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Demand for green and fossil fuel automobiles

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ABSTRACT

Net-zero policy targets will require a transition from conventional vehicles (CVs) to greener alternative fuel vehicles (AFVs). This paper examines what influences the demand for AFVs and CVs in the UK's large automobile market, looking at vehicle attributes, prices, and other factors, such as brands, country of origin, car segments, and vehicle equipment. Using an extensive, unique dataset covering the period 2008–2019, we compute own-price, cross-price, and demand elasticities for CVs and AFVs. Applying a random-coefficient discrete-choice model of demand, and controlling for consumer heterogeneity, unobserved product characteristics, and price endogeneity, we find that the key drivers of demand are prices, fuel consumption, and vehicle size, with similar demand sensitivity between CVs and AFVs. Demand falls by 3%–5% for a £1,000 increase in price for both CVs and AFVs, conditional on the quality and availability of substitutes. This indicates that UK consumers are not willing to pay a price premium for AFVs, suggesting little value placed on the "greenness" of AFVs. We estimate that a £1,000 subsidy to AFV purchases would lead to 4% of consumers switching to the greener vehicles. While CVs and AFVs exhibit similar price elasticities, vehicle size affects AFV demand by about 40% more, as their purchasers value smaller sized vehicles. Our results indicate that without financial incentives, the uptake of AFVs may remain low, as the higher cost and lower convenience outweighs the environmental considerations for the majority of consumers.

1. Introduction

The use of petrol and diesel vehicles contributes to increasing air and noise pollution and associated CO_2 emissions in the world. The increasing concentration of anthropogenic greenhouse gas (GHG) emissions in the atmosphere is considered (IPCC, 2022) to be the primary contributor to climate change, where the consequences include more frequent extreme weather events, melting of ice caps and rising of sea levels, ocean acidification, damage to agriculture, infrastructure, and health, loss of biodiversity, and the subsequent heavy costs to the economy. In the UK, the large economic costs of climate change are predicted to reach 1–1.5% of GDP/year by 2045, even if the goals of the 2015 Paris Agreement on climate change are reached (HM Government, 2022b). The UK automobile market represents one of the largest markets in the world, being 3rd largest in Europe, and 7th largest overall in 2021, in terms of sales (OICA, 2021). According to a report from the UK Department for Transport (2023), the transport sector is the biggest contributor of GHG emissions, responsible for 26% of total emissions in 2021. Such adverse economic and environmental impacts, contributed to by the use of petrol and diesel cars, are currently of a growing concern to the public and the UK government (Joireman et al., 2004; PwC, 2007; Hascic et al., 2008; Bicer and Dincer, 2018; ONS, 2019; SMMT, 2022; Sacchi et al., 2022). In an effort to

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List of abbreviations

AFV	Alternative fuel vehicle
BLP	Berry, Levinsohn, and Pakes (1995)
CCC	Climate Change Committee
CV	Conventional vehicle
EV	Electric vehicle
GDP	Gross domestic product
GHG	Greenhouse gas
GMM	Generalised method of moments
HM	His Majesty's
IPCC	Intergovernmental Panel on Climate Change
IV	Instrumental variable
MEPS	Management Engineering and Production Services
NCAP	New Car Assessment Programme
OECD	Organisation for Economic Co-operation and Development
OICA	International Organization of Motor Vehicle Manufacturers
OLS	Ordinary least squares
ONS	Office for National Statistics
PwC	PricewaterhouseCoopers
R&D	Research and development
SMMT	The Society of Motor Manufacturers and Traders
SUV	Sport utility vehicle

meet the targets of the Paris Agreement and the national goals of net-zero emissions by 2050, the UK has banned the sale of all new petrol and diesel cars by 2035. Therefore, to keep up with these plans, manufacturers are investing significantly[1] in research and development (R&D) in order to provide consumers with more environmentally friendly vehicles (Hashmi and Biesebroeck, 2016).

However, a full switch to green automobiles may not be easy. Recent evidence suggests that from a consumer perspective, travelling in cars is considered to be not only affordable, comfortable, and private, but it has also become a status symbol or a way to reflect one's identity (Bergstad et al., 2011; Redman et al., 2013; Ramakrishnan et al., 2020; Moody et al., 2021; Gössling et al., 2022). Consumers who are more status-conscious may ignore the environmental aspect and prefer to purchase a large conventional vehicle (CV). Similarly, convenience-oriented consumers would prefer CVs as an established proven technology, despite having a poor outlook for the future with the planned governmental banning of CV sales, fuel taxes, and rising fuel prices (Özdemir and Hartmann, 2012; Brito et al., 2020; HM Government, 2021; Liu et al., 2021). Furthermore, environmentally conscious consumers may prefer to buy hybrid cars rather than the greener fully electric vehicles (EVs), as they are still cleaner than CVs and have a higher maximum range than EVs[2] (Sioshansi and Miller, 2011; Fantin Irudaya Raj and Appadurai, 2021; Serrano et al., 2021; Plötz et al., 2021).

Therefore, in light of the growing concern of the large environmental footprint of the car industry, technological advances in green vehicles, and changing consumer preferences, the automobile market is going through an era of transition, from a fully CV market to a semi-CV market, and eventually to a market fully dominated by alternative fuel vehicles (AFVs[3]). This is well portrayed by the overall increase in the sales of AFV models from around 9,000 cars in 2008 to more than 73,000 in 2019, and the number of models available for purchase from just 2 to 29 (Fig. 1).

As the automobile industry is transforming rapidly, this paper makes an important contribution to the academic literature by examining the current impacts of different vehicle characteristics influencing the consumer demand for automobiles in the UK. More specifically, we address the following research questions. First, what is the effect of different physical vehicle attributes, prices, and factors, such as the brand, country of origin, car segment,[4] and safety or performance-assisting equipment on consumer demand for petrol/diesel cars and clean automobiles in the UK in 2008–2019[5]? Second, we estimate realistic patterns of substitution

[1] For example, Toyota spends about 1 million dollars an hour on average on R&D of cleaner automobiles (Kushwaha and Sharma, 2016; Opazo-Basáez et al., 2018). Volkswagen aims to lower average new car emissions by 30% by 2025, and achieve carbon neutrality by 2050. Porsche wants half of its cars to be electric by 2050 (World Economic Forum, 2019).

[2] Consumers who are very environmentally conscious may still prefer to buy an EV, because these provide further utility from the good synergy with photovoltaic panels (Mandys et al., 2023a,b).

[3] AFVs currently available include hybrids, electric vehicles, and hydrogen vehicles.

[4] Cars are divided into segments, based on their type and features. These segments typically consist of: A: mini cars, B: small cars, C: medium cars, D: large cars, E: executive cars, and F: luxury cars.

[5] The focus of this paper is to examine specifically the inherent vehicle characteristics in relation to demand. Therefore, it is out of the scope of this study to examine external factors, such as e.g., the network effects of the charging stations network, etc.

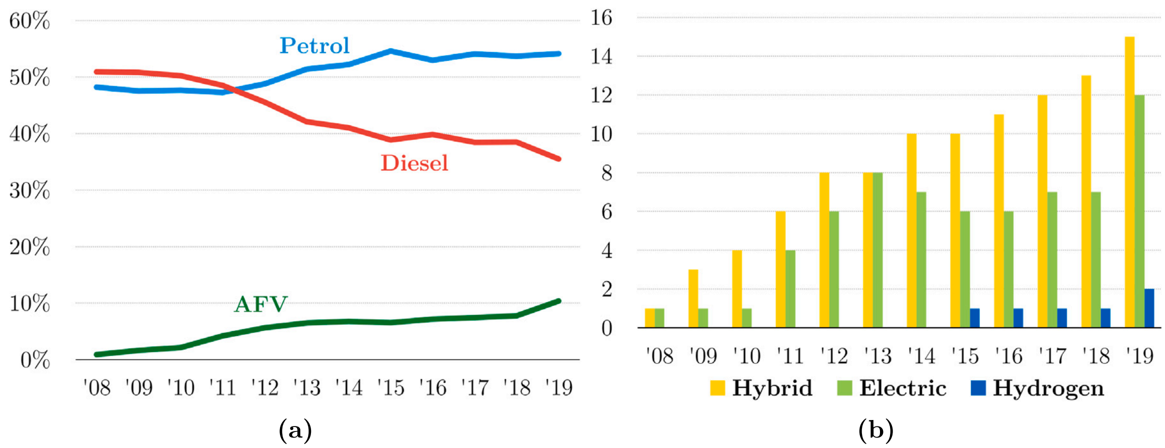

Fig. 1. (a) Share of models by engine type, and (b) the number of AFV models available, UK car market 2008–2019 (authors' own work).

between different products, and compute own-price, cross-price, and demand elasticities separately for CVs and AFVs. An in-depth understanding of the contemporary UK car industry, and robust insights into the key drivers of demand, are still limited in the academic literature. Do UK consumers have a preference for providing the societal positive externality of lower emissions when purchasing a vehicle? And is there an inherently different optimal way of motivating consumer demand for AFVs versus CVs? Providing answers to these questions along with a comprehensive evidence of what the consumers want in the current market can have huge impacts on overall sales, thus affecting the volumes manufactured, international trade, and GDP.

To answer our research questions, we carefully specify and estimate the structural random-coefficient discrete-choice model of demand, applying it to a unique large-scale dataset. Our paper represents a departure from the existing research, innovates in several ways, and fills this gap in the literature by studying the demand for both CVs and AFVs, using this novel dataset for the period of 2008–2019. Such analysis provides a significant update on the current car market, especially with the rise in AFV sales that happened during this time period. To the best of our knowledge, our paper is the first to use such recent and extensive dataset, and apply the random-coefficient discrete-choice model of demand, to explore the drivers of automobile demand in the UK car market (Fridstrøm and Østli, 2021). The primary reason for the gap in knowledge is the lack of rich contemporary data.[6] Our paper draws attention to the identification of consumer preferences and is thus useful to car manufacturers, as they can greatly benefit from understanding the demand drivers for optimising their competition and innovation strategies. In other words, using our results, manufacturers can predict the effect of new products in the market, evaluate their market power, and also optimise their marketing strategies. Furthermore, our results can benefit the UK government in their environmental and trade policies, and contribute towards reaching the goal of net-zero emissions by 2050 by enhancing the sale numbers of AFVs and cleaner hybrid vehicles.

To briefly emphasise on our econometric techniques, we estimate the structural random-coefficient discrete-choice model of demand (henceforth BLP) by Berry (1994) and Berry et al. (1995). The BLP approach involves techniques such as contraction mapping, Monte Carlo integration, and generalised method of moments (GMM), in order to examine the demand for differentiated products, while carefully addressing consumer heterogeneity, realistic substitution patterns among a large number of products, accounting for price endogeneity, as well as generating better price and demand elasticities. Additionally, we compare the results from the BLP with real-world consumer demographics to the BLP estimates without demographics, as well as to the estimates from simpler models, such as ordinary least squares (OLS) and instrumental variable (IV) regressions.[7]

Another novel aspect of our study is that we use the most recent pre-pandemic year (2019) to investigate the substitution patterns among different products after an increase in price, and therefore compute own-price, cross-price, and demand elasticities. In addition, we calculate the elasticities separately for CVs and AFVs, allowing for an examination of any difference between the two vehicle types. This can greatly benefit manufacturers, retailers, and fuel companies when setting prices, as they would understand how automobile demand would respond to changes in price. Similarly, policy makers would benefit from this knowledge when determining the optimal tax levels. The full BLP model with demographics is able to estimate realistic patterns of substitution among different products, allowing for consumers to not substitute according to the market share of the competing products, but instead substitute realistically, according to their and each product's characteristics. Therefore, if the price of a vehicle rises, consumers are most likely to substitute to the most similar product — the closest substitute. Moreover, we also estimate the percentage of

[6] Existing work and evidence typically comes from the application of dated datasets (e.g., Grigolon et al. (2018) - data from 1998–2011; Cerruti et al. (2019) - data from 2005–2010), small samples, or short periods (e.g., Zhang et al. (2016), data from 2011–2013) (Grigolon et al., 2018).

[7] As the OLS does not account for price endogeneity, consumer heterogeneity, and other issues, we expect the least accurate results. On the other hand, while the IV approach benefits from controlling for price endogeneity, it still assumes consumer homogeneity. The BLP without consumer demographics should give us better predictions than the OLS and IV (as it assumes consumer heterogeneity), however, these results are based on assumed distribution of consumer attributes rather than empirical, making it inferior to the full BLP model incorporating real-world demographics.

consumers that would decide to substitute to the outside good (i.e., leave the automobile market) after a marginal increase in the car price.

It is important to point out that it is the novelty and comprehensiveness of the dataset introduced in this research that makes it possible to conduct the empirical analysis. We put together an extensive dataset from various sources, representing over 99% of the UK car market. This dataset includes rich information on sales, prices, physical characteristics, safety features, and equipment from 2008–2019. Nevertheless, the dataset does not include any information on the socio-economic characteristics of the buyers, and we would thus have to rely on sub-optimal assumptions about the distribution of these characteristics, or on consumer homogeneity (Nevo, 2000). To overcome this problem, we obtain direct measures of consumer socio-economic characteristics by combining our dataset with the Annual Population Survey, in order to include real-world consumer characteristics and account for consumer heterogeneity. Having a recent dataset is crucial for understanding the contemporary demand drivers of automobiles in the transforming UK car market.

Our data portray well a series of facts about the development of the UK car market since 2008. There is a considerable variation in the characteristics of the available automobiles in the market; with the prices typically ranging (in terms of the interquartile range) from £14,000 to £29,000, and sales from 1,000 to 12,000 units per car model per year. The median UK car costs about £19,500 and sells 3,730 units annually, with the majority of vehicles considered to be quite safe, having a median European New Car Assessment Programme (Euro NCAP) safety rating of 76/100 and 1.4 airbags per seat. The cars available in the market experienced substantial improvements in quality across the board between 2008 and 2019. This is particularly true in terms of performance and fuel efficiency/environmental impact. The average fuel consumption and CO_2 emissions fell by almost 15% and 20% respectively, while average engine power rose by 25%. Average safety rating also rose by nearly 10%. These facts nicely show that while UK cars are becoming more powerful, they are at the same time becoming cleaner, more efficient, and safer as well.

