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Estimating the longevity of electric vehicles: What do 300 million MOT test results tell us?

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Abstract
Knowing how long the average vehicle remains roadworthy before being scrapped is a crucial input into life cycle assessment (LCA) and total cost of ownership (TCO) studies of different vehicle powertrains. This study leverages a dataset of over 300 million MOT records from 2005 to 2022 for over 30 million vehicles registered in Great Britain and uses parametric survival analysis with interval-censored data to examine the longevity of various powertrains under real usage conditions. Our findings reveal that (plugin) hybrid electric vehicles have the longest expected longevity in terms of years and mileage, both of which are about 50% higher than those of an average fleet vehicle. Battery electric vehicles (BEVs), while initially showing lower reliability, have benefited from rapid technological improvements such that the latest BEVs in our sample match the lifespan of petrol vehicles despite being used more intensively. Longevity is also impacted by engine size, location, and make of vehicle. The results provide parameter estimates that can be used to update TCO and LCA models and also shed light on EV diffusion patterns, fleet replacement strategies, and end-of-life treatment planning, including the increasingly important debate around EV battery recycling and second-life options.

Keywords: electric vehicles, survival analysis, total cost of ownership, life cycle assessment

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1 Introduction

The electric vehicle revolution is widely considered as a way to decarbonize the transport sector and to reduce air pollution from tailpipe emissions (Carey, 2023). However, there are numerous economic, infrastructural, and behavioural challenges before full electrification can be achieved and explains why hybrid (HEV) and plug-in hybrid electric vehicles (PHEVs) are still seen as important transition products towards a fully battery electric vehicle (BEVs) future.

To estimate the true environmental benefits of HEVs, PHEVs, and BEVs (hereafter referred to collectively as EVs) and how they compare with existing petrol and diesel vehicles with internal combustion engines (ICEVs), one needs to consider the entire life cycle of a vehicle and how any benefits are spread across the life cycle. For example, the production of a typical EV is relatively resource-intensive and is estimated to require six times the critical mineral inputs of a conventional vehicle (IEA, 2022). According to Hill et al. (2023), the environmental impact from the production of a BEV is 50% higher than an ICEV. The key argument in favour of an EV transition is that this additional initial environmental cost is more than offset during the use phase if the vehicle has a long enough useful life. For example, HEVs and PHEVs consume less fuel than pure internal combustion engine vehicles (ICEVs) to travel the same distance (Zahabi et al., 2014) while PHEVs and BEVs offer the opportunity to entirely replace fossil fuels with low-carbon electricity generated from renewable sources such as solar, wind, tidal, and geothermal energy.[1] Assuming that travel demand remains constant, the current energy mix in Europe means that the longer an EV stays on the road, the greater the environmental benefits (Hill et al., 2023).

The economic justification for the introduction of policies to promote wider EV adoption is also strengthened with a a prolonged EV use phase. Putting the environmental impact of production aside, although typically EVs have a higher upfront cost than traditional ICEVs (currently around \$12,000 according to Baik et al. (2019)), owners tend to benefit from lower operating costs due to the typically lower cost of electricity compared to gasoline and lower maintenance costs. Argonne National Laboratory (Burnham et al., 2021) estimate maintenance costs to be \$0.06 per mile for BEVs and \$0.10 per mile for ICEVs (with HEV and PHEVs somewhere in the middle). Overall costs may also be reduced further as a result of various policies that improve the financial incentives for purchasing an EV which range from direct subsidies to reduced or waived road taxes, parking fees, and tolls (Zhang et al., 2016; Jenn et al., 2018; Clinton and Steinberg, 2019).

[1] Charging PHEVs and BEVs with electricity from coal or gas-fired plants could reduce the environmental benefits. The overall impact can then be varied and spatially dispersed (Holland et al., 2016, 2019).

