A greening of the private vehicle fleet? An examination of the market for low emission vehicles in London

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ABSTRACT

Historically, the role of car-ownership models has typically been to forecast the number of cars owned or operated by individuals or households. The policy context was the implication of car-ownership growth for increasing highway congestion and a parallel reduction in the use of public transport. In London, however, the policy context has shifted in the last few years. Car ownership has stabilised or even declined, while public transport use has risen dramatically. Of interest now for London policy-makers is not just the number of cars owned but also their types, and in particular the factors – interventions or exogenous – that will influence a shift towards lower emission vehicles.

Current forecasts of the potential market share for low emission vehicles make extensive use of supply side production figures and stated policy goals, essentially a 'top down' approach to the problem. This paper reports the development of a vehicle-type policy-responsive forecasting model, incorporating also the response of vehicle use, for Transport for London (TfL) by MVA Consultancy in association with RAND Europe and John Bates Services. The vehicle-type and use model extends the cars-per-adult model previously supplied to TfL by the MVA-led team. The overall outcome is therefore a joint model of car number, type and use, with a sufficiently fine degree of segmentation such that key policy outcomes can be addressed. Importantly, this new model reverses the 'top down' trend to deliver a more consumer centric, demand-led, 'bottom up' approach to forecasting, addressing the full spectrum of attributes which previous studies have found to determine choice of vehicle type (not just the propulsion method and its directly correlated attributes).

In the first instance, TfL's focus of policy interest is CO_2 emissions. Consequently, the extended model differentiates vehicles in dimensions which include fuel type, engine size, and fuel efficiency, and correspondingly forecasts changes in the vehicle-mix and usage in response to a series of "what if?" tests, including:

- changes in fuel price across the different energy sources;
- improvements in conventional fuel efficiency, potentially negating some of the environmental gains of low emission fuels;
- developments in range, weight and size of low-emission vehicles, and the extent to which they can compete with conventionally fuelled vehicles on such key attributes;
- lower purchase prices of low-emission vehicles, potentially supported by grants and/or subsidies;
- mid-term costs such as vehicle taxation, etc, related to emissions performance;
- for electric propulsion, number of charging points, both private and public; and
- changes in other 'out-of pocket' costs, particularly differentials between low emission and conventionally fuelled vehicles for parking and the congestion charge.

To achieve its objectives, the model integrates several secondary data sources. The main dataset for distinguishing between base year vehicle-types is the UK Driver and Vehicle Licensing Agency (DVLA) database of licensed vehicles (appropriately anonymised). Variation in intensity of use of vehicles of different types is proxied by linking observations from TfL's extensive deployment of automated number-plate recognition (ANPR) cameras to the DVLA database. This link makes use of TfL's in-house London Vehicle Analysis Tool (LVAT). The London Travel Demand Survey (LTDS) – essentially travel and vehicle-use diaries of about 8,000 London households per year – provides a estimate of vehicle-km undertaken but with very small samples outside the conventionally-fuelled vehicle types.

The final model incorporates the key attributes of interest in determining vehicle type choice, and subsequent use, enabling TfL to understand the impact of policy decisions on CO_2 production across the private vehicle fleet in London.

1 Introduction

The context of this study is that car ownership, vehicle type choice, and subsequent use are critical issues in transport planning and policy-making, in terms of who travels, how frequently, where to, and by what means, and the implications for parking vehicles at both production and attraction ends of a trip. With increasing stress on the "carbon agenda" and local air quality management, choice of the type of car is of growing interest also. Car ownership and use also have major implications for land use, energy consumption, health, and wellbeing, and consequently for policy-making in these areas too.

Car ownership per (adult) capita is lowest in London of all GB regions, and has been growing at a slower rate; car use has also been static or declining at a personal level. A modelling framework which aids understanding of these car ownership and use patterns, which may be specific to the capital, was therefore recognised as being important to policy development.

In 2010, MVA Consultancy, RAND Europe, and John Bates Services delivered to Transport for London (TfL) a model (LONCOME) to forecast car ownership per adult (CpA) at the Lower Super Output Area (LSOA) of spatial detail. Subsequently, TfL commissioned an extension to the model to cover choice of vehicle type and, following ownership and type choice estimation, use.

The specific objectives for this extension were to:

- build on the existing estimate of CpA to include estimates of vehicle type and use;
- identify a level of vehicle type segmentation which enables the environmental externalities, carbon and local air quality, associated with choices of different vehicle types to be estimated;
- source or estimate behavioural parameters which ensured that the model is sensitive to (Local and Central) Governmental policy levers and exogenous influences;
- assist in the development and assessment of relevant policy interventions and planning scenarios;
- improve TfL's modelling capabilities; and
- provide future year estimates of car availability, vehicle type choice, and subsequent vehicle use.

2 Understanding choices of vehicle type and use

This section presents a distillation of the evidence base and most pertinent supporting datasets for the estimation of vehicle type and use models for London. In particular, it seeks to identify attributes, and supporting parameters, that are most relevant for the spatial and temporal context in question.

There is a significant body of literature on car type choice models from which (monetary) cost elasticity estimates, and other insights, can be obtained. The majority of the literature is from North America, but there are also a number of European studies, including a London-specific dataset based on Stated Preference (SP) data which provides insight into cost sensitivities for the capital.

In terms of segmentation, a common approach in the US is to differentiate vehicle make and model combinations. However, this approach can suffer from an explosion in the number of alternatives, and some studies adopt alternative sampling procedures to deal with the associated estimation issues. In the context of this study, and in particular that of CO_2 estimation, make/model does not provide what is required, eg different Ford (make) Focus (model) variants are available with significantly different emission levels, and Ford Focus 1.8 diesel (fuel type) would result in a further explosion in the number of possible alternatives.

Another type of segmentation adopted in a number of studies is body type, (passenger car, Sports Utility Vehicle (SUV), minivan, etc). However, this approach has the same limitation for this study, in that within a given category further segmentation would be required to differentiate emissions. Another issue if that the US vehicle fleet is different to the London fleet, with body types such as SUV and pick-up more prevalent.

Attributes other than cost are identified as important in car type choice; vehicle characteristics (acceleration, fuel efficiency, capacity etc) are important, indeed one US study concluded that the decline in US automakers share in their home market can be explained almost entirely by quality and value attributes of vehicles. Brand loyalty is identified as an important effect in a number of studies.

Socio-economic and demographic factors also play a role, though they are not as prominent as the vehicle characteristic and price factors. Examples are preferences for pick-ups for males in the US, and household size and type factors when considering body types such as SUVs and minivans. Some studies have also identified land-use and attitudinal influences on car type choice.

Alternative Fuel Types

In terms of alternatively fuelled vehicles (including the low emission technologies that this paper explicitly considers), price, range and recharge time are key attributes, and in many scenarios low shares were forecast relative to conventionally fuelled vehicles based on the characteristics of alternatively fuelled vehicles that were available when the study in question was undertaken. Values from the studies were reviewed, with the intention of incorporating the impact of range, and possibly acceleration and re-charge time, into the type choice model for the electric and alternative fuelled vehicle alternatives.

One US study suggested females, minority groups, and residents of more densely population areas were more likely to switch to alternatively fuelled vehicles. It was noted that this result was obtained after taking account of differences in income.

In terms of policy simulations, a Montreal study suggested the only effective policy lever to increase the demand for electric vehicles was cash incentives. The same study demonstrated allocating road space to electric vehicles only would make emissions worse, as only a marginal shift to electric vehicles would be achieved, and congestion for conventionally fuelled vehicles would worsen. The key barriers to take-up were seen to be price, range, and re-charge time.

Studies on the take up of electric and alternatively fuelled vehicles that quote parameters from models that represent the choice between conventional, electric and alternatively fuelled vehicles were reviewed. The objective of the review was to determine parameter sensitivities for transfer into the type choice model developed for this study. This enables the model to predict how take up of these vehicle types would increase as their performance characteristics improve.

From this review, the sensitivity of electric and alternatively fuelled vehicles to acceleration (expressed as 0-60 mph) has been drawn from a 2007 London study undertaken on behalf of TfL. To give insight into the impact of range, information was drawn from a 2008 study undertaken in Montreal Canada, as no London-specific valuation was available. To transfer the parameters to the London model, they were expressed relative to well estimated purchase price parameters, and appropriate adjustments were made to convert the sensitivities to 2008 price levels.

Sensitivity of Type Choice to Cost Changes

The key sources for UK parameters for the sensitivity of type choice to cost changes are the 2008 EFTEC study[1], and the 2008 Cambridge Econometrics study[2]. The EFTEC study developed aggregate discrete choice models using Driver Vehicle Licensing Agency (DVLA) car registrations data, JATO vehicles dynamics data, EURO Tax Glass data on the cost of used vehicles, and data on insurance costs from the Automobile Association (AA).

The Cambridge Econometrics’ study developed disaggregate mixed logit models using bespoke data collected by the British Marketing and Research Bureau (BMRB). Vehicle attribute data was obtained from JATO Dynamics. Both purchase cost and variable cost, eg fuel, elasticities were available, broken down by VED band.