Applying this dataset, a number of interesting findings arise from our research. The results from the full BLP model show that fuel consumption, vehicle size and price have the strongest impact on automobile demand. While it is not surprising that demand is highly influenced by prices, lower fuel consumption can result in fuel savings and lower emissions. Moreover, the demand for smaller vehicles is considerably higher, especially for those with a greater seating capacity. In other words, consumers prefer more compact cars, but particularly those that do not give up seating capacity for the compactness. Next, we report the own-price and cross-price elasticities of popular CVs and AFVs in order to analyse the demand and substitution dynamics. We provide evidence that a £1,000 increase in prices consistently results in a decrease in demand by about 3% for expensive and 5% for cheaper vehicles. This decline appears to be consistent, regardless of whether the car is a CV or an AFV, suggesting that consumers are not willing to pay a significant price premium for AFVs. Consequently, we estimate that a subsidy of £1,000 for AFV purchases would lead to about 4.1% of UK consumers to switch to the greener vehicles. Additionally, we explore the demand elasticities with respect to several vehicle characteristics, and find that while CVs and AFVs do not differ systematically in their exhibited elasticities, vehicle size affects AFV demand by about 40% more. These findings suggest that the drivers of demand for AFVs are similar to CVs, and therefore, manufacturers' strategies of motivating greater demand for AFVs do not have to be very different from the traditional CVs. Estimating the share of consumers that would substitute to the outside good (i.e., leave the market), about 0.15% of consumers would not purchase any other vehicle after a price increase, and rather leave the market.

The rest of the paper is organised as follows. Section 2 reviews the policies that UK had in place during the period examined. Section 3 reviews the relevant literature. Section 4 presents the datasets constructed. Section 5 describes the methodology, and theoretical background. Section 6 presents and discusses the main results, and Section 7 concludes and suggests policy implications.

2. UK policies on Green automobiles

The transition to a net-zero economy has motivated the UK government to implement several policies during the period covered by our research, i.e., 2008–2019, aimed at transforming the car market. This section provides a summary of the main UK policies that aimed to support the adoption of low-emission vehicles, and reduce the CO_2 emissions of the UK transportation sector. The government implemented several policies to promote the switch to green vehicles, with the most notable example being the Plug-in Car Grant . The grant was introduced in January 2011 and aimed to reduce the cost of purchasing low-emission vehicles, by offering a discount on the cost of eligible new plug-in automobiles. The grant gave consumers a 25% discount on the vehicle's price, up to a maximum of £5,000. In 2015, the discount was increased to 35%, with eligibility criteria requiring automobiles to have their CO_2 emissions below a certain threshold (typically 75g/km of CO_2 or less) and be able to travel a minimum distance between charges. The car grant was not applied for by the consumers, but rather was included in the purchase price by the sellers (Parliamentary Office of Science and Technology, 2010; HM Government, 2022a). Between 2011 and 2021, the maximum discount was gradually reduced to £1,500, with support scheme officially ending in 2022.

In addition, the UK government introduced the Plug-in Van Grant, to motivate businesses to transition to lower-emission vehicles. The scheme works in a similar way to the Plug-in Car Grant ; however, unlike the latter, it remains in effect as of 2024. Under this programme, eligible small vans up to 2.5 tonnes can receive a discount of up to £2,500, while larger vans up to 4.25 tonnes can get up to £5,000.

UK consumers were further motivated to adopt greener automobiles through lower car taxes, in the form of the Vehicle Excise Duty. This car tax has to be paid upon the first registration of the vehicle, and then on an annual basis. Under this policy, fully electric vehicles with CO_2 emissions of 0g/km would be exempt from the tax. On the other hand, owners of cars with higher emissions would pay a progressive tax, based on the emissions of their car (RAC, 2024). For example, the owner of an EV registered in 2018 would pay £0 annual tax, while a similar petrol or diesel car would pay a yearly tax of £190.

Buyers of low emission automobiles were also able take advantage of the London Congestion Charge discounts, specifically through the Greener Vehicle Discount, and later, the Ultra Low Emission Discount. The London Congestion Charge is a fee imposed on most vehicles in Central London during specific hours (e.g., 7:00 to 18:00 from Monday to Friday). The charge was £8 per day until January 2011, when it increased to £10. This further rose to £11.50 in June 2014, and finally to £15 in June 2020. During the period of our research, the owners of greener cars could receive a 100% discount on the congestion charge, given that their vehicle was eligible. The eligibility criteria typically required cars to emit 75g/km of CO_2 or less, and meet the Euro 5 standards for air quality.

From the above policies, we expect the Plug-in Car Grant to have the largest effect on our research. The dataset used for this paper includes information on the purchase prices of all automobiles, and therefore, the discount from the scheme is controlled for in our research, with lower prices of eligible vehicles. On the other hand, policies such as the Plug-in Van Grant or the London Congestion Charge discounts are expected to have a negligible effect on our research. This is due to the fact that our research focuses on the demand for automobiles, and does not examine the demand for vans, or the driving routines across UK regions.

3. Literature review

Our study is inspired by earlier works focusing on estimating the demand in the car industry. The earliest works treated the automobile as a fully homogeneous product, ignoring its large number of characteristics (Brems, 1956; Bandeen, 1957; Suits, 1958). With the rediscovery of hedonic modelling by Griliches (1961), researchers (e.g., Griliches (1971), Ohta and Griliches (1976), Berkovec and Rust (1985)) began to consider a car as a product of many attributes (such as acceleration, range, or safety), each having an influence on consumer utility. Eventually, authors attempted to simultaneously model the demand and production side of the market (Bresnahan, 1987), while accounting for cars being differentiated across multiple dimensions (Boyd and Mellman, 1980; Atkinson and Halvorsen, 1984; Feenstra and Levinsohn, 1995). However, estimating demand suffered from several significant issues — typically high dimensionality of various models, consumer heterogeneity (variability in tastes), and the endogeneity of prices. The multinomial logit model introduced by McFadden et al. (1973), or the nested logit, can solve some of these issues, however, they also introduce new problems.[8] Therefore, Berry (1994), Berry et al. (1995) introduced their random-coefficients discrete-choice model of demand (BLP) to solve these issues

Specifically, Berry et al. (1995) used product-level and aggregate consumer-level data to estimate the demand and cost parameters for most car models in 1971–1990, to examine the equilibrium in the US car industry. Their results suggest that correcting for price endogeneity matters, with the BLP results being superior to both the IV and the OLS. The authors found that characteristics such as specific engine power and size have a significant impact on consumer demand, with an own-price elasticity of car demand (i.e., percentage change in car demand after a 1% increase in price) of about -5%. The frequency of previously found own-price elasticities of automobile demand in the past literature can be seen in Fig. 2. Nevo (2000) provides a comprehensive guide to estimating the BLP model, with the aim of reducing the difficulty in applying this framework among researchers. The author also provides an example of the application of the BLP model, using a simulated dataset from the ready-to-eat industry. Similarly, Rasmusen et al. (2007) offers an in-detail description of the BLP methodology, attempting to help researchers who may feel dissuaded from using the BLP method due to its significant computational intricacy. More recently, Vincent (2015) explains the algorithm of Berry et al. (1995) in greater detail, along with the use of optimal instrumental variables in the estimation. The author introduces a way of estimating the BLP framework using modern statistical software, and discusses the effect of various assumptions on the estimation.

To demonstrate the use of the BLP, Nevo (2001) applied the framework to the cereal industry, estimating the markups without observing actual costs, and separated the markups caused by product differentiation, multi-product firm pricing, and potential price collusion. The results suggest that the first two effects explain the majority of the markups, rejecting price collusion. These two effects then lead to the observed high price-cost margins. Petrin (2002), analysed how the introduction of the minivan in 1984 in the US affected consumer welfare, by using 1981–1993 market-level data, and supplementing these with information on consumer demographic averages (e.g. income) from 1987–1992. The author found that the introduction of the minivan brought substantial benefits to both the consumers and the innovator. Furthermore, the results suggested a strong negative effect of fuel consumption and a positive effect of size on car demand, while also showing that implementing the auxiliary micro data leads to considerably larger welfare numbers. More recently, Rahmati and Yousefi (2013) applied the multinomial logit and the BLP to analyse the behaviour of manufacturers in the Iranian car industry in 2005. Using three datasets on car characteristics, household demographics, and car ownership, they concluded that the two major Iranian car companies collude to manufacture low quality products, while charging high markups. The authors find an expected negative effect of prices on automobile demand, as well as a significant positive impact of greater car performance and safety. Focusing on US hybrid vehicle purchases in 1999–2006, Beresteanu and Li (2011) evaluated the demand in relation to government support programs and increasing petrol prices. Using a similar approach to Petrin (2002), they found that with constant gasoline prices, the hybrid sales in 2006 would have been 37% lower. An increase of automobile prices by 1% would thus reduce car demand by about 8%. Furthermore, a flat rebate program would achieve the same increase in demand as a tax credit program, while costing 15% less.[9] Consequently, the authors conclude that both high fuel prices and government

[8] Multinomial logit suffers from the strong assumptions that it makes, and unrealistic substitution patterns. The nested logit on the other hand requires the researcher to subjectively sort every product into a chosen nest before the estimation.

[9] Hybrid vehicle demand (albeit without employing the BLP) was examined by e.g., Kahn (2007), Gallagher and Muehlegger (2011), finding that local incentives, petrol prices, and environmental concerns have strong influence on sales, and Mandys (2021) for the UK market.

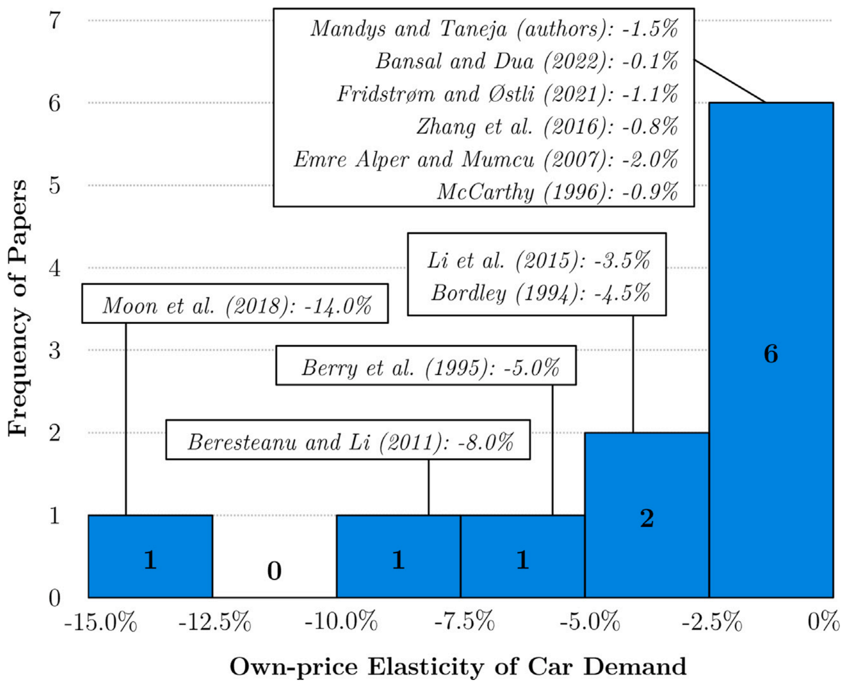

Fig. 2. Frequency of found own-price elasticities of automobile demand in the past literature (authors' own work).

support are needed for a significant hybrid uptake. Incentives and environmental tax policy were more recently evaluated using BLP by Grigolon et al. (2018), searching whether fuel taxes (reducing ineffective driving) are more effective than product taxes (persuading to buy more efficient cars). Using a panel of seven European countries in 1998–2011, the authors concluded that accounting for mileage heterogeneity is crucial. Consequently, fuel taxes were shown to be more effective, convincing high mileage drivers to switch to more efficient vehicles (e.g., EVs).

The demand specifically for EVs was investigated by Zhang et al. (2016), for Norway in 2011–2013. The authors applied the BLP method, examining consumer utility of car characteristics, government incentives, and prices. The results showed that improvements in EV technology, number of charging stations, and toll waivers have a substantial positive impact on the demand of EVs, similarly as in Sierzchula et al. (2014). The results indicated an own-price elasticity of car demand of about −0.8%. Sierzchula et al. (2014) analysed the adoption of EVs in 30 different countries in 2012, concluding that financial incentives and charging stations in particular have the greatest effect on EV demand. On the other hand, education and income were not found to have a significant impact. EV adoption rates in Norway were also examined more recently by Springel (2021) and Fridstrøm and Østli (2021). More specifically, Springel (2021) analysed the effect of different subsidies. The author found a strong positive effect of car price and charging point subsidies on demand. However, subsidies of charging points were about twice more effective than price subsidies in stimulating EV demand in 2010– 2015. On the other hand, Fridstrøm and Østli (2021) examined the own and cross-price elasticities of different automobile engine types, and how car and energy prices affect CO_2 emissions. The authors found an own-price elasticity of demand of about −1.1%, which is the closest to our own result (−1.5%). The automobile demand in China was analysed by Li et al. (2015), using a dataset from 2004 to 2009. The results suggested that quality adjusted car prices dropped by about a third in the period examined, mainly due to a decrease in markups and manufacturing improvements. The authors also found an own-price elasticity of demand of about −3.5%, albeit this included a limited number of models in China. Moon et al. (2018) altered the BLP to include interactive fixed effects for the unobserved product characteristics, by applying a two-step least squares minimum distance estimator to the US car demand. However, this method requires a balanced panel dataset due to the application of principal components. The authors also found a large own-price elasticity of car demand, at around -14%. Recently, Xing et al. (2021) examined the type of car that consumers would choose to purchase given EVs were not an option, using US data (2010–2014). The authors discovered that not having the EV option would increase the demand for more fuel-efficient CVs, as well as some hybrid cars. The results also showed that income tax credits increased EV sales by 29%; however, 70% of the credits were purchased by households that would have bought an EV anyways.

