	61.8	30
Vehicle information						
Vehicle type						
Automobile	74.0	67.5	76.0	70.8	81.4	73.7
SUV	26.0	32.5	24.0	29.2	18.6	26.3
Engine size (L)						
< 1.6	61.2	44.5	62.5	73.8	60.9	63.8
1.6–2.4	23.9	34.0	23.0	17.3	28.6	17.7
> 2.4	14.8	21.5	14.5	8.9	10.5	18.5
Fuel						
Gasoline	88.3	86.5	87.0	83.2	94.1	89.7
Diesel	8.4	13.5	10.5	7.9	3.6	7.0
CNG	3.4	0.0	2.5	8.9	2.3	3.3

Table 5 Respondents choices

Fuel	Total (%)	Bogotá (%)	Bucaramanga (%)	Medellin (%)	Cali (%)	Barranquilla (%)
Gasoline	30.2	27.5	28.2	35.2	26.5	33.5
CNG	19.3	20.3	7.6	24.4	23.8	19.8
EV	9.5	6.4	5.0	6.2	15.0	13.6
HEV	30.7	29.1	52.8	24.6	28.8	20.7
Diesel	10.3	16.9	6.6	9.6	5.9	12.5

and act rationally, choosing the alternative that maximises their personal utility or satisfaction (Ortúzar and Willumsen 2011).

Different approaches have been used to estimate demand for alternative fuel vehicles. On the one hand, there are macroeconomic approaches like time series analysis (Sobh

Table 6 Indicator responses for each city

Indicator	Responses above 3					
	BOG (%)	BGA (%)	MDE (%)	CLO (%)	BAQ (%)	
1. More public areas available for parking	42	45	35	66	76	
2. No gasoline taxes to reduce prices	74	76	66	77	76	
3. Congestion charging	44	44	60	41	39	
4. Use sidewalks for green areas, bike paths and pedestrians	51	71	45	87	70	
5. Air pollution does not affect my life	34	7	24	6	15	
6. Industries must be asked for the use of recycled products	81	74	74	94	84	
7. I would rather buy an environmentally friendly item even if they are more expensive	56	55	64	49	55	
8. Environmental requirements are an obstacle for progress	18	8	4	4	11	
9. I like top-notch technology	69	58	68	65	66	
10. Most problems could be solved with technology	49	54	40	44	59	
11. Technology does more harm than good	9	15	8	8	16	
12. A car is vital in my life	28	31	43	69	44	
13. When my car does not work, I will use public transport instead of a taxi	74	51	34	29	47	
14. I use a vehicle for all my trips, even for short distances	44	24	27	39	35	
15. Invest in public transport, improving the BRT infrastructure	10	28	15	21	30	

BOG Bogotá, *BGA* Bucaramanga, *MDE* Medellín, *CLO* Cali, *BAQ* Barranquilla

2015) and diffusion models (See Gnnann and Plötz (2015) for a comprehensive review of diffusion models). On the other hand, there are microeconomic approaches like those based on random utility maximisation theory. Within microeconomic approaches, the discrete choice models are accepted as a robust framework. Also, because this research aims to evaluate individual behaviour and choices, disaggregate demand models are more efficient than aggregate models in terms of information usage.

Several studies on the estimation of preferences for alternative fuel vehicles have been conducted in past years using discrete choice models. The majority of them analyse the effect of car features like purchase price, fuel costs and range (Beggs et al. 1981; Brownstone et al. 2000; Horne et al. 2005; Potoglou and Kanaroglou 2007; Collantes 2010; Caulfield et al. 2010; Mabit and Fosgerau 2011; Achtnicht et al. 2012; Hess et al. 2012; Daziano and Bolduc 2013; Hackbarth and Madlener 2013; Hoen and Koetse 2014; Tanaka et al. 2014; Galván et al. 2016).

Because individual preferences toward alternative fuels may not be homogeneous across the whole population and could also be affected by latent factors,¹ it is common to consider more flexible choice frameworks, such as the hybrid choice models (Ben-Akiva et al. 2002; Walker 2001). Hybrid choice models integrate unobservable variables within the traditional discrete choice framework and also accommodate preference heterogeneity. In the context of the study of alternative fuel vehicle demand, latent class models (Hackbarth and Madlener 2016; Hidrue et al. 2011) and integrated latent variable and discrete choice models have been used to analyse the effect of environmental concern (Bolduc et al. 2008; Daziano and Bolduc 2013; Jensen et al. 2013; Soto et al. 2014); safety (Daziano 2012); convenience and vehicle lease (Glerum et al. 2013); appreciation of car features (Mabit et al. 2015); social influences (Kim et al. 2016; Cherchi 2017) and habitual behaviour (Valeri and Cherchi 2016) in the decision making process when there are alternative fuel vehicles involved.

Taking advantage of having preference data from several cities in Colombia, a multinomial logit with the panel effect feature was used, allowing for scale differences among the cities. Considering disagreements over the scale parameters gives an added value for the model regarding data enrichment (Louviere et al. 2000).

We considered differences in taste preferences among individuals of different cities. Primarily, separate models for each city were estimated, following the approach by Hensher et al. (1998) when estimating models with different data sources. Then, for the pooled model, Bucaramanga was defined as the base city.

The latent variables were initially obtained through an exploratory factor analysis considering the ratings to the indicators questionnaire. Four latent variables were defined: (a) support for green transport policies (GP); (b) environmental concern (EC); (c) attitudes pro-car use (PC) and (d) attitudes pro-technology (TEC).

The latent variable model presented here consists of two parts: the structural equations, which are equations that relate socioeconomic characteristics with the latent variables; and the measurement equations, that express the relationship between the latent variables and the indicators (see Fig. 1). Table 7 shows the variables used in the estimated models.

The structural equations for an individual q and latent variable l can be expressed as (1). The measurement equation for a given indicator m can be formulated according to

¹ Latent factors are variables that are not directly measured, given their intangibility or subjectivity, but are rather inferred from other observed variables.

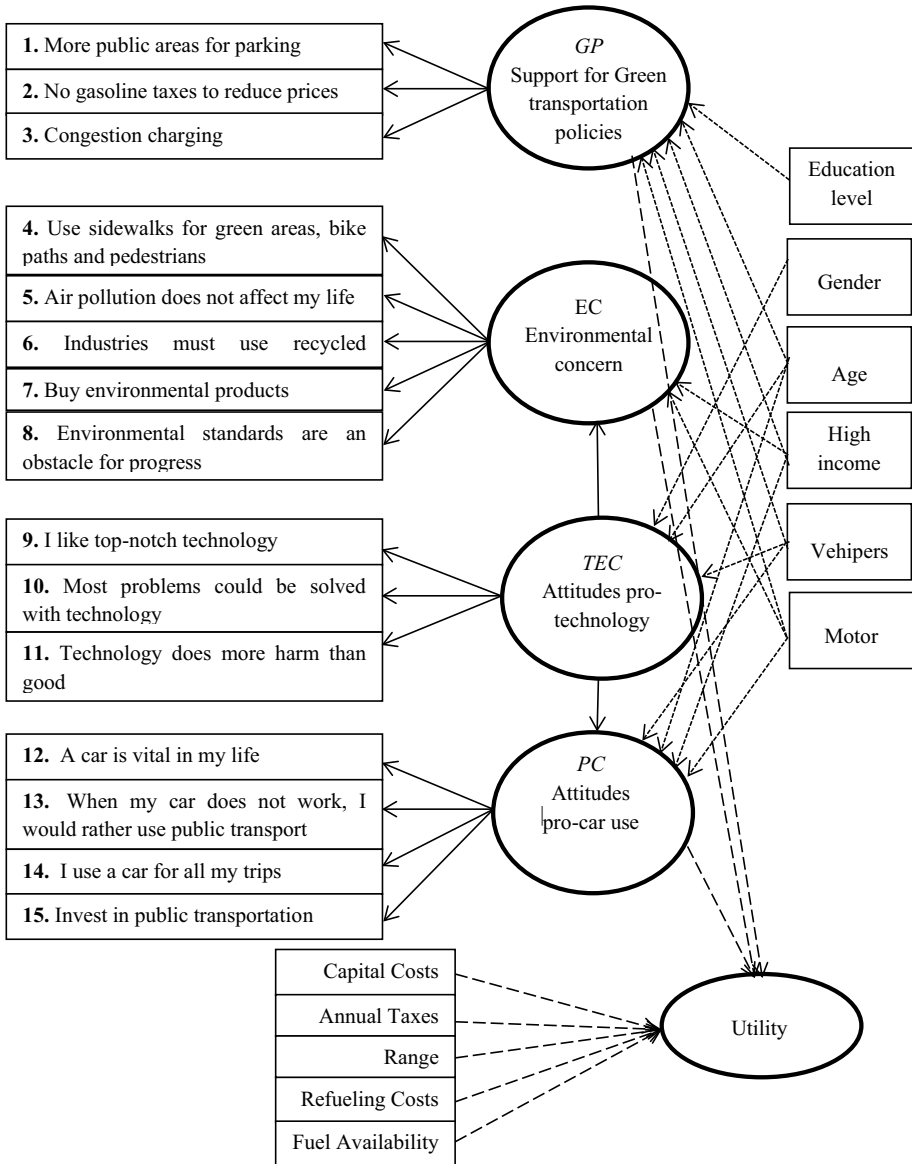


Fig. 1 Hybrid choice model (HCM) framework

(2), whether it refers to continuous indicators, or as with (3), if categorical indicators are used. In the last case, when the continuous latent variable lies within some defined threshold limit values (τ), then it will assume a particular value of the categorical indicator through a censorship mechanism.

