Simulating the market penetration of cars with alternative fuel\powertrain technologies in Italy

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Abstract

This paper evaluates the market penetration of cars with alternative fuel\powertrain technologies in Italy under various scenarios. Seven cars on sale in 2013 are considered: the Ford Fiesta (diesel), the VW Polo (gasoline), the Fiat Punto Evo (bi-fuel - CNG), the Natural Power Alfa Romeo Mito (bi-fuel - LPG), the Toyota Yaris (hybrid - gasoline), the Peugeot iOn (BEV – owned battery), the Renault Zoe (BEV – leased battery). A Mixed Error Component Logit model is estimated based on data collected via a *stated preference* choice survey administered in 2013 in various Italian cities. The model's parameters are then used to build a Monte Carlo simulation model which allows evaluating, under different scenarios, the market penetration of the seven cars. The main findings are that: a) the subsidies enacted by the Italian government in favour of the low CO_2 emitting cars appear to favour mostly the Ford Fiesta (diesel); b) a three-fold increase in the BEVs range would not change their market share significantly (about 2%); and c) only a combination of changes such as the introduction of a subsidy equal to €5,000, the decrease of the purchase price for BEVs by €5,000, the increase in the battery range, and the increase in the conventional fuel price would significantly increase the BEVs' market share, raising it to about 15%.

Keywords

Car choice, market scenario, stated preference, discrete choice, policy simulation.

Acronyms

AFV: alternative fuel vehicle;
BEV: battery electric vehicle;
BV: biofuel vehicle;
CNGV: compressed natural gas vehicle;
CV: conventional vehicle (including SGV and DV);
DV: diesel vehicle;
HEV: hybrid electric vehicle;
HFCV: hydrogen fuel cell vehicle;
LPGV: liquefied petroleum gas vehicles (bi-fuel);
SGV: standard gasoline vehicle.

1. Introduction

The car market is extremely diversified by segment and by fuel\powertrain technology. Auto manufacturers continuously improve their models and increase their differentiation in an effort to satisfy customers' needs, to gain a competitive edge over their competitors and to meet the various

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energy and environmental regulatory constraints. An interesting recent development is the process of electrification that is gradually gaining momentum in the passenger car market. The hybrid, the plug-in and the battery electric vehicle (HEV, PHEV, BEV) are the new entrants in the car market with gradually growing market shares, with the hydrogen fuel cell vehicles (HFCV) in the process of going from the concept stage to the manufacturing one. These engine technologies, together with the Compressed Natural Gas vehicles (bi-fuel CNGV) and the Liquefied Petroleum Gas Vehicles (bi-fuel LPGV) ones, make up what is known as Alternative Fuel Vehicles (AFV) as opposed to the more traditional and largely established gasoline and diesel cars.

In our view, in relation to these developments, there are some very relevant research questions such as: how will the consumers react to the new fuel\powertrain technologies? Will they gradually penetrate the market and with which speed? In which market segments? Do public policies interested in gaining independence from oil, reducing energy consumption or local and global pollution influence consumers' choices and by how much? All these questions are of great significance to the auto manufacturers, to the policy makers and to the general public and, most likely, the answers will be quite differentiated among countries and population segments. The discrete choice methodology, based on data collected at individual level on both stated and revealed choices, is a largely established methodology which could help understand and predict consumers' choices.

Our specific interest is to provide some answers for the Italian car market, a task not yet performed in the scientific literature. Compared with other western countries, Italy appears to be lagging behind in the penetration of the AFVs, though having high air and noise pollution levels and a strong economic dependence from oil imports. Only bi-fuel CNGVs and bi-fuel LPGVs have recently gained relevant market shares in some regions of the country.

This paper focuses on seven specific cars on sale in Italy with the following fuel\powertrain technologies: the Ford Fiesta (diesel), the VW Polo (gasoline), the Fiat Punto Evo (bi-fuel - CNG), the Natural Power Alfa Romeo Mito (bi-fuel - LPG), the Toyota Yaris (hybrid - gasoline), the Peugeot iOn (BEV – owned battery), the Renault Zoe (BEV – leased battery). The data collected via a *Stated Preference* (SP) choice survey and administered in 2013 in three Italian cities are used to estimate a Multinomial Logit (MNL) model and a Mixed Error Component Logit (MECL) model. The estimated parameters are used in a Monte Carlo simulation model to evaluate, under different scenarios, the potential market penetration of the seven cars in Italy.

Notwithstanding the national dimension of the market analysed, the techniques used in the paper to collect the data, to estimate the econometric model and to perform policy simulation represent a potential contribution to the international literature, and the results obtained might be of interest not only for the Italian policy makers.

The paper is organised as follows: a review of the literature is presented in Section 2; the SP experiment is illustrated Section 3, the descriptive, econometric and simulation results are reported and discussed in Section 4, and the conclusions and policy implications are drawn in Section 5.

2. Literature review

Car choice and its use is certainly not a new topic. It has been studied extensively since the pioneering contributions by Lave and Train (1979), Manski and Sherman (1980), Berkovec and Rust (1985). Yet, it is still a difficult topic as the paper by Daziano and Chiew (2012) theoretically, methodologically and empirically demonstrates. From a theoretical point of view, the car is a durable good to be used for mobility reasons but with obvious social and cultural implications. The importance attributed to the car changes over time and varies among individuals: from a symbol of independence of the early years, to a status symbol of driving a Ferrari or a SUV, to a mere tool to

be used and not owned with carsharing. Car choice is also a family matter, discussed with the other family members, in a context where more than one car is available. From a methodological point of view, various approaches has been used to study car choice and car use, including (macro) time series analysis, (macro) diffusion models, (micro) economic preference models and attitudinal (hybrid) models. Empirically, with special reference to the last two types of models, and considering the newly introduced engine technologies (hybrid, plug-in, electric, fuel cell) the SP data have prevailed over the *revealed preference* ones, simply because these are a not yet-existing- or sufficiently widespread technology.
The focus of this review is on the economic preference and attitudinal (hybrid) models, based on individual data, aimed at forecasting or policy analysis more than at analysing the preference structure.
Table 1 lists some recent studies focusing on forecasting market penetration. Quian and Soopramanien (2011), with reference to the Chinese market, reach the conclusion that the Chinese consumers are more likely to consider switching from SGVs to HEVs than to BEVs. Mabit and Fosgerau (2011) estimated a ML model with four alternatives (CV, HFCV, HEV, BV, BEV) and performed a market penetration analysis taking into account the CV and the BEV. They reach the optimistic conclusion that the BEV could gain a market share between 48% and 72%. On the contrary, Link et al. (2012) predict that the BEVs could increase in Austria to a modest 2.5% in 2020 and to 5.7% in 2025, whereas HFCVs have a considerable higher potential (11.5%). Glerum et al. (2013) use a logit model to analyze the market potential of the Renault cars compared to the other brands. They conclude that the Renault BEVs have a stronger potential that the conventional Renault cars. Jensen et al. (2014) add to the hybrid model a diffusion model in order to better take into account the technology diffusion process. They state that in Denmark a 3% BEVs market share would not be reached until 2021. In summary, although no consensus predictions are reached, many studies warn again too optimistic prediction for the market share penetration of the AFVs in general and the BEVs specifically.
A set of recent studies, listed in Table 2, perform simulative analysis – based on economic preference or attitudinal models estimated with SP data – in order to understand which policies would be more effective in altering the current car market shares in favour of the AFVs. The policies analysed are the ones described by Daziano and Chiew (2012, Table 1), including subsidies for purchase, feebates, tax credits, gas taxes, rising gas prices, tighter energy-efficiency standards, better electric batteries, investments in charging infrastructure, specific incentives (access to HOV/HOT[3] lanes, devoting parking), marketing campaigns or mechanical improvements. An unsolved issue of most of these studies is that the baseline scenarios, derived from the experimental SP scenarios is not close to the real world market shares. Daziano and Achtnicht (2013) and Hackbarth and Madlener (2013) try to solve this problem by estimating the simulated market shares under the average attribute levels in the German market. However, the results do not match the current market shares, in which, for instance the HFCVs play no role. Hence, the simulations should be interpreted as variations from the experimental market shares and not as realistic market shares which could be realized in the real world. The main results are that the pricing policies and the density of the charging network have a strong influence on AFVs penetration. In the only study that considers the impact of raising the social awareness, the one by Daziano and Bolduc (2013), it is found that also social campaigns could be extremely effective. However, the conventional vehicles appear to keep playing a relevant role in the future, unless very dramatic changes in technology and relative prices occur.