A related strand of literature focuses on automobile demand without the application of the BLP methodology. Early example of such works includes Bordley (1994), introducing the overlapping choice set model — an alternative to a multinomial or nested logit model. Using 1986 US data, the author estimated the own-price elasticity of car demand to be just below −5%. A different result was reached by McCarthy (1996), using a disaggregated demand model and household survey data from 1989. The author estimated that for a 1% increase in car prices, demand would fall by about 0.9%, suggesting that automobile demand is inelastic. Forecasting automobile demand was explored by Abu-Eisheh and Mannering (2002) and Li et al. (2022), applying a dynamic simultaneous-equation system and a machine learning approach, respectively. Abu-Eisheh and Mannering (2002) focused specifically on transitional economies, and the forecasting system allowed to control for aspects, such as growth, operating costs, government trade policies, or demographic and employment shifts. On the other hand, Li et al. (2022) employed the machine learning approach within a structural auto-regressive model, and found that the selection of a training set has a substantial impact on demand forecasting accuracy. New automobile demand in Turkey was analysed by Emre Alper and Mumcu (2007), using a dynamic generalised least squares model and data from 1996–1999. The results indicated that Turkish consumers care significantly about country of origin and general car quality, with own-price elasticity of demand estimated at about −2% in the medium run. Car demand in relation to consumer obesity was estimated by Li et al. (2011), using annual US sales data in 1999–2005. The authors found that a rise in obesity reduces the demand for more fuel-efficient cars, with a 12% increase in fuel prices needed to counteract this effect. Mulalic and Rouwendal (2015) used a hedonic model to investigate the impact of fixed and variable costs on car demand in Denmark in 2004. The results suggested a considerable impact of variable costs on consumer willingness to pay. The effect of expert reviews on car demand in Germany was explored by Dewenter and Heimeshoff (2015). Using data from 2001 to 2007 and applying both a static and a dynamic OLS model, the authors found that a 1% increase in expert test scores increases automobile demand by about 0.05%. Jayarajan et al. (2018) analysed the effect of automobile durability on demand in the US between 2003 and 2006. The results indicated that manufacturers that increase the durability of their products can expect to see a net gain in sales, due to the competition effect (taking over sales of new and used cars from the competition). Fuel consumption elasticities in India and China were explored by Bansal and Dua (2022), using data from 2016 and 2017. The authors identified a small own-price elasticity of demand, at about −0.1%. In the United Kingdom, automobile demand has only been examined specifically for EVs in terms of consumer innovativeness (Morton et al., 2016), and the early phase of the market using a spatial analysis (Morton et al., 2018). Morton et al. (2016) found that consumer adoptive innovativeness significantly influences demand for EVs, while Morton et al. (2018) identified the presence of spatial clustering, showing that education, household size, dwelling type, employment, income, and the number of charging points all significantly influence EV demand.

Therefore, as seen, the examination of the demand drivers in the UK car market and the application of the random-coefficient discrete-choice demand model is fairly sparse, and our research significantly adds to the academic literature on this topic. Using our recent and extensive data, this study provides updated results on the demand drivers of clean and conventional automobiles in the UK, which was lacking in the existing literature.

4. Data

4.1. Datasets used

For our empirical analysis, we constructed an original, extensive, and contemporary dataset of the UK automobile market, for the period 2008–2019.[10] Using several different online and physical sources, we constructed a unique large-scale dataset, containing rich information on vehicle characteristics for nearly all of the car models in the UK market. The full dataset includes sale numbers/market shares, list prices (in 2019 pounds sterling), physical characteristics (e.g., max speed), safety attributes (e.g., number of airbags), equipment (e.g., number of speakers), and others (e.g., country of origin,[11] car segment, etc.). Representing more than 99% of the UK car market in terms of sales, our dataset contains information on hundreds of models from 47 car manufacturers and 12 countries. The only vehicles not reported are special or niche vehicles (e.g., expensive sports cars, such as Lamborghini or Ferrari), as these outliers are likely to skew the data and the results. Overall, the dataset contains 3,028 observations (each model in one year represents one observation), with 68 distinct attributes, and 150 different variables, representing altogether around 450,000 unique data-points, as in Mandys (2023).

We collected the information from a wide range of sources, both physical and online. In particular, data on sales (in units sold each year per car model) are taken from the Society of Motor Manufacturers and Traders (SMMT), the Mark Lines data site, and the manufacturers' websites, while the list prices were collected from the historical physical issues of the Auto Express magazines. The physical characteristics of each model are taken from the Auto Express car review magazines, the Parkers database, and the manufacturers' websites, with the characteristics of EVs taken from the Database of Electric Vehicles. The data on equipment are collected from the Parkers database, the Auto Express magazines, and the Auto123 database.[12] And finally, the safety characteristics of each vehicle (including safety gear and ratings) are taken from the Euro NCAP.[13]

All cars typically have different trim levels, and the difference in price, characteristics, and equipment between the basic and the top trim can be substantial. We ensured that our dataset is consistent across years, to draw direct comparison. Thus, our dataset only includes data of the most basic trim[14] for each car model, allowing for a direct comparison in different time periods. We

[10] The first year of the dataset is 2008, as that is the oldest data available for the UK car market. Data for later time periods are not included due to the disruption caused by the Covid-19 pandemic.

[11] We assume that vehicle's country of origin is the one that the manufacturer is traditionally associated with – e.g., Vauxhall is treated as British, even though its models are same as the German Opel.

[12] Available online respectively at: SMMT, MarkLines, Auto Express, Parkers, EV Database, Auto123.

[13] Euro NCAP is the European assessment program for car safety, performing independent crash tests and granting safety ratings of various vehicle attributes. Available at: Euro NCAP.

[14] The collected data on car sales only include total sales, rather than sales "per trim". Thus, a single trim level is chosen for all models, to stay consistent and allow for direct comparability between models. As different models have different number of trims, the most basic trim of each car has been chosen.

would additionally like to point out that changes in vehicle generations are accounted for with updated prices, characteristics, and equipment.

An "outside good" observation is added to each year of the dataset, representing the number of people that could have bought a vehicle, but decided not to. As such, the size of the good is the difference between the size of the UK market, and the number of sales of all cars in the given year. The key decision is how to define the total size of the market, as the size of the outside good is not observed. We follow Berry et al. (1995) and set the market size in any given year as the total number of UK households. We assume that any one household will buy at the maximum one vehicle — the one that maximises its utility. Therefore, if the total car sales in a particular year are 3 million vehicles, and the number of households in the same year is 25 million, the "sales" of the outside good will be 22 million. Similarly as in previous works (e.g., Berry et al. (1995), Nevo (2001)), the price and product characteristics of the outside good are normalised to 0. The data for the yearly number of UK households are from the Office for National Statistics (ONS), namely the Families and Households Dataset[15] (ONS, 2020).

Apart from the main dataset discussed above, we also constructed an auxiliary consumer-level dataset.[16] This auxiliary dataset contains various demographic information about households, such as household size, income, or age of the representative person. The source of this data is the UK Annual Population Survey,[17] where household size was computed from information on the number of people in different age groups, and income was deflated to be in 2019 pounds sterling (same as car prices). Including this auxiliary dataset into our BLP model and allowing the consumer tastes to vary with the observed demographics brings several benefits.[18] First, it brings information on the real-world distribution of the demographics in the UK population, and second, we do not have to rely on assumptions about the distribution of the random coefficients (Nevo, 2000).

4.2. Variable construction

Our main dependent variable for the BLP estimations is the market share (demand) of each car. We define this as the ratio between the number of sales of each model and the size of the UK car market (i.e., the total number of UK households) in a given year. Several characteristic variables are constructed from multiple variables. In particular, the specific engine power variable is calculated by dividing engine power by weight. The variable labelled as "size" comes from multiplying length, width, and height, and therefore represents the volume of each automobile. The various engine types (i.e., petrol, diesel, or AFV) are also accounted for. Furthermore, several sets of control dummy variables are created, including manufacturers, car segments, country of origin, years, and equipment. These take the values of 1 or 0 respectively, dependent on whether a car model belongs to a particular manufacturer, segment, country, has been in the market in a particular year, or has particular equipment fitted as standard.

A small number of variables in the dataset suffers from missing information for several observations. For example, the Euro NCAP has missing data, such as information on rear airbags and specific safety ratings for two-seater cars, since two seaters do not have any rear compartment and therefore, no airbags. A value of zero cannot be assigned to this missing data, because not having rear airbags is simply the nature of the vehicle, not a flaw. We solve this issue by calculating "airbags per seat" and "average Euro NCAP ratings" variables, rather than using each particular safety rating. The last few remaining gaps in the data are filled using the regression imputation method, where the missing values are replaced with predicted scores from a regression equation.

4.3. Descriptive statistics

Table 1 reports the percentile values of key variables of our dataset over the entire period examined. We can see considerable differences in the values between the lowest and the highest percentiles. For example, the difference in the price of average cars and the most expensive cars is massive, and we observe similar significant differences in variable values across percentiles in Table 1. The median automobile in the UK market costs just over £19,500, selling 3,730 units annually. Typically, a vehicle will cost between £14,000 and £29,000, with sales between 1,000 and 12,000 units per car model per year. The car performance characteristics vary greatly across the distribution, with the median car having a maximum speed of 185 kilometers per hour (km/h), accelerating from 0 to 100 km/h in 11.5 s, having a range of just over 900 km, and consuming 5.6 liters of fuel per 100 km. Conversely, characteristics such as the turning circle (maneuverability), and the cabin interior noise vary very little across vehicles, with the interior noise interquartile range of only 3 decibels. In terms of safety, typically vehicles have a safety rating between 70 and 80 NCAP points and 1.4 airbags per seat. However, for some especially older vehicles, the safety rating is as low as 37/100, and no airbags present as standard.

We also examine several interesting trends in some of the car characteristics between 2008–2019. Fig. 3(a) reports the share of car models offered by segment. Sport utility vehicles (SUVs) are in general becoming increasingly more popular among the UK consumers compared to multi-purpose vehicles/minivans (MPVs) and standard cars (i.e, all cars not in the SUV or MPV segment).

[15] The Families and Households is a dataset provided by the ONS on families, children, and households in the UK by family type. For more information, please see Families and Households.

[16] As we do not have data connecting buyers with the vehicle purchases they made, we use the auxiliary dataset of consumer characteristics in order to supplement this kind of information.

[17] The Annual Population Survey is a continuous household survey by the ONS, covering various socio-economic variables. For more information, please see Annual Population Survey.

[18] This means that substitution patterns between different cars will not only depend on car characteristics, but also on the consumers'. Correlation will be between cars of comparable attributes, and consumers of comparable characteristics.

Table 1
Car characteristics across percentiles of the UK automobile dataset.

Car Characteristics	Percentile 0	25	50	75	100
Price (£)	08 Hyundai Amica 4,880	09 Vauxhall Tigra 13,880	16 DS 4 19,595	09 BMW X3 28,845	19 Rolls-R. Phantom 364,190
Sales	09 Citröen DS3 1	19 Lexus ES 1,018	19 Suzuki Ignis 3,730	19 Volvo XC60 11,766	15 Ford Fiesta 133,434
Displacement (cm^3)	08 Chevrolet Matiz 796	09 Toyota Urban Cruiser 1,364	16 Honda CR-V 1,597	19 Subaru BRZ 1,998	19 Rolls-R. Phantom 6,751
Specific Power (horsepower/ton)	08 Reva G-Wiz 27	10 Toyota Verso 71	08 Jeep Wrangler 82	19 Jaguar XF 99	10 Mercedes SLS 332
Maximum Speed (km/h)	08 Reva G-Wiz 80	08 Chevrolet Aveo 171	13 Ford Mondeo 185	10 Audi Q7 204	16 Audi R8 320
Acceleration (*0 to 100* km/h *in* s)	16 Honda NSX 3.3	14 BMW 5 Series 9.5	13 Dacia Duster 11.5	09 Renault Clio 13.4	10 L. Rover Defender 18.8
Interior Noise (decibels)	19 Rolls-R. Phantom 57	19 Lexus LC 65	09 SEAT Ibiza 66	14 Citröen Berlingo 68	14 Toyota Aygo 78
Fuel Consumption (*l*/100 km)	08 Reva G-Wiz 0.5	11 Toyota Yaris 4.9	11 Ford Mondeo 5.6	15 BMW Z4 6.9	10 Audi R8 14.9
Range (km)	08 Reva G-Wiz 77	14 Škoda Citigo 792	16 Honda Civic 921	09 Renault Kangoo 1,146	15 Ford Mondeo 1,659
Size (m^3)	08 Reva G-Wiz 5.27	11 Nissan Note 10.70	18 Subaru WRX 12.18	13 Porsche Panamera 13.73	17 L. Rover Discovery 19.40
Turning Circle (m)	08 Reva G-Wiz 3.8	14 Mercedes SLK 10.5	18 A. Romeo Giulia 10.9	08 Honda CR-V 11.5	10 Mercedes G 13.6
NCAP Safety Rating *(out of 100)*	13 Fiat Punto 37	19 BMW i3 70	17 Hyundai i30 76	14 Nissan Qashqai 80	12 Volvo V40 90
Airbags per Seat	09 L. Rover Defender 0.0	11 Chevrolet Cruze 1.2	08 Mazda 6 1.4	14 Citröen C4 1.6	19 BMW Z4 4.0

Note: Each field gives the year, the manufacturer, the name of the car, and the value of the car characteristic (underlying data are from the constructed dataset).

The proportion of SUV models was 21% in 2008, and this steadily increased to 38% in 2019, showing a substantial increase of almost 81%. This rise can be attributed to the greater availability of smaller and cheaper SUVs, as the growth was mainly driven by the cheaper SUV-B and SUV-C segments. Fig. 3(b) also portrays that the share of vehicles offering various equipment as standard, even at the most basic trim level, increased substantially between 2008–2019. For example, the availability of a rear-view camera and a USB jack as standard has been only at around 10% of all models in 2008, but this increased considerably to around 50% of all models in 2019.

Fig. 4 examines the trends in the development of performance and fuel efficiency. Performance has steadily increased between 2008 and 2019 — average engine power increased from 124 brake horsepower (bhp) to 160 bhp, and even when taking into account weight (i.e., specific engine power), rising from 84 horsepower/ton (hp/t) to 105 hp/t. At the same time, the average fuel consumption per 100 km has fallen from 6.7 liters in 2008 to 5.8 liters in 2019. Similarly, CO_2 emissions fell by almost 20%, from 163 grams(g)/km to 134 g/km. Therefore, cars offered in the UK are becoming more powerful, while simultaneously becoming more efficient.

Furthermore, analysing the trends in vehicle safety, Fig. 5 shows the development of the Euro NCAP safety ratings. The average cumulative safety rating of UK automobiles enjoyed a consistent increase, rising from 280 in 2008 to 306 in 2019. This increase in safety was primarily driven by improvements to pedestrian safety (from 50 to 68), and secondarily by improvements to child safety (from 74 to 81). Adult safety and safety assistance on the other hand remained fairly constant throughout the years.

Therefore, Figs. 3–5 capture several specific and interesting trends and patterns within the UK automobile market. The market is increasingly moving towards SUVs, greater amount of equipment, safer and cleaner cars, but which are also more powerful at the same time. The illustrated trends showcase the extent, broadness, and originality of our data, allowing us to provide a more complete and relevant analysis of the UK automobile market.