$$X_{lq}^* = \sum_s \gamma_{ls} S_{sq} + \delta_{lq} \tag{1}$$

Table 7 List of used variables

Used in	Variable	Type	Description	
Choice models	ASC_n	Continuous	Specific constant for alternative n	
	μ_c	Continuous	Scale factor for city c	
	Capital cost (<i>PRICE</i>)	Continuous	Purchase cost (million \$COL)	
	Range (<i>RANGE</i>)	Continuous	Kilometres travelled by the vehicle with a full charge	
	Annual taxes (<i>TAX</i>)	Continuous	Annual taxes (thousand \$COL)	
	Refuelling cost (<i>REFUEL</i>)	Continuous	Total cost of refuelling (thousand \$COL)	
	Fuel availability (<i>AVAIL</i>)	Continuous	Percentage of fuel stations (ratio to gasoline stations)	
	Latent variables	<i>EC</i>	Continuous	Environmental concern latent variable
		<i>PC</i>	Continuous	Attitudes pro-car use latent variable
		<i>GP</i>	Continuous	Support for green transport policies latent variable
<i>TEC</i>		Continuous	Attitudes pro-technology latent variable	
<i>EC_EV</i>		Continuous	Coefficient of EC on Electric vehicles	
σ		Continuous	Panel effect	
I_m		Categorical	Indicator m	
$Threshold_{mj}$		Continuous	Threshold j of indicator m	
Structural equations		<i>D_m</i>	Continuous	Regression weight of indicator m
		<i>Vehipers</i>	Continuous	Number of cars/number of family members
	<i>Age</i>	Continuous	Respondent's age	
	<i>Engine</i>	Continuous	Engine size (litres)	
	<i>EdLevel</i>	Dummy	1: Educational level is college or higher, 0: otherwise	
	<i>Gender</i>	Dummy	1: Female, 0: Male	
	<i>HighClass</i>	Dummy	1: If social class is 5 or 6, 0: otherwise	

$$I_{mq}^* = \sum_l \lambda_{lm} X_{lq}^* + \omega_{mq} \tag{2}$$

$$I_{mq} = \begin{cases} 1 & \text{si } \tau_0 < I_{mq}^* < \tau_1 \\ 2 & \text{si } \tau_1 < I_{mq}^* < \tau_2 \\ \dots & \\ c & \text{si } \tau_{c-1} < I_{mq}^* < \tau_c \end{cases} \tag{3}$$

where \mathbf{X}_q^* = Vector of latent variables for individual q ; \mathbf{S}_q = Vector of socioeconomic characteristics (denoted by s); \mathbf{I}_q = Vector of attitudinal and perception indicators; λ, γ = Vectors of unknown parameters to be estimated; δ_q, ω_q = Error terms.

If F is the cumulative distribution function, the probability of observing I_{mq} , within a discrete indicator or category c , can be written as (4):

$$Pr\{I_{mq} = c | X_{lq}^*\} = F\left(\tau_c - \sum_l \lambda_{lm} X_{lq}^*\right) - F\left(\tau_{(c-1)} - \sum_l \lambda_{lm} X_{lq}^*\right) \tag{4}$$

The error terms (ω) were assumed to follow a logistic distribution and are independent from the set of parameters λ . The logistic distribution form was used due to its close cumulative form that reduces the difficulty on the evaluation of the function (Daly et al. 2012). In this case, the scale factor associated with the logistic function was normalized to one. Then the probability of observing an outcome category c on the indicator m for individual q can be expressed as (5):

$$Pr\{I_{mq} = c | X_{lq}^*\} = \frac{e^{(\tau_c - \sum_l \lambda_{lm} X_{lq}^*)}}{1 + e^{(\tau_c - \sum_l \lambda_{lm} X_{lq}^*)}} - \frac{e^{(\tau_{(c-1)} - \sum_l \lambda_{lm} X_{lq}^*)}}{1 + e^{(\tau_{(c-1)} - \sum_l \lambda_{lm} X_{lq}^*)}} \tag{5}$$

If there are m indicators' categories, only $m - 1$ thresholds (τ) need to be estimated. The first and the last threshold were fixed to $-\infty$ and ∞ , respectively.

In this paper, the discrete choice model (DCM) component was formulated using a mixed logit framework (ML), considering panel effect and different scale factors for different cities. ICLV models are already a mixture model and therefore can capture a part of the randomness due to panel effects. However, to separate effects due to multiple error terms, we decided to estimate the variance for the panel effect. The significance of the variance of the panel effect suggests that correlation among responses of the same individual does not have to be neglected. Also, it is important to clarify that we estimated models with and without considering the panel effect. The ICLV model including the panel effect resulted in being better fitted. Finally, because of the presence of 3 SP games, each one with 4 technological alternatives, there are 12 utility functions in the model. The utility functions have the following general structure:

Table 8 Structure of the measurement equations

Indicators	Latent variables			
	GP	EC	PC	TEC
1. Parking charge in public areas	1			
2. Raise gasoline taxes with the objective to reduce car use and emissions	1			
3. Congestion charging	1			
4. Use sidewalks for green areas, bike paths and pedestrians		1		
5. Air pollution does not affect my life		1		
6. Industries must be asked for the use of recycled products		1		
7. I would rather buy an environmentally friendly item even if they are more expensive		1		
8. Environmental requirements are an obstacle to progress		1		
9. I like top-notch technology				1
10. Most problems could be solved with technology				1
11. Technology does more harm than good				1
12. A car is vital in my life			1	
13. When my car does not work, I will use public transport instead of a taxi			1	
14. I use a vehicle for all my trips, even for short distances			1	
15. Invest in public transport infrastructure			1	

$$U_{ijqt} = \mu_j \left(ASC_i + \sum_k \beta_{ik} X_{ikt} + \sum_l \alpha_{il} X_{lq}^* + \epsilon_{ijqt} + \varphi_{ijq} \right) \tag{6}$$

where \mathbf{X}_{it} : Is the attribute vector for observed variables k of technological alternative i , for a given choice scenario t ; \mathbf{X}_q^* : Is the latent variables vector; ASC_i : is the alternative specific constant; α, β : are vectors of parameters to be estimated; ϵ_{ijqt} : are the error terms for the DCM component. They are assumed to be iid Gumbel; φ_q : Are the error terms associated with the panel effect; μ_j : Is the scale factor for city j .

For identification issues, it was necessary to set the specific constant and the coefficients for the latent variables associated with the gasoline alternative for all SP games as zero. Then the total likelihood was estimated as the product of the likelihoods of the DCM component and the latent variable model, using a simultaneous estimation code written in OX (Doornik 2007), and defined as follows:

$$L_{Hybrid} = \prod_q \left\{ \int_{\delta, \varphi} \left[\prod_i \frac{e^{V_{iqt}}}{\sum_r e^{V_{riq}}} \right] * \prod_m \left[\sum_c \left(\frac{e^{(\tau_c - \sum_l \lambda_{lm} X_{lq}^*)}}{1 + e^{(\tau_c - \sum_l \lambda_{lm} X_{lq}^*)}} - \frac{e^{(\tau_{(c-1)} - \sum_l \lambda_{lm} X_{lq}^*)}}{1 + e^{(\tau_{(c-1)} - \sum_l \lambda_{lm} X_{lq}^*)}} \right) * D_{cmq} \right] dF_1(\delta) dF_2(\varphi) \right\} \tag{7}$$

In (7), D_{cmq} is a dummy taking the value of one if the individual q rated c on the indicator m ; $F_1(\delta), F_2(\varphi)$ are density probability functions assumed to distribute independent normal with mean zero and unknown covariance to be estimated. For identification purposes, the variances associated to $F_1(\delta)$ were set to one.

The relationship between indicators and latent variables were calculated through a factorial analysis using maximum likelihood estimates and then confirmed in the hybrid choice model. The measurement equations are as shown in Table 8. Each “1” represents a relationship among variables (arrows represent the same relationships in Fig. 1).

Even though four latent variables are estimated in the model, only three of them have a direct impact on the utility function. Pro-technology attitudes (TEC) are hypothesised to influence the vehicle purchase through the environmental concern (EC) and the pro-car use attitudes (PC) instead of affecting the choice directly. The fact that the TEC variable is considered to be an explanatory variable of two other latent variables using a factor on factor regression defines what we called a second-order latent variable structure. To our best knowledge, no previous studies of alternative fuel vehicle purchases have used such a framework within an integrated choice and latent variables model.

Results

We used modified Latin Hypercube Sampling (Hess et al. 2006) to generate quasi-random numbers to estimate the simulated log-likelihood of the HCM. Results for MNL and the choice component of the second and first order HCM are shown in Table 9. Table 10 presents the socioeconomic and latent variables of the choice models.