The purpose of this paper is to use the compulsory roadworthiness tests (MOT tests) in Great Britain to estimate the longevity of different powertrains with particular emphasis on providing estimates for a range of newer EV vehicles. More specifically, statistical analysis on over 300 million compulsory MOT tests allows us to provide timely information on the survival rates of different vehicles including the newer EV powertrains. The advantage of using MOT data is twofold. First, as MOT tests are legally required for almost every vehicle on the road, the dataset is comprehensive and representative of the actual vehicle fleet. As such, analysing MOT data provides a more holistic view of the fate of the fleet at the end of its life rather than estimates derived from studies that use the small set of vehicles included in commercial survey datasets. Second, anonymised MOT test data are freely available and provide a source of information that is transparent and regularly updated. Unlike other free administrative vehicle registration datasets, anonymised MOT test data includes mileage (odometer reading), cylinder capacity, colour, and test location. Mileage data and the date of first registration are particularly important as they allow us to estimate longevity in terms of both years and distance travelled.

Having an accurate measure of the longevity of different powertrains, whether the lifetime is measured in time or distance, matters because it is an important input into Life Cycle Assessment (LCA) and Total Cost of Ownership (TCO) models that compare the environmental impact and economic cost between EVs and ICEVs.[2] LCA and TCO estimates are also important for forecasting automotive sales and planning for end-of-life vehicle treatment. However, knowledge about the longevity of EVs remains relatively limited and what research does exist tends to assume a common functional unit for all EVs and is often extrapolated from an estimate based on the evidence from ICEVs, despite the increasing variety of EVs available on the market, differences in their usage patterns, and large technological differences between EVs and ICEVs.

There are two relevant previous studies in this regard. First, Hutchinson et al. (2014) assumes a common life mileage of 130,000 to compare the emission and cost of 44 hybrid and plug-in hybrid vehicle models in the US. Second, a recent study commissioned by the UK Department of Transport to assess the environmental impact of a wide range of hybrid and electric vehicles in the UK assumes that all vehicles stay on the road for 200,000 km (around 124,000 miles) over 14 years (Ricardo Energy, 2021). However, the estimates from Hutchinson et al. (2014) and Ricardo Energy (2021) are based on restrictive assumptions due to the difficulty of accessing data on

[2]LCA is a methodology used to assess the environmental impacts of a product or process throughout its entire life cycle and includes raw material extraction, production, use, and disposal. See Hellweg and Milà i Canals (2014) for a review and Verma et al. (2022) for an LCA comparison of EVs and ICEVs. TCO is an estimation of the expenses associated with buying, deploying, using and retiring a product. Recent TCO studies include Hagman et al. (2016); Letmathe and Suares (2017); Palmer et al. (2018).

scrappage rates by powertrain (Chatterton et al., 2015). While there is scrappage data that can provide insights into the longevity of some already scrapped vehicles, this data does not help with estimating future scrappage rates of newer vehicle models, particularly those that use newer technology stacks. The lack of data is most keenly felt for EVs where the main source of information on lifespan is based on lab-based data, expert judgement, and educated guesses (Weymar and Finkbeiner, 2016). It is this gap in knowledge that we attempt to fill in this study.

A concern one might have using MOT test data to determine a vehicle's lifespan is that the dataset does not provide the exact date when a vehicle retires. In order to classify a vehicle as no longer on British roads, extra steps need to be taken. In statistical terms, our dataset includes two types of censored data. Right censored data consists of vehicles that have attended a recent MOT test, providing information about the 'survival' of the vehicle up to that point and interval censored data that includes vehicles that have missed a recent MOT test, indicating that they may have been retired at some point between the previous MOT test and the expected but missing MOT test. To address these censoring issues we employ a parametric regression model with a Weibull distribution, commonly employed to model the survival of vehicles in a fleet.[3]