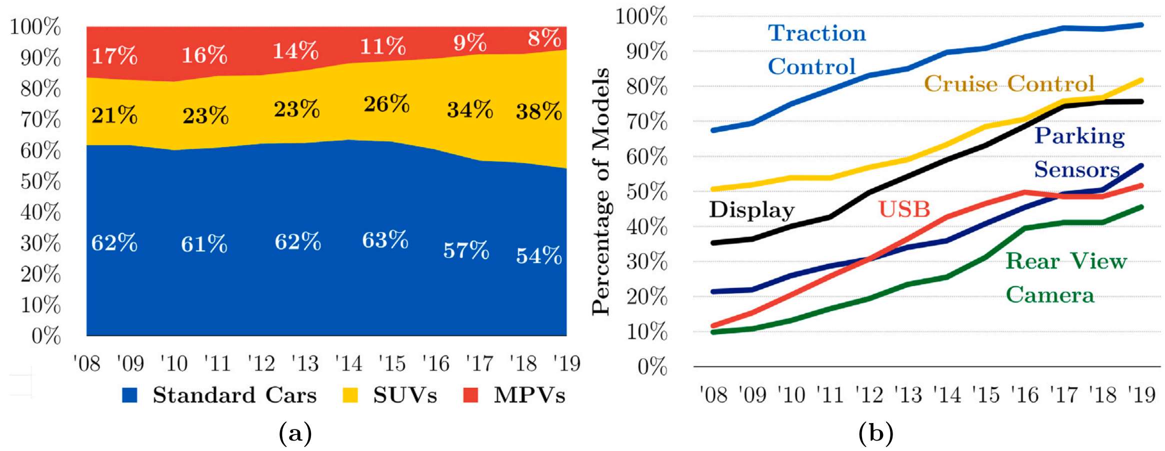

Fig. 3. (a) Share of models belonging to each vehicle segment, and (b) share of cars offering selected equipment as standard, UK car market 2008–2019. In (a), the segment *standard cars* includes all cars not in the SUV or MPV segment (i.e., segments A–F, and S). Panel (b) includes six types of equipment which went through the largest change in share size (authors' own work).

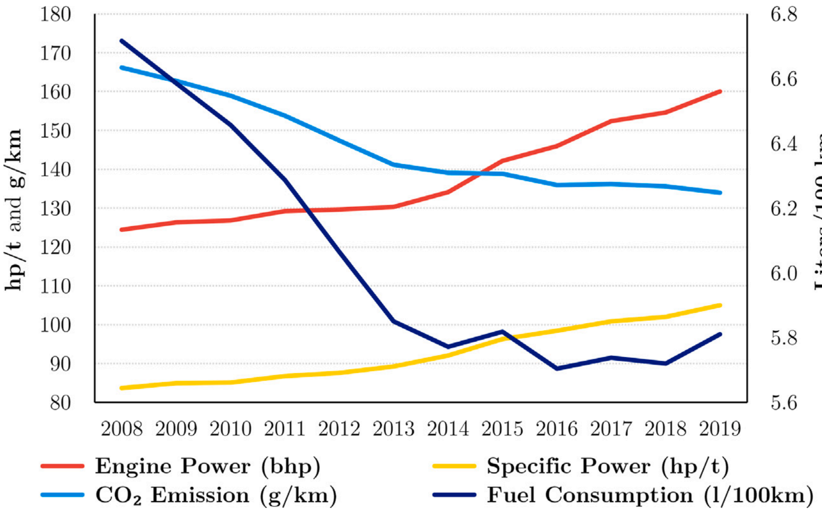

Fig. 4. Development of vehicle average performance and efficiency in the UK car market, 2008–2019 (authors' own work).

4.4. Instrumental variables

The BLP methodology requires the specification of a set of instrumental variables, which are then used in the GMM part of the method to solve the price endogeneity problem, and estimate the variance of the random coefficients (heterogeneous tastes of the consumers). In order to be valid, the instrumental variables used have to be relevant (i.e., correlated with the independent variables that we are instrumenting for), as well as exogeneous (i.e., uncorrelated with the error term). We follow Reynaert and Verboven (2014) and Vincent (2015), and apply both standard instruments, as well as Chamberlain (1987) optimal instruments. As noted by previous studies, standard instruments generally account for the endogeneity of prices, while optimal instruments are applied for the random coefficients (Reynaert and Verboven, 2014; Vincent, 2015; Armstrong, 2016).

When constructing the standard instruments, we follow Reynaert and Verboven (2014), who combine the instrument sets of Berry et al. (1995), and Dubé et al. (2012). These instruments consist of product characteristics, cost shifters (i.e., variables that influence the cost to produce a car), their squares, and their interactions, and provide consistent estimates in most cases (Armstrong, 2016). The product characteristics are available from our main dataset, while we obtain additional data to include the cost shifters. This additional data encompass unit labor costs, steel prices per ton, and producer price indices,[19] and these are matched to each car

[19] Unit labor costs and producer price indices by country come from the OECD database. Steel prices are differentiated only by continent due to lack of data, and come from Platts and MEPS.

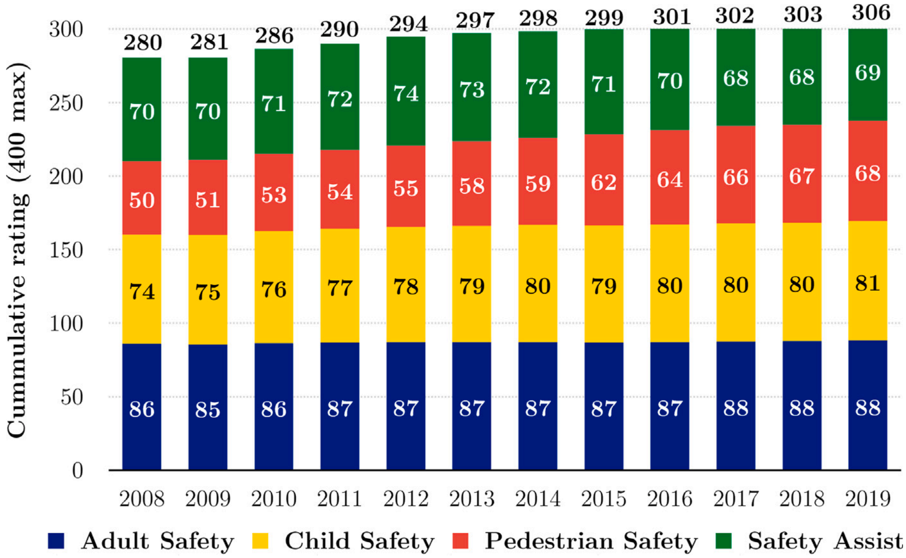

Fig. 5. Development of Euro NCAP average safety ratings; 100 is maximum for each individual category (authors' own work).

model's country of production. Therefore, the cost shifters for each car model include real unit labor cost (i.e., deflated by the producer price index), and real steel price (i.e., deflated steel price per ton interacted with the car's weight). Additionally, we construct 2 extra types of standard instruments from each product characteristic and cost shifter. For every car, we firstly calculate the sum of each product characteristic and cost shifter across all cars made by the same firm, and secondly, we calculate the sum of each product characteristic and cost shifter across all cars made by all the other firms.[20] To summarise, for a single product characteristic and a single cost shifter, our standard instruments set are:

$$z_{jt}^{S} = \quad x_{jt}, x_{jt}^{2}, w_{jt}, w_{jt}^{2}, x_{jt}w_{jt}, \Sigma_{k\in F_j,k` j}(x_{kt}, w_{kt}), \Sigma_{k\notin F_j,k` j}(x_{kt}, w_{kt}) \tag{1}$$

where z_{jt}^{S} is the standard instruments set, x_{jt} is the product characteristic, w_{jt} is the cost shifter, j and k are car models, t is the market (the UK car market in a given year), and F_j is the portfolio of cars manufactured by the same company as car j.

The optimal instruments of Chamberlain (1987) are shown to improve the performance, efficiency, and stability of the BLP estimator, as well as reduce bias (Reynaert and Verboven, 2014). This is especially true, when vehicle characteristics are the same across years (markets), which is our case. The estimation of optimal instruments is achieved by specifying the subsets and functions of standard instruments, which can be used to predict vehicle prices (through a regression). Reynaert and Verboven (2014) report that the most accurate prediction is gained from a polynomial of product attributes, cost shifters, sums of characteristics from the cars of the same firm, and sums of characteristics from the cars made by all other firms. The extensive theoretical description of the optimal instruments is out of the scope of this paper, and can be seen in detail in Chamberlain (1987), Reynaert and Verboven (2014), and Vincent (2015).

All data that were used in the BLP modelling have been fully standardised, as recommended by e.g., Romeo (2013). This includes the main dataset of the product characteristics, the auxiliary dataset of the consumer demographics, as well as all of the instrumental variables that have been used in the estimation. The data have been standardised to mean 0 and standard deviation 1, and the results thus allow for a direct comparison of magnitude between the coefficients of any used variables. Standardisation can be beneficial for improving computational performance, as well as reducing the round off error (Dubé et al., 2012; Romeo, 2013). Furthermore, unstandardised data may cause problems in convergence of the BLP algorithm, even under a tight tolerance.

5. Methodology

5.1. Intuition behind the BLP model

The approach to modelling and estimation of the demand for differentiated products underwent a significant evolution in the last several decades. The original technique involves modelling the utility of buyers across all of the products, and thus estimating a separate demand curve for each product (e.g., Stone (1954)). However, a major problem with this approach is that the number of

[20] These instruments (also called BLP instruments) were introduced by Berry et al. (1995), who followed Bresnahan (1981). The idea is that a firm will lower its markup if the characteristics of competing products improve. These changes of characteristics should aid in correctly estimating the substitution patterns (Berry and Haile, 2014).

parameters that need to be estimated is usually significantly higher than the number of data-points available (due to large number of products). An alternative method is to make the consumer utility depend on product characteristics, rather than the actual products. The logit model of McFadden et al. (1973) can thus solve the problem of dimensionality, measuring the probability of any consumer buying a specific product, depending on the product prices, characteristics, etc. Nevertheless, the multinomial logit (while simple to implement) suffers from two significant drawbacks. Firstly, multinomial logit assumes that prices are exogeneous, when in fact these are endogenous due to hidden or hard-to-measure characteristics, such as style or prestige. These unobserved product attributes will be part of the error term. Secondly, the model assumes that all consumers are identical, rather than having individual unique tastes. Consumer homogeneity brings unrealistic substitution patterns into the logit model based only on product market shares, which can substantially affect any policy conclusions (Nevo, 2000). For example, if the price of car *j* increases, then the multinomial logit predicts that *j* will lose market share to all other products proportionally to their respective market shares (Rasmusen et al., 2007). In reality, consumers would likely substitute to products that are the most similar to product *j*. A possible solution to this second problem is the use of the nested logit model. This model requires the researcher to preselect each product into a group (nest), where similar products are grouped together. Thus, substitution is more likely among products of the same nest (similar products), rather than across nests. However, the issue with the nested logit is that this prior selection depends on the opinion of the researcher, is consequently arbitrary, and substitution patterns within the nests are still based on market shares (Nevo, 2000). Therefore, our preferred option is to use the Berry et al. (1995) BLP discrete-choice random-coefficient model.

The BLP model is considered the current "state of the art" and it solves the aforementioned issues. Albeit complicated, the BLP accounts for the large number of products, solves the endogeneity of prices using instrumental variables and GMM, and produces realistic substitution patterns due to the assumption that each consumer has a unique marginal utility of product characteristics (Nevo, 2000). The method only needs market-level data on prices, sales, and product characteristics — data on buyers' individual purchases is not required (Nevo, 2000). To achieve realistic substitution patterns and avoid reliance on assumptions, real-world data on the distribution of consumer demographics may be included. For example, including the distribution of income may illustrate the greater sensitivity of poor people to price.

5.2. BLP theoretical model

As noted by Rasmusen et al. (2007), the BLP is a structural model, where any empirical application begins with a theoretical model and consumers maximising utility, and each aspect of the model has an economic meaning (the error terms included). Following Berry et al. (1995), Nevo (2000), and Vincent (2015), the BLP theoretical model starts with defining the consumer utility function as:

$$U_{ijt}\ \ p_{jt}, x_{jt}, \xi_{jt}, \tau_i; \theta\ \ = \alpha_i(y_i - p_{jt}) + \beta_i x_{jt} + \xi_{jt} + \epsilon_{ijt}, \quad i = 1,\dots,I \quad j = 1,\dots,J \quad t = 1,\dots,T \tag{2}$$

where p_{jt} is the price, x_{jt} are the observable and ξ_{jt} the unobservable product characteristics, τ_i are the consumer characteristics, θ are the unknown parameters, α_i is the income marginal utility, β_i is the marginal utility of product characteristics, y_i is income, ϵ_{ijt} is the error term, I is the number of consumers i, J is the number of products j, and T is the number of markets t.

We assume that each consumer i buys exactly one product j in each market t, yielding the highest utility. If a consumer decides to not buy any product, they choose the outside good (product 0). The outside good has price and all characteristics normalised to 0, and thus the utility from consumption is:

$$U_{i0t} = \alpha_i y_i + \xi_{0t} + \epsilon_{i0t} \tag{3}$$

The BLP model allows for the consumer preferences/tastes to be affected by consumer characteristics τ_i (consumer heterogeneity). These consumer characteristics are composed of two terms, the observable consumer characteristics (D_i) that we know the distribution of, and the unobservable consumer characteristics (υ_i) that we do not know the distribution of. The observable consumer characteristics, which we include into the model using our auxiliary demographics dataset, include household size, income, and age. The unobservable characteristics include demographics which may be affecting consumer decisions and tastes, but which are not typically known, such as owning a pet (Nevo, 2000). The consumer heterogeneity is modelled as:

$$\begin{bmatrix} \alpha_i \\ \beta_i \end{bmatrix} = \begin{bmatrix} \alpha \\ \beta \end{bmatrix} + \quad D_i + \quad \upsilon$$

$$\begin{bmatrix} \alpha_i \\ \beta_i \end{bmatrix} = \begin{bmatrix} \alpha \\ \beta \end{bmatrix} + \begin{bmatrix} {}_{\alpha} \\ {}_{\beta} \end{bmatrix} D_i + \begin{bmatrix} {}_{\alpha} \\ {}_{\beta} \end{bmatrix} \upsilon_{i\alpha} \quad \upsilon_{i\beta} \ , \quad D_i \sim P_D^*(D), \quad \upsilon_i \sim P_\upsilon^*(\upsilon) \tag{4}$$

If we let K represent the number of product characteristics and d the number of consumer characteristics, then α_i is the marginal utility of income, β_i is a $K \times 1$ vector of the marginal utility of product characteristics, α is the average of α_i, and β is the average of β_i across all consumers respectively, D_i is a $d \times 1$ vector of consumer observed characteristics, is a $(K+1) \times d$ matrix defining how observed consumer characteristics affect consumer preferences, υ_i is a $(K+1) \times 1$ vector of consumer unobserved characteristics, is a $(K+1) \times (K+1)$ matrix defining how unobserved consumer characteristics affect consumer preferences, $P_D^*(D)$ is the distribution of D_i, and $P_\upsilon^*(\upsilon)$ is the distribution of υ_i.

