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Role of car segment and fuel type in the choice of alternative fuel vehicles: A cross-nested logit model for the English market

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HIGHLIGHTS

- Fuel type choice is not independent from vehicle segment choice.
- Cars from the same segment are strongly perceived as similar by users.
- Correlation due to fuel type is weaker.
- These user perceptions can be key to foster adoption of electric cars.
- Operating cost and second-hand cars are relevant attributes for policy design.

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ABSTRACT

In this article, we study the role of car segment and fuel type in the choice of alternative fuel vehicles and in the prediction of its market. For this purpose, we propose a joint choice cross-nested logit model to understand the demand for alternative fuel vehicles (AFV) and to study substitutional patterns between fuel types and vehicle segments with a full revealed preference approach, using only publicly available real data at disaggregate (household) level in England. Our results show that, as hypothesised, fuel type choice is not independent from car segment choice. The correlation patterns in the chosen specification reveal that individual car alternatives belonging to the same car segment are strongly correlated, while a weaker correlation exists between alternatives from different segments which share the same fuel type. The results suggest that creating awareness for cleaner fuel alternatives might be more effective if a targeted approach that considers these substitutional patterns is used. From a policy standpoint, while purchase prices play an important role and government policies have been concentrated in reducing the gap between ICE vehicles and AFVs in this dimension, our models stress the relevance of the operating cost variable, suggesting that its effect might also be crucial in the purchase decision.

1. Introduction

The transport sector is responsible for about 24% of direct carbon dioxide emission from fuel combustion, and roughly three quarters of these emissions come from road vehicles [1]. In a scenario of climate emergency, reducing transport emissions is imperative, and this goal requires encouraging active and public transport as well as fostering cleaner technologies for private cars. In 2021, alternative fuel vehicle (AFV) registrations were almost doubled compared to 2020, with around 6.6 million cars sold during the year. However, AFVs only represent 8% of the sales share and about 1% of the global fleet worldwide [2]. In the UK, while ultra-low emission vehicles, including battery electric vehicles (BEVs) and hybrid-electric vehicles (HEVs)[1] reached a record share of 34% of the total new registrations in 2021 [3], BEVs and HEVs together represent only about 5.0% of the vehicles licenced [4].

Governments in developed countries have been investing hefty amounts of resources to boost AFV adoption, and considerable efforts have been devoted to forecast their potential demand over time. Accurate predictions are a necessity for the formulation and evaluation of policy measures. Most AFV demand studies focused on the choice component have aimed to forecasting fuel type choice relying on stated

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[1] For the purposes of this paper, the "hybrid electric vehicle" (HEV) denomination includes both regular hybrid electric cars and plug-in hybrid vehicles.

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preference (SP) experiment data, mainly because the AFV market is still relatively recent and not enough detailed historical records are available for estimation (see [5] for a review). Typically, these SP experiments ask first the car segment respondents bought or plan to buy and then customise the design for different car segments. This involves an implicit assumption of an order of priority in the decision process. However, the choice of fuel type and the choice of car segment (defined as groupings of vehicles that share similar attributes, market characteristics or design features) are often joint decisions. For example, an AFV in the UK is 1.4 times more likely to belong to the SUV or multi-purpose car segments than its ICE counterpart, while ICE vehicles are 1.8 times more likely to be a mini or a small car than AFV [6].

Few authors have explicitly estimated joint models of car segment and fuel type choice with emphasis on AFV [7,8,9] or simultaneously with car use [10,11]. These works still rely on SP data to predict the demand for fuel type. As known, models estimated with SP data are unsuitable for market forecasting, mainly because of the lack of information to calibrate the model to reproduce the real market [12,13]. The review in Domarchi and Cherchi [14] shows that several forecasts based on discrete choice models have not proven to be accurate, with possible reasons for this discrepancy being the use of SP data for calibration, and the use of parameters imported from external sources for the utility functions. Frameworks that forecast EV market shares using discrete choice models to account for individual choices using RP data have an average root mean square error (RMSE) of 0.50, while the error in the SP-based model is 0.62. While this can also be attributed to several other factors – such as the technique used to model the diffusion component, and the quality of data sources for the rest of the parameters –, the figures still reveal that deriving parameter sensitivities from actual observed choices increases the reliability of the choice modelling results, obtaining a better representation of the population of interest.

In this article, we aim to contribute to the current research by trying to understand the variables that influence household choices of fuel types and the substitutional patterns between fuel types and vehicle segments, using only real data at disaggregate (household) level. We propose a joint choice model of vehicle segment and fuel type estimated with a full revealed preference (RP) approach, i.e., fully grounded on publicly available real data, and use our results to forecast the AFV market under different policy scenarios.

Brownstone et al. [7] estimate a similar model using a mixture of RP and SP data; however, they use a multinomial logit specification to account for vehicle replacement decisions. Similarly, the nested logit model in Fridstrom and Østli [15], estimated with disaggregate sales data, includes nests defined by vehicle makes and models, and does not address substitution among segments and fuel types. Fernández-Antolín et al. [16] is the only paper we are aware of that estimates joint fuel type/car segment models using disaggregate sales information using a cross-nested logit (CNL) structure. However, our study differs in several ways. First, we have available all information on car attributes (they use a heuristic to impute vehicle attributes of the unchosen alternatives). Second, our model also includes the decision of purchasing "new" versus "second-hand" vehicles. This is important because about 73% of UK cars are purchased second-hand [17], and second-hand purchases might provide medium and low-income households with the opportunity of purchasing vehicle models or types that might not be affordable as new, such as AFV [18,19]. Third, our model includes also HEVs among the available alternatives in the choice set. This is also important because HEVs currently represent a significant share of the AFV market. Fourth, other than the vehicle attributes, our model also considers the effect of charging infrastructure availability, a relevant policy variable which might contribute to facilitate the behavioural changes required when owning an AFV. Fifth, we validate the model with a holdout validation sample. Even though model validation is essential for reproducibility and for deriving policy recommendations, a surprisingly reduced number of transport preference studies consider it (see for example, [20,21]). Some of the previous studies carried out some sensitivity analyses, but to our knowledge, this is the first joint car segment/fuel type choice modelling study to include an actual validation analysis.

The remainder of the article is organised as follows. Section 2 includes a review of the literature with a specific focus on vehicle segment and fuel type choice models. Section 3 provides a description of the datasets and the modelling methodology, while Section 4 includes estimation and validation results as well as policy recommendations from the analysis of demand forecast, elasticities, correlations, and monetary valuations. Finally, Section 5 summarises the conclusions and recommendations for further work.

2. Literature review

The problem of personal vehicle choice has been studied since the first developments of discrete choice modelling. Lave and Train [22] and Manski and Sherman [23] were pioneers in studying the household vehicle purchase decision using disaggregate data. Estimating simple multinomial logit (MNL) models, they showed that preferences for vehicle segments are heterogeneous, and they vary as a function of vehicle and sociodemographic attributes. Later, Berkovec and Rust [24] reached a similar result using a nested logit (NL) model. Subsequent vehicle segment choice model applications incorporate additional dimensions to the analysis, including whether the car was purchased new or second hand [25], attitudes and lifestyle [26], geographic and spatial attributes [27], and neighbourhood characteristics [28,29]. More recent works analyse the influence of household structure in vehicle choices [30,31] or study the vehicle segment choice as part of more complex frameworks that model more than one decision at once. Mannering et al. [32] study vehicle segment choice as part of their model of the car leasing market in the US, while Rith et al. [33] estimate a joint vehicle segment choice-energy consumption model using a Gaussian copula-based discrete-continuous model. Finally, Bhat et al. [34] estimate a joint model of car ownership, vehicle type and usage. While these studies reveal heterogeneity in preferences towards different car segments, they do not consider fuel type part of the choice of a specific car segment.

Fuel type choice has mostly been studied independently from that of vehicle segment. A vast amount of literature focuses on modelling preferences for fuel type with special emphasis on cleaner technologies [5]. The applications include: SP experiments to estimate fuel type choice models (e.g. [35,36,37,38,39,40,41,42,43,44]), joint latent class-choice models to identify consumer profiles [45,46], hybrid choice models with latent variables to test the effect of attitudinal variables [47,48,49] or to model diffusion of BEVs [50], and reference-dependent choice models capturing differing preference directions [51,21]. Fuel type choice has also been jointly modelled with other decisions like car ownership [52], car ownership and use [53,54], and car use and preferences for advanced vehicle technology options [55]. These studies, however, do not model the vehicle segment dimension.

Modelling simultaneous vehicle segment and fuel type choices requires integrating information from the deciding household and the available vehicle alternatives. Ahn et al. [10] and Jäggi et al. [11] both estimate joint models of vehicle segment, fuel type, and car use –in terms of annual mileage– using SP data. These models use detailed information on car purchase and use, and the authors find that vehicle attributes and fuel prices are much more significant in explaining vehicle fleet choice than vehicle use. Higgins et al. [9] use SP data to estimate preferences for fuel types. They estimate seven Probit models –one for each US car segment–, which allows for a comparison of parameter sensitivities among car segment users. However, the models are estimated separately for each segment, which does not make it possible to study the correlation patterns among vehicle segments, or their interaction with fuel type. Hess et al. [8] estimate a cross nested logit (CNL) model that considers correlation patterns among both dimensions but using only SP data. While these studies allow a meaningful analysis of parameter estimates, substitution patterns, and correlation structures, they cannot be used for forecasting, as they are estimated with datasets that do not reflect the current market conditions.