To briefly summarise our results, findings suggest that there are a variety of observable factors that can predict the lifespan of vehicles, such as the intensity of use, engine size, colour, location, and make. However, the magnitude of the impact of each factor depends on the type of powertrain. Simulations indicate that a good approximation for the lifespan of a typical vehicle in the fleet is 138,000 miles. (P)HEVs exhibit a 50% longer lifetime mileage, while BEVs have nearly doubled their lifespans and seen a sixfold mileage increase over the twelve-year period that our data covers. The latest average BEVs in our study are projected to survive for approximately 18.4 years. Remarkably, this lifespan is very similar to traditional petrol vehicles even when EVs are subjected to more intensive use, hence newer BEVs are expected to surpass their petrol counterparts in terms of overall lifetime mileage predicted to be 124,000 miles.

Our study relates to several strands of literature. Researchers have long been interested in modelling the scrappage and survival rates of petrol and diesel cars (Parks, 1977; Gilbert, 1992; Jong, 1996; Yamamoto et al., 2004; Rashidi and Mohammadian, 2011; Ghasri et al., 2018) as well as the impact of policies aimed at encouraging vehicle scrappage (Gruenspecht, 1982; Goulder et al., 2012; Jacobsen and van Benthem, 2015; Alberini et al., 2018; Li et al., 2022). The rise of electric vehicles has also

[3]Additional assumptions regarding the functional form significantly enhance computational efficiency, a crucial benefit given the unusually large size of the dataset for this type of non-linear estimation.

led to a growing interest in understanding the adoption and diffusion of these new powertrains (Hagman et al., 2016; Li et al., 2017; Palmer et al., 2018; Gillingham, 2022; Muehlegger and Rapson, 2023). To date, however, there has been limited research on estimating the longevity of newer powertrains at the fleet level. This study makes a unique contribution using the anonymised MOT test dataset which is increasingly being recognised as a valuable source of big data for addressing different management and socioeconomic issues (Chatterton et al., 2015; Heap and Talavera, 2019). To this end, we demonstrate how big data can be used to better support risk analysis (Cox and Lowrie, 2021) especially in the transport sector (Xie et al., 2017).

The paper is structured as follows. In Section 2, we provide background information on the electrification of vehicles in the UK. Section 3 describes the datasets and main variables used in the study. In Section 3 we outline our methodological approach. Section 4 presents and discusses the results of the analysis. Finally, in Section 5, we provide a conclusion and suggest areas for future research.

2 The Electrification of Vehicles in the UK

As economies transition from agriculture to manufacturing and then to service-based economies, the relationship between economic development and environmental degradation tends to follow a U-shape pattern. More precisely, after a turning point, advances in technology and increased environmental awareness slow and then reverse the damage to the environment. This is particularly evident in the UK, where, in recent years, decoupling has seen CO2 emissions decrease by 34.2% despite an increase in GDP of 70.7% (Agbugba et al., 2019). Largely as a result of deindustrialisation, the transport sector has become the largest emitter, accounting for 28% of end user greenhouse gas emissions (Department for Business, Energy & Industrial Strategy, 2022). Therefore, electrification of transport, particularly road transport, is expected to play a crucial role in further decarbonising the economy as vehicles powered by traditional fuels, such as high-emission petrol and diesel, are replaced with more modern and cleaner powertrains. However, the magnitude of the environmental benefits associated with electrification will depend on the power mix in the grid and how the contribution of electricity generation from renewables compares to that from burning fossil fuels.

Zero-emission options for the transport sector include BEVs and Fuel cell electric vehicles (FCEVs) (HM Government, 2018). Unlike traditional powertrains, both rely solely on an electric motor for propulsion and have no combustion engine. A BEV stores energy for its electric motor in a battery that can be recharged by plugging it into an electrical source, whereas an FCEV uses compressed hydrogen. The alternative to a BEV is a hybrid vehicle of which there are different types. Hybrid electric vehicles which combine electric batteries and a combustion engine are widely accepted as a transition option as long as full electrification remains economically and technically challenging. Some hybrids have an electric motor that supports the main engine, while other hybrids have an electric motor that can propel the vehicle for a limited range, typically 1-2 miles. A plug-in hybrid can be connected to an external power source to recharge its battery, and both its engine and electric motor can propel the vehicle independently. Finally, Range-Extended Electric Vehicles (REEVs) have an internal combustion engine that does not directly power the vehicle, but recharges the battery that propels the vehicle, much like a BEV. In this paper, we separate BEVs and ICEVs as well as a hybrid category that combines HEVs and PHEVs.[4]