We know the distribution $P_D^*(D)$ from our auxiliary consumer demographics dataset, while $P_\upsilon^*(\upsilon)$ is assumed to be multivariate normal (Nevo, 2000; Vincent, 2015). Using Eqs. (2) and (4), we get the final consumer utility, taking into account both observed and unobserved consumer characteristics:

$$U_{ijt} = \alpha_i y_i + \delta_{jt}(x_{jt}, p_{jt}, \xi_{jt}; \theta_1) + \mu_{ijt}(x_{jt}, p_{jt}, D_i, \upsilon_i; \theta_2) + \epsilon_{ijt}$$

$$\delta_{jt} = \beta x_{jt} - \alpha p_{jt} + \xi_{jt}, \quad \mu_{ijt} = (-p_{jt}, x_{jt})(\quad D_i + \quad \upsilon_i) \tag{5}$$

where $\theta = (\theta_1, \theta_2)$ is a vector that encompasses all model parameters, $\theta_1 = (\alpha, \beta)$ is a vector representing only linear parameters, $\theta_2 = (\quad,\quad)$ is a vector representing only nonlinear parameters, δ_{jt} is the consumer mean utility — the portion of utility same for each consumer, and μ_{ijt} is the deviation from the mean utility representing the varying tastes of consumers.

Accounting for consumer heterogeneity, the utility of a consumer that chooses the outside good rather than the product will change from Eq. (3) to:

$$U_{i0t} = \alpha_i y_i + \xi_{0t} + \pi_0 D_i + \sigma_0 \upsilon_{i0} + \epsilon_{i0t} \tag{6}$$

Consumers will only purchase the product that will give them the highest utility among all the products available (including the outside good). The set of consumers deciding to purchase some product j in market t can be defined as:

$$A_{jt}(x_t, p_t, \delta_t; \theta_2) = (D_i, \upsilon_i, \epsilon_{i0t}, \dots, \epsilon_{iJt} : U_{ijt} \geq U_{ikt}), \quad \forall j \neq k \tag{7}$$

where (x_t, p_t, δ_t) are the product attributes, prices and mean utilities of all products, and A_{jt} is the set of consumers who prefer product j to all other products $j \neq k$.

Assuming there are no ties among products (i.e., each consumer always buys the one best product), the probability of consumers purchasing product j will be the integral over all consumers in the A_{jt} region (Nevo, 2000). This probability will consequently be identical to the market share of product j in market t:

$$\begin{aligned} Pr_{jt} = S_{jt}^p(x_t, p_t, \delta_t; \theta_2) &= \int_{A_{jt}} dP^*(D, \upsilon, \epsilon) \\ &= \int_{A_{jt}} dP_\epsilon^*(\epsilon) dP_D^*(D) dP_\upsilon^*(\upsilon) \end{aligned} \tag{8}$$

where Pr_{jt} is the probability of consumers buying product j in market t, S_{jt}^p is the predicted market share, and P^* are the distributions of the respective variables.

Thus, we can predict the market share of any product depending on product characteristics, prices and mean utility, if we are given parameters D and υ. If we integrate the chosen market shares of each consumer i across both observable and unobservable consumer characteristics, weighting each by their probability to appear in the population, then the market share S_{jt}^p is given by:

$$S_{jt}^p = \int_{D_i} \int_{\upsilon_i} S_{ijt}^p dP_D^*(D_i) dP_\upsilon^*(\upsilon_i) \tag{9}$$

where S_{ijt}^p is the market share of product j in market t picked by consumer i.

To estimate these integrals, we need to make several assumptions about the errors (ϵ_{ijt}). Firstly, we assume the errors are independently and identically distributed (i.i.d.), and secondly, they come from the Type I extreme value distribution.[21] The market share of product j picked by consumer i is then:

$$S_{ijt}^p = \frac{e^{\delta_{jt} + \mu_{ijt}}}{1 + \Sigma_{k=1}^K e^{\delta_{kt} + \mu_{ikt}}} \tag{10}$$

and Eq. (9) becomes:

$$S_{jt}^p = \int_{D_i} \int_{\upsilon_i} \left[\frac{e^{\delta_{jt} + \mu_{ijt}}}{1 + \Sigma_{k=1}^K e^{\delta_{kt} + \mu_{ikt}}} \right] dP_D^*(D_i) dP_\upsilon^*(\upsilon_i) \tag{11}$$

The integrals of Eq. (11) are impossible to estimate analytically. However, we can approximate their solution using Monte Carlo integration, as in Vincent (2015), by taking random draws of D_i and υ_i from their respective distributions $P_D^*(D)$ and $P_\upsilon^*(\upsilon)$. Before we can approximate the integrals in (11) and calculate the predicted market shares S_{jt}^p, we need to estimate the mean utility δ_{jt}. For an ordinary logit model, we can calculate mean utility analytically (Nevo, 2000):

$$\delta_{jt} = \ln S_{jt}^o - \ln S_{0t}^o \tag{12}$$

where S_{jt}^o is the observed market share of product j in market t, and S_{0t}^o is the observed market share of product 0 – i.e., the outside good.

[21] With a mean of 0 and a standard deviation of 1, the density of the distribution is $f(x) = e^{-x} e^{-e^{-x}}$, and a cumulative distribution of $F(x) = e^{-e^{-x}}$.

However, this is not possible in the BLP model, and the mean utility has to be solved numerically. We apply the contraction mapping technique[22] as in Berry et al. (1995), which involves evaluating the series in the following equation:

$$\delta_t^{n+1} = \delta_t^n + \ln S_t^o - \ln S_t^p \tag{13}$$

where n represents the iteration period in the contraction mapping loop.

The contraction mapping starts from arbitrary values of and to get μ, and arbitrary value δ_t^0, which allows us to solve Eq. (11) using Monte Carlo integration. With the predicted market shares, we can use Eq. (13) to get a more accurate prediction of the mean utility δ_t^1, while keeping and fixed. We can now take the updated mean utility to (11), to calculate a new prediction of market shares, and so on. This loop continues until the difference $\delta_t^n - \delta_t^{n-1}$ is below some defined tolerance level, and we get the values of mean utility.

The BLP model is finalised with using the GMM (Hansen, 1982) estimator to identify all of the demand parameters and control for price endogeneity. Using the estimated value of the mean utility δ and arbitrary starting values for α and β, we can calculate the error term from Eq. (5):

$$\xi_{jt} = \delta_{jt} - \beta x_{jt} + \alpha p_{jt} \tag{14}$$

Using the error term, and the sets of standard and optimal instrumental variables Z, we can set up our GMM objective function. This needs to be minimised, in order for us to get the optimal estimates of our demand parameters θ $\theta = (\theta_1, \theta_2), \theta_1 = (\alpha, \beta), \theta_2 = (\; , \;)$). However, we need a weighting matrix to construct the objective function, which is the variance–covariance matrix of all moment conditions. We use the following weighting matrix as a starting point:

$$\;^{-1} = \; Z'Z \;^{-1} \tag{15}$$

where Z is the matrix of instrumental variables. The constructed GMM objective function then takes the form:

$$\hat{\theta} = \underset{\theta}{\operatorname{argmin}} \quad Z \quad ^{-1} Z' \tag{16}$$

If we define $x_{jt}^\dagger = \; x'_{jt}, p_{jt} \;'$, and $X^\dagger = \; x_{1,1}^\dagger, \dots, x_{J,T}^\dagger$, then we can find new values of α and β using the GMM estimator:

$$\hat{\theta}_1 = \; \hat{\alpha}, \hat{\beta} \; = \; X'^\dagger Z \quad ^{-1} Z' X^\dagger \;^{-1} X'^\dagger Z \quad ^{-1} Z' \tag{17}$$

We can take the updated better values of α and β into Eq. (14), and find a better prediction of the error term ξ. This allows for a better value of the weighting matrix to be computed for the GMM objective function:

$$\;^{-1} = \; Z' \quad ' Z \;^{-1} \tag{18}$$

The last step is to use a search algorithm to find new, better values for and , go to the beginning of the loop at Eq. (11), and rerun the process again. The BLP iteration continues running loops, searching for the parameter values that would minimise the objective function in (16). Once the difference in value of two iterations of the GMM objective function is below a certain threshold, the algorithm has converged, and we get the final demand parameter values $\hat{\theta}$.

Following from Eq. (11), we can additionally calculate the price elasticities of the market share of product j, with respect to the price of product k. Due to the inclusion of the terms D_i and υ_i, we have correlation between products of comparable characteristics. Additionally, those consumers that have similar characteristics will have similar tastes, and thus comparable substitution patterns (Vincent, 2015). Thus, the computed price and demand elasticities will encompass realistic substitution patterns among products. The elasticity of the market share of product j with respect to the product k price is:

$$\varepsilon_{jkt} = \frac{\partial S_{jt}^p}{\partial p_{kt}} \cdot \frac{p_{kt}}{S_{jt}^p} = \begin{cases} -\frac{p_{jt}}{S_{jt}^p} \int_{D_i} \int_{\upsilon_i} \alpha_i S_{ijt}^p \; 1 - s_{ijt} \; dP_D^* \; D_i \; dP_\upsilon^* \; \upsilon_i \;, & \text{if } k \in F_j, k \; j \\ \frac{p_{kt}}{S_{jt}^p} \int_{D_i} \int_{\upsilon_i} \alpha_i S_{ijt}^p S_{ikt}^p dP_D^* \; D_i \; dP_\upsilon^* \; \upsilon_i \;, & \text{if } k \notin F_j, k \; j \end{cases} \tag{19}$$

where F_j is the portfolio of products produced by the company producing product j.

6. Results

6.1. Estimated demand drivers

We first present the basic results of the UK demand drivers from the OLS and IV methods (Table 2). These primarily serve as a starting robustness check and a comparison point to the full BLP results examined later on. The OLS and IV regressions follow Berry et al. (1995) and Nevo (2001), and are run by regressing $\ln \; S_j \; - \ln \; S_0$ on prices, vehicle characteristics, and several groups of control dummy variables. For each method, we report 4 different model specifications, each controlling for a different set of

[22] This can also be referred to as the nested fixed-point algorithm (Vincent, 2015).

Table 2
Effect of car attributes on market share — OLS and IV regressions.

Variables	OLS				IV			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Price	−0.123 **	−0.177 ***	−0.111	−0.405 ***	0.086	0.046	0.125	0.206
	(0.057)	(0.062)	(0.074)	(0.116)	(0.082)	(0.080)	(0.077)	(0.137)
Diesel Vehicle	−0.998 ***	−1.075 ***	−0.939 ***	−1.128 ***	−0.979 ***	−1.055 ***	−0.934 ***	−1.188 ***
	(0.116)	(0.116)	(0.112)	(0.116)	(0.116)	(0.116)	(0.111)	(0.115)
Alt. Fuel Vehicle	−3.302 ***	−3.725 ***	−2.575 ***	−2.618 ***	−3.346 ***	−3.777 ***	−2.630 ***	−2.973 ***
	(0.222)	(0.228)	(0.222)	(0.239)	(0.223)	(0.225)	(0.217)	(0.235)
Displacement	0.349 ***	0.291 ***	0.267 ***	0.425 ***	0.223 **	0.176 *	0.186 **	0.425 ***
	(0.099)	(0.098)	(0.090)	(0.095)	(0.102)	(0.103)	(0.091)	(0.095)
Sp. Engine Power	−0.124	−0.035	0.002	−0.025	−0.209 **	−0.133	−0.104	−0.237 **
	(0.096)	(0.103)	(0.103)	(0.115)	(0.097)	(0.104)	(0.104)	(0.115)
Maximum Speed	−0.269 **	−0.393 ***	0.127	0.110	−0.289 ***	−0.393 ***	0.167	0.073
	(0.107)	(0.113)	(0.127)	(0.137)	(0.106)	(0.112)	(0.126)	(0.132)
Acceleration	−0.189 **	−0.039	0.075	0.083	−0.238 ***	−0.089	0.048	0.020
	(0.083)	(0.084)	(0.089)	(0.093)	(0.083)	(0.083)	(0.088)	(0.092)
Interior Noise	−0.410 ***	−0.310 ***	−0.348 ***	−0.290 ***	−0.358 ***	−0.261 ***	−0.314 ***	−0.242 ***
	(0.049)	(0.055)	(0.057)	(0.062)	(0.050)	(0.056)	(0.057)	(0.061)
Fuel Consumption	−0.900 ***	−0.959 ***	−0.861 ***	−0.818 ***	−0.839 ***	−0.904 ***	−0.837 ***	−0.840 ***
	(0.104)	(0.101)	(0.100)	(0.099)	(0.102)	(0.100)	(0.099)	(0.098)
Range	0.190 ***	0.172 **	0.335 ***	0.362 ***	0.238 ***	0.217 ***	0.369 ***	0.373 ***
	(0.071)	(0.069)	(0.067)	(0.068)	(0.071)	(0.068)	(0.066)	(0.067)
Size	−0.178 *	−0.114	−0.566 ***	−0.183 *	−0.241 ***	−0.186 **	−0.673 ***	−0.344 ***
	(0.092)	(0.092)	(0.109)	(0.112)	(0.091)	(0.092)	(0.110)	(0.113)
Turning Circle	−0.052	0.016	−0.150 **	−0.393 ***	−0.084	−0.008	−0.165 **	−0.404 ***
	(0.077)	(0.079)	(0.076)	(0.082)	(0.079)	(0.080)	(0.076)	(0.081)
Seating Capacity	0.178 ***	0.160 ***	0.285 ***	0.195 ***	0.205 ***	0.189 ***	0.311 ***	0.232 ***
	(0.055)	(0.057)	(0.061)	(0.061)	(0.055)	(0.056)	(0.061)	(0.061)
Trunk Capacity	0.116 **	0.077	0.131 ***	0.042	0.130 ***	0.092 *	0.142 ***	0.065
	(0.047)	(0.050)	(0.051)	(0.050)	(0.047)	(0.049)	(0.049)	(0.048)
Avg. Safety Rating	0.129 ***	0.146 ***	0.074	0.036	0.123 ***	0.139 ***	0.061	0.031
	(0.046)	(0.049)	(0.049)	(0.049)	(0.046)	(0.048)	(0.048)	(0.048)
Airbags per Seat	0.181 ***	0.158 ***	0.077 *	0.027	0.181 ***	0.152 ***	0.077 *	0.008
	(0.044)	(0.046)	(0.046)	(0.046)	(0.044)	(0.046)	(0.045)	(0.045)
Years	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Equipment	—	**Yes**	**Yes**	**Yes**	—	**Yes**	**Yes**	**Yes**
Segments/Countries	—	—	**Yes**	**Yes**	—	—	**Yes**	**Yes**
Brands	—	—	—	**Yes**	—	—	—	**Yes**
R-squared	**0.321**	**0.367**	**0.443**	**0.537**	**0.318**	**0.365**	**0.441**	**0.530**

Notes: The OLS and IV regression for finding the effect of vehicle attributes on market share (data are from the constructed dataset).
* Significance levels are: $p < 0.1$.
** Significance levels are: $p < 0.05$.
*** Significance levels are: $p < 0.01$.

dummy variables (years, equipment, car segments, country of origin, and brands). While model 1 is the simplest, with vehicle characteristics and year dummies included, the models get increasingly more complete in terms of controls, with model 4 having all control variables included, and consequently, the highest R-squared. The fact that our coefficients are generally consistent, across the specifications used and control variables included, provides evidence of the robustness and validity of our results. Nevertheless, our preferred model is model 4 for several reasons. Firstly, model 4 is the most complete model, including all key variables, such as prices, vehicle characteristics, year dummies, equipment, car segments, countries of origin, and vehicle brands. These variables and attribute groups are expected to have a significant effect on the estimation, both intuitively, as well as based on previous research. This includes, for example, the incorporation of different car segments to account for consumer preference heterogeneity across segments (e.g., Qian and Soopramanien (2015)). Similarly, the importance of including brand dummy variables was pointed out by e.g., Nevo (2000, 2001) or De Oliveira et al. (2015). Controlling for brand-level fixed effects allows for a better fit of the model, as well as accounting for the brand-specific unobserved vehicle attributes (Nevo, 2000). Secondly, model 4 generally reports smaller standard errors, and more intuitive results (e.g., turning circle being significant and negative rather than positive or insignificant).