Brownstone et al. [7], on the other hand, employ revealed preference (RP) data to model preferences for vehicle segments and fuel types, albeit in combination with data obtained from an SP experiment. They include fuel types as dummy variables interacting with car segments. Their work is interesting because it considers both the purchases destined to replace an already existing vehicle, and those that add new vehicle to the household, in a hierarchical structure. However, the modelling structure requires estimating separate models for one- and two-household vehicles, and involves detailed information about car purchases over time, which might not always readily available.

Fernández-Antolín et al. [16] instead estimate a joint car purchases and vehicle type CNL model with using car sales data from France. This is the only work we are aware of that uses real market data; however, lacking a detailed characterisation of the unchosen alternatives, they have to propose an alternative approach that use the empirical distributions of the attributes in the observed choices to impute vehicle attributes in the unchosen alternatives. In addition, they only consider the sale of new cars, and do not include HEV as an alternative.

3. Datasets

Information about the vehicle market was obtained from a privately sourced dataset that synthesises catalogue records from UK vehicle sellers since 1970 [56]. This dataset includes fields as car makes, models, trims, engine versions, specifications, and features, and was built using information from specialised magazines such as *Auto Motor und Sport* from Germany. The set contains 105 makes, 1107 models and 90,046 model variations. With this dataset detailed consideration of makes, models, and trims would involve the estimation of a model with over 4200 alternatives. Modelling the choice of car makes and models is of interest mainly to car manufacturers and sellers on the marketing side. From a transport policy and planning perspective, the interest lies in understanding preferences for vehicle attributes and how they influence fuel type choice. Therefore, our joint model of car segment and fuel type choice assumes then that the alternatives are not specific makes and models, but rather aggregations of car segment/fuel type combinations. We considered four fuel types (petrol, Diesel, electric, and hybrid-electric), and the nine vehicle segments as defined in the European classification scheme [57,58],[2] and listed in Table 1 along with their respective UK market shares.

The segment classification was not present on any of the datasets that we used for modelling purposes and thus we imputed it by hand into all the relevant datasets.

Household information was sourced from the National Travel Survey (NTS), an annual household survey designed to monitor long-term trends in personal travel in England. Data from the NTS are available via the UK Data Service [6]. The relevant variables for modelling purposes include household characteristics, sociodemographic profile, and approximate location,[3] plus a characterisation of each car in the household, up to the make/model/fuel type level. The dataset considers vehicles belonging to one of five fuel categories: Petrol, Diesel, BEV, PHEV (plug-in hybrids), and HEV (“pure” hybrids). For consistency, only data from the 2013–2020 period could be used in this study.[4] We made an explicit distinction between PHEV and HEV considering that, while both combine an internal combustion engine with an electric drivetrain, user behaviour might be different since only pure hybrids do not use a plug and therefore drivers might not be influenced by EV-specific variables such as driving range or the network of charging points.

The NTS dataset for this timeframe contains 53,505 households. Since we are interested in modelling the choice of vehicle segment and fuel type – conditional on having chosen to purchase at least one vehicle – we excluded carless households from the analysis. We also rule out vehicles that were not destined to personal use (e.g., commercial cars) or with incomplete key information such as make, model and/or fuel type. The final dataset includes information from 47,375 vehicles belonging to 34,081 households.

Table 2 summarises the main socioeconomic attributes of the final dataset used in the modelling and a comparison with those obtained from the complete NTS sample for the same period (2013−2020). Excluding households without cars implies considering a low fraction of households from London – the region with the lowest motorisation rate in the nation – and also implies that the income distribution in the final dataset differs from the NTS distribution. Apart from these differences, no relevant biases seem to have been introduced by this change.[5]

As Fig. 1 shows, the market share of petrol cars has been steadily reducing in the sample, from 66% in 2013 to 61% in 2020, while the share of Diesel cars is relatively constant. HEVs, PHEVs, and BEVs represent about 2% of the cars in the sample in 2019 and 3% in 2020. Fig. 2 shows that most of the vehicle fleet belongs to the B and C segments (small and medium cars) although the participation of the latter segment is slightly decreasing. The proportion of large cars decreased from 14% in 2013 to 11% in 2020, while cars from the J segment (sport-utility vehicles) more than doubled their share in the same timeframe (9% to 19%).

Since we are interested in modelling purchase decisions, we require information about purchase dates, which are not directly available in the NTS dataset. The sample, however, provides information about vehicle age, which can be used to estimate the year of first registration. As both the date of first registration and the date of purchase by the last owner are available online for *any* UK car licence plate, we carried out an independent data collection process to obtain an estimation of purchase dates for each vehicle in the NTS sample. The resulting distribution of purchase years in the sample can be seen on Fig. 3, and it shows that the average ownership length is 2.71 years, with 58% of the cars in the sample having been purchased during the 2012–2016 period.

Using this information, we built the set of alternatives (vehicle segment/fuel type) for each purchase year. The *year of availability* is specified in our source dataset (Teoalida), which includes information about the initial and final year of availability of each car make and model (sold as new), and these were used to obtain the new vehicle options that would have been available for the household at that time.

Table 1
Vehicle segment definition and UK share.

Segment	Segment name	Example models	UK share (%) (NTS 2020)
A	Mini cars	Fiat 500, Hyundai i10	11.2
B	Small cars	Renault Clyo, Vauxhall Corsa	25.3
C	Medium cars	Ford Focus, Volkswagen Golf	20.7
D	Large cars	Peugeot 406, Mazda 6	10.8
E	Executive cars	Mercedes Benz E220, Jaguar XF	2.7
F	Luxury cars	Porsche Panamera, BMW 7-Series	1.3
J	Sport utility cars	Hyundai Tucson, Toyota RAV-4	18.9
M	Multi-purpose cars	Citroën C4 Picasso, Ford Galaxy	6.3
S	Sport cars	Audi TT, Porsche 911	2.8

[2] The classification has been used for market categorisation, regulation, and for modelling purposes, even though it lacks a specific definition of each segment. Example models are included in Table 1 for illustration.

[3] Up to the local authority level, distinguishing between urban and rural areas.

[4] Prior to 2013, the NTS used a different classification scheme for fuel types.

[5] The smaller sample size in 2020 is likely explained because of the effects of the COVID-19 pandemic in the sampling protocols.

Table 2
Comparison of socioeconomic and vehicle attributes from our sample and NTS survey.

Variable	Value	% of modelling subsample	% of complete NTS sample
Cars per household	0	0	22.6
	1	53.9	43.1
	2	37.0	27.4
	3 or more	9.0	6.8
	Average	*1.39*	*1.24*
Survey year	2013	14.3	14.6
	2014	14.0	13.9
	2015	14.1	14.1
	2016	13.7	13.7
	2017	12.7	12.8
	2018	12.4	12.5
	2019	12.8	12.7
	2020	6.0	5.7
England region	North East	4.9	5.5
	North West	13.8	13.3
	Yorkshire & The Humber	10.5	10.0
	East Midlands	9.5	8.6
	West Midlands	10.2	10.1
	East of England	13.0	11.3
	London	8.8	14.4
	South East	17.7	16.6
	South West	11.5	10.2
Region type	Urban[a]	74.0	75.8
	Rural	26.0	24.2
Household Income level (Thousands of GBP per year)	<15	15.6	24.5
	15–29	25.9	25.7
	30–44	25.8	22.5
	45–60	8.6	7.3
	>60	24.0	20.2
	Average income	*44.7*	*39.5*
Household size (persons)	1	19.4	27.7
	2	41.7	36.9
	3	16.3	15.0
	4	15.6	13.6
	5 or more	7.0	6.6
	Average size	*2.5*	*2.4*
Car fuel type	Petrol	62.0	60.7
	Diesel	36.6	38.0
	Electric (BEV)	0.1	0.1
	Plug-in hybrid (PHEV)	0.2	0.2
	Hybrid-electric (HEV)	1.0	1.0
Vehicle age (Years)	*Average age*	*7.8*	*8.5*
Annual distance travelled (Thousands of km)	<10	49.1	50.7
	10–20	39.6	37.5
	>20	11.3	11.8
	Average distance	*12.5*	*12.5*
Sample totals	Number of households	34,081	53,505
	Number of cars	47,375	66,571

[a] The NTS considers households in a built-up area with 10,000 inhabitants or more, as "urban". The rest of the households are deemed "rural".

The market for used cars was built assuming that every car is available to be purchased as second-hand from its initial year of availability to the present date.

Theoretically, 45 aggregate alternatives (9 segments × 5 fuel types) could have been generated for each household. We computed the attributes of each aggregate alternative as the arithmetic mean of their value across all these 45 elementary alternatives (makes and models) that are part of that vehicle segment and fuel type. This aggregation produces some high variances in important attributes – mainly engine size and vehicle price – and several tests with different aggregation strategies showed that it could lead to biased parameters. Moreover, some segment–fuel type combinations do not exist in the dataset (for example, no cars from the A segment use Diesel from 2018 onwards, and no BEV sport cars or small PHEV cars appear in the dataset). To overcome these difficulties, we first generated basic aggregate alternatives (car segment–fuel type combinations), and then created sub-groups for those aggregate alternatives with a high variance in a relevant attribute. After testing several possible configurations and verifying the stability of the results, we generated the final choice set, whose size varies over time considering the evolution of the market for each segment and fuel type combination. Table 3 presents its general structure, in addition to the minimum, mean, and maximum number of available alternatives per segment and fuel type. For example, the A segment (mini car) includes minimum 1 Petrol vehicle alternative, and maximum 3 different Petrol alternatives, with an average of 1.9. The smallest choice set consists of 21 aggregate vehicle alternatives, the biggest 79.