When analysing the results presented in Table 9, several noteworthy inferences can be made. Regarding the socioeconomic variables included in the reduced form MNL model (Table 10), it can be inferred that the higher the income, the lower the preference for NGV vehicles. Meanwhile, at bigger engine sizes, NGV vehicles are preferred. The former result could be because of operational costs savings when compared to conventional fuels. Highly educated users prefer EV; however, when cars per household rates increase, EV's become less attractive. HEV's become more likely to be chosen when income increases.

All parameter signs are consistent with their economic expectations. Indeed, all the cost related variables (purchase price, annual taxes and refuelling costs) have a negative orientation and are statistically significant. Both alternative fuel availability and vehicle range have a meaningful and positive influence on the choices. All the scale parameters are significant, confirming the initial assumption about differences among cities.

Most of the latent variable coefficients of the second order model are statistically significant. The environmental concern (EC) coefficients are significant in all available technologies. The support for green transport policies (GP) parameters are significant in almost all alternatives (except natural gas), and the pro-car use attitudes (PC) are only significant in electric and diesel vehicles. In the first order model, the latent variable GP is not significant at all; the latent variable TEC only has a significant coefficient for the electric vehicles, meaning high tech individuals are more likely to purchase an electric car. Besides, in Table 11, the goodness of fit of both MIMIC models is presented. Results demonstrate a relative improvement of the indicators when the second order relationship is considered.

The coefficients of variables associated with the HCM have reasonable orientations. As expected, the direction of the Environmental Concern (EC) coefficient is positive, so the people with a higher environmental conscience are more likely to buy alternative fuel vehicles. Also, GP coefficients have a positive direction, which means that the users open to policies that encourage green transport modes are more likely to buy alternative fuel vehicles.

Table 9 Car choice models

Coefficient	MNL		HCM_Second Order		HCM_First Order	
	Coefficient	Robust <i>t</i> test	Coefficient	Robust <i>t</i> test	Coefficient	Robust <i>t</i> test
ASC						
<i>NGV_S</i>	1.76	2.05	2.72	3.3	2.1	2.1
<i>EV_S</i>	3.77	3.28	4.02	2.89	4.85	3.31
<i>HEV_S</i>	0.55	0.69	-1.29	-1.65	-0.36	-0.28
<i>NGV_M</i>	1.54	1.48	2.78	2.71	1.82	2.29
<i>EV_M</i>	3.35	2.45	3.61	2.1	4.49	1.45
<i>HEV_M</i>	1.03	1.13	-1.12	-1.13	-0.07	-0.09
<i>NGV_{SUV}</i>	0.39	0.34	1.72	1.4	0.04	0.02
<i>D_{SUV}</i>	3.09	3.01	3.47	4.22	3.99	3.8
<i>HEV_{SUV}</i>	1.04	1.04	-1.24	-1.09	-0.31	-0.16
Attributes (β)						
<i>Capital cost</i>	-0.1733	-11.03	-0.1757	-10.52	-0.1766	-7.69
<i>Range</i>	0.00483	5.40	0.00492	5.4	0.00492	5.29
<i>Annual taxes</i>	-0.00154	-5.94	-0.00150	-5.61	-0.00152	-5.61
<i>Refuelling cost</i>	-0.02076	-6.16	-0.02042	-5.86	-0.02033	-5.84
<i>Fuel availability</i>	5.1497	8.26	5.19	7.83	5.31	6.37
Scale Factors						
μ_1	0.42	11.55	0.43	10.5	0.41	10.6
μ_3	0.84	10.10	0.85	9.62	0.86	8.2
μ_4	0.50	11.35	0.47	10.17	0.49	6.14
μ_5	0.83	11.66	0.83	11.04	0.81	5.09
Panel effect						
σ_φ	-2.50	-16.41	0.3	1.1	0.03	0.03
Parameters DCM	43		31		35	
Observations	10650		10,650		10,650	
LL HCM			-32,467.6		-32,462.6	
LL DCM	-10,712.9		-10,676.4		-10,681.3	

NGV Natural gas vehicles, *EV* electric vehicles, *HEV* hybrid vehicles, *D* diesel vehicles

Regarding the latent variables *PC*, those that achieved statistical significance have negative orientations, except the *NGV*'s in the first order model. The previous results could be caused by a lack of knowledge of alternative technologies (e.g. Electric Vehicles) or because of certain prejudices or misconceptions about alternative technologies. This result seems to indicate that the users of conventional fuel vehicles are more attracted to continue using traditional cars than to buy alternative fuel vehicles.

Tables 12 and 13 contain the estimated parameters for the structural and measurement model components, respectively. According to the results of the latent variable *TEC*, women have less interest in technology, contrasting with younger people, who show the opposite behaviour. Also, the higher the number of cars per household, the higher the tech attitudes. Regarding the latent variable *GP*, the ratio between the number of vehicles and the number of household members was not found to be significant. On the other hand, users with a higher education level, income and age are more willing to support sustainable transport policies. In the latent variable *PC*, there are no significant

Table 10 Car choice models. Socioeconomic and latent variables

Coefficient	MNL		HCM_Second Order		HCM_First Order	
	Coefficient	Robust <i>t</i> test	Coefficient	Robust <i>t</i> test	Coefficient	Robust <i>t</i> test
Socioeconomic variables						
<i>HighInc_NGV</i>	-0.79	-2.55				
<i>Motor_NGV</i>	0.45	1.66				
<i>StudyLevel_NGV</i>	0.18	0.47				
<i>Vehipers_NGV</i>	-0.04	-0.07				
<i>Age_NGV</i>	1.14	0.90				
<i>Gender_NGV</i>	0.26	0.82				
<i>HighInc_EV</i>	0.14	0.44				
<i>Motor_EV</i>	-0.41	-1.14				
<i>StudyLevel_EV</i>	0.90	2.08				
<i>Vehipers_EV</i>	-1.92	-3.03				
<i>Age_EV</i>	0.66	0.47				
<i>Gender_EV</i>	-0.40	-1.18				
<i>HighInc_HEV</i>	1.09	3.60				
<i>Motor_HEV</i>	0.13	0.52				
<i>StudyLevel_HEV</i>	-0.12	-0.30				
<i>Vehipers_HEV</i>	-0.71	-1.16				
<i>Age_HEV</i>	-0.70	-0.66				
<i>Gender_HEV</i>	-0.10	-0.33				
<i>HighInc_D</i>	-0.25	-0.62				
<i>Motor_D</i>	-0.44	-1.55				
<i>StudyLevel_D</i>	0.61	1.00				
<i>Vehipers_D</i>	-0.95	-1.70				
<i>Age_D</i>	-0.44	-0.30				
<i>Gender_D</i>	-0.53	-1.36				
Latent variables						
<i>EC_NGV</i>			2.36	6.32	2.56	4.53
<i>EC_EV</i>			3.57	3.54	3.48	5.05
<i>EC_HEV</i>			1.29	2.63	0.56	1.07
<i>EC_D</i>			1.77	3.25	0.39	0.19
<i>GP_NGV</i>			-0.29	-0.9	0.45	0.2
<i>GP_EV</i>			1.95	2.42	1.42	0.59
<i>GP_HEV</i>			3.16	8.26	3.08	1.08
<i>GP_D</i>			1.33	3.23	0.08	0.02
<i>PC_NGV</i>			0.22	0.6	1.07	5.62
<i>PC_EV</i>			-2.4	-3.23	-2.39	-3.28
<i>PC_HEV</i>			0.03	0.06	-1.08	-2.47
<i>PC_D</i>			-1.93	-2.67	-1.52	-0.46
<i>TEC_NGV</i>					1.66	1.1
<i>TEC_EV</i>					2.25	2.74
<i>TEC_HEV</i>					1.6	0.39
<i>TEC_D</i>					2.53	1.28

EC Environmental concern, *GP* support for sustainable transport policies, *PC* attitudes pro-car use, *TEC* attitudes pro-technology, *NGV* natural gas vehicles, *EV* electric vehicles, *HEV* hybrid vehicles, *D* diesel vehicles

Table 11 Goodness of fit MIMIC models

	Second order	First order
Number of parameters	65	63
Degrees of freedom	125	127
Chi squared	461	511.316
p (Chi squared)	0	0
$p(\chi)/df$ (<3)	3.688	4.026
GFI (Close to 1)	0.954	0.948
CFI (Close to 1)	0.824	0.799
RMSEA (<0.05)	0.051	0.054

Table 12 Latent variable structural model

γ_{is}	TEC	GP	EC	PC
	Estimate (Rob t test)	Estimate (Rob t test)	Estimate (Rob t test)	Estimate (Rob t test)
Gender	-0.18 (-3.72)			
Age	-0.9 (-4.52)	0.39 (1.97)		-0.18 (-0.33)
VEHIPERS	0.28 (2.4)	0.09 (0.74)		0.98 (1.52)
Education level		0.19 (2.9)		
High income		0.24 (3.39)	0.01 (0.11)	0.22 (1.78)
Motor		0.1 (2.07)	-0.13 (-1.84)	0.18 (1.65)
TEC			-0.9 (-5.42)	-0.82 (-1.06)

variables at a 95% confidence level. It seems to indicate that those users with a higher income, a higher rate of vehicles per household and bigger vehicles overall, have preferences towards car use.