The OLS and IV results of Table 2 are relatively comparable in terms of coefficient signs and sizes across different specifications. In particular, across both the OLS and the IV, the car characteristics strongly influencing demand include fuel consumption, maximum range, vehicle size, and seating capacity. All these variables have the expected intuitive coefficient signs — automobiles that are more fuel efficient and have a greater maximum range experience a higher demand. Similar negative effect of fuel consumption was found also by Berry et al. (1995) and Beresteanu and Li (2011), while the effect of range is usually rated positively by consumers (e.g., Lin (2014) or Dimitropoulos et al. (2013)). Consumers also appear to prefer smaller vehicles, but which do not give up seating capacity at the same time. This is in contrast to previous research, such as Berry et al. (1995) or Petrin (2002), suggesting that contemporary UK consumers are more focused on smaller sized automobiles, compared to US consumers at the turn of the millennium. The dummy

Table 3
Effect of car attributes on market share — BLP without demographics.

Variables	BLP without demographics			
	(1)	(2)	(3)	(4)
Price	−0.022	−0.039	−0.270	−0.225
	(0.075)	(0.079)	(0.229)	(0.205)
Diesel Vehicle	−1.053 ***	−1.004 ***	−0.824 ***	−1.184 ***
	(0.105)	(0.107)	(0.108)	(0.110)
Alt. Fuel Vehicle	−3.180 ***	−3.603 ***	−2.355 ***	−2.759 ***
	(0.191)	(0.213)	(0.223)	(0.303)
Displacement	0.295 ***	0.236 **	0.150	0.359 ***
	(0.094)	(0.096)	(0.092)	(0.095)
Sp. Engine Power	−0.342 ***	−0.253 **	−0.186 *	−0.314 ***
	(0.097)	(0.102)	(0.107)	(0.114)
Maximum Speed	−0.537 ***	−0.283 ***	0.236	−0.370
	(0.197)	(0.110)	(0.160)	(0.230)
Acceleration	−0.172 **	−0.064	0.081	−0.029
	(0.080)	(0.084)	(0.088)	(0.086)
Interior Noise	−0.286 ***	−0.265 ***	−0.316 ***	−0.220 ***
	(0.054)	(0.060)	(0.061)	(0.065)
Fuel Consumption	−0.847 ***	−0.815 ***	−0.731 ***	−0.761 ***
	(0.088)	(0.090)	(0.091)	(0.088)
Range	0.239 ***	−0.007	0.356 ***	0.407 ***
	(0.065)	(0.168)	(0.065)	(0.063)
Size	−1.171 ***	−0.258 *	−1.296 ***	−0.725 ***
	(0.225)	(0.156)	(0.253)	(0.200)
Turning Circle	0.018	0.000	−0.068	−0.215 ***
	(0.069)	(0.071)	(0.072)	(0.072)
Seating Capacity	0.190 ***	0.159 ***	0.268 ***	0.244 ***
	(0.060)	(0.062)	(0.064)	(0.061)
Trunk Capacity	0.122 ***	0.086 *	0.130 ***	0.051
	(0.044)	(0.045)	(0.044)	(0.043)
Avg. Safety Rating	0.152 ***	0.131 ***	0.048	0.022
	(0.043)	(0.045)	(0.044)	(0.043)
Airbags per Seat	0.134 ***	0.119 **	0.049	0.006
	(0.047)	(0.051)	(0.050)	(0.049)
Years	**Yes**	**Yes**	**Yes**	**Yes**
Equipment	**—**	**Yes**	**Yes**	**Yes**
Segment/Countries	**—**	**—**	**Yes**	**Yes**
Brands	**—**	**—**	**—**	**Yes**

Note: BLP estimation without demographics for the effect of car attributes on market share (underlying data are from the constructed dataset).

* Significance levels are: $p < 0.1$.

** Significance levels are: $p < 0.05$.

*** Significance levels are: $p < 0.01$.

variables for diesel and AFVs are also very strong and significant, showcasing that diesel engines and AFVs experience a lower demand compared to petrol automobiles. This is likely caused by the higher price and nitrogen oxide (NO_x) emissions of the diesel automobiles.

The main difference between the OLS and the IV lies in specific engine power becoming significant in the IV regression, vehicle size effect becoming both stronger and more significant (from -0.18^{*} to -0.34^{***}), and the price coefficient becoming insignificant. This is likely caused by the fact that under OLS, price suffers from endogeneity. When implementing the IV estimation, controlling for endogeneity causes the coefficients of price for all specifications to become insignificant. The insignificant effect of price is then also confirmed through the estimation of the BLP model without demographic variables, which can be seen in Table 3. Similar result of reduction in the significance of the price coefficient after application of the IV can be seen in e.g., Berry et al. (1995).

Consequently, while some of the coefficients of the IV estimation are comparable to the OLS regression, there are several larger differences, which include in particular specific engine power, automobile price, and the overall size. As the IV estimation controls for variable endogeneity using instrumental variables while the OLS does not, the IV results can be taken as more accurate compared to the OLS results. Therefore, the IV coefficients should be closer in size and significance to the results of the BLP estimation without demographic variables.

The second set of results comes from the BLP estimation without the use of auxiliary consumer demographic variables (Table 3). As expected, the estimated BLP coefficients of model 4 are more comparable to the coefficients of the IV regression, rather than the OLS. Similarly to the IV regressions, the car characteristics that particularly influence automobile demand are fuel consumption, vehicle size, and maximum range, with consumers also caring about the seating capacity and performance (engine power and speed). Similar effect of performance was found by e.g., Rahmati and Yousefi (2013). All of the significant variables have the expected, intuitive coefficient sign, where demand is typically increasing for an increase in quality (i.e., better car characteristics).

Table 4
Effect of car attributes on market share — full BLP model.

Variables	BLP without demographics	Full BLP with demographics			
		Coefficient	Demographic interaction		
			Income	Age	H. Size
Price	−0.225	−0.653 ***	0.175 ***	–	–
	(0.205)	(0.236)	(0.052)		
Diesel Vehicle	−1.184 ***	−1.160 ***	–	–	–
	(0.110)	(0.112)			
Alt. Fuel Vehicle	−2.759 ***	−2.836 ***	0.370 **	–	–
	(0.303)	(0.316)	(0.175)		
Displacement	0.359 ***	0.337 ***	–	–	–
	(0.095)	(0.096)			
Sp. Engine Power	−0.314 ***	−0.346 ***	–	–	–
	(0.114)	(0.116)			
Maximum Speed	−0.370	0.387 **	0.207 ***	–	–
	(0.230)	(0.155)	(0.036)		
Acceleration	−0.029	−0.180 **	–	–	–
	(0.086)	(0.089)			
Interior Noise	−0.220 ***	−0.235 ***	–	–	–
	(0.065)	(0.064)			
Fuel Consumption	−0.761 ***	−0.758 ***	–	–	–
	(0.088)	(0.091)			
Range	0.407 ***	0.314 ***	0.108 *	–	–
	(0.063)	(0.072)	(0.060)		
Size	−0.725 ***	−0.718 ***	−0.264 ***	0.246 ***	0.166 **
	(0.200)	(0.173)	(0.077)	(0.079)	(0.070)
Turning Circle	−0.215 ***	−0.205 ***	–	–	–
	(0.072)	(0.072)			
Seating Capacity	0.244 ***	0.242 ***	–	–	–
	(0.061)	(0.062)			
Trunk Capacity	0.051	0.057	–	–	–
	(0.043)	(0.043)			
Avg. Safety Rating	0.022	0.031	–	–	–
	(0.043)	(0.043)			
Airbags per Seat	0.006	0.004	–	–	–
	(0.049)	(0.049)			
Years	**Yes**		**Yes**		
Equipment	**Yes**		**Yes**		
Segment/Countries	**Yes**		**Yes**		
Brands	**Yes**		**Yes**		

Note: Results of the full BLP estimation with demographics (income, age, household size) for finding the effect of car characteristics on market share. Results are for the preferred model 4, and the demographic variables are shown for cases where full convergence was achieved (underlying data are from the constructed dataset).
* Significance levels are: $p < 0.1$.
** Significance levels are: $p < 0.05$.
*** Significance levels are: $p < 0.01$.

For example, lower fuel consumption, greater range, lower interior noise, or greater displacement all significantly increase demand for an automobile. The coefficients that were found to be significant in the IV regression are also found significant in the BLP, with comparable coefficient sizes. The main change lies in the growth of the magnitude and significance of the engine power coefficient (from -0.24^{**} to -0.31^{***}), and more than doubling of the coefficient for vehicle size (from −0.34 to −0.73). This is a further change for these two variables compared to the OLS results. Note that both the BLP without demographics and the IV regressions estimate the price coefficient to be insignificant, which is different compared to the full BLP model, described in Table 4.

The final key set of results is from the full BLP model with real-world consumer demographic variables, namely income, age, and household size (Table 4). This model fully accounts for price endogeneity, consumer heterogeneity, and unobserved car characteristics, while also providing realistic patterns of substitution. The results in Table 4 are significantly better and more intuitive compared to the BLP without auxiliary demographics. The most significant changes can be seen in the coefficients for prices, speed, and acceleration. These variables become very significant and their effect intuitive – i.e., lower price, higher speed, and faster acceleration increase automobile demand. The estimation results suggest that the key variables with by far the strongest effect on automobile demand are fuel consumption (coefficient of −0.76), overall vehicle size (−0.72), and prices (−0.65). The majority of the BLP coefficients are highly statistically significant, many even at the 0.001 or lower level. The UK consumers therefore appear to be strongly favouring vehicles with lower fuel consumption, presumably due to the expected savings on fuel costs, and growing environmental concerns of the society. Furthermore, demand is significantly higher for smaller vehicles, which also have a greater

Table 5
Example of own-price and cross-price semi-elasticities.

Selected models	Own-price and cross-price semi-elasticities						Price (')	Segment
2019	(1)	(2)	(3)	(4)	(5)	(6)		
Citröen C1 (1)	−5.4069	0.0047	0.0064	0.0107	0.0003	0.0005	10,140	A (mini cars)
Peugeot 108 (2)	0.0048	−5.2065	0.0062	0.0105	0.0003	0.0005	11,935	A (mini cars)
Škoda Superb (3)	0.0048	0.0045	−4.4579	0.0139	0.0007	0.0023	24,655	D (large cars)
Audi A4 (4)	0.0040	0.0039	0.0070	−4.4427	0.0007	0.0018	29,260	D (large cars)
BMW 8 Series (5)	0.0011	0.0011	0.0036	0.0069	−1.1883	0.0025	71,840	F (luxury cars)
Mercedes S-Class (6)	0.0012	0.0012	0.0036	0.0064	0.0010	−1.8364	75,390	F (luxury cars)

Note: Own and cross-price semi-elasticities of six selected 2019 vehicles, divided into three groups – mini cars, large cars, and luxury cars. Semi-elasticities are for an increase of ' 1,000 in price.

seating capacity at the same time. This suggests that on average, consumers prefer more compact cars (possibly due to better parking and city driving opportunities), which also do not give up seating capacity for the compactness. The demand for smaller vehicles can also be seen in the growing numbers of SUVs — majority of new SUV sales are small or smaller mid-sized SUVs, rather than large ones. Additionally, consumers have understandably greater demand for cars that cost less on average. Further car characteristics also considerably affecting demand include: speed (0.39), displacement (0.34), and range (0.31) with only about half the effect compared to the primary demand drivers, as well as interior noise (−0.24), turning circle (−0.21), and acceleration (−0.18), with less than a third of the effect.

In terms of engine types, automobiles that have a diesel rather than a petrol engine experience lower demand, on average. While diesel engines have lower average CO_2 emissions, they have a higher average price compared to petrol cars, and their higher NO_x emissions affect the environment more so (O'Driscoll et al., 2018; Dimaratos et al., 2020; Hu et al., 2022). Consequently, environmentally conscious consumers would rather prefer to purchase different engine types. The future of diesel engines also looks bleak in light of the planned banning of all new UK CV sales by 2035, further reducing the attractiveness of diesels. Similarly, AFVs are still in a significantly lower demand, despite both their sales and market share increasing swiftly in the last decade. Furthermore, examination of the demographic coefficients shows that higher consumer income results in a purchase of a higher quality vehicle across the board, as expected. Richer consumers would be especially more prone to buying AFVs (coefficient of 0.37), as well as faster cars (0.21) compared to consumers with lower income. On the other hand, while richer consumers do favour automobiles with greater range, this effect is relatively smaller (0.11) compared to the other variables. Consumers with higher income are also found to be generally less sensitive to prices (0.18) compared to poorer consumers. In addition, larger households tend to have, understandably, a greater demand for automobiles that are larger (0.17), as do consumers that are older (0.25), possibly due to a greater desire for added comfort of the roomier automobiles.