4. Modelling framework

To model jointly the choice of car segment and fuel type accounting for possible cross-correlation between them, we used a cross-nested logit (CNL) model with 3 fuel type nests (ICE, EVs, and HEVs) and 9 vehicle segment nests. In a CNL specification [59], alternatives can belong to more than one nest, and allocation parameters α_{im} measuring the degree of membership of alternative i to nest m must be estimated. The choice probabilities have the following form:

$$P(i) = \sum_{m=1}^{M} \frac{\left(\sum_{j\in S_m}\left(\alpha_{jm} exp\left(\widehat{V}_j\right)\right)^{1/\phi_m}\right)^{\phi_m}}{\sum_{l=1}^{M}\left(\sum_{i\in S_m}\left(\alpha_{jl} exp\left(\widehat{V}_j\right)\right)^{1/\phi_l}\right)^{\phi_l}} \bullet \frac{\left(\alpha_{im} exp\left(\widehat{V}_i\right)\right)^{1/\phi_m}}{\sum_{j=1}^{J}\left(\alpha_{jm} exp\left(\widehat{V}_j\right)\right)^{1/\phi_m}}$$

Where $\widehat{V}_j$ are alternative-specific utilities and ϕ_m are nest parameters to be estimated. Economic consistency of the correlation structure requires that $0 < \phi_m \leq 1\ \forall m$ (and the allocation parameters must comply with two consistency restrictions: $0 \leq \alpha_{jm} \leq 1\ \forall j, m$ and $\sum_{m=1}^{M}\alpha_{jm} = 1 \forall j$. In practice, these restrictions are imposed before estimation.

Our model assumes that each alternative simultaneously belongs to exactly one car segment nest and one fuel type nest. Theoretically, this would require estimating 2 allocation parameters per alternative (up to 158 parameters), which would unnecessarily increase the complexity of the estimation process. Several approaches exist to overcome this difficulty. In this work, we adapt the simplification proposed by Hess and Palma [60], which, under the assumption that alternative j simultaneously belongs to one fuel type nest m_1 *and* to one car segment nest m_2, uses a logistic transformation of the allocation parameters such that:

$$\alpha_{j,m_1} = \frac{exp\left(\alpha_{0j,m_1}\right)}{exp\left(\alpha_{0j,m_1}\right) + exp\left(\alpha_{0j,m_2}\right)}$$

and $\alpha_{j,m_2} = 1 - \alpha_{j,m_1}$. For normalisation purposes, we restrict $\alpha_{0j,m_2} = 0$ and only estimate the α_{0j,m_1} parameters. After several tests, our preferred CNL model specification restricts all the α_{0j,m_1} parameters to be equal, allowing for a realistic representation of the correlation structure while keeping estimation times manageable.

2-level nested logit models were also estimated for comparison. NL1 accounts for correlation due to car segment only (i.e., one nest for every segment). NL2 includes three nests, one for ICE vehicles, one for plug-in electrics (BEV/PHEV), and one for pure hybrids (HEV). NL3 is a 3-level nested logit model (NL3), which simultaneously considers correlations due to both factors (car segment and fuel type), with the superior hierarchical level accounting for correlation due to car segment, and the

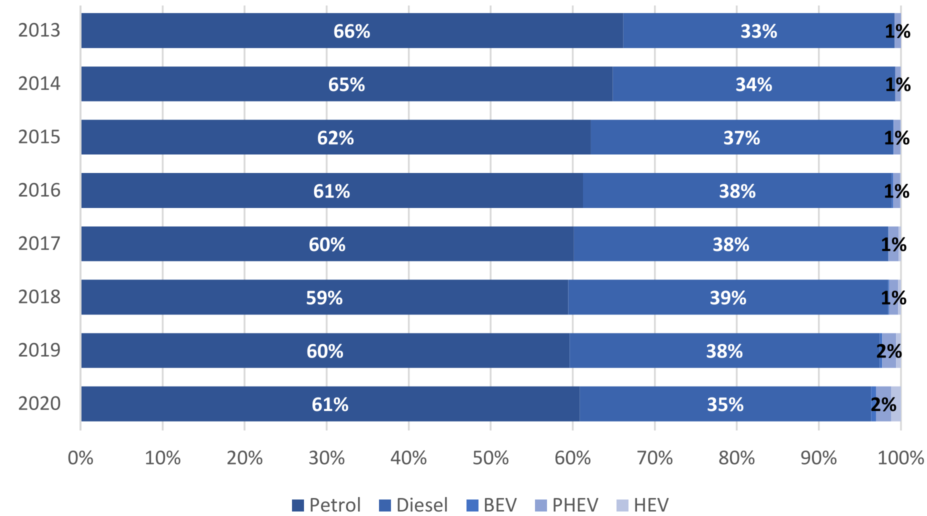

Fig. 1. Fleet composition by fuel type and survey year (NTS).

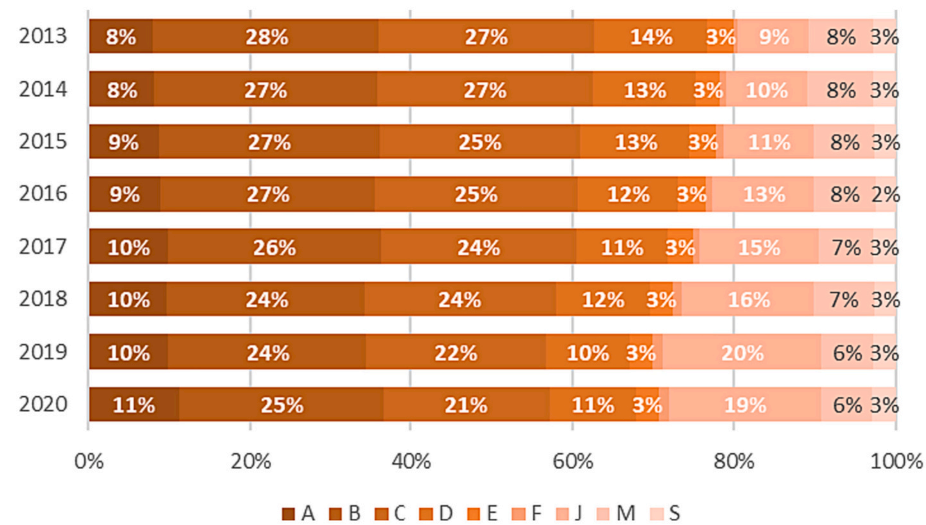

Fig. 2. Fleet composition by car segment and survey year (NTS).

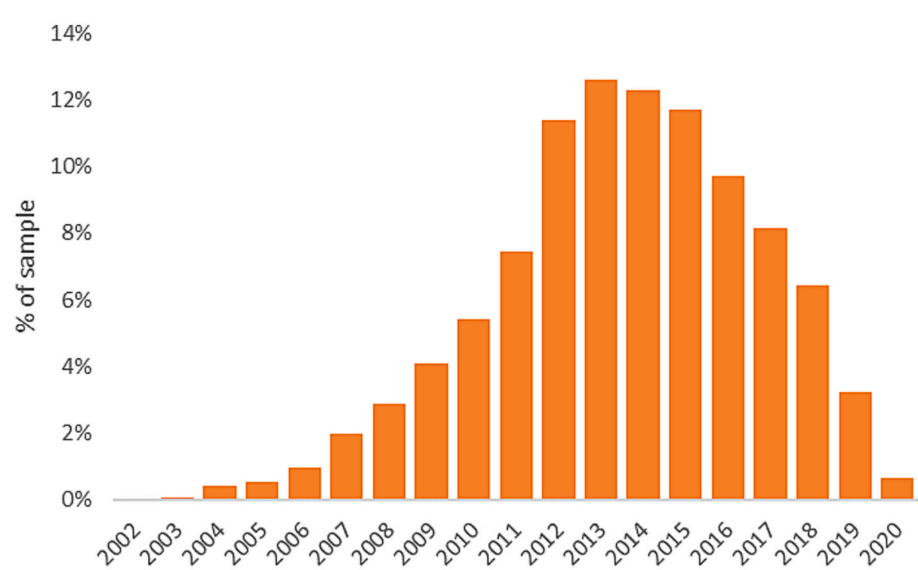

Fig. 3. Sample distribution by date of car purchase.

Table 3
General structure of the choice set.