[3] HOV - high occupancy vehicle; HOT - high occupancy toll.

Compared with the above-mentioned literature, this study is characterized by the following features: a) more than one hundred face-to-face interviews are administered in the first half of the year 2013. It is the first time that the Italian car market is researched in relation to the AFVs. The SP data collected are used to estimate a MNL and MECL car choice models. Contrary to the existing literature seven specific cars (labelled alternatives) with different fuel\powertrain technologies are tested, including two BEV types, one with a leased and one with an owned battery (similarly to Hackbarth and Madlener 2013);

b) based on the MECL model's parameters, a Monte Carlo policy simulation model is developed. The model is designed to predict the car market share in 32 market segments. The segments are derived from 5 socio-economic and behavioral dichotomous variables: gender, income, number of cars, number of car trips longer than 400km, and garage availability. Italian National Statistics data are used to estimate the national aggregate market share;

c) policy simulations are then performed considering five scenarios combining several instrumental variables (subsidies for purchase, rising gas prices, better electric batteries, and decrease in the purchase price for electric cars as a result of a decrease in the production costs or of an aggressive market penetration strategy).

Table 1 – Overview of selected SP studies on consumer preferences and market penetration of AFVs

Authors	Methodology	Car types	Attributes	Forecasting market penetration
Quian and Soopramanien (2011)	SP MNL and NL model	SGV, HEV, BEV	Purchase price, annual running cost, incentives, availability of charging facilities, vehicle range with full charging	Chinese consumers are more likely to consider switching from SGVs to HEVs than to BEVs.
Mabit and Fosgerau (2011)	SP Mixel Logit Model and simulation	CV, HFCV, HEV, BV, BEV	Purchase price, annual cost, Range, refuelling frequency, acceleration time, service	In forecasting analysis only two car types are compared (CV and BEV). The results from "Expected" scenario A show that BEVs obtain a market share of 48%. In "Probable" scenario B this market share has increased to 72%.
Link et al. (2012)	SP Multinomial Logit Model	CV*, HEV, BEV	Purchase price, range, charging time, running cost, CO_2 emission, engine power	Austrian consumers prefer CVs compared with both BEVs and HEVs. They estimate a new car market share of BEVs of 0.04% and 0.7% for HEVs (2010). Forecasting predict a BEVs market increase to 2.5% in 10 years (2020) and to 5.7% after 15 years (2025). HEVs have a considerable higher share compared with the BEVs (11.5%).
Glerum et al. (2013)	SP logit choice model and Renault market data	CGV, Renault CV, Renault BEV	Purchase price, cost of driving 100km, governmental incentive, monthly cost of leasing the BEV battery	The market share of CGV is 68.3%, Renault CV (gasoline or diesel) cars is 4.6%, Renault BEVs is 27.1%.
Jensen et al. (2014)	Hybrid choice and diffusion models	CV, BEV	Purchase price, driving distance, driving costs, driving performance, CO_2 emission, charging options, EV battery lifetime	In Denmark a 3% E market share is not reached until 2021 but after this year, a higher increase is seen each year. The highest increase in the share of adopters is seen in 2023 (6%).

Notes: conventional vehicles (CV, including SGV and DV), * = own vehicle

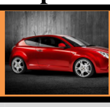
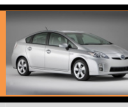
Table 2 – Overview of selected SP studies with policy simulations

Authors	Methodology	Car types	Attributes	Evaluated policy	Simulations
Ewing, Sarigollu (1998)	SP Multinomial logit model	SGV, more fuel-efficient gasoline or AFV, EV	Purchase price, maintenance cost, refueling time, emission rate, acceleration, range, commuting cost, commuting time	1) Subsidies for purchase, 2) Better electric batteries.	The results reveal a large potential demand for cleaner fuel-efficient and BEVs among suburban Montreal car commuters, if these can compete with CVs in price and performance. AVF from 51 in the base case scenario to max 57. EV from 24 in the base case scenario to 50, when range increases to 300 miles.
Horne et al. (2005)	MNL parameters derived from the literature used in CIMS	SGV, CNG, HEV, EV, HFC	Capital cost, fuel cost, fuel availability, express lane access, power	1) A $50/tonne carbon tax; 2) GV disincentives (increasing the fuel availability of methanol, ethanol, natural gas, propane, diesel, and hydrogen fuel cell vehicles by 25%, giving express lane access to HFCVs and BEVs, and increasing the power of every vehicle except diesels and low-efficiency gas. A surcharge of $1000, and $3000 was also applied to high, and low-efficiency gasoline vehicles, respectively), 3) Single occupancy vehicle disincentives.	The impact on CO2 emissions is simulated. Policy 3 (SOV disincentives) is found to be more effective, Policy 1 (carbon tax) and 2 (gas disincentives) would not generate a significant reduction.
Achtnicht et al. (2008)	SP Nested logit model	DV, SGV, HEV, LPGV/CNGV, BV, EV, HFC	Purchase price, variable cost, engine power, CO_2 emissions, service station network, fuel type	1) Service station availability.	In the case of a full service station network of all technologies, LPG/CNG and hydrogen cars would achieve substantial market shares (about 14%), whereas the biofuels and electric power trains only 10%.
Daziano and Bolduc (2013)	Baysian hybrid choice model	SGV, AFV, HEV, HFC	Purchase price, monthly operating costs, fuel availability, express lane access, emissions data, power	1) Increasing in fuel network density, 2) Tax on fossil fuel, 3) Purchase subsidies, 4) Increase price of HEV and HFC by 50%, 5) Concerns and awareness for the natural environment (women only).	Relative to the baseline scenario (11.35% SVG, 3.73% AFV, 48.85% HEV and 36.07% HFC), the increase fuel network density for the AFV and HFC to a level equivalent to the SGV, would increase their share to 5.16% and 50%, respectively. A 25% fuel tax increase to 4.1% and 38%. A purchase price subsidy on green vehicles would produce only a minor effect to 3.79% and 35.55%. A social marketing campaign would have a large impact, raising the market share of AFV to 6% and of HFC to 48.6%. Women have a slightly higher share of AFV equal to 3.9%.
Daziano and Achtnicht, (2013)	Bayes estimates of a multinomial probit model	SGV, DV, HEV, LPGV/CNGV, BV, HFC, EV	Purchase price, fuel costs, engine power, CO_2 emissions, fuel availability, and fuel type	1) Increasing qualitatively charging infrastructure density.	Relative to the baseline scenario derived from the experimental market shares of SP studies (SGV 21.9%, LPG/CNG 11.43%, HEV 29.97%, EV 2.78%, BV 6.01%, HFC 7.28%, DV 26.55%), the density of the charging network for EVs or HFC, would raise their share up to 11.97% and 22.44%, respectively.
Hackbarth and Madlener (2013)	MNL, Mixed error component Logit Model.	CV (SGV and DV) CNGV, HEV, PHEV, BEV, BV, HFC	Purchase price, fuel cost, driving range, fuel availability, CO_2 emissions, refueling time, battery recharging time, policy incentives	1) Incentives (vehicle circulation tax exemption, bus lane access, and free parking) for PHEVs, BEVs, BVs, and HFCs, 2) Purchase premiums of €2500 for PHEVs, and €5,000 for BEVs and HFCs, 3) Purchase price of €21,800 for all vehicles, 4) Battery leasing contract of €80/month for an annual mileage of 10,000 km and purchase price reduction of €10,000 for BEVs, 5) 750 km driving range for BEVs, 6) 100% fuel availability for all AFVs, 7) Battery recharging time of 5 min., 8) Combination of Scenarios 1, 2, 6 and 7.	Base case: CV-30.35%, NGV-17.82%, HEV-20.08%, PHEV-10.85%, BEV-2.24%, BV-12.47%, FCEV-6.19%. Their simulations show that CVs can be expected to further dominate the vehicle market, with CNGs and HEVs being the most likely AFVs, although policy initiatives can affect preferences for the various AFVs. An increase in the battery BEVs' range to 750 km would increase their market shares from 2.24% to 5.45%.