Some socioeconomic variables included in the structural model have different signs across latent variables. For instance, the elderly are the least pro-technology (TEC); meanwhile, according to the model, they are more prone to support green transport policies (GP). In the case of the variable motor, respondents with low environmental concern (EC) and high pro-car use attitudes (PC) prefer bigger engine sizes.

Although the second-order latent variable, *TEC*, has a clear structure, it is not significant in the pro-car attitudes (*PC*) variable. However, the second order relationship between the EC results is highly significant with a negative coefficient, meaning that some users are more worried about technology but less concerned about the environment. These findings are in line with Kollmuss and Agyeman (2002), who indicate that people with a strong belief in growth and technological solutions might not see the need and will be less willing to engage in the pro-environmental behaviour. On the other hand, Jansson (2009) show that, in Sweden, green consumers have more AFV's replacement intentions and an earlier adoption rate. In Colombia, according to the survey, approximately half of the respondents would instead use proven technology than an unproven novelty, suggesting a more traditionalist behaviour.

The second order model tries to provide a better understanding of the psychology underlying the attitudes. An attitude might not have a straightforward influence on the utility, but

Table 13 Latent variable measurement model

Latent variable	Indicator	λ_{lm}	Threshold (τ_c)				
			1	2	3	4	
TEC	19	Coefficient	3.99	-8.19	-5.96	-2.51	0.35
		Robust <i>t</i> test	1.99	-2.37	-2.34	-2.17	0.86
	110	Coefficient	1.00	-3.29	-2.12	-0.19	1.14
		Robust <i>t</i> test	8.11	-15.19	-12.92	-1.60	9.78
	111	Coefficient	-0.78	-0.43	0.84	2.42	3.48
		Robust <i>t</i> test	-7.01	-4.37	7.80	17.36	18.28
GP	11	Coefficient	-1.89	-3.61	-2.20	-1.54	-0.06
		Robust <i>t</i> test	-7.51	-7.59	-5.66	-4.36	-0.19
	12	Coefficient	-1.18	-4.35	-3.08	-2.18	-0.57
		Robust <i>t</i> test	-9.91	-16.03	-13.47	-10.65	-3.21
	13	Coefficient	1.59	-0.24	1.02	1.41	2.69
		Robust <i>t</i> test	9.31	-1.01	3.91	5.17	8.45
EC	14	Coefficient	0.70	2.85	1.77	0.83	-0.36
		Robust <i>t</i> test	7.31	14.94	10.92	5.68	-2.56
	15	Coefficient	-0.88	-0.26	-1.30	-2.09	-2.92
		Robust <i>t</i> test	-7.04	-1.49	-7.15	-10.60	-12.88
	16	Coefficient	1.32	5.30	4.05	2.37	0.89
		Robust <i>t</i> test	6.55	11.79	10.13	7.32	3.25
17	Coefficient	0.64	3.23	1.54	0.35	-0.59	
	Robust <i>t</i> test	7.30	16.40	10.00	2.53	-4.39	
PC	18	Coefficient	-0.75	-0.40	-1.49	-2.76	-4.33
		Robust <i>t</i> test	-7.17	-2.63	-8.88	-14.01	-15.75
	I15	Coefficient	-0.41	-0.79	0.52	0.89	1.99
		Robust <i>t</i> test	-2.45	-4.40	3.14	5.44	11.68
	I12	Coefficient	1.37	-1.09	0.28	2.04	3.42
		Robust <i>t</i> test	2.51	-2.82	0.77	5.30	7.90
I13	Coefficient	-0.85	-2.35	-1.56	-0.75	0.22	
	Robust <i>t</i> test	-2.43	-6.15	-4.53	-2.39	0.78	
I14	Coefficient	0.82	-0.47	0.65	1.80	2.75	
	Robust <i>t</i> test	2.55	-2.08	2.90	7.75	11.20	

it may have an effect through another latent variable, which indeed reinforces the complexity of the decision process. So, it seems that the second order relationship is a successful way of dealing with poorly specified structural equations, but it needs further research and more testing.

Policy evaluation

Despite the recent developments of hybrid models, few studies use them either to forecast or to evaluate policies. Some of them include the role of individual attitudes and

perceptions predicting demand for electric vehicles (Glerum et al. 2013) and cycling (Maldonado-Hinarejos et al. 2014). Regarding their use for policy evaluation, changes in the forecast choice probabilities may arise from variations in the explanatory variables (usually socioeconomic, which affect the choices implicitly through the latent variables) or changes in the tangible attributes (which affect the decisions directly through the utilities) (Yáñez et al. 2009). However, there is still a gap in using hybrid models for prediction. That is because, on the one hand, latent attitudes and perceptions are partly endogenous on travel behaviour, precluding a strong inference of causality and, on the other hand, such variables are measured by a single data moment in time (cross section data), precluding an inference of within-person variation.

One of the potential attractions of hybrid choice models is that they appear to offer a mean to predict the impact of policies designed to change the perceptions and attitudes of decision makers (so-called soft measures). However, a challenge is how to predict the effect of policy interventions on latent variables and associated indicators. That is, how a real-world policy (e.g., a specific advertising campaign) might change perceptions. What is easier to predict is how changes in socioeconomic variables affect perceptions (through structural equations), and through this, the utility function and then, the choice probabilities.

Several authors have highlighted the problems of using hybrid choice models (Chorus and Kroesen 2014; Vij and Walker 2016) and stated preference data (Fujii and Gärling 2003) to predict demand. Although it is a matter of discussion, the use of stated preferences to evaluate the sensibility of the demand is extensive, especially when assessing several policy scenarios that are not currently available or alternatives that are not in the market. In this particular case, given that alternative fuel vehicles have a low market share, and some technologies lack a market presence in Colombia, it makes it impossible to use revealed preference data. Therefore, the estimated hybrid choice model was used to evaluate the expected impact of several attributes in car purchase behaviour.

Elasticity analysis

In discrete choice models, the coefficients represent the marginal effect of the attribute over the utility function. This effect can be better understood with the estimation of the elasticity. Table 14 shows the direct and the cross-elasticities and Table 15 compares our estimates with other studies found in the literature. Analysis of the direct elasticities lets us infer that the capital costs have the greater impact on the choice probability. The average direct purchase price elasticity of the demand is between values of -0.9 to -1.4 , indicating a higher sensitivity compared to other attributes. This value is lower than the -2.05 elasticity found by Mabit and Fosgerau (2011) and values within -1.3 to -2.4 found by Dagsvik et al. (2002). However, it is in the same order of magnitude of -1.02 found by Jensen et al. (2013) in Denmark and values around -0.8 found by Bittencourt et al. (2016) in Brazil.

At the same time, a rise in the alternative fuel vehicle's range does not produce a significant increase in demand. The direct elasticity for range increase in electric cars is between 0.12 and 0.25 , which is lower than Mabit and Fosgerau's (2011) documented value of 0.34 . Jensen et al. (2013) find values of 0.66 and 0.44 for a single car and multiple car households, respectively. These values were even higher after the respondents

Table 14 Direct and cross elasticities

	Capital cost elasticity					Range elasticity					
	G	CNG	EV	HEV	D	G	CNG	EV	HEV	D	
Gas	-0.89	0.43	0.30	0.35	0.33	Gas	0.19	-0.10	-0.07	-0.08	-0.06
CNG	0.30	-1.22	0.35	0.26	0.15	CNG	-0.03	0.12	-0.04	-0.02	-0.01
EV	0.10	0.15	-1.39	0.16	-	EV	-0.01	-0.01	0.11	-0.01	-
HEV	0.47	0.49	0.56	-1.11	0.52	HEV	-0.11	-0.12	-0.14	0.24	-0.12
Diesel	0.19	0.17	-	0.19	-0.94	Diesel	-0.04	-0.04	-	-0.04	0.20
	Annual taxes elasticity					Refuelling cost elasticity					
	G	CNG	EV	HEV	D	G	CNG	EV	HEV	D	
Gas	-0.19	0.09	0.06	0.07	0.07	Gas	-0.24	0.11	0.08	0.09	0.08
CNG	0.05	-0.26	0.06	0.05	0.03	CNG	0.02	-0.07	0.02	0.01	0.01
EV	0.00	0.00	-0.04	0.00	-	EV	0.00	0.00	-0.04	0.00	-
HEV	0.05	0.06	0.07	-0.11	0.06	HEV	0.09	0.10	0.13	-0.21	0.09
Diesel	0.05	0.04	-	0.04	-0.24	Diesel	0.04	0.03	-	0.04	-0.18
	Fuel availability elasticity										
	G	CNG	EV	HEV	D						
Gas	0.44	-0.23	-0.17	-0.18	-0.10						
CNG	-0.05	0.23	-0.07	-0.05	-0.02						
EV	-0.01	-0.01	0.13	-0.01	-						
HEV	-0.21	-0.22	-0.32	0.42	-0.17						
Diesel	-0.06	-0.05	-	-0.06	0.31						

Table 15 Elasticity comparison

Authors	Country	Capital cost	Operational cost	Range	Fuel availability
This study	Colombia	-0.9 to -1.4	-0.1 to -0.24	-0.11 to -0.24	0.13 to 0.44
Dagsvik et al. (2002)	Norway	-1.3 to -2.4			
Mabit and Fosgerau (2011)	Denmark	-2.05	-0.87	0.34	
Jensen et al. (2013)	Denmark	-1.02	-0.3 to -0.36	0.44 to 0.66	
Glerum et al. (2013)	Switzerland	-0.92			
Bittencourt et al. (2016)	Brazil	-0.8			
Valeri and Cherchi (2016)	Italy	-1.8 to -4.9	-2.3 to -4.5	-0.8 to -1.9	-0.08 to -0.68

had hands-on experience with electric vehicles. The 0.19 elasticity for conventional fuel vehicles is in the same order of magnitude than Jensen et al. (2013).