In both the ETFEC and Cambridge Econometrics studies, elasticity tests are presented which allow shifting between different make-model combinations with a given VED band. These are not directly applicable for the current study because the primary response to an increase in purchase cost within a given VED band is to switch to similar vehicles within the same band.

The EFTEC study presents, in Chapter 6, the results of demand elasticity and demand forecasting tests where the purchase price of all vehicles in a given CO_2 band are increased, and forecasting tests where the fixed costs of all vehicles in a given CO_2 band are increased. These tests give the direct and cross-elasticities required for this study to give insight into the cost sensitivity by VED band.

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1 EFTEC (2008) Demand for cars and their attributes, prepared for the Department for Transport, London.

2 Cambridge Econometrics (2008) Demand for cars and their attributes, Prepared for the Department for Transport, London.

The purchase cost elasticities are presented in Table 2.1, and the variable cost elasticities are presented in Table 2.2. To read the table, imagine a uniform increase in vehicle cost is applied to all vehicles in the band shown by the columns, the rows then show the change in demand across all the bands. The direct elasticities are highlighted in bold, and are negative as the impact of cost increases in a given band is reductions in the number of vehicles owned in that band.

Table 1: Vehicle Purchase Cost Elasticities by CO_2 Emissions Band (Source: Cambridge Econometrics (2008), Table 6.17)

		CO_2 Emissions Band										
		101-120	121-135	136-150	151-158	159-165	166-175	176-185	186-205	206-225	226-299	>=300
CO_2 Emissions Band	101-120	**-2.882**	0.346	1.648	0.314	0.228	0.201	0.105	0.043	0.039	0.039	0.003
	121-135	0.289	**-3.066**	1.262	0.341	0.385	0.362	0.206	0.123	0.090	0.062	0.007
	136-150	0.345	0.316	**-2.054**	0.303	0.305	0.333	0.172	0.114	0.087	0.075	0.006
	151-158	0.227	0.295	1.041	**-3.154**	0.509	0.444	0.256	0.158	0.112	0.088	0.009
	159-165	0.127	0.261	0.812	0.398	**-2.918**	0.524	0.319	0.205	0.159	0.133	0.011
	166-175	0.098	0.216	0.782	0.306	0.464	**-2.929**	0.333	0.300	0.230	0.194	0.014
	176-185	0.082	0.198	0.652	0.286	0.454	0.536	**-3.173**	0.342	0.298	0.289	0.020
	186-205	0.044	0.148	0.535	0.219	0.364	0.601	0.426	**-3.163**	0.396	0.422	0.028
	206-225	0.042	0.120	0.453	0.174	0.316	0.517	0.417	0.447	**-3.190**	0.594	0.041
	226-299	0.042	0.083	0.393	0.137	0.264	0.437	0.405	0.476	0.592	**-3.057**	0.054
	>=300	0.037	0.121	0.403	0.187	0.293	0.438	0.390	0.430	0.566	0.745	**-3.928**
	Households in sample	20	28	83	37	52	52	76	70	126	156	35

It can be seen that, in general, the cross-elasticities are higher for nearer CO_2 bands. For example, for the 101-120 band, the highest cross-elasticity is observed for the 136-150 band (though not for the closest 121-135 band), and for the >= 300 band the highest cross-elasticity is observed for the

226-299 band. This pattern appears plausible in explaining how consumers trade between vehicle types.

Table 2: Operating (Variable) Cost Elasticities by CO_2 Emissions Band (Source: Cambridge Econometrics (2008), Table 6.20)

CO_2 Emissions Band		CO_2 Emissions Band										
		101-120	121-135	136-150	151-158	159-165	166-175	176-185	186-205	206-225	226-299	>=300
	101-120	**-4.190**	0.512	2.463	0.464	0.337	0.295	0.153	0.066	0.055	0.055	0.004
	121-135	0.422	**-4.419**	1.868	0.492	0.561	0.525	0.297	0.179	0.128	0.088	0.009
	136-150	0.503	0.463	**-2.997**	0.441	0.445	0.486	0.249	0.166	0.123	0.106	0.008
	151-158	0.329	0.424	1.526	**-4.518**	0.737	0.643	0.369	0.231	0.160	0.125	0.012
	159-165	0.183	0.368	1.172	0.561	**-4.230**	0.758	0.458	0.298	0.227	0.188	0.015
	166-175	0.142	0.305	1.129	0.433	0.669	**-4.245**	0.479	0.437	0.329	0.276	0.020
	176-185	0.119	0.279	0.935	0.402	0.655	0.770	**-4.562**	0.497	0.425	0.409	0.029
	186-205	0.063	0.206	0.764	0.309	0.523	0.869	0.610	**-4.590**	0.565	0.596	0.039
	206-225	0.060	0.168	0.648	0.245	0.453	0.746	0.596	0.644	**-4.549**	0.837	0.058
	226-299	0.060	0.117	0.563	0.192	0.378	0.630	0.577	0.684	0.884	**-4.324**	0.076
	>=300	0.053	0.168	0.575	0.263	0.421	0.630	0.557	0.618	0.805	1.047	**-5.523**
	Households in sample	20	28	83	37	52	52	76	70	126	156	35

The pattern in the variable cost elasticities is similar to that observed in the purchase cost elasticities, with cross-elasticities typically higher for neighbouring CO_2 bands relative to CO_2 bands further apart.

Driver Vehicle Licensing Agency Data on Vehicle Type Distribution in London

The London Vehicle Analysis Tool (LVAT) is a bespoke piece of software for processing and analysing data from Automatic Number Plate Recognition (ANPR) cameras around the capital. As well as the spatial and temporal reference that the camera provides, the data is matched to a quarterly update from the Driver and Vehicle Licensing Agency (DVLA) on registered vehicles in the

UK, considerably enriching the data's potential. It has been in operation since 2007, with 2008 considered as the start year at which data became robust for detailed policy analysis.

LVAT compiles data on a daily, weekly or monthly basis under the following headings:

- capture date;
- vehicle (body) type;
- age profile;
- euro class;
- CO_2 Vehicle Excise Duty (VED) band;
- discount status (for congestion charge);
- engine capacity;
- fuel type;
- postcode sector;
- camera site;
- time period of day; and
- number of days seen (if weekly or monthly).

Although the main segmentation process only made use of VED band, postcode sector, and fuel type, the other headings offered strengths in terms of understanding the distribution of missing or erroneous data. For example, Euro Class was taken as a proxy for age and thus acted as both a filter and additional segmentation variable for older vehicles (pre-2002).

Data can be extracted for both the base DVLA database and the ANPR camera data. Examination of the relative merits and plausibility of each revealed that whilst the former was more desirable, as it provided universal coverage of the private vehicle fleet, it carried with it an implausible distribution across VED band segments. By contrast, the ANPR data revealed a distribution which was broadly comparable to UK wide data available from The Society of Motor Manufacturers and Traders[3] (SMMT).

There were four major considerations with the use of ANPR data from the underlying DVLA database, namely the:

- sample will be prone to errors or missing data in the extract provided by the DVLA. Previous studies have identified this as a considerable problem[4];
- spatial detail at which the DVLA data is aggregated. In order to maintain anonymity, data is aggregated to a postcode sector level resulting in 19 zones/postcode areas;
- lack of VED band information for many cars in Euro Classes I and II (pre 2002); and
- spatial coverage of the ANPR cameras, and the fact that only using vehicles observed by cameras might lead to an unrepresentative sample of the average kilometres across the entire private vehicle fleet.

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[3] Please see http://www.smmt.co.uk/ for further details.

[4] Note that this is irrespective of LVAT itself.

Missing or erroneous data could only be accounted for by contrasting the distribution from LVAT with that obtained from the SMMT, recognising that London is likely to have different characteristics in vehicle type choice to the UK as a whole. These proved to be broadly comparable and the assumption was therefore made that any effect was evenly distributed across the preferred segmentation and would therefore have no effect on market shares.

The different spatial definition provided through LVAT was accounted for prior to model estimation by:

- creating a new GIS layer for the postcode sectors;
- assigning the proportions available from LVAT at postcode area to each individual UK CodePoint (individual postcode) which falls within it;
- once split to the point level, using a weighted average (by the number of domestic delivery points at each point) summation to produce the shares at any coarser level; and
- estimating shares (proportions and absolutes) at an LSOA level and summing to produce borough shares for model estimation.

Pre Euro Class II (introduced in 2002) cars in the LVAT extract were allocated to a VED band by:

- estimating the change in CO_2 emissions for each vehicle (body) type, termed M1 Class, from 1997 to 2009 using SMMT data;
- using additional data for M1 Class, pre-2002, vehicles from ANPR sightings, via LVAT, to estimate shares in 1997 (as an average age for pre-2002 vehicles);
- using the 1997 CO_2 estimate for each M1 class allocate a proportion to each A-G VED bands. For example, 147.5g/km of CO_2 sits on the border of bands C and D and the proportions were assumed to be 50% to each; and
- re-aggregating the resulting shares to the VED band A-G distribution by fuel type.