3. Methodology and data collection

The methodology consists of two steps. First, individual preferences towards the selected 7 cars are estimated via MNL and MECL models based on the data collected with a SP survey. Then, a Monte Carlo simulation model is developed and used for scenario analysis.
Disaggregate demand analysis based on the random utility theory is one of the most established approaches to estimate demand (Anderson et al., 1992; Ben-Akiva and Lerman, 1985; Louviere and Hensher, 1983; McFadden, 1981; Train, 2002). The probability that an individual chooses the alternative with the highest utility, among a specific set of choice profiles, is estimated and the main factors that influence her/his choice are identified. Assuming that the parameters in utility function have a random nature, the MECL model allows for preference heterogeneity, correlation between alternatives and correlation between the explanatory coefficients of variables (McFadden and Train, 2000).
Table 3 shows an example of a SP choice experiment, containing the 7 cars: Ford Fiesta (diesel), VW Polo (gasoline), Fiat Punto Evo (bi-fuel - CNG), Natural Power Alfa Romeo Mito (bi-fuel - LPG), Toyota Yaris (HEV - gasoline), Peugeot iOn (BEV – owned battery), Renault Zoe (BEV – leased battery). These specific cars were chosen because they are very popular in Italy and representative of their fuel\powertrain technology. They all belong to the same car segment (B segment), apart from the Peugeot iOn that belongs to the A segment.
Face-to-face interviews were administered in three cities (Trieste, Bologna, Pesaro) with different size and availability of refuelling station.

Table 3 – Example of a SP choice experiment

Car features							
	Ford Fiesta *(diesel)*	**VW Polo** *(gasoline)*	**Fiat Punto Evo** *(bi-fuel - CNG)*	**Alfa Romeo Mito** *(bi-fuel - LPG)*	**Toyota Yaris** *(hybrid - gasoline)*	**Peugeot iOn** *(BEV – own battery)*	**Renault Zoe** *(BEV – leased battery)*
Purchase price *(€)*	14,000	11,900	15,425	20,600	18,650	30,369	21,650
Range *(km)*	980	900	800	1200	1,000	150	210
Acceleration *(0-100 in sec.)*	15	13	15	15	13	12	12
Annual operating cost *(€)*	1,894	2,081	1,757	1,784	1,920	1,681	2,553
Refuelling *(km)*	1	1	5	5	1	0	0
Which car would you buy?							

During each interview, the following data were collected: *i)* socio-economic characteristics of the respondent (gender, level of education, current employment, family size, net yearly household income, self-evaluated level of expertise with cars); *ii)* characteristics of 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, main travel purpose, etc.); and, *iii)* 12 stated choice experiments for each respondent. Each interview lasted about 45 minutes. Due to time and budget constraints only 121 interviews could be collected in the first semester of the year 2013. Although the sample size is admittedly small, we decided not to carry out other interviews in 2013 and to devote more resources for the year 2014 as new AFVs enter in the Italian car market and the consumers get acquainted to the new technologies.
Drawing from the literature, 5 attributes were included in the SP choice experiments: purchase price (€), annual operating cost (gasoline, insurance, tax, maintenance) (€), acceleration (seconds), range (kilometres), and refuelling distance (kilometres). The Status Quo (SQ) attributes for each car were set equal to the Italian average values reported in Table 9. They were varied as follows: i) purchase

price: -20%, SQ, +20%, +40%; ii) annual operating cost: -20%, SQ[4], +20%; iii) range: SQ, +20%, +40%; iv) acceleration: SQ, -10%, -20%; v) refuelling distance: gasoline, diesel and hybrid (1 km, 5km, 10km); CNGV and LPGV (5km, 20km, 50km) and BEVs (0km, 5km, 10km).
An efficient experimental design strategy was used with 4 waves in order to minimize the asymptotic standard error (Bliemer & Rose, 2010, 2011; Huber & Zwerina, 1996; Yu et al., 2009).

4. Descriptive and econometric results

4.1. Descriptive statistics of the sample

Table 4 reports some descriptive indicators of the socio-economic data of the sample. Men and women are equally represented in the sample. The prevailing level of education is the bachelors/graduate degree (50%), followed by high school (26%) and post-doc experience (20%). Thirty per cent of the sample are students (plus an additional 9% of student-workers) and 26% are unemployed. The sample includes both singles and families with up to 6 people. The net yearly household income is between €30,000 and €70,000 for 52% of respondents. With regard to the self-evaluated level of expertise with cars, half of the sample deems to have medium or high knowledge of cars.
Table 5 contains some descriptive indicators of the family cars' features in the sample. Seventy percent of the sample owns 2 or more cars, mainly with gasoline- (67%) or diesel- (25%) operated engine. More than half of the sampled individuals own a garage.
Overall, the sample seems to over-represent the better educated, young, well-off segment of the population: this might lead to an over-prediction in favour of the AFVs.

Table 4 – Descriptive indicators of the socio-economic data of the sample

Features:	**Levels:**							
Gender:	*M:* 50%	*F*: 50%						
Level of Education:	*Primary:* 3%	*High school*: 26%	*Bachelors/graduate degree:* 50%	*Post-doc experience*: 20%				
Current employment:	*Employee*: 11%	*Manager*: 3%	*Freelancer*: 14%	*Student:* 30%	*Student-worker*: 9%	*Retired*: 5%	*Housewife*: 4%	*Unemployed*: 26%
Family size:	*1 person*: 18%	*2 people*: 13%	*3 people:* 25%	*4 people*: 26%	*5 people*: 4%	*6 people*: 14%		
Net yearly household income:	*< €30.000:* 21%	*from €30.000 to €70.000*: 52%	*> €70.000*: 22%	*missing value*: 5%				
Car expertise level: (1=None, 7=Very high)	1: 18%	2: 12%	3: 18%	4: 14%	5:14%	6: 11%	7: 13%	

Table 5 – Descriptive indicators of the family cars' features in the sample

Features:	**Levels:**					
No. of owned cars:	0 cars: 10%	*1 car*: 21%	*2 cars*: 41%	*3 cars*: 12%	*>4 cars*: 16%	
Type of engine technology:	*SGV:* 67%	*DV:* 25%	*CNGV:* 2%	*LPGV:* 5%	*HEV:* 1%	*BEV:* 0%
Availability of an owned garage :	*Yes:* 65%	*No:* 31%	*Missing values:* 3%			

[4] The SQ operating cost are calculated in Rusich and Danielis (2013)

Table 4 presents some descriptive indicators of the car mobility habits of the sample. The transport mode mainly used is the car (55%). For 49% of respondents, the numbers of weekly (return) car trips varies from 5 to 15, and for 28%, it varies from 15 to 30 trips. With regards to the average distance per trip, 63% of them are less than 10 km long, 32% are from 10 to 40 km long.
The car is mainly used for leisure purposes (50%), followed by family management, visiting relatives and parents (20%), and business reasons (19%). Finally, half the sample made from 5 to 10 journeys over 400 km per year and 37% from 2 to 4 trips.