Fuel availability is another relevant attribute according to the elasticities, giving the results of 0.44 in gasoline and hybrid vehicles. On the other hand, the direct elasticity for natural gas and electric vehicles are 0.22 and 0.13, respectively. This could mean that if

some planning policies for alternative fuel vehicles are proposed, it will be necessary to produce a significant raise (not marginal) in the fuel availability and range of the AFV to increase the demand for them to obtain a comparable result with a price subsidy policy.

However, the results of the cross elasticities show a high sensitivity of the alternative fuel vehicles capital cost over the demand for conventional fuel vehicles. In that case, a price subsidy for AFV will reduce the market share of gasoline and diesel vehicles. At the same time, an increase in the charging costs of conventional fuels and annual taxes will have a positive impact on the demand for alternative fuel vehicles.

Table 16 shows the model obtained across the five Colombian cities included in the analysis. Bucaramanga is treated as the base, and there are other city indicator dummy variables with each of the choice attribute variables. All the base estimates are statistically significant at the 5% level. Using Medellín as an example, the capital cost parameter is not significant; in consequence, the preferences for such attribute are not different between the base (Bucaramanga) and Medellín. Nevertheless, the parameters for refuelling cost and fuel availability are higher in Medellín than in Bucaramanga, while the coefficients for range and annual taxes are lower than in the base city. Different trends apply to other cities.

The direct elasticities for each city are estimated (Table 17). Regarding capital cost and range, cities have similar elasticities, except for higher values in Bogotá. This case can be explained because Bogotá is the largest city in the country, where the car market is very price competitive, and travel distances are usually longer than other cities.

In the case of annual taxes, similar values can be found across cities, with the exception of Barranquilla and Cali that show a lower and a higher sensitivity, respectively. People living in Medellín also show the highest sensitivity for refuelling cost and fuel availability, which can be due to the city topography and high-grade roads. Barranquilla has the lowest elasticities for annual taxes, refuelling cost and fuel availability, suggesting that the car market in Barranquilla is mainly (and almost only) influenced by capital cost.

According to the results, there are some differences in sensitivity to changes in attributes among cities. However, in all cases, the highest elasticity is concerning capital cost. Although there are variations, which are explained by the marked regional differences in the country, trends in behaviour are similar. On that matter, policy transferability regarding alternative fuel vehicles could be probable for Colombian cities.

Willingness to pay

The willingness to pay (WTP) for an attribute may be estimated as the marginal rate of substitution between such alternative attribute and the price at constant utility. In other words, how much someone is willing to pay, more, or less, for the increase or decrease of an attribute, keeping the same level of utility (Daziano and Bolduc 2013). In Table 18 the variation of the attributes equal to a willingness to pay of \$COP 1,000,000 (500 \$USD as \$1 USD = 2000 \$COP at the time of the study) of capital costs.

As a result, there is a WTP \$COP 1,000,000 of additional capital cost if the vehicle provides an extra range of 35 km (14 \$USD/km, 11 €/km). The previous value lies within the interval € 8.32–€ 16.82/km (Hackbarth and Madlener 2013); is lower than € 16–€ 34/km values (Jensen et al. 2013); but higher than 3.44 \$USD/km (Tanaka et al. 2014).

Consumers are also willing to pay \$COP 1,000,000 additional capital cost for an annual reduction of \$COP 117,000 (60 \$USD) in annual taxes. This value is significantly lower than € 2327–€ 4704 (Hackbarth and Madlener 2013), € 1500 (Hoen and Koetse 2014), and CAN\$ 2104–CAN\$ 4985 (Potoglou and Kanaroglou 2007). However, it is important to

Table 16 Estimation results across five Colombian cities

Coefficient	HCM_Cities	
	Coefficient	Robust <i>t</i> test
ASC		
NGV_S	3.02	3.69
EV_S	3.08	2.98
HEV_S	0.03	0.04
NGV_M	2.72	2.41
EV_M	2.81	1.69
HEV_M	0.44	0.25
NGV_{SUV}	2.01	1.55
D_{SUV}	1.88	1.97
HEV_{SUV}	0.30	0.16
Base attributes—Bucaramanga		
<i>Capital cost</i>	− 10.29	− 4.52
<i>Range</i>	5.63	4.19
<i>Annual taxes</i>	− 20.78	− 5.12
<i>Refuelling cost</i>	− 10.36	− 2.05
<i>Fuel availability</i>	5.96	6.59
Bogota interaction term		
<i>Capital cost</i>	− 26.43	− 5.27
<i>Range</i>	11.56	4.12
<i>Annual taxes</i>	2.43	0.48
<i>Refuelling cost</i>	− 17.36	− 2.04
<i>Fuel availability</i>	− 5.23	− 3.73
Medellin interaction term		
<i>Capital cost</i>	− 2.79	− 0.70
<i>Range</i>	− 4.55	− 2.33
<i>Annual taxes</i>	11.45	2.40
<i>Refuelling cost</i>	− 37.62	− 3.64
<i>Fuel availability</i>	3.18	2.03
Cali interaction term		
<i>Capital cost</i>	− 13.75	− 3.52
<i>Range</i>	− 1.54	− 0.80
<i>Annual taxes</i>	− 11.72	− 1.82
<i>Refuelling cost</i>	− 10.36	− 1.25
<i>Fuel availability</i>	− 2.24	− 1.99
Barranquilla interaction term		
<i>Capital cost</i>	− 4.30	− 1.12
<i>Range</i>	− 3.12	− 1.99
<i>Annual taxes</i>	12.93	2.84
<i>Refuelling cost</i>	5.10	0.84
<i>Fuel availability</i>	− 4.03	− 4.49
Scale factors		
μ_1	0.39	8.80
μ_3	0.85	6.14
μ_4	0.51	9.21

Table 16 (continued)

Coefficient	HCM_Cities	
	Coefficient	Robust <i>t</i> test
μ_5	0.99	7.49
Latent variables		
<i>EC_NGV</i>	−0.53	−1.53
<i>EC_EV</i>	−0.60	−1.31
<i>EC_HEV</i>	−0.03	−0.05
<i>EC_D</i>	−0.86	−1.42
<i>GP_NGV</i>	0.81	1.14
<i>GP_EV</i>	−1.62	−1.27
<i>GP_HEV</i>	−0.46	−1.45
<i>GP_D</i>	1.46	1.67
<i>PC_NGV</i>	−0.47	−0.58
<i>PC_EV</i>	−0.05	−0.20
<i>PC_HEV</i>	1.42	2.46
<i>PC_D</i>	−1.28	−2.41
Panel effect	σ_φ	−1.77
Parameters DCM		51
Observations		10,650
LL HCM		−32,238
LL DCM		−10,466

acknowledge that in those three cases, the incentive offered was the tax exemption, not the annual tax reduction.

Also, regarding the refuelling cost, the users expect a reduction of \$COP 8600/charge for \$COP 1,000,000 additional capital cost; which corresponds a reduction of \$COP 34,400/month (\$USD 17.2/month), assuming four recharges per month. These values are in line with those presented in Daziano and Bolduc (2013). If the fuel availability is increased by 3.4%, consumers will be willing to pay \$COP 1,000,000 more (147 \$USD/%). This value is larger than €45–€92 (Hackbarth and Madlener 2013), but in the same order of magnitude as \$CAN 166 (Daziano and Bolduc 2013), and within the €73–€824 interval (Achtnicht et al. 2012).

Nevertheless, it is important to highlight that the previous estimations were calculated on an existing base of service stations, and the willingness to pay to increase fuel availability decreases as fuel availability itself increases (Hackbarth and Madlener 2016; Achtnicht et al. 2012). In this case, Hackbarth and Madlener (2016) found a WTP within the range of €35–€960 for an increase of 1% in fuel availability using a 20% base and a €7–€194 range using a 99% base. Our experiment used fuel availability base values from 12.5 to 25%, which makes reasonable the estimated WTP.