Pre and post 2002 cars were then aggregated. Figure 2.1 presents the base market shares estimated from the LVAT extract and original total cars in London estimate available from LONCOME, grouped by the pre-2010 VED bands (A to G) for petrol and diesel vehicles only. Figure 2.2 presents the corresponding data with the introduction of fuel type and the data for alternative fuel types.

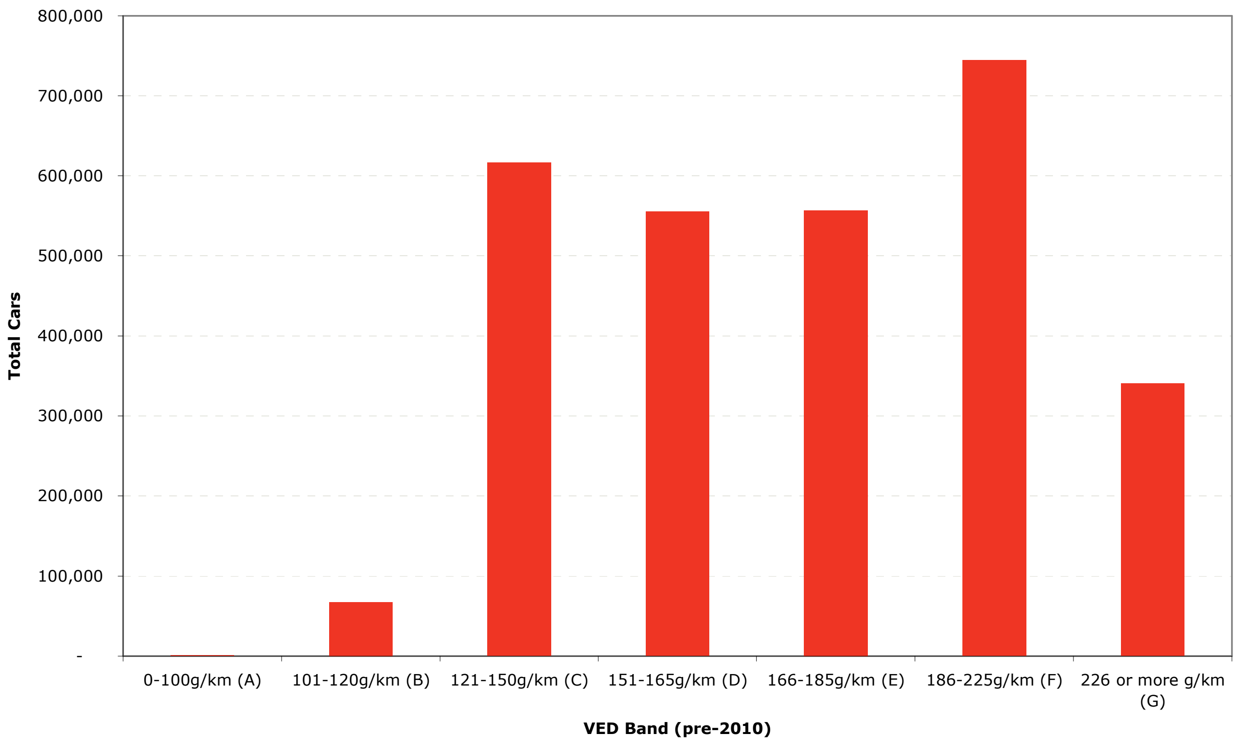

Figure 2.1: 2008 Distribution of Registered Petrol and Diesel London Cars by VED Band (Source: LVAT/DVLA 2011)

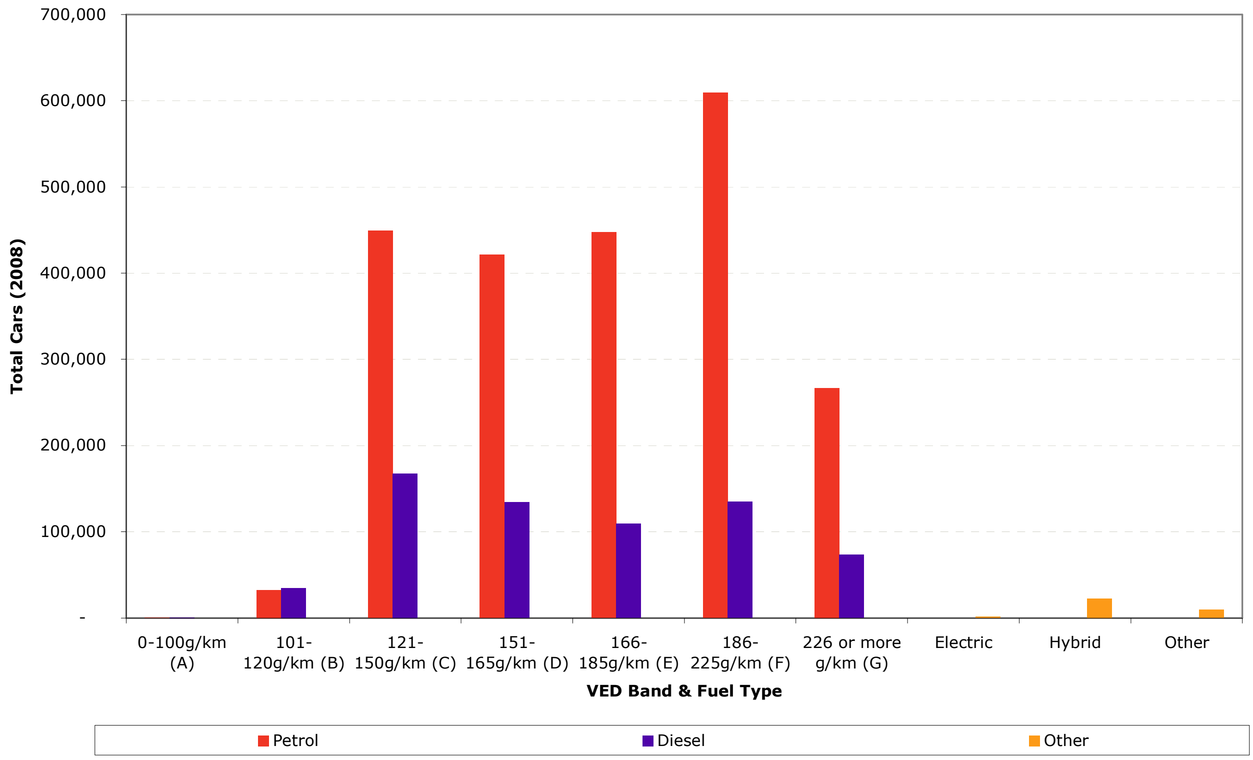

Figure 2.2: 2008 Distribution of Registered London Cars by VED Band and/or Fuel Type (Source: LVAT/DVLA 2011)

It is recognised that the base market shares are still vulnerable to possible bias from the use of ANPR data due to:

- locations of the ANPR cameras are not optimised to capture a representative sample of vehicle kilometres by car in London, but are sited to fit requirements of the Central London Congestion Charging and Low Emission Zone (LEZ) schemes; and
- camera data being more likely to capture vehicles with high use/kms.

Market Share 'Forecasts' for Low Emission Vehicles

MVA Consultancy reported on 'Developing Parking Standards for Electric Vehicle Charge Points' for Transport for London (TfL) in July 2010. This report included forecasts for uptake of Electric Vehicle (EV) and Petrol Hybrid Electric Vehicle (PHEV) take-up in the capital to 2025. These initial forecasts, and the studies which underpinned them, were revisited to attempt to identify new inputs for the car ownership model extension.

The evidence base for incorporating low emission vehicle[5] uptake is overwhelmingly skewed towards EVs and PHEVs, potentially excluding technologies such as hydrogen and biofuel; however, whilst this undoubtedly raises some issues in relation to objectively assessing the market for all alternative forms of propulsion, it was felt that a nested structure, separating low emission and internal combustion at its highest level, and associated composite utilities will go some way to addressing this drawback.

Factors driving take-up of electric vehicles and petrol hybrid electric vehicles

A report[6] for the Department for Transport (DfT) and, the then, Department of Business Enterprise and Regulatory Reform (BERR), suggested that in the medium term, EV sales will be very heavily dependent on the strength of Government incentives [to influence both demand and supply]. An important disclaimer by the authors, that this study aimed partly to address, is given at the start of the report, stating that scenarios do not represent forecasts or estimates of the future, but are rather built to understand the potential magnitude of electrical energy required over time, ie a supply [as opposed to demand] side perspective. It is clear across the available evidence that the focus to date has been on how vehicle production and infrastructure provision can match to stated ambitions and targets, rather than how consumers will actually make their choice of vehicle type. Whilst the factors that are assumed to drive that choice are relatively consistent across the studies, there is little documentation on assumed sensitivities to alternative scenarios within each.