Table 6 – Descriptive indicators of the car mobility habits of the sample

Features:	Levels:			
Frequency use of transport modes:	*Bike/walking*: 10%	*Scooter/motorbike*: 8%	*Car*: 55%	*Public transport:* 28%
Number of weekly (return) car trips:	*< 5*: 23%	*5 to 15:* 49%	*15 to 30:* 28%	
Average distance by car per trip:	*< 10 km.*: 63%	*10 to 40 km:* 32%	*> 40 km:* 5%	
Reason for travelling by car:	*Business*: 19%	*Study*: 11%	*Family management, visiting relatives, parents*: 20%	*Leisure*: 50%
Number of yearly return trips by car over 400 km:	*1 trip/year*: 13%	*2 to 4 trips/year*: 37%	*5 to 10 trips/year*: 50%	

4.2. The Multinomial and Mixed Error Component Logit models

This section reports the results obtained estimating 1) a MNL model, allowing us to evaluate in a simple manner the monetary value of the nonmonetary attributes, and 2) a MECL model, allowing us to take into account the random nature of the model coefficients; to explore the role played by the socio-economic variables in determining the model coefficients, and; to account for the correlation among alternatives and the panel features of the data set.

The MNL model is specified as follows:

$$U_{\text{Gasoline.car}} = \beta_{\text{G}}\text{ASC}_{\text{G}} + \beta_{\text{PP}}\text{PurchasePrice}_{\text{G}} + \beta_{\text{R}}\text{Range}_{\text{G}} + \beta_{A}\text{Acceleration}_{G} + \beta_{AOC}\text{AnnualOperatingCost}_{G} + \beta_{RD}\text{RefuellingDistance}_{G} + \varepsilon_{G}$$

$$U_{\text{Diesel.car}} = \beta_{\text{D}}\text{ASC}_{\text{D}} + \beta_{\text{PP}}\text{PurchasePrice}_{\text{D}} + \beta_{\text{R}}\text{Range}_{D} + \beta_{A}\text{Acceleration}_{D} + \beta_{AOC}\text{AnnualOperatingCost}_{D} + \beta_{RD}\text{RefuellingDistance}_{D} + \beta_{LDTD}\text{LongDistanceTrips}_{D} + \varepsilon_{D}$$

$$U_{\text{CNG.car}} = \beta_{\text{CNG}}\text{ASC}_{\text{CNG}} + \beta_{\text{PP}}\text{PurchasePrice}_{\text{CNG}} + \beta_{\text{R}}\text{Range}_{\text{i}} + \beta_{A}\text{Acceleration}_{\text{CNG}} + \beta_{AOC}\text{AnnualOperatingCost}_{\text{CNG}} + \beta_{RDCNG}\text{RefuellingDistance}_{\text{CNG}} + \varepsilon_{CNG}$$

$$U_{\text{LPG.car}} = \beta_{\text{LPG}}\text{ASC}_{\text{LPG}} + \beta_{\text{PP}}\text{PurchasePrice}_{\text{LPG}} + \beta_{\text{R}}\text{Range}_{\text{LPG}} + \beta_{A}\text{Acceleration}_{\text{LPG}} + \beta_{AOC}\text{AnnualOperatingCost}_{\text{LPG}} + \beta_{RDLPG}\text{RefuellingDistance}_{\text{LPG}} + \varepsilon_{LPG}$$

$$U_{\text{Hybrid.car}} = \beta_{\text{H}}\text{ASC}_{\text{H}} + \beta_{\text{PP}}\text{PurchasePrice}_{\text{H}} + \beta_{\text{R}}\text{Range}_{\text{H}} + \beta_{A}\text{Acceleration}_{\text{H}} + \beta_{AOC}\text{AnnualOperatingCost}_{\text{H}} + \beta_{RD}\text{RefuellingDistance}_{\text{H}} + \varepsilon_{H}$$

$$U_{\text{Electric.car-owned.battery}} = \beta_{\text{E-ob}}\text{ASC}_{\text{E-ob}} + \beta_{\text{PP}}\text{PurchasePrice}_{\text{E-ob}} + \beta_{\text{RE}}\text{Range}_{\text{E-ob}} + \beta_{AE}\text{Acceleration}_{\text{E-ob}} + \beta_{AOC}\text{AnnualOperatingCost}_{\text{E-ob}} + \beta_{RDE}\text{RefuellingDistance}_{\text{E-ob}} + \beta_{CEE}\text{CarExpert}_{\text{E-ob}} + \beta_{CGE}\text{CarGarage}_{\text{E-ob}} + \varepsilon_{\text{E-ob}}$$

$$U_{\text{Electric.car-leased.battery}} = \beta_{\text{E-lb}}\text{ASC}_{\text{E-lb}} + \beta_{\text{PP}}\text{PurchasePrice}_{\text{E-lb}} + \beta_{\text{RE}}\text{Range}_{\text{E-lb}} + \beta_{AE}\text{Acceleration}_{\text{E-lb}} + \beta_{AOC}\text{AnnualOperatingCost}_{\text{E-lb}} + \beta_{RDE}\text{RefuellingDistance}_{\text{E-lb}} + \beta_{\text{CEE}}\text{CarExpert}_{\text{E-lb}} + \beta_{\text{CGE}}\text{CarGarage}_{\text{E-lb}} + \varepsilon_{\text{E-lb}}$$

Table 7 reports the results for the MNL model.

Table 7 – MNL model's estimates

Variables	Estim.Coeff.	Std.Err.	t-ratio	P-value
Alternative Specific Constants:				
ASC DV(Ford Fiesta) (β_D)	0.124	0.129	0.964	0.335
ASC CNGV (Fiat Punto Evo NP) (β_{CNG})	0.337	0.180	1.871	0.061
ASC LPGV (Alfa Romeo Mito) (β_{LPG})	0.385	0.194	1.979	0.048
ASC HEV (Toyota Yaris) (β_H)	-0.151	0.117	-1.292	0.196
ASC BEV-owned battery (Peugeot iOn) (β_{E-ob})	-0.465	1.041	-0.447	0.655
ASC BEV-leased battery (Renault Zoe) (β_{E-lb})	-1.526	0.927	-1.646	0.100
Generic attributes:				
Purchase Price (€1.000) (β_{pp})	-0.208	0.010	-20.575	0.000
non-BEV Range (1.000km) (β_R)	1.554	0.241	6.448	0.000
non-BEV Acceleration (β_A)	0.005	0.024	0.192	0.848
Annual operating cost (€1.000) (β_{AOC})	-1.287	0.079	-16.326	0.000
Refuelling distance (β_{RD})	0.013	0.010	1.317	0.188
Fuel-specific attributes:				
Refuelling distance*LPGV (β_{RDLPG})	-0.017	0.005	-3.554	0.000
Refuelling distance*CNGV (β_{RDCNG})	-0.015	0.004	-3.540	0.000
Refuelling distance*BEVs (β_{RDE})	0.005	0.020	0.254	0.800
BEV Acceleration (β_{AE})	0.018	0.054	0.326	0.745
BEV Range (1.000km) (β_{RE})	10.485	2.556	4.102	0.000
Socio-economic variables:				
Long Distance Trips*DV (β_{LDTD})	-0.002	0.026	-0.084	0.933
Car Expert*BEVs (β_{CEE})	-0.472	0.182	-2.590	0.010
Car Garage*BEVs (β_{CGE})	-0.123	0.166	-0.740	0.459
Adjusted Rho squared no coefficients:	*0.15*			
Number of observations:	*1.452*			
Log likelihood function:	*-2,152.25*			

The SP alternatives present jointly the brand of the car and the fuel\powertrain technology. Consequently, it is not possible to disentangle the brand effect from the fuel\powertrain effect and the ASCs should be interpreted as a preference for the brand and the fuel type jointly considered[5]. Keeping this in mind, taking the gasoline VW Polo as a reference point, *ceteris paribus*, the diesel Ford Fiesta is deemed equivalent, the CNG Fiat Punto Evo Natural Power and the LPG Alfa Romeo Mito are considered superior, whereas the hybrid Toyota Yaris and the electric Peugeot iOn with owned battery are, again, considered equivalent or slightly worse. The electric Renault Zoe with leased battery is the least preferred among the 7 cars, showing that the Italian buyers do not favour the Renault strategy of selling the car at a lower price but with the need to spend monthly a fixed amount for the battery.