Segment	Fuel type				
	Petrol	Diesel	BEV	PHEV	HEV
A	1–3 [1.8]	0–3 [1.8]	0–1 [0.8]	0–0 [0.0]	0–1 [0.2]
B	1–3 [1.8]	2–3 [2.7]	0–1 [0.6]	0–0 [0.0]	0–1 [0.9]
C	1–3 [2.4]	0–2 [1.3]	0–1 [0.8]	0–1 [0.2]	1–3 [1.5]
D	1–3 [2.4]	1–3 [2.4]	0–1 [0.0]	0–1 [0.0]	0–3 [1.2]
E	1–3 [2.1]	1–2 [1.9]	0–0 [0.0]	0–1 [0.2]	0–1 [0.8]
F	1–3 [2.8]	1–2 [1.7]	0–1 [0.0]	0–1 [0.0]	0–3 [1.5]
J	1–3 [2.3]	1–3 [2.6]	0–3 [0.5]	0–1 [0.1]	0–1 [0.8]
M	1–3 [1.8]	1–3 [2.2]	0–1 [0.5]	0–1 [0.1]	1–1 [1.0]
S	3–3 [3.0]	0–2 [1.3]	0–0 [0.8]	0–1 [0.1]	0–1 [0.2]

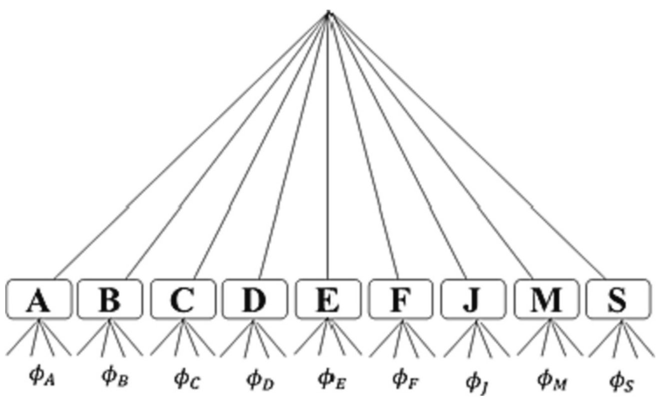

Fig. 4. 2-level nested model NL1.

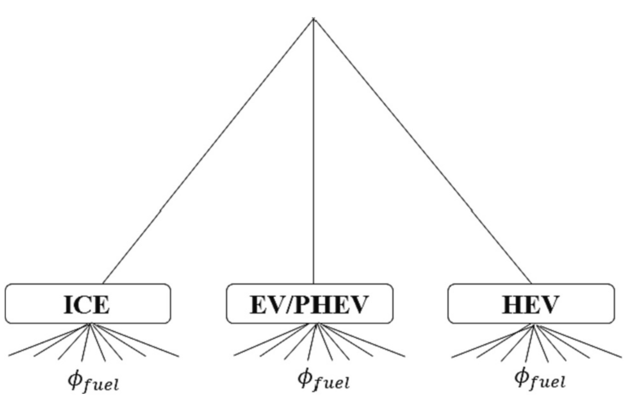

Fig. 5. 2-level nested model NL2.

inferior level considering correlation due to fuel type.[6] Figs. 4 to 7 illustrate the hierarchical structures that were tested in our models.

We specify the utility functions considering vehicle and household attributes, including both generic coefficients (those that are the same for all alternatives), and specific coefficients (those that might be different for some vehicle segments and fuel types). Table 4 presents a summary of these attributes.

Following previous applications, our model assumes that the car purchasing decision might depend on whether the vehicle is bought *new or second-hand*. The widespread presence of second-hand alternatives also implies more variability in the vehicle market, as car brands or models that are no longer in production might still be available as used vehicles. The NTS dataset does not provide information on this attribute. Instead, we rely on a different nationwide survey – the *Understanding Society Survey* (USS; [17]),[7] according to which about 73% of the vehicles in the UK are purchased second-hand. Using USS data, we estimated a binary choice model that predicts whether each vehicle in the dataset was bought new or second-hand.

Both new and second-hand *purchase prices* are available for each alternative. Due to the lack of specific information on the substitution patterns between new and second-hand vehicles, we assume that the decision of purchasing a new or a second-hand vehicle precedes the decision of which vehicle segment or fuel type to buy, and thus households that purchased a second-hand vehicle only observe second-hand vehicle prices for their chosen and non-chosen alternatives. Prices are available for 95% of the records in our dataset. We imputed the remaining purchase prices using a simple regression model.

We got an estimation of fuel consumption per vehicle, in terms of distance travelled per volume unit of fuel from the Teoalida dataset.[8] However, the impact of fuel consumption in the household budget also depends on fuel prices and travel routines. To consider this, an *expected annual expense AE* indicator was calculated for each alternative *j*, vehicle *v*, and purchase year *t*, as follows:

$$AE_{hjt} = FC_j \bullet KM_v \bullet FP_t$$

In this expression, FC_q is the fuel consumption (in litres per kilometre) of vehicle type *j*, obtained from the Teoalida dataset; while KM_v is the annual distance currently travelled by vehicle *v* (in kilometres), as reported in the NTS. Finally, FP_t is the average price of fuel (in pence per litre) during year *t*. This information was sourced from Department for Business Energy and Industrial Strategy [61].

This calculation is only valid for petrol, Diesel, HEVs, and PHEVs. In the case of BEVs, their annual expense must be estimated considering their battery size and range. The corresponding annual expense is computed as:

$$AE_{hjt} = \frac{BS_j}{BR_j} \bullet KM_v \bullet EP_t$$

Here BR_j, is the battery range (in kilometres) reported by the manufacturers of vehicle type *j*, while BS_j is the battery size (in kWh). EP_t represents the average energy price for the purchase year *t*, sourced from Department for Business Energy and Industrial Strategy [62].

We also tested the influence of variables that are specific to the AFV segment, namely *battery size* (in kWh) and *driving range* (in km). Most of them were non-significant in our models, likely due to the very low share of BEV and PHEV users in the sample (0.1%) which does not allow evaluating the importance of attributes specific to this category. In addition, for the driving range we had available a range of values provided by the manufacturers and we took the average. These values depend on the battery size and the efficiency estimated by the manufacturers, which we believe might be problematic. We then keep battery size, which is a more direct indicator, as an explanatory variable for illustrative purposes, as we believe that its effect should be significant in fuel type choice provided that further information is available to estimate the models. As seen in the model results, this variable is indeed significant in our chosen specification.

[6] We tested another 3-level structure – with fuel types in the superior nests and car segments in the inferior nests; however, we obtained parameters incompatible with the theoretical formulation and decided to discard the results.

[7] The USS is a UK-based household longitudinal study that measures several social, economic, and behavioural factors, including some transport behaviour questions.

[8] CO_2 emissions were highly negatively correlated with fuel consumption. The models including it as an explanatory variable resulted in decreased levels of fit, so the variable was discarded.

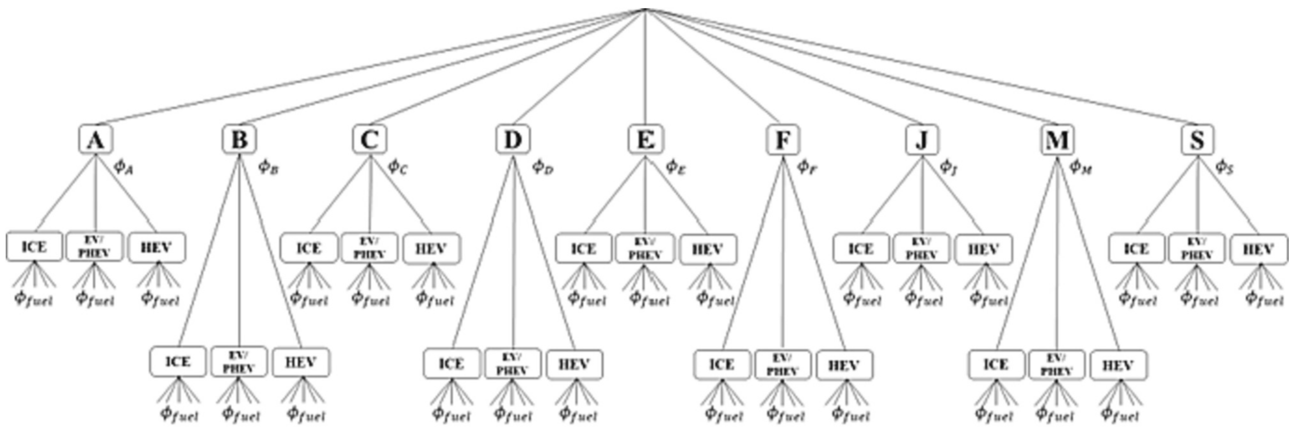

Fig. 6. 3-level nested model NL3.

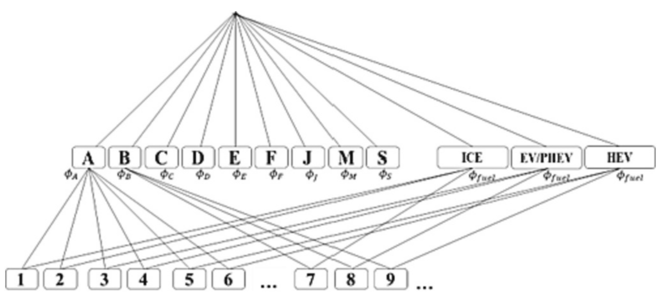

Fig. 7. Cross-nested logit model CNL.

Table 4
Summary of attributes in the utility functions.