As can be seen in Figure 1, by 2022 the UK stock of electric vehicles, including HEVs, exceeds 2.35 million and accounts for 8% of the entire fleet operating on British roads. Although HEVs still make up the majority of the EV stock, sales of BEVs outsold HEVs for the first time in 2021. From a global perspective, data in 2022 indicate that the UK has the fourth largest PHEV fleet (behind China, the USA, and Germany) and the six largest BEV fleet (behind China, the USA, Germany, France, and Norway) (IEA, 2023).[5] The UK law mandates that GHG emissions be reduced to net zero by 2050 leading the government to pledge to end the sale of new petrol and diesel cars and vans by 2030 although this date was pushed back to 2035 in 2023.

3 Data

3.1 Anonymised MOT Test Dataset

The main dataset used in this study is the anonymized MOT (Ministry of Transport) test database. The MOT test is mandatory for almost all passenger and light-goods vehicles, private buses, and motorbikes in the UK, as required by the Road Traffic Act

[4]We were unable to split the hybid category into HEVs and PHEVs due to data availability. We did not analyze FCEVs due to their small sample size, reflecting the lesser importance of these new technologies in the study period. REEVs could be either (P)HEVs or BEVs in our dataset although they are also very small in number and indistinguishable given the available data. REEVs, once considered a practical solution for addressing range anxiety, have become less appealing due to advances in battery technology and an expanded charging network.

[5]The combined market share of BEVs and PHEVs in the UK's vehicle fleet is 2.8% and ranks twelfth, trailing Norway, Iceland, Sweden, Denmark, the Netherlands, Finland, China, Belgium, Switzerland, Germany, and Austria.

of 1988.[6] In order to ensure vehicles are roadworthy and meet minimum environmental requirements an MOT test must be taken at least once a year for vehicles that are three years or older.[7] The dataset includes information about the time, location, and final outcome of the MOT test, but also a number of vehicle characteristics. MOT test outcomes were computerised in 2005.[8] We waited for the May 2023 update which covers tests from 2005 to 2022 and also includes test results for 2017 that were previously missing due to a recording error.

MOT tests are carried out primarily in private garages and by certain local authorities. The locations, known as Vehicle Testing Stations (VTS), are authorised and designated as appropriate by the Driver and Vehicle Standards Agency (DVSA). The VTS and their staff are subject to inspections by the DVSA to ensure that testing is conducted properly using approved equipment. Only specifically approved individuals are permitted to conduct tests, sign official test documents, and make database entries. Information about the vehicles, such as the mileage, colour, fuel type, and cylinder capacity, is entered or validated by the tester at the time of the test. Vehicles can be tracked using the Vehicle ID field which is based on the registration and Vehicle Identification Number (VIN). A high-level postcode region (the first 1-2 digits of the postcode of the VTS) is also provided, but to prevent identifying any individual VTS any region with fewer than five active sites is merged under the code ‘XX’.

3.2 Data Processing

The first stage was to download the MOT test data for each year between 2005 and 2022 from the UK’s Department for Transport (DfT) website and combine them into a single dataset. During the initial cleaning process, we removed a small number of records with missing vehicle IDs. As part of data quality control it was discovered that there were occasional discrepancies in the information provided for the same vehicle in different tests. As a result, rules were established to deal with these inconsistencies. For vehicle types and fuel, information from the most recent test was used, as the classification of vehicles tends to improve over time as testers become more familiar with the new technologies. Information provided in the first test was used for colour and first use time. For cylinder capacity, a majority rule was used and the odometer information and test date from the last test in the dataset was taken to calculate the average mileage of each vehicle throughout its lifetime. After resolving conflicts in the data, we removed all vehicles that had their first MOT test before it was two years old

[6]The anonymised MOT test dataset used in this study however only covers tests in Great Britain.