[5] We thank an anonymous referee for pointing this out.

All attributes except acceleration and refuelling distance are significant with the expected sign. The purchase price and the annual operating cost are highly significant. As expected, the coefficient of the annual operating cost is much larger than the coefficient of the purchase price. It is estimated that the former is six times larger than the latter. The respondents recognize that €1,000 purchase price is a one off cost whereas €1,000 annual operating cost is spent for the entire lifetime of the car.

The range generic attribute is also highly significant (the WTP for a 1 km range increase is equal to €7.47). For the BEVs the range specific attribute is much higher (equal to 10.49) which corresponds to a WTP of €50.4 per a 1 km range increase. These results are intermediate relative to the ones obtained by Hackbarth and Madlener (2013) and by Jensen et al. (2013). Hackbarth and Madlener (2013) find WTP values equal to 16.21 and 32.76 per km, for the BEVs priced below and above 20,000€, respectively, and values 8.32 and 16.82 km, for the non-BEVs priced below and above 20,000€, respectively. Jensen et al. (2013) distinguish between single car and multicar households, before and after testing the BEV and find values equal to 65€ (before) and 134€ (after) per km for single car households and values equal to 46€ (before) and 84€ (after) per km for multiple car households. Dimitropoulos et al. (2012) find values very close to ours, ranging for the BEVs from €52 to €58 per km.

Acceleration is not significant for the choice between cars, neither as a generic attribute nor when tested specifically for the BEVs. Since the acceleration performance of the BEVs is much discussed and promoted in the non-scientific literature, this is a somewhat surprising result, although common to other discrete choice studies (e.g. Mabit & Fosgerau, 2011). This result is to be further verified since it might reflect the lack of actual experience with the BEVs of the Italian users.

In contrast with the recent literature (Achtnicht et al., 2008; Daziano and Bolduc, 2013; Daziano and Achtnicht, 2013; Hackbarth, Madlener, 2013), we find that the refuelling distance attribute for the SGV, DV, HEV and BEVs plays no role in the car choice-making process. However, it is significant when the LPGV and CNGV are considered. This latter result is very realistic since the Italian refuelling stations network for these two fuel types is not sufficiently dense.Furthermore, we have tested whether the respondents who make long distance trips (at least 4 longer than 400 km per year) would favour the more fuel-efficient diesel cars, finding a negative answer, and whether the car experts or the garage owners are more likely to buy a BEV. We find that the Italian "car experts" do not like BEVs and that no evidence exists that garage ownership has a role in buying a BEV. The stability of these results, as BEVs enter the market, should be subject to a future test and investigated with more sophisticated discrete choice models (e.g. hybrid choice model).

Next, by using a MECL model, we tested whether there is heterogeneity in the attribute parameters and what determines it, using the socio-economic data collected during the interview. Furthermore, this model accounts for the correlation among alternatives and the panel features of the data set.

Having tried several specifications, the best one is reported in Table 8.

Table 8 – Results of the Mixed Error Component Logit model

Variables	Coeff.	Std.Err.	t-ratio	P-value
Random parameters:				
Purchase Price (€1.000) (β_{pp}) *	-0.633	0.053	-11.878	0.0000
Annual operating cost (€1.000) (β_{AOC}) *	-4.616	0.333	-13.841	0.0000
non-BEV Range (1.000km) (β_{R}) *	3.417	0.488	6.999	0.0000
non-BEV Acceleration (β_{A}) **	-0.126	0.066	-1.912	0.0559
BEV Range (1.000km) (β_{RE}) *	21.695	2.769	7.836	0.0000

BEV Acceleration (β_{AE}) *	-0.113	0.038	-2.953	0.0031
Non-random parameters:				
Refuelling distance (β_{RD})	-0.002	0.012	-0.183	0.8550
ASC DV (Ford Fiesta) (β_{D})	0.357	0.153	2.330	0.0198
Long Distance Trips*DV (β_{LDTD})	0.032	0.033	0.969	0.3325
ASC CNGV (Fiat Punto Evo NP) (β_{CNG})	0.406	0.214	1.900	0.0574
Refuelling distance*CNGV (β_{RDCNG})	-0.018	0.005	-3.551	0.0004
ASC LPGV (Alfa Romeo Mito) (β_{LPG})	0.596	0.243	2.458	0.0140
Refuelling distance*LPGV (β_{RDLPG})	-0.017	0.005	-3.171	0.0015
ASC HEV (Toyota Yaris) (β_{H})	0.138	0.145	0.951	0.3415
ASC BEV-owned battery (Peugeot iOn) (β_{E-ob})	-1.512	1.229	-1.230	0.2186
Car Expert*BEVs (β_{CEE})	-0.294	0.504	-0.583	0.5598
Car Garage*BEVs (β_{CGE})	-0.815	0.382	-2.137	0.0326
Refuelling distance*BEVs (β_{RDE})	-0.001	0.028	-0.047	0.9622
ASC BEV-leased battery (Renault Zoe) (β_{E-lb})	-1.462	1.119	-1.307	0.1912
Heterogeneity sources:				
Purchase Price: Older age	-0.013	0.038	-0.336	0.7366
Purchase Price: Female	0.132	0.031	4.319	0.0000
Purchase Price: Higher income	0.151	0.041	3.689	0.0002
Annual operating cost: Older age	0.404	0.285	1.418	0.1561
Annual operating cost: Female	1.221	0.192	6.359	0.0000
Annual operating cost: Higher income	0.702	0.296	2.374	0.0176
non-BEV Range: Older age	-0.142	0.484	-0.294	0.7687
non-BEV Range: Female	-1.740	0.377	-4.613	0.0000
non-BEV Range: Higher income	0.948	0.491	1.932	0.0533
non-BEV Acceleration: Older age	0.070	0.039	1.813	0.0698
non-BEV Acceleration: Female	0.072	0.038	1.890	0.0588
non-BEV Acceleration: Higher income	0.0004	0.039	0.009	0.9930
BEV Range: Old age	0.547	3.164	0.173	0.8627
BEV Range: Female	-11.08	2.771	-4.000	0.0001
BEV Range: Higher income	-6.150	3.413	-1.802	0.0716
BEV Acceleration: Older age	0.0683	0.049	1.381	0.1673
BEV Acceleration: Female	0.088	0.041	2.166	0.0303
BEV Acceleration: Higher income	0.087	0.049	1.748	0.0804
Spreads and standard deviations of parameter distributions:				
Ts Purchase Price	0.633	0.053	11.878	0.0000
Ts Annual operating cost	4.616	0.333	13.842	0.0000
Ts non-BEV Range	3.417	0.488	6.999	0.0000
Ns non-BEV Acceleration	0.090	0.016	5.786	0.0000
Ts BEV Range	21.695	2.769	7.836	0.0000
Ts BEV Acceleration	0.113	0.038	2.953	0.0031
Standard deviations of latent random effects:				
SigmaE01 (E-ob/E-lb)	0.295	0.042	6.988	0.0000
Adjusted Rho no coefficients:	*0.377*			
Number of observations:	*1.452*			
Log likelihood function:	*-2,825*			

Notes: ASC = alternative specific constant. The ASC base is the BEV with an owned battery; * = random variables with a restricted triangular distribution. ** = random variable with a normal distribution.