Variable type	Name	Alternatives	Unit
Vehicle	Purchase cost	All (Generic)	GBP (thousands)
	Expected annual expense	Petrol and Diesel (Specific)	GBP (thousands)
	Expected annual expense	BEV, PHEV and HEV (Specific)	GBP (thousands)
	Engine size	Petrol, Diesel, HEV (Specific)	Litres
	Vehicle length	All (Generic)	Meters (m)
	Battery size	BEV and PHEV (Specific)	Kilo-watt x hour (kWh)
Other	Charging points network	BEV and PHEV (Specific)	# of points
	New vehicle dummy	BEV; HEV (Specific)	Dummy
	Density in the household area	Segments J and M only (Specific)	persons per hectare
Interactions	Vehicle length × Household size	All (Generic)	metres x persons
	Purchase cost × Low income	All (Generic)	GBP (thousands)
	Purchase cost × Medium income	All (Generic)	GBP (thousands)
	Engine size × Urban household	Petrol, Diesel, and HEV (Specific)	Litres

We also tested the influence of the national *network of charging points* in the probability of choosing BEVs and PHEVs. The historical information about the network of charge stations in the UK[9] was obtained from European Alternative Fuels Observatory [63]. We expected the variable to have a positive influence in the probability of selecting both BEVs and PHEVs. Moreover, we hypothesised that the probability of buying an AFV should increase if the car is bought new, and if the household has more than one car. However, only the first effect was statistically significant in the models.

Brake horsepower, *torque*, and *engine size* were preliminary chosen as variables that characterise vehicle power. Since they are highly correlated, we tested different model specifications including them and finally, *engine size* was chosen as the attribute to represent vehicle power in our model. Interestingly, this effect was only significant for households in urban areas (74% of the sample). A similar analysis led to *vehicle length* being chosen as the representative geometric attribute for each car.

As Cao et al. [27], Potoglou [29] and Chen et al. [28] show, household location might have an influence in the preferences for certain vehicle segments. Our model specification accounts for the effect household zone classification (*urban or rural*) and the *urban density* of the area as spatial variables that might influence the choice of specific car segments. We tested several effects in our formulation, and the only significant result was obtained considering that the probability of choosing larger vehicles – e.g., those belonging to segments J and M – increases when the household is located in a zone with low *population density* (persons per hectare). Similarly, we found that *rural* households positively value cars with a larger engine size.

Finally, we added a series of *dummy* variables to control for fixed effects. In each model, we estimate 3 constants for fuel type, 8 for English region, 19 for purchase year, and 8 for car segment. Our model assumes that the preference parameters are constant regardless of year or purchase and geographic location. We explored an alternative formulation of the model considering systematic taste variations to analyse preference heterogeneity due to the purchase year. However, the coefficients were non-significant, and we have not included them in our preferred specifications.

[9] While it would certainly be desirable to test this variable in a more disaggregate fashion – i.e., considering the availability of charging points that are geographically close to each household – we only have access to this information about public charging stations for the current year (2022). The lack of historical information conspires against the incorporation of this disaggregate variable in the utility functions.

5. Results

In this section we present the modelling results. We retained 80% of the household dataset for modelling estimation and held the remaining 20% for validation. First, we detail the estimation results and then analyse model validation results. We then use the parameters to obtain some derived monetary valuations and elasticities.

5.1. Estimation results

As both the NL and the CNL models require an a priori definition of the correlation structure, we estimated several versions of the models to test different nest configurations and parameters. Several structures were discarded because of microeconomic inconsistencies (i.e., nest parameters >1), while others presented identification issues. The results in this section stem from the preferred specifications, chosen because of their internal consistency.

Modelling results are reported in Table 5 (modelling attributes and goodness-of-fit), Table 6 (structural parameters), and Table 7 (constants). First, we note that the estimated parameters for the utility functions are similar in all specifications and the marginal utilities of all attributes have the expected sign. While all coefficients in all models are significantly different from zero at 99%, with few exceptions, the CNL results appear to be the strongest. More importantly, looking at the goodness-of-fit indicators, the CNL has by far the lowest values of AIC and BIC, indicating that the additional parameters estimated in the CNL do significantly improve the overall level-of-fit. All the NL specifications, although overall good models, are clearly inferior to the CNL. Interestingly, among the NL models, the basic 2-level nested model (NL1), has the best overall fit in terms of AIC and BIC values. It should also be noted that model NL1 performs better than model NL3 that considers a 3-level hierarchy of car segment a fuel type, while model NL2, which only accounts for the correlation due to engine type, is the worst. This suggests that indeed the correlation due to car segments seems to be prevalent, but there is also correlation among fuel type across segments, which is not captured by model NL3, reinforcing that the cross-nested specification is the best formulation to account for correlation between fuel types and car segments.

Looking at the single attributes, results in Table 5 show that, as expected, individuals on lower (low and medium) income have a higher sensitivity to purchase price, but further tests did not suggest the presence of possible income effect. Similarly, an additional monetary unit spent in annual cost is significantly more highly valued than an additional pound added to purchase price, which can be explained by considering that such an increase would represent a much higher *relative* expense in terms of annual costs than purchase prices. Moreover, households appear to value the annual operation cost of an electric vehicle less than its non-electric counterpart. This interesting result could be explained by the lower average operation costs of a BEV considering the current patterns of fuel and electric energy prices, and by the more negative perceptions usually associated with “out of pocket” expenditures – as opposed to purchase prices, usually perceived as long-term investments (e.g., [64]). This might imply that monetary reductions in energy cost could have a positive effect in boosting demand for AFV over time. Interestingly, this effect is not captured by model NL1, which is the only specification that does not consider correlation between vehicles that operate using the same fuel type.

Users appear to prefer cars with a larger engine size, although the effect was only significant for urban households. As Wicki et al. [65] report, this is the most frequent outcome of choice models that predict AFV choice; however, the effect might not be the same for the whole population, and some differences have previously been observed in the literature (e.g., [66]). The impact of vehicle length depends on the household size, i.e., larger households would generally prefer bigger cars, as expected, but living in an area of high density decreases the probability of households purchasing SUVs (segment J) and multi-purpose vehicles (segment M).

As expected, the likelihood of buying a BEV or PHEV increases with the number of charging point. Similarly, the effect of the battery size is significant in both the NL3 and CNL models, implying that the effect of driving autonomy could only be captured by the specifications that simultaneously address correlation due to car segment and fuel type. Finally, the probability of buying an electric or hybrid vehicle significantly increases if the car is purchased new. This is also an expected effect, as the proportion of second-hand purchases is significantly lower for AFVs than for ICE cars and the second-hand market of EVs, PHEVs, and HEVs has still not reached its full potential.

Table 6 shows the structural parameters estimated. As discussed in section 4, for economic consistency, parameters need to be in the range [0,1]. Parameters whose estimated values was higher than 1 were constrained to the upper limit. The t-test values compare each coefficient with 1. Understandably, the CNL model shows strong correlations between cars belonging to the same segment – except for luxury cars (F) and sport cars (S), where the structural parameters were in fact fixed to

Table 5
Model results (I) – general indicators and parameters of the utility functions.

Alternative	Name	NL1		NL2		NL3		CNL	
		Est.	*t*-test	Est.	t-test	Est.	t-test	Est.	t-test
Main coefficients									
All	Purchase price	−0.020	−13.11	−0.027	−2.03	−0.008	−5.29	−0.017	−15.31
Petrol, Diesel; HEV	Expected annual expense	−0.316	−13.81	−0.427	−2.13	−0.274	−5.55	−0.315	−17.63
BEV; PHEV	Expected annual expense	−0.519	−12.32	−0.128	−0.51	−0.247	−3.25	−0.384	−9.37
J, M segments (All fuels)	Urban density	−0.175	−3.33	−0.067	−1.81	−0.176	−3.34	−0.175	−3.36
BEV, PHEV	Charging points	0.068	8.05	0.279	12.40	0.140	9.80	0.099	6.58
BEV, PHEV	Battery size	0.001	1.07	0.006	1.45	0.002	2.60	0.005	4.97
BEV, PHEV, HEV	New car dummy	0.296	8.92	1.176	11.48	0.716	11.61	0.527	8.88
Interactions									
All	Purchase price × Medium income	−0.005	−5.89	−0.013	−1.96	−0.003	−3.88	−0.003	−5.48
All	Purchase price × Lower income	−0.006	−6.73	−0.024	−2.02	−0.004	−4.30	−0.004	−6.31
All	Engine size × Urban household	0.023	5.67	0.038	2.00	0.029	5.31	0.019	5.05
All	Vehicle length × Household size	0.030	6.26	0.077	2.04	0.050	5.00	0.020	4.52
Goodness-of-fit indicators									
–	Log-likelihood*	−117,457		−121,644		−119,723		−116,950.8	
	Sample size	37,814		37,814		37,814		37,814	
	Number of parameters	56		50		57		58	
–	ρ^2 (market share)	0.066		0.033		0.048		0.070	
	Akaike Information Criterion (AIC)	235,026		243,387		239,560		234,018	
	Bayesian Information Criterion (BIC)	235,504		243,814		240,046		234,513	

Table 6
Model results (II) – structural parameters.