Policy simulations

Finally, to appraise possible scenarios for AFV implementation, twelve scenarios were simulated (Table 19). The main barriers addressed were the financial one, regarding the capital cost, operational costs and fuel availability; the technical barrier, concerning the

Table 17 Cities direct elasticities

	Direct elasticities					
	Total	Bogota	Bucaramanga	Medellin	Cali	Barranquilla
Capital cost						
Gas	-0.895	-1.413	-0.528	-0.710	-0.961	-0.864
CNG	-1.221	-1.944	-0.951	-0.875	-1.273	-1.089
EV	-1.391	-1.985	-1.037	-1.272	-1.539	-1.159
HEV	-1.115	-1.743	-0.495	-0.848	-1.241	-1.215
Diesel	-0.944	-1.638	-0.623	-0.617	-0.888	-0.962
Range						
Gas	0.186	0.463	0.219	0.043	0.124	0.107
CNG	0.122	0.284	0.185	0.024	0.075	0.060
EV	0.112	0.250	0.169	0.029	0.074	0.054
HEV	0.245	0.637	0.220	0.056	0.174	0.164
Diesel	0.202	0.541	0.241	0.036	0.107	0.116
Annual taxes						
Gas	-0.194	-0.181	-0.197	-0.125	-0.309	-0.026
CNG	-0.258	-0.236	-0.264	-0.139	-0.385	-0.031
EV	-0.041	-0.024	-0.045	-0.027	-0.066	-0.004
HEV	-0.113	-0.110	-0.114	-0.073	-0.194	-0.018
Diesel	-0.243	-0.238	-0.244	-0.127	-0.348	-0.034
Refuelling cost						
Gas	-0.240	-0.246	-0.125	-0.601	-0.193	-0.016
CNG	-0.068	-0.073	-0.048	-0.155	-0.054	-0.004
EV	-0.044	-0.039	-0.026	-0.117	-0.033	-0.002
HEV	-0.212	-0.221	-0.086	-0.521	-0.185	-0.017
Diesel	-0.176	-0.217	-0.109	-0.390	-0.133	-0.014
Fuel availability						
Gas	0.440	0.052	0.662	0.992	0.320	0.052
CNG	0.226	0.024	0.441	0.460	0.145	0.022
EV	0.133	0.013	0.226	0.315	0.082	0.012
HEV	0.420	0.053	0.503	0.980	0.340	0.059
Diesel	0.309	0.047	0.525	0.623	0.201	0.042

Table 18 Willingness to pay

Attribute		Units
Expected WTP	1,000,000	\$COP
Annual taxes	-117,000	\$COP
Refueling cost	-8600	\$COP
Vehicle range	36	km
Fuel availability	3.40%	%

Table 19 Scenarios description

Scenario	Description
1	Base situation
2	Equal purchase price for all vehicles
3	10% decrease in AFV purchase price
4	10% increase in gasoline price
5	10% decrease in gasoline price
6	Driving range increase of 50% in EV (15% in HEV)
7	50% decrease in AFV annual taxes
8	50% increase in AFV fuel availability
9	25% increase in AFV fuel availability
10	Increase of EC to its mean value
11	Increase of GP and EC to its first quartile
12	Increase of PC to its first quartile and decrease of GP to a third quartile maximum
13	Combination of 2, 5, 6 and 8

driving range; and the awareness of people through campaigns that change the latent factors of each individual.

The simulated scenarios involve possible policies such as price subsidies, tax exemptions, fuel availability increases and improving driving range for AFVs. It is important to acknowledge that forecasting market share is a challenging task in the case of innovations and products with a low market share (Jensen et al. 2016). Therefore, the baseline scenario was estimated using the experimental design and does not follow the current market conditions, but it helps to evaluate the impact of the different policies simulated. The estimate was made by calculating individual probabilities and using sample enumeration to obtain the aggregated probabilities.

The first simulated scenario considered the same purchase price for all vehicles. Noticing this scenario is quite extreme, we evaluated another one for a 10% decrease in the purchase price for AFVs. Also, to account for the negative externality produced by conventional fuels, we simulated a scenario with a gasoline price raised by 10%. On the other hand, the effect of a gasoline price reduction was simulated as well, because it is a crowd-pleaser policy and it is highly demanded in the country.

One of the major concerns of the EV is the driving range. This concern is often increased when the person has the opportunity to drive an electric vehicle (Jensen et al. 2013). Therefore, some scenarios were simulated with the intention to estimate the effect of the increase of driving range in electric (50%) and hybrid vehicles (15%); and the impact of the expansion of the fuel availability for AFV (50 and 25%).

Also, as moving people towards a more advanced state-of-change might be a more cost-effective strategy for alternative fuel vehicles purchase (Langbroek et al. 2016), we simulated three scenarios to evaluate the variation of the consumer demand for AFV when the population has different values for the latent constructs. (1) The scenario in which the environmental concern is higher for the respondents. (2) The scenario in which the support for sustainable transport policies and environmental concern is higher for the respondents. (3) The scenario in which the attitudes towards car use increases, while the support for sustainable transport policies decreases. We considered a censorship mechanism on the density function of the latent factors, constraining the respondents to have certain levels of each

Table 20 Choice probabilities across policy scenarios

Scenario	Scenario Percentages				
	G (%)	CNG (%)	EV (%)	HEV (%)	D (%)
Observed	30.2	19.3	9.5	30.7	10.3
Base	29.1	15.9	15.6	27.7	11.7
2	17.1	13.8	20.7	39.3	13.2
Difference	-12.0	-2.1	5.1	11.6	1.4
Variation	-70.33	-15.21	24.61	29.54	10.90
3	22.5	18.4	16.5	33.3	11.3
Difference	-6.6	2.5	1.0	5.6	-0.5
Variation	-29.17	13.66	5.79	16.90	-4.15
4	28.3	16.9	16.0	27.1	8.2
Difference	-0.8	1.0	0.4	-0.6	-3.5
Variation	-2.94	6.07	2.59	-2.07	-42.69
5	29.9	14.9	15.2	28.2	8.3
Difference	0.8	-1.0	-0.4	0.5	-3.4
Variation	2.73	-6.57	-2.75	1.94	-41.06
6	27.6	14.9	16.4	29.9	9.2
Difference	-1.5	-1.0	0.8	2.3	-2.5
Variation	-5.52	-7.05	5.16	7.56	-27.14
7	26.0	21.0	14.7	27.7	8.5
Difference	-3.1	5.1	-0.9	0.0	-3.2
Variation	-12.03	24.25	-5.81	0.06	-37.23
8	25.7	22.2	15.8	25.2	8.0
Difference	-3.4	6.3	0.2	-2.5	-3.8
Variation	-13.38	28.37	1.35	-9.82	-47.11
9	27.4	18.9	15.7	26.5	8.1
Difference	-1.7	3.0	0.1	-1.2	-3.6
Variation	-6.08	15.84	0.91	-4.51	-44.14
10	18.3	21.5	17.4	30.0	8.8
Difference	-10.8	5.6	1.8	2.3	-2.9
Variation	-59.05	26.13	10.36	7.72	-33.19
11	16.0	18.2	16.3	36.5	10.2
Difference	-13.1	2.3	0.8	8.8	-1.5
Variation	-82.03	12.59	4.61	24.21	-14.56
12	37.0	23.8	8.4	20.0	6.2
Difference	7.9	7.9	-7.1	-7.6	-5.6
Variation	21.31	33.05	-84.78	-38.17	-90.40
13	15.7	29.8	16.5	31.4	11.5
Difference	-13.4	13.9	0.9	3.7	-0.3
Variation	-85.84	46.60	5.40	11.84	-2.27

one according to the scenario. To be precise, in scenario 10, the environmental concern was constrained in all consumers to have an EC at least equal to the mean value of the previously calculated distribution.

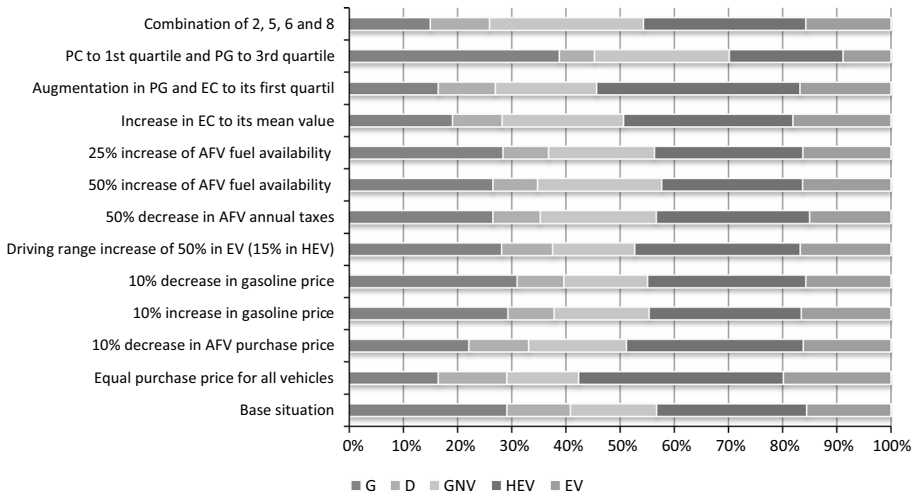


Fig. 2 Simulated scenarios

Indeed, those last three scenarios were estimated to evaluate the impact on choice probabilities when latent variables are higher (or lower) than actual values amongst respondents. The mechanism used to achieve those increases (or decreases) need to be assessed, taking into account the scale of the latent variable, and studying a reliable and credible change in those perceptions post-measures, to better frame the impact.

The last scenario was a combination of specific simulated scenarios, which were thought to be the likeliest to encourage the use of alternative fuel vehicles around the country. The outcomes of the simulation scenarios are reported in Table 20 and Fig. 2.

The results show that, at equal prices, a significant increase occurs for the alternative fuel vehicles. At the same time, an increase in gasoline taxes, fuel availability and operational range have a positive impact on the demand as well, especially on hybrid and electric vehicles. It is interesting to note that in the policy-mix scenario 13, the reduction of 10% in the gasoline price (5) counteracts the effect of the other policies favouring alternative fuel vehicles (2, 6 and 8).