6.2. Own-price, cross-price, and demand elasticities

Apart from finding the key drivers of demand, we also estimate own-price, cross-price, and demand elasticities for all automobiles in the UK car market. This analysis allows for an understanding of how consumer demand will change with different vehicle characteristics and attributes, separately for fossil fuel and clean automobiles. Furthermore, it provides more accurate predictions of how the market would react to changes in car prices, or to the introduction of a completely new potential product. In order to illustrate the calculated realistic substitution patterns, we report the own-price and cross-price semi-elasticities of six selected cars of 2019, divided into three distinct groups (Table 5). These groups are the mini cars (low end of the spectrum of quality and price), large cars (middle of the spectrum), and luxury cars (high-end of the spectrum). Under the realistic substitution patterns of our model, if the price of a large car increases, we would expect consumers to primarily substitute to the most similar product – i.e., another large car, rather than a mini car or a luxury car. And indeed, this is what we can see in Table 5, with larger cross-price semi-elasticities for automobiles of similar characteristics. Consumers of mini cars predominantly substitute to another mini car, next to large cars (the subsequent closest substitute), and only then to luxury cars. For example, after an increase in price of Peugeot 108 by £1,000, consumers are most likely to substitute to the Citröen C1 mini car (with a semi-elasticity of 0.0047), then to large cars such as Audi A4 (semi-elasticity of 0.0039), and only then to luxury cars such as Mercedes S-Class (semi-elasticity of 0.0012). Similarly, buyers of luxury cars, like the BMW 8 Series, prefer to switch to another luxury car, such as the Mercedes S-Class (semi-elasticity of 0.0010), rather than a mini car, such as the Citröen C1 (semi-elasticity of 0.0003). This is the case for each vehicle in Table 5, where for a £1,000 increase in price, the greatest substitution happens to the other vehicle of the same segment, then to the second closest segment, and the remainder to the last segment. In addition, our analysis shows that vehicle own-price semi-elasticities are higher for cheaper cars, and tend to decrease significantly as vehicle quality and prices increase. For mini cars, the own-price semi-elasticities are around 5.5%, for large cars this is about 4.5%, and for luxury cars, this is only between 1% and 2%. This means that the consumer demand for cheaper cars is more price sensitive than for expensive cars, decreasing considerably more after a £1,000 increase in price. This is likely to be partly because of the greater number of close substitutes for cheaper vehicles, and partly because a £1,000 increase in price represents a greater percentage change for a cheap car compared to an expensive car.

The own-price and cross-price semi-elasticities for the 15 most popular CV and AFV models of 2019 (out of 279 models overall) can be seen in Table 6, showcasing the overall sensitivity of consumer demand to changes in car prices. In terms of sales, these

Table 6
Own-price and cross-price semi-elasticities of the most popular CVs and AFVs.

Popular CVs	Own-Price and Cross-Price Semi-elasticities															Price	CV
2019	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(£	Type
Vauxhall Corsa (1)	−5.191	0.011	0.013	0.031	0.014	0.024	0.027	0.024	0.017	0.014	0.020	0.021	0.018	0.010	0.010	11,730	Petrol
Toyota Yaris (2)	0.021	−5.122	0.013	0.030	0.014	0.023	0.026	0.023	0.016	0.013	0.019	0.020	0.018	0.010	0.010	13,515	Petrol
Volkswagen Polo (3)	0.019	0.010	−4.994	0.027	0.014	0.021	0.023	0.021	0.014	0.012	0.018	0.018	0.016	0.009	0.009	14,330	Petrol
Ford Fiesta (4)	0.021	0.011	0.013	−5.025	0.014	0.024	0.027	0.024	0.017	0.014	0.020	0.021	0.018	0.010	0.010	15,995	Petrol
MINI Cooper (5)	0.016	0.009	0.011	0.023	−4.759	0.018	0.020	0.017	0.012	0.010	0.016	0.014	0.013	0.008	0.008	16,195	Petrol
Ford Focus (6)	0.023	0.012	0.014	0.032	0.015	−4.937	0.029	0.026	0.019	0.015	0.022	0.024	0.020	0.011	0.011	18,305	Petrol
Volkswagen Golf (7)	0.024	0.012	0.014	0.034	0.016	0.027	−4.967	0.028	0.020	0.017	0.023	0.026	0.022	0.011	0.012	18,765	Petrol
Nissan Qashqai (8)	0.024	0.013	0.015	0.035	0.016	0.028	0.032	−4.938	0.021	0.017	0.023	0.027	0.023	0.012	0.012	19,995	Petrol
Kia Sportage (9)	0.027	0.014	0.016	0.038	0.016	0.031	0.036	0.032	−4.993	0.020	0.025	0.031	0.026	0.012	0.013	20,670	Diesel
Hyundai ix35 (10)	0.027	0.014	0.016	0.038	0.016	0.030	0.036	0.032	0.024	−4.954	0.025	0.031	0.026	0.012	0.013	22,060	Diesel
Mercedes A-Class (11)	0.020	0.010	0.013	0.029	0.014	0.023	0.026	0.023	0.016	0.013	−4.616	0.020	0.018	0.010	0.010	23,160	Diesel
Ford Kuga (12)	0.028	0.014	0.016	0.040	0.017	0.032	0.038	0.034	0.026	0.021	0.026	−4.963	0.028	0.013	0.013	23,375	Petrol
Volkswagen Tiguan (13)	0.026	0.013	0.016	0.038	0.016	0.030	0.036	0.032	0.024	0.019	0.025	0.031	−4.859	0.012	0.013	23,990	Diesel
BMW 1 Series (14)	0.019	0.010	0.012	0.027	0.014	0.022	0.024	0.021	0.015	0.012	0.019	0.018	0.016	−4.559	0.010	24,430	Diesel
BMW 3 Series (15)	0.020	0.010	0.013	0.029	0.014	0.023	0.026	0.023	0.016	0.013	0.021	0.020	0.019	0.011	−4.297	32,565	Diesel

Popular AFVs	Own-Price and Cross-Price Semi-elasticities															Price	AFV
2019	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(£)	Type
Renault Zoe (1)	−4.8448	0.0015	0.0056	0.0020	0.0064	0.0011	0.0027	0.0025	0.0042	0.0032	0.0033	0.0065	0.0017	0.0026	0.0010	21,220	EV
DS3 Crossback (2)	0.0018	−4.7734	0.0057	0.0020	0.0064	0.0012	0.0027	0.0025	0.0041	0.0031	0.0034	0.0066	0.0018	0.0027	0.0010	21,555	EV
Hyundai Ioniq (3)	0.0015	0.0013	−4.3939	0.0021	0.0062	0.0012	0.0026	0.0024	0.0034	0.0027	0.0033	0.0065	0.0018	0.0027	0.0011	21,795	Hybrid
Toyota Prius (4)	0.0015	0.0013	0.0058	−4.3106	0.0062	0.0012	0.0025	0.0024	0.0034	0.0027	0.0033	0.0066	0.0018	0.0028	0.0012	24,245	Hybrid
Kia Niro (5)	0.0016	0.0014	0.0060	0.0021	−4.4905	0.0012	0.0027	0.0025	0.0037	0.0029	0.0035	0.0067	0.0019	0.0028	0.0011	24,590	Hybrid
Lexus CT (6)	0.0014	0.0012	0.0055	0.0020	0.0057	−4.1727	0.0024	0.0022	0.0031	0.0026	0.0031	0.0064	0.0017	0.0028	0.0012	25,550	Hybrid
Toyota Prius Plus (7)	0.0017	0.0015	0.0061	0.0022	0.0067	0.0012	−4.4362	0.0026	0.0039	0.0031	0.0036	0.0070	0.0020	0.0030	0.0012	27,830	Hybrid
Lexus UX (8)	0.0017	0.0014	0.0060	0.0022	0.0066	0.0012	0.0028	−4.2967	0.0039	0.0031	0.0036	0.0072	0.0020	0.0031	0.0013	29,905	Hybrid
Nissan Leaf (9)	0.0019	0.0016	0.0057	0.0021	0.0066	0.0012	0.0028	0.0026	−4.5247	0.0033	0.0035	0.0070	0.0019	0.0029	0.0011	31,495	EV
BMW i3 (10)	0.0017	0.0015	0.0055	0.0020	0.0062	0.0012	0.0027	0.0025	0.0040	−4.1712	0.0034	0.0072	0.0019	0.0031	0.0013	35,350	EV
Lexus NX (11)	0.0017	0.0014	0.0062	0.0022	0.0068	0.0013	0.0029	0.0027	0.0039	0.0031	−4.0989	0.0075	0.0021	0.0033	0.0014	36,300	Hybrid
Tesla Model 3 (12)	0.0015	0.0013	0.0058	0.0021	0.0062	0.0013	0.0026	0.0026	0.0037	0.0031	0.0036	−3.5979	0.0022	0.0038	0.0017	42,400	EV
Lexus RX (13)	0.0016	0.0014	0.0062	0.0022	0.0067	0.0013	0.0028	0.0027	0.0038	0.0031	0.0039	0.0083	−3.6140	0.0039	0.0017	49,705	Hybrid
Jaguar I-Pace (14)	0.0015	0.0013	0.0058	0.0021	0.0062	0.0013	0.0027	0.0026	0.0037	0.0032	0.0037	0.0090	0.0024	−3.0331	0.0021	64,495	EV
Tesla Model S (15)	0.0013	0.0012	0.0058	0.0022	0.0060	0.0013	0.0026	0.0026	0.0034	0.0032	0.0038	0.0097	0.0026	0.0050	−2.6517	76,350	EV

Note: Own-price and cross-price semi-elasticities of 15 most popular 2019 CV and AFV models. The models represent about a third of the 2019 UK car market in terms of sales. Semi-elasticities for a price increase of £1,000 (underlying data are from the constructed dataset).

models represent about a third of the UK car market in 2019. We can see a similar pattern as in Table 5 – cheaper vehicles of lower quality are generally more price sensitive, and this sensitivity diminishes as quality and price increases. More specifically, Table 6 shows the percentage fall in vehicle demand within the UK automobile market, after a £1,000 increase in price. On the cheaper end of the market, the own-price semi-elasticity for the cheapest CV (Vauxhall Corsa) and AFV (Renault Zoe) is 5.2% and 4.8% respectively. This falls to 4.6% and 4.1% respectively for the middle-priced CV Mercedes A-Class and AFV Lexus NX. On the expensive side of the market, the own-price semi-elasticities are only 4.3% (CV - BMW 3 Series) and 2.7% (AFV - Tesla Model S). As such, our results suggest that overall, for a £1,000 increase in price, the demand for a vehicle falls by about 3% for expensive automobiles, and by roughly 5% for cheaper automobiles. This fall in demand appears to be consistent, regardless of whether the vehicle in question is a CV or an AFV. This suggests that consumers are not ready to pay a significant price premium for the cleaner AFVs. When examining the semi-elasticities for all AFVs in the market, we consequently estimate that a subsidy of £1,000 to AFV purchases would lead 4.1% of UK consumers to switch to the greener vehicles. In percentage terms, a 1% increase in car price would decrease demand by about 1.5%. As such, our results are most similar to Zhang et al. (2016), McCarthy (1996), and Fridstrøm and Østli (2021), who found an effect of −0.8%, −0.9%, and −1.1%, respectively. This is significantly higher than e.g., Bansal and Dua (2022) at −0.13%, but lower than Li et al. (2015) (−3.5%), Berry et al. (1995) (−5%), or Beresteanu and Li (2011) (−8%).

While our estimated cross-price semi-elasticities are relatively small (similarly as in e.g., Zhang et al. (2016)) due to the large number of substitutes as well as the outside good (purchasing no automobile at all), they are significantly smaller for the AFVs. For example, for the CV (5) MINI Cooper, the cross-price semi-elasticity to the next cheaper CV (4) Ford Fiesta is 0.014. For the AFV (5) Kia Niro however, the cross-price semi-elasticity to the next cheaper AFV (4) Toyota Prius is 0.0062 — less than half of the CV semi-elasticity. Similar or larger differences can be seen also for the remaining CV and AFV models. This suggests that while the demand sensitivity to a price increase is comparable between CVs and AFVs, there tends to be more substitution from AFVs towards CVs after a price increase, rather than from CVs to AFVs. Furthermore, we find no evidence of preferred substitution to the same type of engine (e.g., hybrid consumers substituting to another hybrid, rather than an EV), suggesting that consumers focus mainly on other vehicle characteristics, rather than on the engine type.

In summary, our results show that an increase of car price by £1,000 reduces the demand by about 3%–5%, depending on the availability and quality of substitutes. This suggests that UK consumers are not willing to pay a large price premium for an AFV. Consequently, we estimate that a £1,000 subsidy to AFV purchases would lead about 4% of UK consumers to switch to the greener AFVs. Furthermore, the lower cross-price semi-elasticities of AFVs indicate that there tends to be greater substitution from AFVs towards CVs after a price increase.

The elasticities of demand with respect to several vehicle characteristics can be seen in Table 7. We include all vehicle variables that had an interaction with the auxiliary consumer demographics in the full BLP model – i.e., prices, maximum speed, range, and vehicle size. Table 7 reports the own-price semi-elasticity for a £1,000 increase in price levels (as in Table 6), as well as the demand

Table 7
Demand elasticities of the most popular CVs and AFVs in 2019.