Parameter type	Level	NL1		NL2		NL3		CNL	
		Est.	t-test (1)	Est.	t-test (1)	Est.	t-test (1)	Est.	t-test (1)
Car segment	A (Mini cars)	0.051	−245.42	–	–	0.404	−13.72	0.044	−367.67
	B (Small cars)	0.059	−196.75	–	–	0.469	−16.92	0.041	−349.49
	C (Medium cars)	0.157	−67.05	–	–	0.520	−14.00	0.134	−90.57
	D (Large cars)	0.140	−69.75	–	–	0.415	−17.79	0.115	−104.64
	E (Executive cars)	0.171	−47.07	–	–	0.528	−10.67	0.135	−50.08
	F (Luxury cars)	1	NA	–	–	1	NA	1	NA
	J (Sport utility cars)	0.350	−22.77	–	–	0.475	−14.55	0.357	−26.12
	M (Multi-purpose cars)	0.243	−38.56	–	–	0.656	−7.96	0.326	−25.51
	S (Sport cars)	1	NA	–	–	1	NA	1	NA
Fuel type	ICE (Petrol, Diesel)	–	–	0.342	−3.93	0.075	−64.92	0.551	−8.86
Allocation	Parameter	–	–	–	–	–	–	−3.514	−29.31

Table 7
Model results (III) – constants.

Constant type	Level	NL1		NL2		NL3		CNL	
		Est.	t-test (0)	Est.	t-test (0)	Est.	t-test (0)	Est.	t-test (0)
Fuel type	Petrol	0	NA	0	NA	0	NA	0	NA
	Diesel	−0.219	−2.77	−0.710	−1.76	−0.188	−3.27	−0.199	−2.67
	Battery electric (BEV)	−1.601	−9.32	−8.898	−25.25	−4.409	−14.46	−3.137	−12.84
	Plug-in hybrid (PHEV)	−1.916	−10.26	−8.517	−27.56	−4.366	−14.27	−2.780	−10.88
	Hybrid-electric (HEV)	−0.599	−6.28	−5.365	−23.67	−2.657	−14.40	−1.142	−9.67
Purchase year	2002	0	NA	0	NA	0	NA	0	NA
	2003	0.118	1.06	0.114	0.40	0.028	0.46	0.103	0.96
	2004	0.019	0.23	−0.082	−0.37	−0.018	−0.37	0.005	0.06
	2005	0.031	0.39	−0.027	−0.12	−0.006	−0.14	0.025	0.33
	2006	−0.020	−0.25	−0.241	−0.99	−0.051	−1.08	−0.022	−0.30
	2007	−0.023	−0.29	−0.239	−0.99	−0.048	−1.02	−0.026	−0.35
	2008	−0.025	−0.32	−0.235	−0.97	−0.053	−1.14	−0.028	−0.38
	2009	−0.026	−0.33	−0.229	−0.96	−0.046	−1.00	−0.028	−0.38
	2010	−0.022	−0.28	−0.246	−1.01	−0.039	−0.86	−0.021	−0.29
	2011	−0.023	−0.30	−0.287	−1.13	−0.043	−0.94	−0.020	−0.27
	2012	−0.015	−0.20	−0.253	−1.03	−0.036	−0.78	−0.013	−0.18
	2013	−0.026	−0.33	−0.275	−1.10	−0.045	−0.97	−0.024	−0.32
	2014	−0.033	−0.43	−0.290	−1.14	−0.051	−1.09	−0.033	−0.45
	2015	−0.041	−0.53	−0.319	−1.21	−0.060	−1.28	−0.039	−0.54
	2016	−0.057	−0.73	−0.368	−1.32	−0.071	−1.51	−0.052	−0.70
	2017	−0.039	−0.50	−0.322	−1.22	−0.062	−1.32	−0.034	−0.46
	2018	−0.108	−1.38	−0.414	−1.40	−0.087	−1.80	−0.094	−1.27
	2019	−0.095	−1.21	−0.404	−1.37	−0.082	−1.69	−0.076	−1.03
	2020	−0.080	−0.99	−0.394	−1.36	−0.079	−1.61	−0.058	−0.76
Region	North East	−0.031	−4.18	−0.152	−2.10	−0.028	−3.87	−0.031	−4.60
	North West	−0.030	−4.71	−0.122	−2.12	−0.024	−4.03	−0.031	−5.19
	Yorkshire	−0.041	−5.85	−0.173	−2.10	−0.034	−4.47	−0.038	−6.11
	East Midlands	−0.035	−5.10	−0.148	−2.08	−0.025	−3.98	−0.034	−5.36
	West Midlands	−0.035	−5.09	−0.137	−2.12	−0.026	−4.07	−0.034	−5.50
	East England	−0.026	−4.04	−0.112	−2.09	−0.018	−3.40	−0.026	−4.28
	London	0	NA	0	NA	0	NA	0	NA
	South East	−0.022	−3.55	−0.104	−2.08	−0.016	−3.34	−0.022	−3.73
	South West	−0.036	−5.29	−0.135	−2.11	−0.025	−4.05	−0.035	−5.75
Car segment	A (Mini cars)	0	NA	0	NA	0	NA	0	NA
	B (Small cars)	1.026	48.88	0.304	2.05	1.009	47.41	1.023	48.19
	C (Medium cars)	0.853	32.73	0.245	2.06	0.905	36.98	0.871	34.65
	D (Large cars)	0.208	7.02	0.015	1.05	0.200	6.55	0.254	9.03
	E (Executive cars)	−1.185	−27.27	−0.424	−2.02	−1.203	−33.79	−1.117	−24.77
	F (Luxury cars)	−3.624	−56.55	−0.740	−2.02	−2.502	−42.37	−3.554	−56.59
	J (Sport utility cars)	0.084	1.99	0.155	2.10	0.402	15.90	0.087	2.24
	M (Multi-purpose cars)	−0.398	−11.02	−0.098	−1.91	−0.257	−8.81	−0.486	−11.09
	S (Sport cars)	−2.329	−52.13	−0.283	−2.01	−1.243	−34.45	−2.327	−55.16

1, possibly because these more expensive segments usually present higher attribute variability – and strong correlations due to fuel type. It must be noted that the best specification was obtained by imposing equality among all three fuel type nest parameters, i.e., implying that the degree of correlation among alternatives inside each individual nest is the same across all nests. Model NL2, that only accounts for correlation due to fuel type, was estimated using the same restriction.

Models NL1, NL3, and CNL – all addressing correlation at the car segment level – show significant effects in this regard, except for the more expensive alternatives (segments S and F). Correlations appear to be lower for segments J (SUVs) and M (multi-purpose cars), pointing to a higher variability between different makes and models inside these groups. In contrast, car models belonging to the most "traditional" categories (A to D), seem to be perceived as similar alternatives by users, revealing that the effect of specific makes and model could be less relevant for the purchase decision.

In line with this discussion, the allocation parameter shows that alternatives are much more associated with their respective car segment

(97.1%) than with their fuel type (2.9%). This, again, shows that the choice of a specific fuel type is not independent from car segment selection, and that the correlation stemming from belonging to the same car segment is stronger than that derived from using the same fuel type. This is an effect that is clearly captured only by the cross-nested specification.

The NL3 model reveals that users perceive electric vehicles, hybrid cars, or ICE alternatives as similar between each other only if they belong to the same car segment nest. This result is analogous to what can be inferred from the allocation parameter in the CNL model; however, the degree of association of each alternative to both nests cannot be quantified in the NL3 specification.

Finally, the constants in Table 7 control for fixed effects in the dataset. The strongest associations are derived from fuel type and car segments, while the effect of purchase years and England regions appears less relevant.

5.2. Model validation

Using the 20% holdout dataset and the estimated parameters, we compute the Brier score, the mean absolute error (MAE), the Akaike Information Criteria (AIC), and the Bayesian Information Criteria (BIC) to compare the predictive ability of our models. The *Brier score* [67] is calculated as:

$$BS = \frac{1}{N_v} \sum_{n=1}^{N_v} \sum_{m=1}^{M} \left(\widehat{P}(y_{mn}) - y_{mn}\right)^2$$

where $\widehat{P}(y_{nm})$ is the predicted probability that individual n chooses alternative m, y_{mn} is the actual outcome variable, valued 0 (non-chosen) or 1 (chosen), and N_v is the sample size of the validation dataset. This indicator is bounded by the interval [0,2] with a good model closer to $BS = 0$.

The *mean absolute error* is calculated as

$$MAE = \frac{1}{M} \sum_{m=1}^{M} |\widehat{s}_m - s_m|$$

where $\widehat{s}_m$ and s_m is the predicted and observed market shares of alternative m in the sample. The AIC and BIC are the same indicators used to evaluate the models and they measure how well the model fits with the data it was generated from. The validation indicators for the four specifications are listed in Table 8.

The CNL confirms to be the best performing model. It has the best accuracy indicators in 6 of the 8 analysed cases, and it has a marginally inferior Brier Score at the car segment level, compared to the best performing model (NL1). In particular, the CNL performs always better than all the NL models at alternative level.

It is also relevant to mention that our holdout validation sample has a total of 9454 observations, which were randomly chosen from the original NTS sample. This method of splitting the dataset was adopted to avoid issues derived from using smaller holdout samples (as reported by [21]).

5.3. Monetary valuations and elasticities

Despite the similarities among the models, different correlation structures lead to relevant differences in the magnitudes of certain parameters. This can be analysed in more detail using monetary valuations derived from the models. We estimate the monetary valuation of attribute k as the marginal rate of substitution between the perceived attribute and the purchase cost, at constant utility [68]. Table 9 presents the results.