The analysis results indicate that if users had higher environmental awareness (latent variable EC), the demand for alternative fuel vehicles would be higher. In the case of users supporting the implementation of sustainable transport measures (latent variable GP, and indirectly EC), the demand for alternative fuel vehicles would be higher. Otherwise, if users are more attached to the car and support pro-vehicle policies (Increase in latent variable PC and a decrease in latent variable GP), this would lead to an increase in demand for conventional fuel vehicles.

Those policies that combine several interventions using more realistic thresholds achieve a higher increase in the demand for CNG vehicles over that of the EV and HEV vehicles. In other words, under more realistic scenarios (according to the Colombian context), natural gas becomes an important option for alternative fuel vehicles. Perhaps it is the best mid-way alternative to promote the transition to environmentally friendly cars.

Conclusions

This investigation estimated hybrid choice model to study the demand behaviour for alternative fuel vehicles in Colombia. Results show that the inclusion of latent variables in the estimation of discrete choice models could be a more appropriate representation of the consumer behaviour for new vehicle purchases when alternative fuel vehicles are available. The study also shows the relative convenience of including second-order latent variables in the econometric model, as it allows to conclude that some users of alternative technologies could be more excited about technology but less worried about the environment.

A strategy to encourage the use of vehicles powered by alternative energy sources must identify niche markets, considering that there are different segments. Therefore, specific strategies are needed for each segment. The analysis shows that two elements of segmentation of potential consumers could be the attitude of users towards sustainability and their car dependence level.

The estimated models suggest that for the Colombian car user, environmental concern and the support for sustainable transport policies have a positive influence on alternative fuel vehicle acceptability and purchase decision. On the other hand, the users who reveal a propensity for car use prefer well-known fuelling technologies as they are more prone to purchase conventional fuel vehicles.

According to the models, in Colombia, the purchase price along with the refuelling costs and taxes are the most relevant factors in vehicle purchase decision making. For this reason, to increment market share of alternative fuel vehicles, several incentive policies have to be launched, especially subsidies and tax exemptions. New NGV, hybrid and electric cars in the country have been exempt from the sales tax since 2012, in contrast to the 16% tax applied to gasoline and diesel vehicles. Despite this tax benefit, the purchase price for cars with alternative energy is still much higher than for conventional cars. In specific, NGV is exempt from the surtax (20%) that applies to gasoline and diesel. This former incentive has had a significant impact on the NGV level of penetration, particularly in vehicles with high consumption engines.

As it can be observed in the policy scenarios, in the Colombian context, it is necessary to consider more aggressive incentives to make the use of alternative energies more attractive and encourage their use. As successful cases, several policies must be implemented, but they depend on the stakeholder. Also, advertising campaigns have to approach consumers in different ways, considering their socioeconomic characteristics and attitudes. For that matter, the use of policies that promote tariff exemptions or subsidies of capital costs increases the tendency to choose the alternative fuel vehicles and it seems that the most appropriate fuel technology to begin the introduction of alternative fuel vehicles in Colombia is the natural gas, which could be used as a stepping stone to fuel transition in the country.

Another important subject that must be addressed is consumer awareness and acceptability of these new technologies; including environmental awareness, green policies acceptability and less dependence on car use. In that case, there is a need to evaluate measures which could change minds and consumer perceptions, and they should be used to encourage AFV use. For instance, if the governmental policies promote environmental awareness and sustainable transport, people are more likely to choose alternative fuel vehicles. On the contrary, if the policies and measures support car use, the conventional fuel vehicles will remain the market leaders with an increasing market share.

Further research should evaluate the behaviour of new car buyers. This study did not take them into account, in order to diminish the possible bias that can be produced because of insufficient knowledge regarding actual vehicle costs by non-owners. Another suggestion is the inclusion of indicators regarding how familiar are respondents with existing and emerging fuel technologies. The addition of such questions could help to isolate the possible presence of habit or inertia effect.

Another contribution of the paper is the assessment of the preferences in different Colombian cities for the analysed context. The analysis shows some differences in sensitivity to changes in attributes among cities. Although there are variations, which are explained by the marked regional disparities across the country, trends in behaviour are similar. In consequence, transferability of policies to encourage alternative fuel vehicles may be applied in various cases. More research is needed to evaluate if those similarities are also maintained at other geographic scales; maybe between countries or regions, extending the range of application of the results.

References

- Achtnicht, M., Bühler, G., Hermeling, C.: The impact of fuel availability on demand for alternative-fuel vehicles. *Transp. Res. Part D Transp. Environ.* **17**(3), 262–269 (2012)
- Beggs, S., Cardell, S., Hausman, J.: Assessing the potential demand for electric cars. *J. Econom.* **17**, 1–19 (1981)
- Ben-Akiva, M., McFadden, D., Train, K., Walker, J., Bhat, C., Bierlaire, M., Bolduc, D., Boersch-Supan, A., Brownstone, D., Bunch, D.S., Daly, A.: Hybrid choice models: progress and challenges. *Mark. Lett.* **13**(3), 163–175 (2002)
- Bittencourt, M.V.L., Cardoso, L.C.B., Irwin, E.G.: Biofuels policies and fuel demand elasticities in Brazil: an IV approach. In: *Anais do XLIII Encontro Nacional de Economia [Proceedings of the 43rd Brazilian Economics Meeting]* (No. 181). ANPEC-Associação Nacional dos Centros de Pósgraduação em Economia [Brazilian Association of Graduate Programs in Economics] (2016)
- Bjerkkan, K.Y., Nørbech, T.E., Nordtømme, M.E.: Incentives for promoting battery electric vehicle (BEV) adoption in Norway. *Transp. Res. Part D Transp. Environ.* **43**, 169–180 (2016)
- Bolduc, D., Boucher, N., Alvarez-Daziano, R.: Hybrid choice modeling of new technologies for car choice in Canada. *Transp. Res. Rec.* **2082**, 63–71 (2008)
- Brownstone, D., Bunch, D.S., Train, K.: Joint mixed logit models of stated and revealed preferences for alternative-fuel vehicles. *Transp. Res. Part B Methodol.* **34**, 315–338 (2000)
- Cantillo, V., Ortúzar, J., Williams, H.: Modeling discrete choices in the presence of inertia and serial correlation. *Transp. Sci.* **41**(2), 195–205 (2007)
- Caulfield, B., Farrell, S., McMahon, B.: Examining individuals preferences for hybrid electric and alternatively fuelled vehicles. *Transp. Policy* **17**, 381–387 (2010)
- Cherchi, E.: A stated choice experiment to measure the effect of informational and normative conformity in the preference for electric vehicles. *Transp. Res. Part A Policy Pract.* **100**, 88–104 (2017)
- Chorus, C.G., Kroesen, M.: On the (im-) possibility of deriving transport policy implications from hybrid choice models. *Transp. Policy* **36**, 217–222 (2014)
- Collantes, G.: Do green tech policies need to pass the consumer test? The case of ethanol fuel. *Energy Econ.* **32**, 1235–1244 (2010)
- Daly, A., Hess, S., Patrui, B., Potoglou, D., Rohr, C.: Using ordered attitudinal indicators in a latent variable choice model: a study of the impact of security on travel behaviour. *Transportation* **39**, 267–297 (2012)
- Dagsvik, J.K., Wennemo, T., Wetterwald, D.G., Aaberge, R.: Potential demand for alternative fuel vehicles. *Transp. Res. B* **36**, 361–384 (2002)
- Daziano, R.A.: Taking account of the role of safety on vehicle choice using a new generation of discrete choice models. *Saf. Sci.* **50**(1), 103–112 (2012)
- Daziano, R.A., Chiew, E.: Electric vehicles rising from the dead: data needs for forecasting consumer response toward sustainable energy sources in personal transportation. *Energy Policy* **51**, 876–894 (2012)