The purchase price, the annual operating cost, the non-BEV and BEV range, the non-BEV and BEV acceleration are assumed randomly distributed. All but the non-BEV acceleration variables are assumed to have a constrained triangular distribution so that the average is equal by construction to the spread to the distribution. The socio-economic variables such as age, gender and household income are used to explain the parameters' heterogeneity. An error component is included to capture the unobserved error correlation between the two BEVs[6].
Accounting for heterogeneity, largely improves the goodness-of-fit of the model (the adjusted Rho squared improves from 0.150 to 0.380). The error component term is lower than one but highly significant.
Starting from the ASCs and having taken the gasoline VW Polo as a reference point, *ceteris paribus*, the diesel Ford Fiesta, the CNG Fiat Punto Evo Natural Power and the LPG Alfa Romeo Mito are considered superior to the gasoline VW Polo, whereas the hybrid Toyota Yaris is equivalent and the two BEVs (Peugeot iOn and Renault Zoe) are less preferred.
All attributes except refuelling distance are significant with the expected sign. The purchase price and the annual operating cost are highly significant and, as before, the coefficient of the annual operating cost is much larger than the coefficient of the purchase price. The range generic attribute is also highly significant. For the BEVs the range specific attribute is again much higher. Acceleration is significant in this model with an expected sign both for the non-BEVs and the BEVs with a coefficient of a similar magnitude. The refuelling distance attribute is again only significant for the LPGV and CNGV.
The respondents who make long-distance trips (at least 4 longer than 400 km per year) do not revealed a preference for the diesel car. Italian "car experts" are indifferent to the BEVs whereas garage ownership counter-intuitively has a negative preference for the BEVs.
The socio-economic variables explain the random parameters' heterogeneity as follows: a) respondents older than 30 years care slightly less about the non-BEV acceleration properties; b) women are less sensitive to the purchase price, the annual operating cost, the range and the acceleration both of the non-BEVs and BEVs. In short, they differentiate less among the cars; c) respondents with an annual household income higher than €30,000 are less sensitive to the purchase price and to the annual operating cost, although they would prefer non-BEVs with a higher range, they are more willing to accept BEVs with a lower range, most probably as a second car.

4.3. Simulation model

On the basis of the parameters obtained in the MECL model, Monte Carlo simulations are performed using the Frontline risk solver[7] software. The structure of this model is illustrated in Figure 1. The utility of each car is estimated multiplying the attributes' values X_i by the corresponding attribute parameter. Each attribute parameter is specified by its mean and standard deviation or spread. For each Monte Carlo simulation a random draw is taken from the distribution function of each parameter. The value of each attribute coefficient is the sum of its mean, randomly taken from the distribution, and its covariates. Thirty-two ($=2^5$) population segments are identified combining the 5 socio-economic and behavioral dichotomous variables (gender, income, number of cars, number of car trips longer than 400km, and garage availability). The utility of each of the 7

[6] As explained in the Nlogit version 4.0 – Reference Guide (N-14), the error component is an individual specific random effect that is distributed across alternatives according to a tree structure. A sigma variable is estimated that account for choice situation invariant variation that is unobserved and not accounted for by the other model components.
[7] For further details see: http://www.solver.com/risk-solver-platform.

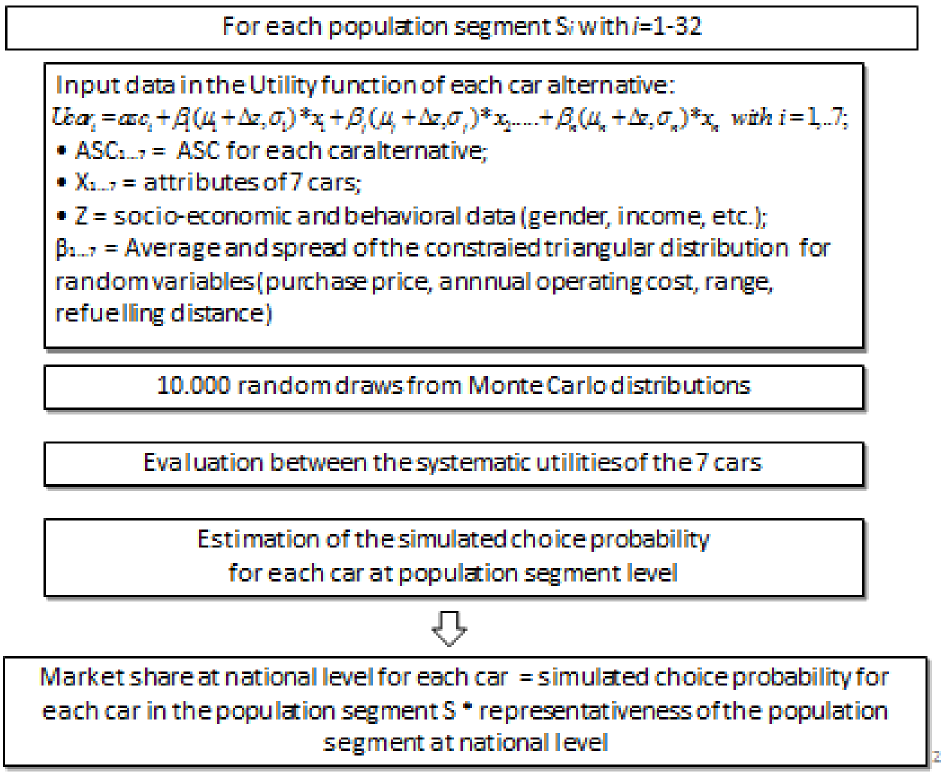
cars is then computed for each of the 32 population segments. For every simulation and for each population segment, the market share of each car is estimated using the *logit* formula. Ten thousand Monte Carlo draws are performed and the market share averages for each car are calculated for each population segment.

The representativeness of each market segment at national level is then computed on the basis of the data available from the National Statistical Institute (Table 16 in Annex 1). Multiplying each car choice probability for the representativeness of the population segment and summing up across all population segments, we obtained the total estimated national market share of each car.

Based on SQ data, we determine the current estimated market shares for Italy for the 7 cars considered ('base case' scenario). Subsequently, we evaluate the impact of potential policy interventions or technological improvements as variations from the base case scenario. More specifically, we tested the impact of:

1. the introduction of a state subsidy for the purchase of low emission cars (scenario 1);
2. the introduction of a state subsidy for the purchase of low emission cars and a threefold increase of the range for BEVs (scenario 2);
3. the introduction of a state subsidy for the purchase of low emission cars and the increase in the price of fossil-based fuels (+20%) (scenario 3);
4. the introduction of a state subsidy for the purchase of low emission cars and the decrease of the purchase price of the BEVs cars (€5,000) (scenario 4);
5. the joint introduction of all previous policies and technological improvements (scenario 5).

Figure 1 – Framework of the simulation model



4.3.1 – Base case scenario with current market values

Table 9 shows an estimate of the Italian market demand for the 7 cars under the *base case* scenario. The first five columns report the purchase price, the annual operating cost, the range, the acceleration and the refuelling distance for each car. The purchase price is the prevailing market price in Italy in 2013. The annual operating cost is calculated by Rusich and Danielis (2013) assuming an annual driving distance of 10,000 km. The range and acceleration are the ones reported by the car manufacturers. The refuelling distance is estimated based on the current Italian fuel distribution network.
The last three columns report the estimated and the actual market shares of the cars registered in the year. The second column before the last shows the market shares as estimated by our model. The first column before the last shows the actual market share in 2012 by brand, that is we have considered how many VW Polo, Ford Fiesta, Fiat Punto Evo, etc. have been registered in 2012. The last column reports the actual market share by car fuel\powertrain technology, that is we have reported the percentage of gasoline, diesel, bi-fuel – CNG, etc. cars have been registered in 2012.
It can be seen that the model is able to sufficiently approximate the actual market share by brand, but it overestimates the VW Polo (gasoline) market share by brand[8]. When the market share by fuel\powertrain technology is considered, the model underestimated the DV and over-estimates the bi-fuel CNGV, bi-fuel LPGV and HEV. The BEVs are pretty well approximated both by car brand and fuel\powertrain technology.