Looking at the CNL, which is the best specification, the monetary valuation of a bigger engine size remains relatively constant across all income groups, with a range valuation between £0.88 and £1.09 per additional cc. Valuations of car length are dependent on household size – for the most frequent household (2 persons), the preferred model gives a range from £1.85 to £2.31 per additional mm, while the monetary valuation of additional charging points varies from £4.70 to £5.85. Finally, the perceived disutility of an additional pound spent on operation costs is constantly higher than the marginal disutility of purchase price, across all vehicle types, with the ratio of operation cost sensitivity over purchase cost sensitivity estimated between 14.88 and 18.52 for Petrol, Diesel, and HEVs. In the case of BEVs, the effect is reduced because, as we have seen, the marginal disutility of operation costs is lower for electric cars.

The alternative NL specifications seem to show some inconsistencies in these valuations. For example, NL1 fails to acknowledge the correlation between alternatives with the same fuel type, which implies an erroneous estimation of the valuations of normal and rapid charging points – both much lower than the other models. Similarly, models NL2 and NL3, with less appropriate correlation structures than the CNL, yield significantly higher estimations for the valuation of vehicle length, which appear to be unlikely.

Next, we study arc elasticities at the alternative level to analyse demand sensitivity against changes in both purchase prices and operation costs. We first calculate the choice probabilities in the modelling dataset using the CNL model, and then compute the variations in these probabilities due to a 10% increase in price and annual operation cost. We then compute the individual arc elasticities as the ratio between the relative variations of demand and price, and aggregate them using a weighted average, where the weights are the predicted choice probabilities [69].

The direct purchase price elasticities range from −0.12 to −3.14, indicating a mostly inelastic demand for car segments and fuel types. Most individual values are lower than the ones reported by Fridstrom and Østli [15] (−0.97 to −1.72), Fernández-Antolín et al. [16] (−0.34 to −2.34) and Train and Winston [70] (−1.7 to −3.2). However, our results are not directly comparable with these studies. Elasticities are expected to be higher in absolute value when modelling purchases at the make-model level because when costs are higher, switching to a different model from the same segment is easier than choosing a different segment altogether. Moreover, these studies model fuel type choice using new vehicle sales data only. As second-hand vehicles tend to be cheaper, users could be less affected by price increases in this case.

We find the highest absolute values of direct purchase price elasticity in Diesel cars from the smaller segments (A and B), and plug-in hybrids

Table 8
Validation indicators.

Indicator	Name (Range)	Desirable qualities	Aggregation level	NL1	NL2	NL3	CNL
BS	Brier score (0–2)	Closer to 0	Per alternative	0.933	0.943	0.939	**0.933**
			Per car segment	**0.791**	0.797	0.791	0.792
			Per fuel type	0.454	0.461	0.444	**0.451**
MAE	Mean absolute error (0% –100%)	Closer to 0%	Per alternative	0.359%	0.535%	0.505%	**0.345%**
			Per segment	0.303%	0.313%	0.295%	**0.300%**
			Per fuel type	1.685%	**0.234%**	0.301%	1.350%
AIC	Akaike information criterion	Lower	Overall (Model)	59,689	62,591	60,452	**59,668**
BIC	Bayesian information criterion	Lower	Overall (Model)	60,104	62,949	60,860	**60,083**

Table 9
Monetary valuations of items by model structure and income level.

Specification	NL1			NL2			NL3			CNL		
	Low	Med	High	Low	Med	High	Low	Med	High	Low	Med	High
Engine size (£/cc)	0.86	0.91	1.12	0.75	0.95	1.41	2.43	2.69	3.60	0.88	0.91	1.09
Vehicle length												
1 person/HH (£/mm)	1.14	1.20	1.47	1.50	1.91	2.83	4.17	4.62	6.17	0.93	0.96	1.15
2 persons/HH (£/mm)	2.27	2.40	2.95	3.01	3.82	5.67	8.34	9.24	12.33	1.85	1.93	2.31
3 persons/HH (£/mm)	3.41	3.60	4.42	4.51	5.72	8.50	12.51	13.85	18.50	2.78	2.89	3.46
4 persons/HH (£/mm)	4.54	4.80	5.90	6.01	7.63	11.33	16.67	18.47	24.67	3.71	3.85	4.61
5 persons/HH (£/mm)	5.68	6.00	7.37	7.51	9.54	14.17	20.84	23.09	30.84	4.63	4.82	5.76
Charging points (x 1000)	2.61	2.76	3.39	5.42	6.88	10.21	11.64	12.89	17.22	4.70	4.89	5.85
Operation cost sensitivity / Purchase cost sensitivity												
Petrol, Diesel, and Hybrid	12.06	12.75	15.66	8.31	10.55	15.66	22.82	25.28	33.76	14.88	15.47	18.52
Electric	19.84	20.98	25.77	2.50	3.17	4.71	20.58	22.80	30.45	18.14	18.85	22.57

and electric vehicles from the larger segments (D and E). While the elasticity values are similar across segments and fuel types, smaller averages are found for cars belonging to the J (sport utility vehicles) and M (multi-purpose vehicle) segments. On the other hand, annual operation cost elasticities range from −0.14 to −2.47. Consistent with the findings by Fridstrom and Østli [15], the demand for AFV appears, in general terms, less sensitive to variations in operation costs than the demand for ICE vehicles.

Cross elasticities tend to be lower in magnitude than direct elasticities, mostly because the lost demand due to the increase of price in one alternative induces demand increases in several other alternatives and the effect is diluted. In terms of purchase price elasticities, the most significant substitutional patterns can be found between petrol and Diesel cars from the same segment. More interestingly, some increases in operational cost appear to induce increased demand for AFVs; for example, for medium cars (C segment), the cross-elasticity between Diesel and plug-in hybrids is 0.82, and for SUVs (M segment), it reaches 0.28.

In general terms, cross-elasticities between vehicle segments seem to be negligible (lower than 0.05). However, while it is known that cost parity between ICE vehicles and AFVs – considering both purchase price and operation costs – plays a crucial factor in AFV diffusion, our results appear to suggest that higher petrol and Diesel prices could play a more significant role in increasing the demand of electric and hybrid-electric vehicles than purchase prices.

5.4. Simulation and policy implications

Finally, taking advantage of the RP nature of the datasets, we were able to evaluate some simulation scenarios. We use the NTS dataset for 2021, which contains vehicles sampled during that year – but which might have been purchased on any given year – and use the parameters of our best model specification (the CNL) to forecast market shares using the demand scenarios presented in Table 10 below. The base scenario (0) was built assuming that average purchase prices and vehicle attributes from the Teoalida dataset for 2021 were valid and estimating operation costs using the predicted average fuel and energy costs from the TAG book [71] for this year.[10] The actual size of the charging points network for 2021 was also imputed to this dataset.

Table 11 presents a summary of the 2021 forecasting results under these scenarios. For simplicity, they are given only at the fuel type level. The table provides a comparison with the reference UK market shares for 2021, sourced from Department for Transport [4], and the percentage variation of shares between each scenario and the base case scenario.

[10] The TAG Data Book is an online source that provides historical and reference information on all the appraisal and modelling values referred to in the transport analysis guidance (TAG).

Looking at the comparison between the “0 – Base forecast” and the 2021 actual shares, we can see that the model has a good predictive accuracy, with a mean absolute error of 2.6% in the forecast. In particular, the accuracy in predicting the AFV alternatives (BEV, PHEV, and HEV) is extremely high (lower than 0.2%). On the other hand, while the model correctly predicts the overall share of ICE cars, there is some error in predicting the shares of Petrol and Diesel cars, with the dataset for validation containing a higher share of Diesel cars than predicted by the model. This is, however, not a cause for major concern, as our main objective is to predict the demand for AFVs compared the ICE cars. We can accept that the model does not perfectly predict the split between Petrol and Diesel within ICE.

In the scenarios, we see that a comprehensive BEV subsidy could generate increases of 16.1% and 31.7% in EV market shares and reductions in all other fuel types. However, more focused subsidies also achieve interesting results – while a subsidy for small BEVs would entail a demand increase of 11.2%, the same policy directed towards SUVs and MPVs would have a higher effect (40.6%). Smaller public expenditures would be expected in this case compared to a “one-size-fits-all” policy. A similar effect would be achieved with the proposed increase in the registration taxes for Petrol and Diesel vehicles (scenario XII). The assumption in this scenario is that the first-year rates for the vehicle excise duty (VED) tax are strongly increased for Petrol and Diesel cars as well as for HEVs. In the UK, these rates are dependent on the energy consumption of each vehicle [72] and are therefore different for each vehicle segment and fuel type. The results of this measure are interesting as they imply an increase in all AFV alternatives (not only BEV), and also highlight the relevance of more focused policies in terms of subsidies and tax increases.