- Daziano, R.A., Bolduc, D.: Incorporating pro-environmental preferences toward green automobile technologies through a Bayesian Hybrid Choice Model. *Transp. A Transp. Sci.* **9**(1), 74–106 (2013)
- DG MOVE: State of the art on alternative fuel transport systems in the European Union, p. 128 (2015)
- Doornik, J.A.: *Object-Oriented Matrix Programming Using Ox*, 3rd edn. London: Timberlake Consultants Press and Oxford (2007). www.doornik.com
- Engerer, H., Horn, M.: Natural gas vehicles: an option for Europe. *Energy Policy* **38**(2), 1017–1029 (2010)
- Ewing, G.O., Sarigollu, E.: Car fuel-type choice under travel demand management and economic incentives. *Transp. Res. D* **3**(6), 429–444 (1998)
- Fujii, S., Gärling, T.: Application of attitude theory for improved predictive accuracy of stated preference methods in travel demand analysis. *Transp. Res. Part A Policy Pract.* **37**(4), 389–402 (2003)
- Galván, J., Cantillo, V., Arellana, J.: Factors influencing demand for buses powered by alternative energy sources. *J. Public Transp.* **19**(2), 23–37 (2016)
- Glerum, A., Stankovikj, L., Thémans, M., Bierlaire, M.: Forecasting the demand for electric vehicles: accounting for attitudes and perceptions. *Transp. Sci.* **48**(4), 483–499 (2013)
- Gnann, T., Plötz, P.: A review of combined models for market diffusion of alternative fuel vehicles and their refueling infrastructure. *Renew. Sustain. Energy Rev.* **47**, 783–793 (2015)
- Hackbarth, A., Madlener, R.: Consumer preferences for alternative fuel vehicles: a discrete choice analysis. *Transp. Res. Part D Transp. Environ.* **25**, 5–17 (2013)
- Hackbarth, A., Madlener, R.: Willingness-to-pay for alternative fuel vehicle characteristics: a stated choice study for Germany. *Transp. Res. Part A Policy Pract.* **85**, 89–111 (2016)
- Hensher, D., Louviere, J., Swait, J.: Combining sources of preference data. *J. Econom.* **89**(1–2), 197–221 (1998)
- Hess, S., Train, K., Polak, J.: On the use of a modified latin hypercube sampling (MLHS) method in the estimation of a mixed logit model for vehicle choice. *Transp. Res. Part B Methodol.* **40**, 147–163 (2006)
- Hess, S., Fowler, M., Adler, T., Bahreinian, A.: A joint model for vehicle type and fuel type choice: evidence from a cross-nested logit study. *Transportation* **39**(3), 593–625 (2012)
- Hidrué, M.K., Parsons, G.R., Kempton, W., Gardner, M.P.: Willingness to pay for electric vehicles and their attributes. *Resour. Energy Econ.* **33**, 686–705 (2011)
- Hoen, A., Koetse, M.J.: A choice experiment on alternative fuel vehicle preferences of private car owners in the Netherlands. *Transp. Res. Part A Policy Pract.* **61**, 199–215 (2014)
- Horne, M., Jaccard, M., Tiedemann, K.: Improving behavioral realism in hybrid energy-economy models using discrete choice studies of personal transportation decisions. *Energy Econ.* **27**, 59–77 (2005)
- International Energy Agency: *Co₂ emissions from fuel combustion highlights*. IEA Publications, p. 136 (2014)
- International Energy Agency: *Global EV Outlook 2016: beyond one million electric cars*, p. 51 (2016)
- Janssen, A., Lienin, S.F., Gassmann, F., Wokaun, A.: Model aided policy development for the market penetration of natural gas vehicles in Switzerland. *Transp. Res. Part A Policy Pract.* **40**, 316–333 (2006)
- Jansson, J.: *Car (ing) for our environment?: Consumer eco-innovation adoption and curtailment behaviors: the case of the alternative fuel vehicle* (2009)
- Jensen, A.F., Cherchi, E., Mabit, S.L.: On the stability of preferences and attitudes before and after experiencing an electric vehicle. *Transp. Res. Part D Transp. Environ.* **25**, 24–32 (2013)
- Jensen, A.F., Cherchi, E., Ortúzar, J.: A long panel survey to elicit variation in preferences and attitudes in the choice of electric vehicles. *Transportation* **41**(5), 973–993 (2014)
- Jensen, A.F., Cherchi, E., Mabit, S.L., Ortúzar, J.: Predicting the potential market for electric vehicles. *Transp. Sci.* **51**(2), 427–440 (2016)
- Kim, J., Rasouli, S., Timmermans, H.: A hybrid choice model with a nonlinear utility function and bounded distribution for latent variables: application to purchase intention decisions of electric cars. *Transp. A Transp. Sci.* **12**(10), 909–932 (2016)
- Kollmuss, A., Agyeman, J.: Mind the gap: why do people act environmentally and what are the barriers to pro-environmental behavior? *Environ. Educ. Res.* **8**(3), 239–260 (2002)
- Langbroek, J.H., Franklin, J.P., Susilo, Y.O.: The effect of policy incentives on electric vehicle adoption. *Energy Policy* **94**, 94–103 (2016)
- Louviere, J.J., Hensher, D.A., Swait, J.D.: *Stated Choice Methods: Analysis and Application*. University Press, Cambridge (2000)
- Mabit, S.L., Fosgerau, M.: Demand for alternative-fuel vehicles when registration taxes are high. *Transp. Res. Part D Transp. Environ.* **16**, 225–231 (2011)
- Mabit, S.L., Cherchi, E., Jensen, A.F., Jordal-Jørgensen, J.: The effect of attitudes on reference-dependent preferences: estimation and validation for the case of alternative-fuel vehicles. *Transp. Res. Part A Policy Pract.* **82**, 17–28 (2015)

- Maldonado-Hinarejos, R., Sivakumar, A., Polak, J.W.: Exploring the role of individual attitudes and perceptions in predicting the demand for cycling: a hybrid choice modelling approach. *Transportation* **41**(6), 1287–1304 (2014). <https://doi.org/10.1007/s11116-014-9551-4>
- Melaina, M., Muratori, M., McLaren, J., Schwabe, P.: Investing in Alternative Fuel Infrastructure: Insights for California from Stakeholder Interviews (No. 17-05279) (2017)
- Melton, N., Axsen, J., Sperling, D.: Moving beyond alternative fuel hype to decarbonize transportation. *Nat. Energy* **1**(3), 16013 (2016)
- Mersky, A.C., Sprei, F., Samaras, C., Qian, Z.S.: Effectiveness of incentives on electric vehicle adoption in Norway. *Transp. Res. Part D Transp. Environ.* **46**, 56–68 (2016)
- Myklebust, B.: EVs in bus lanes—controversial incentive. In: *Electric Vehicle Symposium and Exhibition (EVS27)*, 2013 World. IEEE, pp. 1–7 (2013)
- Ortúzar, J., Willumsen, L.G.: *Modelling transport*, vol. 4. Wiley, Chichester (2011)
- Potoglou, D., Kanaroglou, P.S.: Household demand and willingness to pay for clean vehicles. *Transp. Res. Part D Transp. Environ.* **12**, 264–274 (2007)
- Romm, J.: The car and fuel of the future. *Energy Policy* **34**, 2609–2614 (2006)
- Saldarriaga-Isaza, C.A., Vergara, C.: Who switches to hybrids? A study of a fuel conversion program in Colombia. *Transp. Res. Part A Policy Pract.* **43**(5), 572–579 (2009)
- Sobh, A.S.: *Transportation Economics and Energy*. Doctoral dissertation, Utah State University (2015)
- Soto, J.J., Cantillo, V., Arellana, J.: Hybrid choice model for alternative fuelled vehicles. *Interciencia* **39**(9), 666–672 (2014)
- Tanaka, M., Ida, T., Murakami, K., Friedman, L.: Consumers' willingness to pay for alternative fuel vehicles: a comparative discrete choice analysis between the US and Japan. *Transp. Res. Part A Policy Pract.* **70**, 194–209 (2014)
- Valeri, E., Cherchi, E.: Does habitual behavior affect the choice of alternative fuel vehicles? *Int. J. Sustain. Transp.* **10**(9), 825–835 (2016)
- Vij, A., Walker, J.: How, when and why integrated choice and latent variable models are latently useful. *Transp. Res. Part B Methodol.* **90**, 192–217 (2016)
- von Rosenstiel, D.P., Heuermann, D., Hüsig, S.: Why has the introduction of natural gas vehicles failed in Germany?—Lessons on the role of market failure in markets for alternative fuel vehicles. *Energy Policy* **78**, 91–101 (2015)
- Walker, J.: *Extended Discrete Choice Models: Integrated Framework, Flexible Error Structures, and Latent Variables*. Ph.D. Thesis, Massachusetts Institute of Technology (2001)
- Wang, H., Fang, H., Yu, X., Wang, K.: Development of natural gas vehicles in China: an assessment of enabling factors and barriers. *Energy Policy* **85**, 80–93 (2015)
- Yáñez, F., Raveau, S., Rojas, M., Ortuzar, J.: Modelling and forecasting with latent variables in discrete choice panel models. In *European Transport Conference* (2009)
- Yeh, S.: An empirical analysis on the adoption of alternative fuel vehicles: the case of natural gas. *Energy Policy* **35**, 5865–5875 (2007)

Jose J. Soto is a civil engineer (2011) and M.Sc. (2013) from the Universidad del Norte (Barranquilla, Colombia). He is an auxiliary professor at the Universidad Tecnológica de Bolívar (Cartagena, Colombia). His research areas include transport modelling, advanced econometric modelling and traffic safety. He also works as a consultant.

Victor Cantillo received his B.S. Engineering in Civil Engineering in 1987, from the Universidad del Norte, M.Sc. in Traffic and Transport Engineering in 1990, from the Universidad del Cauca, Colombia and Ph.D. in Engineering Sciences (Transport) in 2004, from the Pontificia Universidad Católica de Chile. He is a Professor at the Universidad del Norte, Colombia, since 1990. His research interests include transport planning, transport economics, transport modelling, econometric and logistics. Education in engineering is other of his relevant topics of interest.

Julian Arellana is a Civil Engineer from Universidad del Norte (2004) and obtained his M.Sc. and Ph.D. degrees at the Pontificia Universidad Católica de Chile in 2012. He is an associate professor and member of the Transport Research Group at Universidad del Norte. Dr Arellana has participated and led different research and consulting projects related to transport and logistics in different Latin American countries. His research areas include non-motorized transport, sustainable and inclusive transport policies, transport modelling, transport economics, transport planning, and advanced econometric modelling.