Both the AEA study[7] for the Committee on Climate Change (CCC), and the original Arup/Cenex study for the DfT and BERR, did most to consider the consumer perspective by identifying alternative future scenarios. The former set out four main scenarios:

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[5] The definition of what constitutes 'low emission' is by no means clear cut; however, for the purposes of this study we have taken it to exclude all petrol and diesel fuelled vehicles, regardless of fuel efficiency, but include hybrids and all other 'clean' technologies that minimise emissions at the point of use.

[6] Ultra Low Carbon Vehicles in the UK'. Department for Transport (DfT) and the Department for Business, Enterprise, and Regulatory Reform (BERR), London UK, 2009.

[7] Market outlook to 2022 for battery electric vehicles and plug-in hybrid electric vehicles. AEA Group, report to the Committee on Climate Change (CCC), UK, 2009.

- (1) Severe Protracted Recession, with a scaling back of EV production by manufacturers to match estimated demand (note income scenarios will, at least in part, capture this effect for the total car market in the main model);
- (2) Green Recovery, there is Governmental support for the necessary infrastructure, but no direct support to reduce the price of low emission vehicles;
- (3) Green Recovery + Price Support, with further Governmental support to reduce the purchase cost of low emission vehicles; and
- (4) Green Recovery + Price Support + Strong Competition from Advanced Diesel, representing a market response by certain manufacturers to the support for low emission vehicles, eg by providing more fuel efficient vehicles thus making these comparatively more attractive.

These scenarios in effect capture four separate factors which will determine market share for low emission vehicles, namely:

- purchase cost;
- operating or 'out of pocket' cost, eg fuel, parking, and congestion charge;
- infrastructure provision; and
- competition from more fuel efficient conventionally fuelled vehicles.

In addition, the AEA study recognises that the size (length x width) of available vehicles will typically differ between alternative fuel types. The DfT and BERR study also describes four scenarios, namely:

- (A) 'Business as Usual', with assumptions regarding congestion charging, charging point distribution, parking provision, VED, fuel costs, and parity in 'whole life' costs;
- (B) 'Mid Range' scenario, with more optimistic assumptions on Governmental support for environmental measures bringing forward parity, with respect to petrol/diesel, in the 'whole life' costs to 2015, and appropriate manufacturer response to match the demand side impacts of these;
- (C) 'Uptake Scenario – High Range', with parity also brought forward to 2015, with further increases in infrastructure and decreases in cost in the longer term; and
- (D) 'Uptake Scenario – Extreme Range', with parity again brought forward to 2015, but with the effect of nearly all new cars from 2025 being low emission.

Assumptions around cost(s) are captured in composite utilities for each nest of a hierarchical vehicle type choice structure, with interactions with the highest level (of total cars) to capture any influences which result in a decrease in average purchase or operating costs. Infrastructure provision will, effectively, place a cap on the demand for low emission vehicles. In the case of EV and PHEV this is the number of charging points (both private and public). Allowing the user of the model to specify provision, and having an internal algorithm to translate that to a change in the constant for the particular fuel type, represented the most transparent means of incorporating infrastructure issues. The effect on the 'constant' for the particular fuel type needs to isolate this effect from:

- vehicle technology, including aspects such as the effective range per charge (currently a maximum of around 100 miles) available on current batteries and the length of time needed to re-charge the battery, plus other aspects related to vehicle size and performance where EVs are currently sub-optimal; and

- levels of knowledge, awareness, and acceptance amongst the car buying market, with low emission vehicles sitting at a very early stage on the typical s-shaped product take-up curve.

The first of these considerations is a constraint on EV and PHEV take-up, compared to petrol/diesel, which we would expect to be increasingly removed in the future due to technological advances by manufacturers; although we may also assume that, possibly in London in particular, some of the current attributes of EVs are beneficial, eg vehicle size when parking. A similar assumption could be made regarding knowledge and awareness, although it will also be dependent on general demand raising awareness of the alternative. The evidence to separate the three effects is likely to be minimal. A degree of judgement, which can then be varied by the model user, was required to incorporate suitable parameters/constants for vehicle type forecasting.

In summary, factors deemed to drive the take-up of low emission vehicles include:

- purchase cost;
- operating costs, including fuel efficiency changes, fuel itself, parking (production and attraction trip-ends), congestion charge;
- mid-term variable costs, eg Vehicle Excise Duty (VED) differentials;
- infrastructure provision;
- vehicle attributes, eg size (length x width) and performance (eg acceleration);
- vehicle technology, affecting range of journeys; and
- market knowledge and awareness.

Low Emission Vehicle Market Shares – Summary of Forecasting Implications

The formulation to include low emission vehicles in the vehicle type choice model required parameters for the sensitivity of vehicle type choice to:

- purchase cost;
- 'out-of-pocket' operating costs;
- mid-term variable costs;
- attributes which may differ in the low emission vehicle market relative to the petrol/diesel market, size (length x width) and performance, recognising that these may offer benefits and disbenefits to different segments of the population; and
- three sub-components of the 'constant' for electric vehicles, which allow for judgment to determine their relative magnitudes at given moments in time. These sub-components are infrastructure provision, and market knowledge/awareness. All three effects are captured within the model through a set of 'constants' which the user specifies.

In addition, the formulation incorporates assumed trends in:

- alternative fuel costs, eg the marginal cost of electricity, hydrogen and biofuel;
- purchase costs, eg batteries for EVs and hybrids;

- VED;
- exemptions on parking and the congestion charge (if these attributes are included in the vehicle type model);
- market equivalency years for knowledge/awareness and technology (proxied by range); and
- charging points, comprising their quantum and distribution.

The possible effect of the economic downturn, highlighted in AEA's scenario(s) for the Committee on Climate Change (CCC), are captured at the top most level of the forecast through its effect on disposable household incomes and total cars owned/CpA, but the constants should also reflect the possible concurrent effect of scaled back production of new vehicle types.

In order to perform 'calibration' of the model to existing industry forecasts, it was possible, by using the same assumptions and/or datasets that underpin the TfL/GLA base market share forecasts, to estimate the constant for the remaining unmeasured factors affecting low emission vehicle take-up at different moments in time, the sub-components of which were discussed above. Once these constants have been estimated, exclusive of any real term changes in monetary costs, forecasts can revert to alternative versions of these other datasets and assumptions.

A composite cost across the petrol/diesel and low emission nests is fed into the top level forecasts as part of an iterative process, ensuring that if 'whole life' cycle costs for low emission vehicles begin to fall below those for petrol/diesel vehicles, then there is an appropriate consumer response.

3 Car Ownership Model for London Vehicle Type Choice Functional Form

This section describes how the existing model of CpA was developed to include forecasts of vehicle type and use which are consistent with the previous estimation(s).

The existing model adopted a logit, or logistic, formulation, which can be represented by:

$$CpA_i = \frac{S}{1 + \exp(\alpha_i + \beta X_i)} \tag{1}$$

where:

CpA_i = Cars per Adult (CpA) in zone i

S = the saturation level

X_i = a vector of explanatory variables for a given area (or zone) i

α_i, β are coefficients to be estimated, with the former being a spatially specific adjustment to ensure forecast matches observed in a given zone i.

Market Segmentation

The level of vehicle type detail was driven largely by data availability, but it also sought to take account of potential policy variation according to vehicle type (which could relate to, for example, congestion charge levels, parking charges, etc) and impact (fuel consumption, emissions, etc). Any vehicle type attributes which cannot be expected to change over the forecasting period do not need to be included, since they will automatically be proxied by the base market shares.

From DVLA data the following information can be obtained:

- make and model;
- year of manufacture and year of first registration;
- body type (13 categories);
- engine size and CO_2 VED band (by old, pre-2010, VED bands)
- Euro Class;
- fuel type; and
- transmission type.

However, the data obtained through the LVAT extract is more limited in nature than that available through the DVLA database; in particular, years of manufacture and registration are grouped to three years and Euro Class designation therefore offers just as reasonable an indicator of age. In addition, the Eftec study revealed many problems with the Make/Model data, which can hinder the process of linking the information to other databases. Thus, while in principle the make/model/year of manufacture should identify various performance characteristics etc, in practice this will be more limited.

The other principal source for vehicle type segmentation variables is that provided by 'The Society of Motor Manufacturers and Traders Limited' (http://www.smmt.co.uk/home.cfm), which groups by:

- Mini;
- Supermini;
- Lower Medium;
- Upper Medium;
- Executive;
- Luxury;
- Sports,
- 4x4; and
- Multi-Purpose Vehicle (MPV).

The LTDS, which was a key source of usage data, classifies vehicles according to fuel type (unleaded petrol, leaded/lead replacement petrol, diesel, Liquid Petroleum Gas (LPG), electricity, petrol/oil mixture, dual fuel (electricity + combustion), biofuel, and 'other'), engine size (cc) and age (presumably year of first registration).