Table 9 – Estimate of the Italian market demand*:* base case scenario

Type of engine technology:	Purchase price	Annual operating cost	Range	Acceleration	Refuelling distance	Estimated Market Shares	Actual Market Share by brand	Actual Market Share by f\p technology
List:	€	€	km.	0-100 km in sec.	km.	%	%	%
VW Polo (gasoline)	11,900	2,081	900	13	1	38.8	22	31.03
Ford Fiesta (diesel)	14,000	1,894	980	15	1	31.1	30	53.83
Fiat Punto Evo (bi-fuel - CNG)	15,425	1,757	800	15	5	16.1	25	5.11
Natural Power Alfa Romeo Mito (bi-fuel - LPG)	20,600	1,784	1,200	15	5	9.8	19	8.91
Toyota Yaris (Hybrid - gasoline)	18,650	1,920	1,000	13	1	4.1	4	1.07
Peugeot iOn (electric – owned battery)	30,369	1,681	150	12	0	0.17	0.21	0.06
Renault Zoe (electric – leased battery)	21,650	2,553	210	12	0	0.03	0.00	0.00
Total:						100	100%	100%

Source: Unione Nazionale Rappresentanti Autoveicoli Esteri (2013)

[8] The sum of the squared errors is equal to 447 when the estimated shares are compared to the actual share by brand, while it is equal to 708 when the estimated shares are compared to the actual share by engine technology.

4.3.2 – Scenario 1 - Introduction of a state subsidy for the purchase of low emission cars

A recently policy adopted by several European countries is the introduction of purchase subsidies to encourage people to buy cars. With the Decree of the Ministry of Economic Development[9], the Italian Parliament has recently allocated funds to subsidize the purchase of cars with low environmental impact, even though the total amount of funds made available was quite limited (€40 million in 2013).

Economic incentives are provided for the purchase of cars with different levels of (low) CO_2 emissions. The subsidy is differentiated between our 7 cars as follows:

- €2,000 for the Ford Fiesta (diesel);
- €3,560 for the Toyota Yaris (hybrid);
- €5,000 for the Peugeot iOn (electric – owned battery);
- €4,330 for the Renault Zoe (electric – leased battery).

The simulation model estimates the impact of the economic incentive as reported in Table 10.
Contrary to the general expectations, the Ford Fiesta (diesel) appears to be the one that benefits the most, increasing its market share up to 51.9% at the expense of the VW Polo (gasoline). The Toyota Yaris (hybrid - gasoline) increases by 5% at the expense of the other cars whereas the BEVs increase their market share only marginally, although they are the recipients of the largest state subsidies.

Table 10 – Estimated market share: introduction of a state subsidy

Type of supply power:	**Purchase price (base)**	**State subsidy**	**Net purchase price**	**Estimated Market Shares**	**Estimated Market Shares (base scenario)**
	€	€	€	%	%
VW Polo (gasoline)	11,900	-	11,900	20.4	38.8
Ford Fiesta (diesel)	14,000	2,000	12,000	51.9	31.1
Fiat Punto Evo (bi-fuel - CNG)	15,425	-	15,425	9.9	16.1
Natural Power Alfa Romeo Mito (bi-fuel - LPG)	20,600	-	20,600	7.8	9.8
Toyota Yaris (hybrid - gasoline)	18,650	3,560	15,090	9.4	4.1
Peugeot iOn (BEV – owned battery)	30,369	5,000	25,369	0.36	0.17
Renault Zoe (BEV – leased battery)	21,650	4,330	17,320	0.19	0.03
Total:				100	100

4.3.3 – Scenario 2: Threefold increase of the range for BEVs

Table 11 shows the potential demand as a result of an increase in the range of BEVs thanks to technological developments. This innovation would solve the well-known *range anxiety* problem associated with the BEVs, that is, the fear of being left with a dead battery. The assumption that we test is that the range of both BEVs would triple.

[9] Decree of the January 11 2013.

Table 11 - Estimated market share: increase of range for BEVs

Type of supply power:	Range	New Range	Estimated Market Shares	Estimated Market Shares (base scenario)
	km.	km.	%	%
VW Polo (gasoline)	900	900	38.5	38.8
Ford Fiesta (diesel)	980	980	30.7	31.1
Fiat Punto Evo (bi-fuel - CNG)	800	800	15.7	16.1
Natural Power Alfa Romeo Mito (bi-fuel - LPG)	1,200	1,200	9.3	9.8
Toyota Yaris (hybrid - gasoline)	1,000	1000	3.8	4.1
Peugeot iOn (BEV – owned battery)	150	450	1.08	0.17
Renault Zoe (BEV – leased battery)	210	630	0.93	0.03
Total:			100	100

The BEVs would increase their market shares by 1% at the expense of the other cars.

4.3.4 Scenario 3 - Increase in the price of fossil fuels (+20%)

Table 12 illustrates the impact of a hypothetical increase of the price of fossil fuel. Such increase is modeled as a 20% increase of the annual operating cost for all cars except the BEVs.

Table 12 - Estimated market share: increase in the price of fossil-based fuel

Type of power supply:	Annual operating cost	New annual operating cost (+20%)	Estimated Market Shares	Estimated Market Shares (base scenario)
	€	€	%	%
VW Polo (gasoline)	2,081	2,497	35.4	38.8
Ford Fiesta (diesel)	1,894	2,273	31.6	31.1
Fiat Punto Evo (bi-fuel - CNG)	1,757	2,108	18.0	16.1
Natural Power Alfa Romeo Mito (bi-fuel - LPG)	1,784	2,141	10.0	9.8
Toyota Yaris (hybrid - gasoline)	1,920	2,304	3.8	4.1
Peugeot iOn (BEV – owned battery)	1,681	1,681	1.03	0.17
Renault Zoe (BEV – leased battery)	2,553	2,553	0.17	0.03
Total:			100	100

Notwithstanding the common cost increase (except for the BEVs), the impact is differentiated, reflecting the relative cost structure between fixed and variable costs. The VW Polo (gasoline) is estimated to loose more than 3%, due to its high variable costs whereas the Fiat Punto Evo (bi-fuel - CNG) and the Natural Power Alfa Romeo Mito (bi-fuel - LPG) would increase their shares. The impact on the BEVs is mostly on the Peugeot iOn (electric – owned battery), which would gain almost 1% market share.

4.3.5 – Scenario 4 - Decrease in the purchase price for BEVs (€5.000)

Table 13 illustrates the impact of a decrease in the purchase price for electric cars (€5,000) as a result of a decrease in the production costs or of an aggressive market penetration strategy undertaken by the car manufacturers.

Table 13 - Estimated market share: decrease in the purchase price of €5,000 for BEVs

Type of supply power:	Purchase price (base)	Final purchase price	Estimated Market Shares	Estimated Market Shares (base scenario)
	€	€	%	%
VW Polo (gasoline)	11,900	11,900	38.7	38.8
Ford Fiesta (diesel)	14,000	14,000	31.0	31.1
Fiat Punto Evo (bi-fuel - CNG)	15,425	15,425	15.9	16.1
Natural Power Alfa Romeo Mito (bi-fuel - LPG)	20,600	20,600	9.7	9.8
Toyota Yaris (hybrid - gasoline)	18,650	18,650	4.0	4.1
Peugeot iOn (BEV – owned battery)	30,369	25,369	0.38	0.17
Renault Zoe (BEV – leased battery)	21,650	16,650	0.28	0.03
Total:			100	100

It is estimated that the impact of such a price cut would be very marginal since the current disadvantages of the BEVs cannot be sufficiently compensated for by such a price cut.

4.3.6 – Scenario 5 - Introduction of a state subsidy, the decrease of the purchase price for BEVs (€5.000), increase in range and increase in fuel price

Scenario 5 assumes that all of the above changes occur simultaneously.