Popular	Elasticity of demand for:				Popular	Elasticity of demand for:			
CVs	Price	Speed	Range	Size	AFVs	Price	Speed	Range	Size
Vauxhall	11,730	163	781	10.32	Renault	21,220	135	225	11.04
Corsa	−5.19	17.75	9.55	−11.74	Zoe	−4.84	15.06	2.15	−18.91
Toyota	13,515	154	861	9.94	DS3	21,555	150	250	11.31
Yaris	−5.12	16.88	10.32	−14.01	Crossback	−4.77	16.61	2.40	−19.03
Volkswagen	14,330	161	924	9.52	Hyundai	21,795	185	1,242	11.80
Polo	−4.99	17.60	10.93	−14.99	Ioniq	−4.39	20.16	13.71	−18.99
Ford	15,995	159	818	10.27	Toyota	24,245	180	1,263	11.75
Fiesta	−5.03	17.39	9.41	−15.74	Prius	−4.31	19.71	13.55	−20.46
MINI	16,195	193	735	9.33	Kia	24,590	163	1,178	12.27
Cooper	−4.76	20.83	8.13	−16.31	Niro	−4.49	17.99	12.59	−20.52
Ford	18,305	177	1,067	11.65	Lexus	25,550	182	1,083	10.98
Focus	−4.94	19.26	12.85	−16.53	CT	−4.17	19.93	10.96	−21.13
Volkswagen	18,765	180	991	12.21	Toyota	27,830	169	918	12.90
Golf	−4.97	19.57	11.85	−16.42	Prius Plus	−4.44	18.66	9.26	−22.19
Nissan	19,995	185	974	12.57	Lexus	29,905	177	768	12.74
Qashqai	−4.94	20.09	11.52	−17.12	UX	−4.30	19.51	7.42	−23.26
Kia	20,670	175	1,250	13.60	Nissan	31,495	143	220	12.36
Sportage	−4.99	19.12	15.83	−16.69	Leaf	−4.52	16.07	1.98	−23.92
Hyundai	22,060	175	1,250	13.62	BMW	35,350	150	233	11.20
ix35	−4.95	19.14	15.54	−17.90	i3	−4.17	16.87	2.01	−24.76
Mercedes	23,160	203	1,019	11.43	Lexus	36,300	180	1,109	14.05
A-Class	−4.62	21.94	11.28	−19.85	NX	−4.10	19.94	10.77	−26.20
Ford	23,375	180	956	14.04	Tesla	42,400	209	310	12.53
Kuga	−4.96	19.66	11.20	−18.57	Model 3	−3.60	22.97	2.61	−27.53
Volkswagen	23,990	185	1,275	13.90	Lexus	49,705	200	1,104	15.61
Tiguan	−4.86	20.17	15.56	−19.18	RX	−3.61	22.26	9.88	−31.18
BMW	24,430	185	1,250	10.84	Jaguar	64,495	200	365	13.89
1 Series	−4.56	20.19	13.96	−20.56	I-Pace	−3.03	22.69	2.83	−32.38
BMW	32,565	203	1,250	11.97	Tesla	76,350	210	394	14.12
3 Series	−4.30	22.14	12.94	−24.18	Model S	−2.65	24.09	2.95	−33.64

Note: Price semi-elasticities and demand elasticities of 15 most popular 2019 CV and AFV models, with respect to price (for a ' 1,000 increase), maximum speed, range, and size (for a 10% increase). For every model, the value of each characteristic is shown, with corresponding demand elasticity at the bottom (underlying data are from the constructed dataset).

elasticities for a 10% increase of maximum speed, range, and size. The results of prices in Table 7 show that cheaper vehicles are the ones displaying the most dominant semi-elasticities. If vehicle prices fall, demand would rise the most for the cheapest automobiles, with the effect being similar for both CVs and AFVs. Similarly, the elasticity of demand with respect to speed is comparable between the two vehicle types. A 10% increase in speed increases vehicle demand by about 15%–20% depending on the vehicle, with the effect being the weakest for slowest vehicles. We conclude that buyers who go for slower vehicles are not significantly interested about speed, compared to consumers of faster cars. Furthermore, a 10% increase in a vehicle's range increases demand by about 10%–15%. This effect is shown to be strongest for long range vehicles at over 15%, while for short ranged EVs, a 10% increase in range only increases demand by about 2%. Similar result was reached by e.g., Berry et al. (1995), who found an effect of 10% for long range vehicles, while this was close to 0% for short range cars. The reason for the lower range elasticities of EVs is that these vehicles generally have a relatively short range, especially when compared to other AFVs, such as hybrids. Therefore, an increase of EV range by 10% is quite small in absolute terms (only about 20–30 km), compared to CVs or hybrids, causing a smaller absolute effect on EV demand. In fact, when comparing the range elasticity of longer-range AFVs, such as hybrids, with CVs, the demand sensitivity in terms of range is quite comparable. The elasticity of demand with respect to size is the largest of the examined elasticities, especially for AFVs. A 10% increase in vehicle size decreases CV demand by about 15%–20%, but by a considerably larger 20%–30% for AFVs (about 40% more compared to CVs), suggesting a greater preference of AFV consumers for smaller vehicles. The elasticity can also be seen to rise directly in relation to price, signifying that buyers of more expensive vehicles are more sensitive to changes in vehicle size. Previous research, such as Berry et al. (1995) or Petrin (2002), found a positive rather than a negative effect of car size, at about 10%. This finding points to a change in consumer preferences in the last two decades, moving from a preference for large cars to smaller vehicles that are more suitable for congested city driving.

Lastly, we estimate the percentage of consumers that would decide to substitute to the outside good (i.e., leave the car market altogether) after a marginal increase in vehicle price (Table 8). Following Berry et al. (1995), we first estimate a simple prediction under a logit specification, given by $\frac{S_0}{(1-S_j)}$, where S_0 is the share of the outside good and S_j is the share of car j. Under this specification, about 90% of consumers who substitute away from model j would choose the outside good. However, as in Berry

Table 8
Share of CV and AFV consumers substituting away after a price increase.

Popular CVs	Substitution to the Outside Good		Price	CV
2019	Logit Model	BLP Model	(')	Type
Vauxhall Corsa	91.87%	0.17%	11,730	Petrol
Toyota Yaris	91.79%	0.09%	13,515	Petrol
Volkswagen Polo	91.82%	0.12%	14,330	Petrol
Ford Fiesta	91.95%	0.25%	15,995	Petrol
MINI Cooper	91.85%	0.16%	16,195	Petrol
Ford Focus	91.88%	0.18%	18,305	Petrol
Volkswagen Golf	91.89%	0.19%	18,765	Petrol
Nissan Qashqai	91.87%	0.16%	19,995	Petrol
Kia Sportage	91.81%	0.10%	20,670	Diesel
Hyundai ix35	91.79%	0.08%	22,060	Diesel
Mercedes A-Class	91.87%	0.17%	23,160	Diesel
Ford Kuga	91.83%	0.12%	23,375	Petrol
Volkswagen Tiguan	91.82%	0.11%	23,990	Diesel
BMW 1 Series	91.79%	0.09%	24,430	Diesel
BMW 3 Series	91.78%	0.08%	32,565	Diesel
Popular AFVs	Substitution to the Outside Good		Price	AFV
2019	Logit Model	BLP Model	(')	Type
Renault Zoe	91.70%	0.008%	21,220	EV
DS3 Crossback	91.70%	0.007%	21,555	EV
Hyundai Ioniq	91.72%	0.029%	21,795	Hybrid
Toyota Prius	91.70%	0.010%	24,245	Hybrid
Kia Niro	91.72%	0.029%	24,590	Hybrid
Lexus CT	91.70%	0.006%	25,550	Hybrid
Toyota Prius Plus	91.71%	0.012%	27,830	Hybrid
Lexus UX	91.71%	0.011%	29,905	Hybrid
Nissan Leaf	91.71%	0.017%	31,495	EV
BMW i3	91.71%	0.014%	35,350	EV
Lexus NX	91.71%	0.014%	36,300	Hybrid
Tesla Model 3	91.73%	0.031%	42,400	EV
Lexus RX	91.70%	0.008%	49,705	Hybrid
Jaguar I-Pace	91.71%	0.012%	64,495	EV
Tesla Model S	91.70%	0.005%	76,350	EV

Note: Percentage of CV and AFV consumers that substitute to the outside good after a marginal increase in each model's price, out of all consumers that substitute away (underlying data are from the constructed dataset).

et al. (1995), this percentage falls to significantly more realistic figures using the full BLP model. Our results suggest that about 0.15% of all consumers that substitute away from a car after a price increase would choose to leave the market. Thus, after a price increase, most consumers would choose to substitute to a different vehicle, rather than not buy any at all. As previously shown, such vehicle would be the one that is the most similar to the original vehicle, with CV buyers likely to substitute to another CV, and AFV buyers to another AFV. This finding is understandable, especially due to the large number of available options in the UK car market in 2019 (almost 300 distinct models). Nevertheless, the percentage is substantially lower for AFVs, where only about 0.015% of consumers would decide to leave the market after a price increase. Therefore, after a comparable increase in prices, AFV buyers are about ten times more likely than CV buyers to stay in the market and purchase a different automobile, before deciding to leave the car market altogether. As such, AFV buyers substitute much less to and from the outside option compared to CV buyers.

7. Conclusion and policy implications

The global automotive markets are currently going through an era of transformation, with the UK representing one of the leading countries. Despite this, there has been a notable absence of comprehensive analyses in the existing literature. This paper addresses this gap, providing a significant update on previous works and a realistic understanding of the demand drivers for both AFVs and CVs. Our research identifies fuel consumption, vehicle size, and price as the primary determinants of consumer demand in the UK car market. The importance of price is expected, as it directly influences consumer purchasing decisions. However, our findings emphasise that lower fuel consumption is a critical factor, not only due to the immediate financial benefits from fuel savings, but also because of its long-term environmental advantages through reduced emissions. Furthermore, the preference for smaller vehicle sizes highlights the practical considerations of urban living, such as the need for easier parking and maneuverability in congested city environments. This is particularly the case for the UK, where the percentage of population living in urban areas grows annually at about 0.3%, and reached over 84% in 2022 — considerably more than other countries with large car markets, such as China (64%), India (36%), Germany (77%), or Italy (72%) (World Bank, 2024). Additionally, we found that performance attributes, such as displacement, speed, and maximum range play a significant role in consumer preferences. Maximum range in particular is important for AFVs in general, addressing the concerns about the practicality and convenience of EVs.

Our findings demonstrate that an increase in price by £1,000 results in a 3%–5% average decrease in demand, a trend observed consistently across both CVs and AFVs. This indicates that UK consumers are unwilling to pay a significant price premium for the cleaner AFVs. Consequently, implementing a subsidy of £1,000 for AFV purchases is estimated to incentivise approximately 4.1% of UK consumers to switch to AFVs. The analysis confirms an expected pattern — consumers are inclined to substitute to vehicles most similar to their initial choice. Importantly, substitution due to price increase is found to go in the direction from AFVs to CVs, rather than the reverse. These results therefore suggest that without financial incentives (or CV disincentives), the uptake of AFVs may remain low, as the economic burden and lower convenience outweighs the environmental considerations for the majority of consumers.

The estimation also reveals that CVs and AFVs exhibit similar demand elasticities with respect to speed and range enhancements. Specifically, a 10% increase in speed results in a significant 15%–20% rise in demand, whereas a comparable increase in range boosts demand by 10%–15%. These results suggest that improvements in maximum speed and, to a lesser degree, range, are valued by consumers, indicating potential areas for technological investment and development. Notably, the demand elasticity with respect to vehicle size differs substantially between CVs and AFVs, with the latter demonstrating about 40% greater sensitivity. A 10% increase in size leads to a 15%–20% reduction in CV demand, but a more pronounced 20%–30% decline in AFV demand. This greater sensitivity of AFV consumers highlights an interesting area for policymakers and manufacturers — optimising vehicle design to balance size with the efficiency and appeal of AFVs. Targeted government policies could incentivise the production of more compact, yet spacious AFVs, potentially through subsidies or tax benefits for manufacturers who innovate in this area.

Furthermore, our analysis indicates that a price increase would persuade approximately 0.15% of consumers to exit the vehicle market entirely, a phenomenon that is significantly less pronounced for AFVs, at only 0.015%. Therefore, AFV consumers are much more likely to substitute to another vehicle, rather than forgoing vehicle ownership altogether. This effect presents an opportunity for policymakers to implement pricing strategies that could support the transition to a greener vehicle fleet. For example, implementing a gradual price increase on CVs, coupled with incentives for AFV adoption, could shift consumer preferences towards more environmentally friendly options, without shrinking the overall UK automobile market.

In general, our results demonstrate that UK consumers exhibit, on average, a preference for purchasing the types of cars that also offer the societal positive externality of reduced carbon footprint. UK consumers strongly prefer automobiles that are more fuel-efficient, physically smaller, and lighter. The implications for manufacturers are that those who can deliver superior fuel economy alongside other desirable car characteristics will likely gain a competitive edge. For policymakers, understanding these consumer preferences is also important, particularly regarding the market for AFVs. The insight that AFV buyers have about 40% greater preference for compact cars than CV buyers should inform government support policies, encouraging the development and promotion of smaller, cost-effective AFVs. This support may take the form of tax benefits, subsidies, or urban design that effectively accommodates such vehicles. More numerous collaborations between the government and automotive manufacturers could encourage innovations, that may enhance the competitiveness of AFVs.

Contrary to what might be expected, we found that investments into greater range of EVs are unlikely to substantially boost their adoption, given the relatively low absolute values of the range demand elasticities. The potential increase in EV range would have to be so significant that it would rival the range of hybrids and CVs, in order to substantially affect EV demand. Instead, investments and grants should focus on expanding the UK's network of fast recharging stations. The Climate Change Committee (CCC) estimates that the number of charging points should increase about twenty fold until 2032, to stimulate extensive EV uptake (CCC, 2020a). A widespread, dense network of EV charging infrastructure would mitigate range anxiety present for the majority of EVs, and make them a more viable option for consumers. Currently, there is a limited capacity and reliability of transmission and distribution network operators in the UK, that would allow for a sufficient EV charging infrastructure (CCC, 2020b). Consequently, electricity grid upgrades are required to meet the demand of future EV consumers. Our research also suggests a strategic way of how the government could effectively speed up transition from CVs to AFVs. As AFV buyers substitute significantly less than CV buyers to and from the outside option, it would be optimal to motivate consumer demand for AFVs versus CVs in different ways. More specifically, it would be more effective for the government to discourage purchases of CVs, rather than heavily incentivise the purchase of AFVs. In other words, increasing the costs of CVs through policies such as higher car and emission taxes would likely be more effective in altering consumer behaviour and accelerating the uptake of AFVs, than decreasing the costs of AFVs through heavy subsidies, tax reductions, or reduced registration fees. Complementary measures, such as public awareness campaigns emphasising the long-term cost savings and environmental benefits of AFVs, could further shift consumer preferences.

Regardless of the final mix of policies selected, continuous assessment and adjustment of subsidy levels and other incentives would be crucial to maintain a path towards widespread adoption of AFVs. Incentives, such as funding, can be directly linked to specific targets, allowing for funding to move on to support the next target once the previous target is reached. For example, tax reductions or subsidies for AFVs can be reduced or removed when AFVs reach a specific targeted market share (CCC, 2020b). For manufacturers, understanding the demand drivers can also allow for strategic decisions in product development and marketing, ensuring alignment with both consumer preferences and regulatory trends. Our results underscore the necessity of a sustained and comprehensive policy support, to overcome the initial cost and range barriers and accelerate the shift from CVs to AFVs. Such shift is vital for achieving the UK's environmental goals, contributing to a sustainable transportation future, and the broader goal of net-zero emissions by 2050.

While our research makes a substantial contribution by utilising a novel dataset and providing a significant update on the previous works, future research can focus on incorporating a broader range of trim levels into the dataset, allowing for a more comprehensive understanding of the UK car market. Achieving this would, however, require an even richer dataset, something which is not easily acquired. Although complicated in terms of data collection, expanding the scope to include the second-hand market and examining the interaction between new and used vehicles may yield valuable insights. Additionally, including data on the availability of charging and fuelling stations, and their subsequent network effects, may clarify their influence on elasticities and substitution patterns. Finally, households that own at least one automobile will likely base their subsequent additional purchase decision on the attributes and experiences of their currently owned car. Addressing these factors would be complicated, but could provide more nuanced and impactful understanding of consumer behaviour in the automotive market.

CRediT authorship contribution statement

Filip Mandys: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Shivani Taneja:** Writing – review & editing, Writing – original draft, Software, Methodology, Investigation, Formal analysis.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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