It should be noted that within each SMMT segment there will be considerable variation in global (CO_2) and local (PMs, NO_X, and CO) emission levels. Both of these issues are of critical importance from a policy perspective. For the former, differentiation by conventional fuel type is less important, as petrol and diesel have comparable levels (CO_2 g/km) between similar makes and models[8]; clearly low emission vehicles are of relevance though. However, diesel engines typically perform worse for local emissions than petrol engines for similar makes and models, particularly for PMs and NO_X (although they are typically better for CO). For practical purposes, especially with respect to emissions forecasting, segmentation by VED bands and fuel type offered a more transparent framework than those based around makes and models.

Marrying the policy perspective with the level of detail within the data suggested a segmentation that splits vehicle types by:

- fuel type (initially 'conventional' and low emission);
- low emission vehicles by electric, hybrid and 'other'; and
- conventional by petrol and diesel, and then by broad VED bands, using the seven bands currently available in the LVAT extract, as opposed to the 13 band (A-M) current structure for VED.

This provided 17 vehicle type segments: petrol by 7 VED bands, diesel by 7 VED bands, electric, hybrid and other.

Vehicle Type Model Structure

The chosen structure of the vehicle type model was 'nested' or 'hierarchical', attempting to capture different degrees of similarity (correlation), or indeed dissimilarity, between potential choices by partitioning them into 'sets'. It is important to note that partitioning does not necessarily occur for behavioural reasons but rather to comply with the underlying conditions imposed on the unobserved effects for each indirect utility expression (the utility term for a vehicle type accounting for the nested structure); intuition can be valuable in specifying nested structures because differences in the variances of unobserved effects are often linked to unobserved attributes which are common to a particular nest or subset of alternatives. The discussion on the make-up of the constant for low emission vehicles is of relevance here. Nested/hierarchical structures provide a means of identifying different behavioural relationships between choices at each level of the nest and to test the consistency of the structure in relation to Random Utility Maximisation (RUM) theory.

The hierarchical structure for the vehicle type model is illustrated in Figure 3.1. This structure aims to explicitly account for the similarity, on a significant number of vehicle type attributes, by fuel type, whilst recognising that the low market shares for low emission vehicles will be a reflection of similar issues related to knowledge, awareness, technology, infrastructure provision etc (and thus their viability as a choice).

[8] Note that high performance vehicles tend to be petrol though, such that the average for the current private vehicle fleet will be higher for petrol than diesel as it will be skewed towards the higher end performance (plus any effect from older cars tending to be petrol fuelled and having higher emissions per km etc).

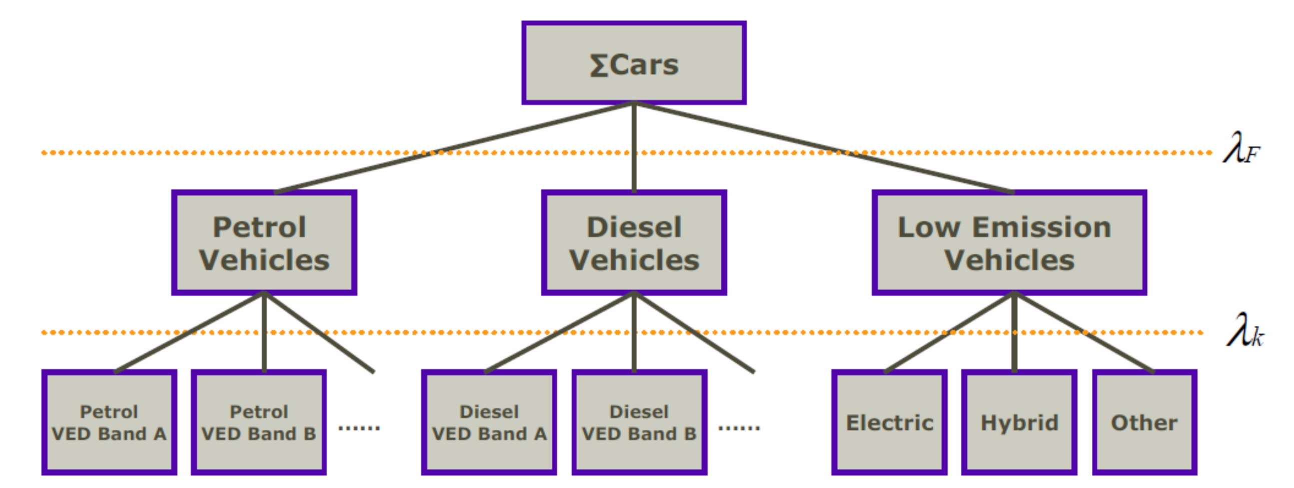

Figure 3.1: Hierarchical Structure for Vehicle Type Choice in the Car Ownership Model for London

The scale factor for the highest choice set of CpA/total cars (λ_{Cars}) is set equal to 1.0, ie normalised, with the scale parameters, λ_V and λ_k, for the vehicle types in each partition calibrated to reproduce the sensitivities presented in Section **Error! Reference source not found.**.

Estimating the Market Share for Low Emission Vehicles

Future trends in monetary cost attributes for low emission vehicles can be readily specified (provided suitably reputable forecasts exist); however, the trend in less readily measurable attributes is more difficult to specify with the same degree of certainty. Considering first the attributes that currently differentiate them (particularly electric vehicles) from conventionally fuelled vehicles, then two alternative futures were hypothesised for how they will develop, namely they may:

- become more similar to conventionally bodied (and fuelled) vehicles; and
- remain small (in dimensions) as now, because of advantages in their manoeuvrability and physical size (which we assume are benefits).

In an absolute type choice model, model estimation would most likely lead to a large negative ASC on low emission vehicles, irrespective of the current differences in levels for the monetary cost attributes. With technological advancements, it could be imagined that this, initially large negative, value could converge to zero over time. In addition to the rate of convergence to an 'equivalency year', where low emission vehicles could be considered comparable to conventionally fuelled vehicles in key decision-making attributes, which may include asymptotic terms, there is also a question on the shape of the trend, ie we may expect the convergence to be gradual at first, increase in the medium term, and then reduce again as convergence is approached. Such considerations were balanced with the knowledge and awareness of the alternative amongst consumers, although it is worth noting we might expect this to also follow an s-shaped market penetration curve as just described.

In this study, a pivot-point model has been developed that predicts changes in low emission vehicles relative to an observed 2008 base point. As discussed in Section 2, the type choice model incorporates parameters for acceleration and range, and so as the performance characteristics of low emission vehicles improves, these will have an impact on the model forecasts through the assumed values for acceleration and range for future years.

As highlighted in Section 2, it will be possible to identify trends in the market shares for low emission vehicles from supply side led studies, which can be translated into ASCs that are additional to acceleration and range effects, and that have a zero value in the 2008 base. As a starting point for the user of the model, we will specify 'central', 'low' and 'high' trends in the ASCs, informed by the existing supplier-led assumptions about market penetration, infrastructure provision etc, ensuring that the latest evidence is incorporated wherever feasible. In addition, backed up by references to the available evidence, we will allow the user to vary the shape of this trend and its rate/equivalency year using a limited set of inputs. These ASCs also take account of:

- improvements in vehicle technology, as engines become more efficient/cleaner; and
- background trends in vehicle type choices, as reflected in SMMT style segmentation.

Functional Form of Vehicle Type Model

Since the existing model produced an estimate of average CpA at an appropriate level of spatial detail, the more detailed model relating to vehicle type was also developed at a personal (as opposed to household) level. This is compatible with the notion of the probability of an adult owning a particular type of car.

The only variables in the previous model of CpA which related specifically to cars (as opposed to other demographic, socio-economic or geographic characteristics) are the four cost variables for an, average, 'generic car':

- purchase cost ($\overline{P}$);
- resale cost ($\overline{R}$);
- mid-term variable (fixed) cost(s), eg MOT, VED, and insurance ($\overline{F}$); and
- operating cost(s) – ($\overline{O}$).

All of these variables may also be considered essential for vehicle type and use models as we would expect divergent trends across the issues of interest, eg fuel type, vehicle size etc. The coefficients for these variables were taken from the Eftec study[9] for the DfT, with elasticities from therein converted to the logistic formulation ensuring that each carried the correct sensitivity at 'average' values[10]. The most straightforward way to deal with these variables in the extended model was to maintain the relativities of the coefficients, but to allow for the additional scaling factors, λ s, which are analogous to (inverse) logsum parameters.

Functional Form – Vehicle Type Choice

By embedding the vehicle type share model below the model of CpA, with an implied scaling parameter of 1/λ (where λ ≥ 1 in a logit formulation), changes in the composite utility, relative to the base, were conveyed to the car ownership model. The implication is that the average values of $\overline{P}$, $\overline{R}$, $\overline{F}$, and $\overline{O}$ should no longer be input to the model of CpA for forecasting purposes, but

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[9] The demand for cars and their attributes. Economics for the Environment Consultancy Ltd (Eftec), report for the Department for Transport (DfT), London UK, 2009.

[10] By the nature of the logistic, s-shaped, formulation, different areas and values will have different sensitivities based on their position on the curve.

that the base year averages should have the scaled incremental utility added to them from changes in the individual vehicle type segments below them. For a change in policy variables, new shares will be predicted, essentially "pivoted" on the base shares.