On the other hand, policies that interfere with operation costs achieve more modest results – a general energy rebate would only mean an increase of <5.7% in BEV shares, while a tax on Petrol and Diesel would reach about 6.4% in BEVs and 13.0% for PHEVs. This would come with the additional benefit of further decreasing the demand for Diesel cars and increasing the share of HEVs. However, as our proposed tax rate is higher for Diesel (considering its higher impact on pollution), this scenario also generates a slight increase in the demand for Petrol cars. It must also be noted that the more focused policy that increases this rebate up to 20% for rural households (assuming that they are most likely to charge their vehicles at home), achieves a slightly more significant increase of 10.5% in the demand for BEVs, while decreasing the demand for the remaining types.

Slight increases in the shares of Petrol and Diesel cars are also present in the two scenarios that combine fuel taxes and focused subsidies (IX and X), and it is not entirely surprising given that, according to our model, Petrol and Diesel cars appear to be close substitutes. This result reveals that, while a fuel tax policy might be effective to foster BEV demand, it must be carefully designed to avoid unintended effects in the market. The policy that augments the network of charging points

Table 10
Simulation scenarios.

Sc	Name	Purchase prices	Operation cost	Others
0	Base	–	–	–
I	Subsidy-New only	20% subsidy for new EVs	–	–
II	Subsidy-All	15% subsidy for new EVs 25% subsidy for second-hand EVs	–	–
III	Subsidy-Small	25% subsidy for A/B/C new EVs 40% subsidy for A/B/C 2nd-hand EVs	–	–
IV	Subsidy-Big	25% subsidy for J/M new EVs 40% subsidy for J/M 2nd -hand EVs	–	–
V	Petrol tax	–	10% Petrol tax 15% Diesel tax	–
VI	Energy rebate (General)	–	10% electric energy rebate	–
VII	Energy rebate (Separate)		5% electric energy rebate for urban households 20% electric energy rebate for rural households	
VIII	Charge	–	–	5% additional increase in charging points 10% additional increase in rapid charging points
IX	III + V	25% subsidy for A/B/C new EVs 40% subsidy for A/B/C 2nd -hand EVs	10% Petrol tax 15% Diesel tax	–
X	IV + V	25% subsidy for J/M new EVs 40% subsidy for J/M 2nd -hand EVs	10% Petrol tax 15% Diesel tax	–
XI	III + V + VIII	25% subsidy for J/M new EVs 40% subsidy for J/M 2nd -hand EVs	10% Petrol tax 15% Diesel tax	5% increase in charging points 10% increase in rapid charging points
XII	Registration tax	50% increase for new Petrol and Diesel cars 20% increase for new HEVs (EVs are exempted from this tax)	–	–

Table 11
Summary of fuel type simulations by scenario.

Scenario	Petrol	Diesel	BEV	PHEV	HEV
2021 shares (Reference)	61.9%	34.9%	0.7%	1.1%	1.5%
0 - Base	67.8%	29.4%	0.8%	0.9%	1.2%
Relative variation (%) with respect to base					
I – Subsidy-New only	−0.1%	−0.1%	16.1%	−1.2%	−0.4%
II – Subsidy-All	−0.2%	−0.3%	31.7%	−1.6%	−0.4%
III – Subsidy-Small	−0.1%	−0.1%	11.2%	−1.2%	−0.1%
IV – Subsidy-Big	−0.3%	−0.4%	40.6%	−1.5%	−0.6%
V – Petrol tax	0.9%	−2.6%	6.4%	13.0%	0.3%
VI – Energy rebate (General)	0.0%	−0.1%	5.7%	−0.4%	−0.1%
VII – Energy rebate (Focused)	−0.1%	−0.1%	10.5%	−0.8%	−0.2%
VIII – Charge	−0.3%	−0.4%	21.4%	20.9%	−0.8%
IX – III + V	0.8%	−2.8%	20.1%	11.4%	0.2%
X – IV + V	0.6%	−3.0%	49.7%	11.2%	−0.4%
XI – III + V + VIII	0.2%	−3.6%	82.4%	34.4%	−1.4%
XII – Registration tax	−0.5%	0.3%	12.7%	10.0%	6.0%

achieves increases of 21.4% for BEVs and 20.9% for PHEVs. Combining this policy with subsidies and fuel taxes could (scenario XI) could mean share increases of 82.4% and 34.4% respectively. While these are significant in relative terms, they would only entail modest effects in terms of global shares, as even in this scenario, BEVs, PHEVs, and HEVs would represent only 1.4%, 1.1%, and 1.1% of the market, respectively. The analysis appears to show that more radical policies should be adopted to boost BEV sales and adoption.

Finally, it must be noted that, since we only carry out a prediction for the short-term (one year ahead of the dataset used for estimating the model), any significant diffusive effects for the innovative alternative should be negligible, as should be the limited share of BEVs in the sample used for estimation. Our forecasts are likely considering early adopters of the technology.

6. Conclusions

In this article, we have provided evidence that the choice of alternative fuel vehicles is a joint choice of type of fuel and vehicle segment (i.e., size and model of the vehicle). We proposed a cross-nested logit model to study substitutional patterns between fuel types and vehicle segments and to understand household preferences for alternative fuel vehicles (AFVs). Our models were estimated using revealed preferences data, i.e., real-world information from several UK data sources properly processed and combined. This allowed us to use our models in predictive mode and to provide grounded policy recommendations. A holdout validation dataset was also used to ensure predictive accuracy.

The models show that, as hypothesised, fuel type choice is not independent from car segment choice. Individual car alternatives belonging to the same car segment are strongly correlated, while a weaker correlation exists between alternatives from different segments which share the same fuel type. As previously reported in the literature, costs are an important barrier for the massive uptake of AFVs. Our model suggests that the marginal utility of operation cost is between 14.88 and 18.52 times the marginal utility of purchase prices for ICE and HEVs, and between 18.14 and 22.57 times for BEVs. As operation costs depend essentially on energy and fuel prices, authorities should aim at reaching cost parity between engine types with a strategy considering both purchase price incentives *and* increasing the difference between petrol/ Diesel prices, on the one hand, and electricity costs, on the other. While purchase prices play an important role and government policies have been concentrated in reducing the gap between ICE vehicles and AFVs in this dimension, our models stress the relevance of the operating cost variable in this decision. Policies that involve fuel taxes or energy rebates, while desirable in principle, should be carefully analysed because, as we showed, they could achieve unintended effects in the market.

The substitutional patterns between car segments in this dataset reveal that, from a policy standpoint, the creation of awareness for cleaner fuel alternatives might be more effective by using a targeted approach that considers these different perceptions. The parameters in our models show that households located in lower density areas have rather low direct price elasticities, are more likely to purchase SUVs and multi-purpose vehicles and unlikely to switch to a different car segment if their circumstances remain unchanged. Considering these results, AFV attractiveness should be promoted for these specific users by focusing on their most valued attributes, such as car power and autonomy, in addition to costs. Similarly, urban households – where the population density is higher – are less likely to choose SUVs and MPVs, and instead tend to prefer the smaller segments (A to C). They are therefore more likely to take better advantage of denser charging networks to obtain a greater flexibility. Furthermore, they should be less concerned with elements such as range anxiety and vehicle power, since their cars are majorly used for driving shorter distances in urban roads. Authorities should design policies that are targeted to different car segment users instead of a "one-size-fits-all" approach that implicitly considers fuel type choice as independent on vehicle type, ignoring other fundamental dimensions of the problem. This could also have an advantage in terms of public expenditure, as more focused subsidy policies can achieve similar results than more expensive, all-encompassing policy measures.

Finally, our results show that the probability of buying an electric or hybrid vehicle significantly increases if the car is purchased new. While the AFV market is still on its first stages of diffusion, the second-hand market of AFVs is still rather limited. Policy makers should turn their attention to this market, as the purchase price barrier is reduced when buying second-hand, which would make cost parity more attainable. While this fact has been previously acknowledged by policy makers (e.g., [73]), only a limited number of specific policy measures for stimulating BEV adoption are currently aimed at this market (in countries such as the Netherlands, Germany, and Spain [74], New Zealand [75], and the United States [76].

From the research point of view, it is fair to note that our sample contains over 47,000 vehicles – however, <0.1% of them were electric. While the effect of a more robust charging network in the adoption of AFVs is significant in our models, we were not able to estimate a significant effect for any variable reflecting driving range (such as battery size). This effect in fact has been found to be significant in studies using SP data where variation in these attributes can be introduced by the modeller as part of the design.

Similarly, we were able to include in our models only two specific spatial variables (population density and type of settlement), and both had a significant effect in vehicle type choice. It is likely that some differences in car segment choices might be explained by neighbourhood attributes – for example, less accessible neighbourhoods might require larger cars because of their need to travel longer distances. More land use information is needed to capture these effects.

While having detailed information on available alternatives contributes to more robust and informative models, this increases the actual size of the choice set, especially when considering the differences between makes, models, and trims. Modelling the choice of a specific trim is not feasible, not only because, as Brownstone and Li [77] correctly point out, information about choices at the trim level is very unlikely to ever be available, but also because it is improbable if not unrealistic that any decision-maker would evaluate this immense number of alternatives when deciding which car to purchase. More work is required to understand this decision-making process, including simplification heuristics that might occur in practice.

CRediT authorship contribution statement

Cristian Domarchi: Writing – review & editing, Writing – original draft, Validation, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Elisabetta Cherchi:** Writing – review & editing, Writing – original draft, Validation, Supervision, Methodology, Investigation, Formal analysis, Conceptualization.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

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Data availability

The data that has been used is confidential.

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