Table 14 - Estimated market share: Introduction of a state subsidy, the decrease in the purchase price for BEVs (€5.000), increase in range and increase in fuel price

Type of engine technology:	Purchase price	Annual operating cost	Range	Acceleration	Refuelling distance	Estimated Market Shares	Estimated Market Shares (base scenario)
List:	€	€	km.	0-100 km in sec.	km.	%	%
VW Polo (gasoline)	11,900	2,497	900	13	1	14.3	38.8
Ford Fiesta (diesel)	12,000	2,273	980	15	1	42.5	31.1
Fiat Punto Evo (bi-fuel - CNG)	15,425	2,108	800	15	5	8.2	16.1
Natural Power Alfa Romeo Mito (bi-fuel - LPG)	20,600	2,141	1,200	15	5	6.4	9.8
Toyota Yaris (hybrid - gasoline)	15,090	2,304	900	13	1	7.3	4.1
Peugeot iOn (BEV – owned battery)	20,369	1,681	450	12	0	6.47	0.17
Renault Zoe (BEV – leased battery)	12,320	2,553	630	12	0	14.89	0.03
Total:						100	100

It is estimated that the impact would be quite large. The VW Polo (gasoline) would loose its competitive advantage and loose about 24% market share. The Ford Fiesta (diesel), that in Italy enjoys a state subsidy of €2,000, would gain 9 points. The Fiat Punto Evo (bi-fuel - CNG) and the Natural Power Alfa Romeo Mito (bi-fuel - LPG) would lose about 8 and 3 points, respectively. On the contrary, the Toyota Yaris (Hybrid - gasoline) would rise to 7.3% of the market and the BEVs would jointly reach a market share of about 21%, with the Renault Zoe (electric – leased battery) enjoying two-thirds of the BEVs' share.

5. Discussion and conclusions

This paper reports the results of a simulation model calibrated for the Italian (segment B) car market. The simulation model is based on parameters derived from a MECL model estimated with data collected via SP interviews in three Italian cities and on 32 market segments aggregated according to their representativeness at national level.
Taking as reference the base case scenario (Table 9), the following 5 scenarios were tested: the introduction of a state subsidy for the purchase of low emission cars (scenario 1); a threefold range increase for the BEVs (scenario 2); a 20% price increase for the fossil-based fuels (scenario 3); a €5,000 purchase price decrease for the BEVs (scenario 4); joint changes of the previous scenarios (scenario 5).

Table 15 – Market share variations relative to the base case scenario

Type of cars:	***Scenario 1:* subsidy**	***Scenario 2:* threefold range increase for electric cars**	***Scenario 3:* 20% fossil-based fuel price increase**	***Scenario 4:* €5.000 price reduction for the BEVs**	***Scenario 5:* scenario 1 to 4 considered jointly**
VW Polo (gasoline)	-18.4	-0.3	-3.4	-0.1	-24.5
Ford Fiesta (diesel)	20.8	-0.4	0.5	-0.1	11.4
Fiat Punto Evo (bi-fuel - CNG)	-6.2	-0.4	1.9	-0.2	-7.9
Natural Power Alfa Romeo Mito (bi-fuel - LPG)	-2	-0.5	0.2	-0.1	-3.4
Toyota Yaris (hybrid - gasoline)	5.3	-0.3	-0.3	-0.1	3.2
Peugeot iOn (BEV – owned battery)	0.19	0.91	0.86	0.21	6.3
Renault Zoe (BEV – leased battery)	0.16	0.9	0.14	0.25	14.86

Table 15 summarizes the simulation results as variations from the base case scenario.
The choice made by the Italian government to subsidize the BEVs, the hybrid cars and - albeit with a lower sum - the diesel cars, greatly favors the Ford Fiesta (diesel) at the expense of the VW Polo (gasoline). The Toyota Yaris (hybrid - gasoline) gains whereas the BEVs are only slightly affected. A threefold range increase for BEVs has the largest impact on their joint market share but still not larger than 2%. It is also interesting to note that the changes assumed in scenario 3 and 4, both in favor of the BEVs, would also only slightly affect their market shares. A 20% fossil fuel price increase impacts negatively the VW Polo (gasoline) and positively the Fiat Punto Evo (bi-fuel - CNG) and the Ford Fiesta (diesel).
It is noteworthy, however, that none of the single changes in the economic or technology factors significantly affect the BEVs' market share. Only when all these changes take place simultaneously (Scenario 5) does a large improvement in the BEVs' market share materialize. The loser would be the VW Polo (gasoline), the Fiat Punto Evo (bi-fuel - CNG) and the Natural Power Alfa Romeo Mito (bi-fuel - LPG), whereas the Ford Fiesta (diesel) and the Toyota Yaris (hybrid - gasoline) do, like with the BEVs, increase their market shares.
Compared with the results achieved in previous research (Table 2), presented and discussed in the review of literature section, our findings confirm that the CV (gasoline and diesel) are going in the near future to maintain their strong position in the market. We also confirm that the pricing strategy *per se*, either in a form of a subsidy, a price cut or a fuel tax, is not sufficient to alter significantly the relative market power between the conventional and AFVs. Only, the HEVs appear to benefit from a reduction in the purchase price whereas the BEVs would not. Similarly, the performance

strategy (increased battery range) appears in our simulations ineffective while previous studies found different results (e.g. Horne et al., 2005). This difference might be due to the fact that our research does not find a strong enough evidence on the effect of the charging network density as some previously studies do (Achtnicht et al., 2008; Daziano and Bolduc, 2013; Daziano and Achtnicht, 2013; Hackbarth and Madlener, 2013). Consequently, the performance strategy associated to the increase in the charging infrastructure density is not tested in our simulations. However, when the pricing and the performance strategies are simultaneously used by the policy makers (car purchase price subsidies and fuel taxes) and car manufacturers (battery improvement and car price reduction) the AFVs, and the BEVs specifically, would penetrate significantly the market. The obvious policy implication is that in order to spur the development of the AFVs in Italy, a combined effort from the policy makers and the car manufactures is need.
This paper represents an initial effort to estimate and simulate the future changes in the Italian car market as a result of a set of potential technological, economic or policy changes. Several improvements are possible and desirable. An increase in the sample size and the geographical coverage is urgently needed. Testing the robustness of the econometric estimates and of the simulations comparing them with similar studies is also required. As some of these engine technologies are quite new, such as the hybrid engine and the BEVs, their knowledge by the Italian drivers is still quite limited and, hence, their preference structures might be unstable. Further elements that can dramatically change the choice preference structure are: the development of the BEVs' charging infrastructure; the appearance of new car types and models both for the hybrid cars and for the BEVs; and the regulations enacted by the national and local authorities with regards to the city center and reserved lane access, as the Norwegian case demonstrates (Nayum et al., 2013). Since, the policy and regulatory framework and the level of knowledge of the AFVs (and BEVs) is gradually changing also in Italy, a further empirical research will be able to test whether changes occurred in the preference structure of the Italian car users.

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Annex 1

Table 16 - Italian population by specific segments (2011)

Population segments	%	Absolute values
a1.b1.c1.d1	1.3%	775,792
a1.b2.c1.d1	3.5%	2,097,512
a1.b1.c2.d1	2.8%	1,687,040
a1.b1.c1.d2	2.8%	1,725,807
a2.b2.c2.d2	17.8%	10,767,770
a2.b1.c1.d1	1.4%	823,265
a2.b2.c1.d1	3.7%	2,225,866
a2.b1.c2.d1	3.0%	1,790,276
a2.b1.c1.d2	3.0%	1,831,415
a1.b2.c2.d1	7.5%	4,561,257
a1.b2.c1.d2	7.7%	4,666,070
a1.b1.c2.d2	6.2%	3,752,945
a2.b2.c2.d1	8.0%	4,840,375
a1.b2.c2.d2	16.7%	10,146,851
a2.b1.c2.d2	6.6%	3,982,600
a2.b2.c1.d2	8.2%	4,951,602
Total:	100.0%	60,626,442

Source: our elaboration on National Statistical Institute (2012)
Notes:
a = gender (1 = M, 2 = F),
b = family income (1 = high level (>51,000 yearly), 2 = low level),
c = children (1 = family with at least a child, 2 = family without children),
d = age (1 =< 30 years old, 2 > 30 years old).

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