Considering the vector of explanatory variables X_i and the geographically-specific constant α_i in Equation (1), then under the new formulation this becomes:

$$X_i^0 = \alpha_i + \gamma_P \bar{P}^0 + \gamma_R \bar{R}^0 + \gamma_F \bar{F}^0 + \gamma_O \bar{O}^0 + \varpi Z_i^0 \tag{2}$$

where:

ϖZ_i^0 = the set of non-cost variables (Z_i^0) and associated suite of parameters ϖ from the original model in the base year, denoted by the superscript 0

γ_P, γ_R, γ_F, and γ_O are the coefficients to monetary costs from the original model

α_i = a constant capturing all other unobserved effects or 'errors' in the model for a given area (or zone) i

For forecast purposes, the variables P, R, F and O in the model were maintained at their base year, average car, levels and had an incremental, composite, utility applied in future years, based on changes for the individual vehicle types (j).

The base vehicle type (j) market shares, denoted by q_j, are then compatible with the formulation:

$$q_j^0 = f_j\left(U_j^0\right) \tag{3}$$

where:

U_j^0 = the utility for vehicle type j at the base year 0

The vehicle type share model also yields a composite utility (logsum) of U^{*0}. Changes in monetary costs, and other vehicle type attributes, are input to the lower level vehicle type share model, leading to revised market shares, and a new composite utility for the future year, t, U^{*t}.

Ignoring for the moment the spatial level, denoted by i, then to reproduce the base year (0) market shares within a single level logit model, the utility for an individual vehicle type must satisfy:

$$U_j^0 = \ln q_j + K \tag{4}$$

where:

K = the composite utility or logsum, and is the same for all vehicle types j

Comparable, though slightly more complicated, formulae apply to the nested/hierarchical logit model which was deployed.

Leaving aside the final definition of vehicle type and segmentation, and, in particular, possible correlations between them (ie allowance for different degrees of "similarity"), then the utility function for vehicle type j in future year t is given by:

$$U_j^t = ASC_j^t + \lambda_V\left(\gamma_P P_j + \gamma_R R_j + \gamma_F F_j + \gamma_O O_j + \phi Y_j^t\right) + \eta_j \qquad (5)$$

where:

ASC_j^t = a 'constant' for vehicle type i which is adjustable in future years (t) and set to zero in the base year

Y_j^t = a vector of non-monetary cost explanatory variables for vehicle type j (see Section **Error! Reference source not found.**), eg vehicle size, performance/range etc

η_j = an error term

λ_V = a scaling parameter to be applied across all segments/vehicle types

ϕ s are a suite of parameters to be either specified or estimated (see Section **Error! Reference source not found.**).

The corresponding base year utility for an average car can be written as:

$$\overline{U} = \gamma_P \overline{P} + \gamma_R \overline{R} + \gamma_F \overline{F} + \gamma_O \overline{O} \qquad (6)$$

The corresponding proportions for each vehicle type, j, can be given by:

$$P_j = f_j(U_j) \qquad (7)$$

Following Bates (1987[11]), we need not produce separate inputs for each cost variable and ASC for each segment in the base year, but instead use an incremental approach where the base shares are included in the formulation (capturing all variation in explanatory variables), such that in future year t the change in utility for a given nest (fuel type, containing all VED bands) k is given by:

$$\Delta U_k^t = \frac{1}{\lambda_V} * Log\left[\sum_{jk}(P_{jk}^0 * Exp\left(\lambda_V * \left(U_{jk}^t - \overline{U}^0\right)\right)) \Big/ \sum_{jk} P_{jk}^0\right] \qquad (8)$$

where:

[11] Bates, J. 1987. *The Nested Incremental Logit Model: Theory and Application to Modal Choice.*

ΔU_k^t = the utility difference or change for a nest k in a future year t

λ_V = a scaling parameter to be applied across all segments/vehicle types

P_{jk}^0 = the base year market share for a given vehicle type j in a given nest k

U_{jk}^t = the utility for a given vehicle type j in a future year t in a given nest k

$\overline{U}^0$ = the base year utility for an average car

The shares for each nest/fuel type in future year t can then be given by:

$$P_k^t = Exp(\lambda_k * \Delta U_k^t) * P_k^0 \Big/ \sum_k Exp(\lambda_F * \Delta U_k^t) * P_k^0 \qquad (9)$$

where:

λ_k = a second scaling parameter applicable across all nests/fuel types k

Forecasting

For a particular scenario in a given future year, which we have denoted with the superscript '*t*', we therefore have:

- from the vehicle type model, U_j^t for each vehicle type, and hence the vehicle type proportions, and a composite utility U^{*t}; and
- for estimates of Cars per Adult, $CpA^t = \alpha + \gamma_p \bar{P}^0 + \gamma_R \bar{R} + \gamma_F \bar{F} + \gamma \bar{O} + \varpi Z^t + (U^{*t} - U^{*0})/\lambda_{Cars}$.

The effect is to add the difference in the composite utilities between the future and base years $(U^{*t} - U^{*0})$, divided by the scaling factor λ (set to one), to the base formulation of explanatory variables X^0.

Calibration of Scaling Parameters

Calibration was undertaken at the geographic level (i) of borough using the base market shares from LVAT. The parameters to be calibrated in order to give the 'correct' behavioural response, from the base year market share data were therefore the λs (λ_V and λ_k), as all other variation by vehicle type j and geographical level i was captured in the base market shares P_{ij}. Following a manual grid search, values of 1.7 and 1.5 were found to give the closest behavioural response to the Cambridge Econometrics study elasticities (see Table 1 and Table 2) for λ_V and λ_k respectively.

Differentiating Usage by Type of Vehicle and Residential Location

In relation to vehicle use, ideally one would wish to incorporate the expected use of the car within the car ownership/type model, either with ownership conditional on use, or by means of a joint model. However, since this was beyond the scope of the current contract, we applied average use values at the appropriate level of detail (eg spatial, i, by vehicle type, j), and allow independently for responses based on elasticities with respect to cost, pivoting around the base values. The value for the usage elasticity for cost changes is -0.3.

As prices change by vehicle type, the model predicts a different type ownership pattern. From this, externalities associated with car use, such as congestion and (global and local) emissions, can be estimated with reference to average vehicle-km figures from the LTDS and behavioural response parameters to changes in explanatory variables.

4 Summary of Trends and Policy Tests

Trends

The 'core' scenario within the model is sensitive to a series of assumptions around both exogenous, eg population and disposable household income, and endogenous, eg monetary costs and background trends in vehicle type choices, influences on demand.

Monetary Costs

Trends in purchase, resale, insurance, fuel duty, and MOT are assumed constant in real terms across the forecasting period in the 'core' scenario, ie equivalent to an indexed value of 100 (where 2008 = 100). The trend in VAT takes account of the permanent uplift from 17.5% to 20% in January 2011[12], and is held constant thereafter.

Fuel costs were sourced from the Department for Energy and Climate Change[13] (DECC); Figure 4.1 presents the assumed real term trend for each fuel type (2008 = 100.0). 'Hybrid' fuel costs are assumed to follow the trend for 'petrol', as the electric motor is powered during petrol operation, and deployed at low speeds. Costs per km are therefore lower, but the trend in resource cost per km will be the same.

[12] http://www.hmrc.gov.uk/vat/forms-rates/rates/rate-increase.htm

[13] Please see http://www.decc.gov.uk/en/content/cms/statistics/publications/trends/trends.aspx for further information.

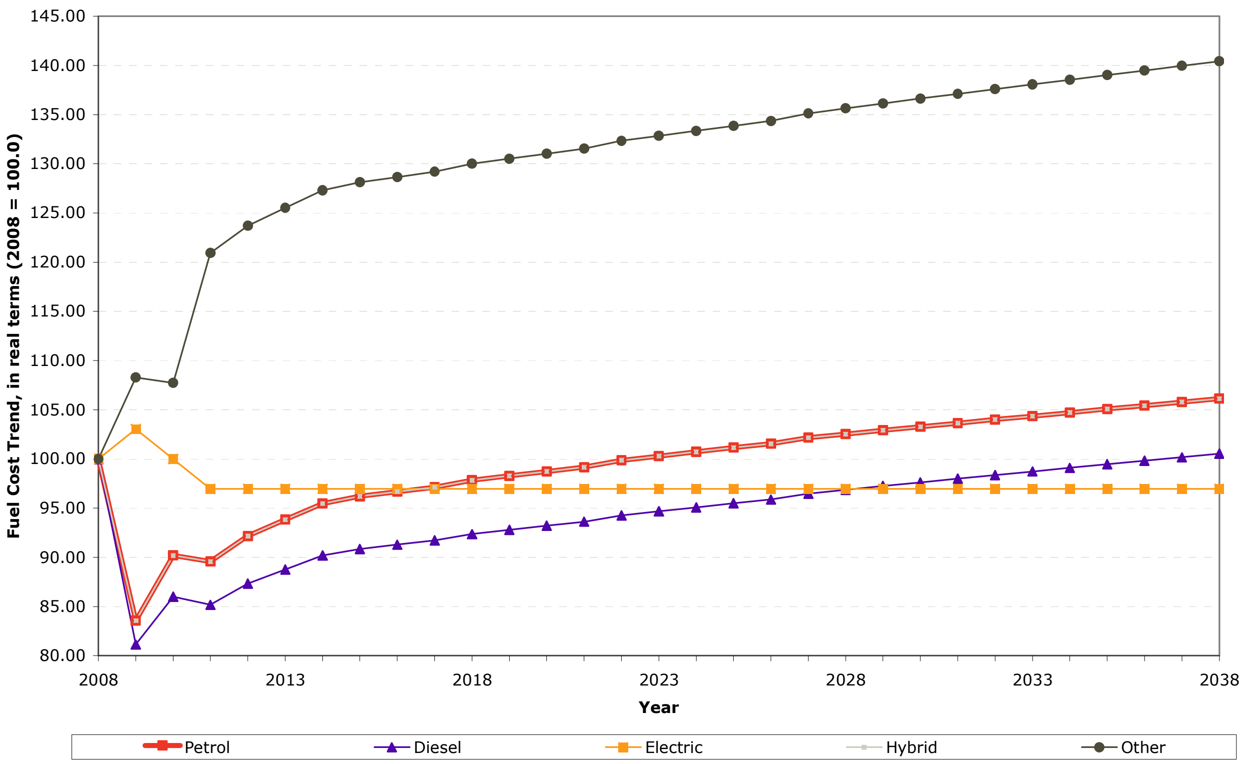

Figure 4.1: LONCOME Core Scenario Assumed Trend in Fuel Costs (Source: Department for Energy and Climate Change, 2010)

Figure 4.2 illustrates the trend in VED per annum from 2008-2011[14], in real terms, for each segment in LONCOME. Whilst the indexed values for Band A (petrol and diesel) and electric are presented as 100.0 in each year, the nominal value is zero as no vehicle tax is paid on these segments. Post-2011 the assumed trend is held constant, ie no change following those announced in January 2011.

[14] Please see http://www.direct.gov.uk/en/Motoring/OwningAVehicle/HowToTaxYourVehicle/DG_10012524 for the current VED rates.

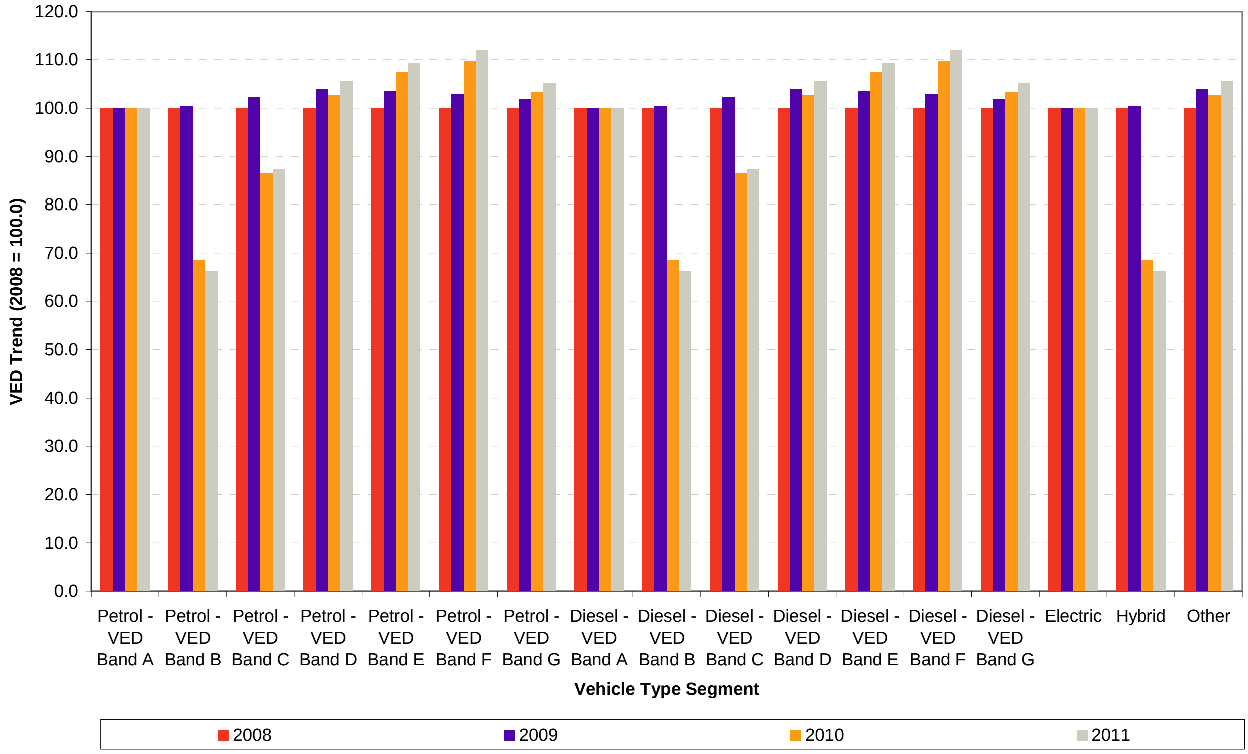

Figure 4.2: LONCOME Core Scenario Assumed Trend in VED Costs (Source: Directgov.uk, 2011)

Alternative Specific Constants by VED Band and 'Other' Fuel Types

Figure 4.3 illustrates the assumed trend in market shares for each vehicle type segment which underpin the Alternative Specific Constants (ASCs) in the 'core' scenario. These market shares are for newly purchased vehicles and are translated into an impact on the entire private vehicle fleet through an assumed ten-year cycle for fleet renewal. 2009 saw some significant volatility in the market shares due to factors such as the scrappage scheme.

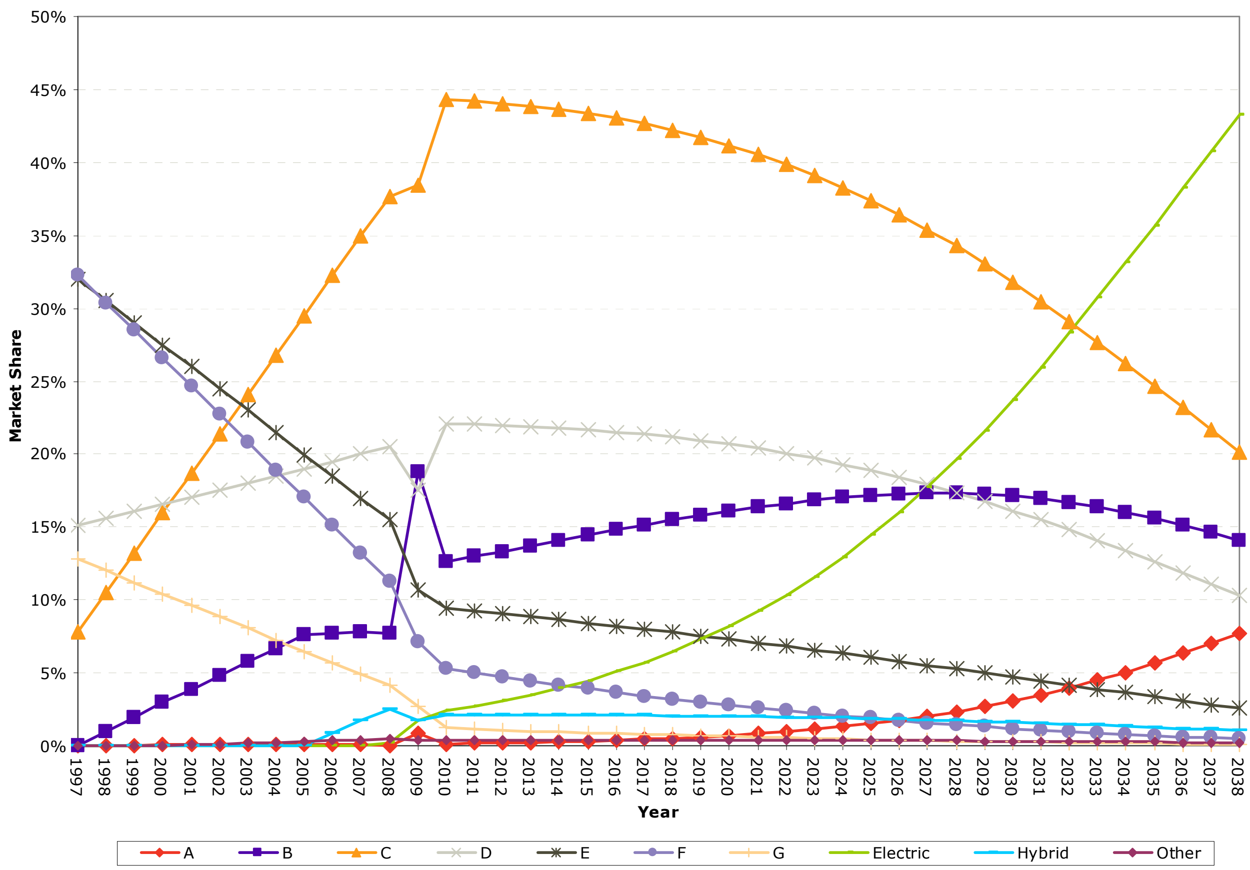

Figure 4.3: Assumed Trend in Market Shares without Change in Monetary Costs

Trends in Acceleration and Range for Electric Vehicles

Acceleration and range were identified as two key, non-monetary, barriers to increased take-up of electric vehicles. Parameters were sourced during the literature review to reflect the sensitivity of the market to these, and have been accompanied by assumed trends in these variables from motor industry literature and announcements. Table 4.1 presents these trends up to 2015, by which time it is assumed that electric vehicles will be broadly comparable to an average car for these variables.

Table 4.1: Core Scenario Assumed Trend in Acceleration and Range of Electric Vehicles

Year	Acceleration (0 to 60mph in seconds)	Range (kilometres)
2008	15	80
2009	14	120
2010	14	160
2011	13	230
2012	12	300
2013	11	333
2014	11	366
2015	10	400

Policy Testing

In order to ensure validity and plausibility of forecasts, a series of policy, and beta, tests were specified, including:

- aggregate sensitivity tests to ensure the model was still capable of producing plausible estimates of total cars and CpA following changes across all vehicles or fuel types; and
- variations in the magnitude of change by segment.

Aggregate Sensitivity Tests

Table 4.2 presents a summary of policy tests for 2021. The model retains the correct sensitivity to changes in key explanatory variables for total car ownership.

Table 4.2: Summary of Aggregate Policy Tests for 2021

Test	Total Cars	Change from Core	Implied Elasticity
Core Scenario	3,348,778	N/A	N/A
5% Purchase cost increase on all segments	3,276,086	-2.2%	-0.45
30% Purchase cost increase on all segments	2,919,899	-12.8%	-0.52
5% increase in Adult Population	3,516,217	5.0%	1.00
High Income scenario	3,412,951	1.9%	0.19
Low Income scenario	3,289,607	-1.8%	0.16
High investment PTAL scenario	3,324,706	-0.7%	N/A

Vehicle Type and Use Segment Tests

The following scenarios were tested to ensure the model was giving plausible behavioural responses for vehicle type choices and subsequent usage estimates:

- [A] petrol and diesel resource costs increases at 5% above the core scenario;
- [B] duty on petrol and diesel fuel increases at 5% above the core scenario;
- [C] resource cost and duty on petrol and diesel both increase at 5% above the core scenario;
- [D] a Vehicle Excise Duty (VED) strategy is employed, reducing rates for Bands A, B and C, and electric vehicles, and increasing them for other bands;
- [E] duty on petrol and diesel fuel increases at 5% above the core scenario, combined with the VED strategy;
- [F] improvement in the acceleration trend for electric vehicles above the core scenario;
- [G] improvement in the range trend for electric vehicles above the core scenario;
- [H] purchase costs decrease for electric (50%), hybrid (25%), Band A (20%), Band B (10%), and Band C (5%); and
- [J] 20% reduction in the resource cost of electricity and a 5% increase for all other fuel types.

In a similar manner to Table 4.2, Table 4.3 summarises their impact at the aggregate level in 2021.

Table 4.3: Summary of 2021 Vehicle Type and Use Segmentation Tests

Test	Total Cars	Change from Core
Core	3,348,778	N/A
[A] petrol and diesel resource costs increases at 5% above the core scenario	3,317,902	-0.92%
[B] duty on petrol and diesel fuel increases at 5% above the core scenario	3,300,679	-1.44%
[C] resource cost and duty on petrol and diesel both increase at 5% above the core scenario	3,269,936	-2.35%
[D] a Vehicle Excise Duty (VED) strategy is employed, reducing rates for Bands B (-20%), C (-10%), and D (-5%), and increasing them for other bands, E (5%), F (10%), and G (20%)	3,306,481	-1.26%
[E] duty on petrol and diesel fuel increases at 5% above the core scenario, combined with the VED strategy	3,258,587	-2.69%
[F] improvement in the acceleration trend for electric vehicles above the core scenario (by 50%)	3,348,823	0.00%
[G] improvement in the range trend for electric vehicles above the core scenario (by 10%)	3,348,785	0.00%
[H] purchase costs decrease for electric (50%), hybrid (25%), Band A (20%), Band B (10%), and Band C (5%);	3,379,625	-0.92%
[J] 20% reduction in the resource cost of electricity and a 5% increase for all other fuel types	3,317,436	-0.94%

Tables 4.4 and 4.5 present the corresponding market shares by vehicle type and the percentage change from the core scenario.

Table 4.4: Summary of Change in 2021 Vehicle Type Market Shares from Core Scenario

	Scenario								
Vehicle Type	**A**	**B**	**C**	**D**	**E**	**F**	**G**	**H**	**J**
VED Band A Petrol	-1%	-2%	-3%	-10%	-12%	0%	0%	20%	-2%
VED Band B Petrol	-1%	-2%	-3%	8%	6%	0%	0%	4%	-2%
VED Band C Petrol	-1%	-2%	-3%	1%	0%	0%	0%	-2%	-2%
VED Band D Petrol	-1%	-2%	-3%	-3%	-5%	0%	0%	-9%	-2%
VED Band E Petrol	-1%	-2%	-3%	-17%	-18%	0%	0%	-9%	-2%
VED Band F Petrol	-1%	-2%	-3%	-29%	-30%	0%	0%	-9%	-2%
VED Band G Petrol	-1%	-2%	-3%	-37%	-39%	0%	0%	-10%	-2%
VED Band A Diesel	-1%	-2%	-3%	-10%	-12%	0%	0%	19%	-2%
VED Band B Diesel	-1%	-2%	-3%	8%	6%	0%	0%	4%	-1%
VED Band C Diesel	-1%	-2%	-3%	1%	-1%	0%	0%	-3%	-1%
VED Band D Diesel	-1%	-2%	-3%	-4%	-5%	0%	0%	-9%	-1%
VED Band E Diesel	-1%	-2%	-3%	-17%	-18%	0%	0%	-9%	-1%
VED Band F Diesel	-1%	-2%	-3%	-29%	-30%	0%	0%	-10%	-2%
VED Band G Diesel	-1%	-2%	-3%	-38%	-39%	0%	0%	-10%	-2%
Electric	1%	2%	3%	-9%	-7%	6%	1%	65%	12%
Hybrid	1%	2%	4%	-9%	-7%	-1%	0%	19%	-3%
Other	1%	2%	4%	-9%	-7%	-1%	0%	-14%	-4%

5 Conclusions

Understanding of the market for low emission vehicles, particularly those propelled by new fuel technologies, has been weak. Previous studies have been overwhelmingly based on supply side assumptions, akin to 'if you build enough vehicles and supply the infrastructure' people will but them. This study reversed that assumption and took a more traditional 'bottom up' approach to forecasting market shares, centred on the factors which will influence consumer choices. In summary:

- a major shift to low emission vehicles in the private fleet is likely to be essential to any aspirations for transport to deliver significant reductions to its carbon footprint and meet desired environmental outcomes;
- different segmentation approaches have been adopted to vehicle type, particularly make/model combinations. However, the number of alternatives can soon 'explode, and often these are difficult to relate to policy levels, eg for emission levels;
- the final segmentation deployed in London split petrol and diesel, for localised emission calculations, and further by VED band giving a direct link to emissions, and included electric, hybrid and 'other' as non-conventionally fuelled low emission vehicle alternatives;
- a number of non-cost attributes were identified as pertinent to the choice of non fossil fuel alternatives and appropriate sensitivities sourced. These included range and acceleration for electric vehicles;
- outside of the top level forecast of total cars and cars per adult, which includes a variety of economic and demographic factors, the vehicle type model was also made sensitive to:
  - purchase and resale costs, including the possibility for grants for low emission vehicles
  - operating costs, eg the cost of diesel versus petrol versus electric
  - mid-term variables, particularly Vehicle Excise Duty
  - acceleration and range of electric vehicles
  - constants capturing three distinct effects: market awareness and background trends in consumer preferences, continuing manufacturer technological advances (at least partly in response to legislation), infrastructure provision, and operational characteristics not otherwise considered (eg size, number of doors etc)
- a review of past studies on the market for low emission vehicles, and in particular the potential for new fuel technologies, have been overwhelmingly supply side focussed on either political targets/aspirations, anticipated production levels, or infrastructure needs (eg number and location of charging points);
- a 'nested' or hierarchical structure was deployed to capture the different degrees of similarity between fuel types; and
- policy testing has proved that the model has plausible sensitivities to key levers, and the extent to which changes in these can influences consumers towards purchasing more environmentally friendly alternatives.