[7]For certain vehicles, such as taxis, ambulances, and some motor caravans and dual-purpose vehicles, the age at which the first test is required is one year.

[8]As MOT computerisation was not fully implemented across Great Britain until April 1, 2006, the dataset is not complete for tests conducted between January 1, 2005 and March 31, 2006.

since these vehicles were more likely to be taxis and ambulances. We only analysed Class 4 vehicles that mainly consist of passenger and light-good vehicles.

The final sample is restricted to four major powertrains: PE (Petrol), DI (Diesel), EL (Electric) or HY (Hybrid). While classifying petrol and diesel was straight-forward it was initially necessary to combine EL and HY together as there was no clear and consistent rule to differentiate them.[9] After an initial pooling we were then able to split the HY/EL pool into two samples. (1) Those with non-missing and non-zero cylinder capacity are put into (P)HEV sample as they all have an electric motor and an engine (suggested by the cylinder capacity information) so must be either an HEV or PHEV.[10] (2) Those with missing or zero cylinder capacity are more likely to have no engine, hence are classified as fully electric vehicles (BEVs). In those cases where vehicles with an engine failed to record an engine size during the MOT test, we consolidated the information on the make and models of these cars and kept only those recognised by DVSA as BEVs so we did not accidentally include other powertrains.[11] For petrol and diesel cars, we also excluded a negligible fraction of vehicles with missing or zero cylinder capacity. Petrol, diesel and (P)HEV were placed into one of three bins based on cylinder capacity: Under 1 litre, between 1-2 litres, and above 2 litres.[12]

Vehicle location was inferred from the postcode area of the first recorded MOT result. Postcodes were then mapped to 11 regions in Great Britain. Relatively aggregated regions were used to speed up the computational process, but also to allow for easier interpretation since these regions are sufficient to capture some aspects of natural driving patterns, weather conditions, and certain socioeconomic characteristics. Vehicles with postcodes coded as 'XX' were excluded. Location assumes that owners take the vehicle to a VTS relatively close to where they live.

Finally, a cohort variable was created to capture the vintage of the technology, determined by 'first use time' information. Each year is defined as a new cohort and our sample includes vehicles registered in 2005 to 2017. Cohorts after 2017 are excluded as we want to follow a vehicle for at least two MOT tests from the first test or roughly five years from the first use if the vehicle still exists. For sample size reasons, only makes with at least 1,000 unique vehicles for petrol, diesel, and (P)HEVs were included. For BEVs the threshold was lowered to 100 as this powertrain was still

[9] For example, there were a large number of Toyota Prius (a famous HEV model) and Mitsubishi Outlander (a famous PHEV model) classified or misclassified as either HY or EL.

[10] Unfortunately, the information provided in the MOT test data did not allow us to differentiate between PHEVs and HEVs so we call this sample (P)HEV.

[11] This means we exclude the small number of (P)HEV vehicles that did not have information on engine size of which the make and model was not recognised by DVSA as a BEV.

[12] We dropped the make 'LONDON TAXIS INT' and standardised major makes. For example, any vehicles with a make of BMW and other characters (i.e., additional details regarding the BMW model) were shortened to just BMW. Similar rules were applied to other makes. We also removed vehicles with unusually high mileages (exceeding 100 miles per day, as recorded at the last test.)

growing from a low base during this period but provides the main motivation for the study. In robustness checks, we also restricted the sample to BEV makes with at least 1,000 vehicles.

4 Methodology

4.1 The Heuristic of Death Definition

As the anonymised MOT dataset does not contain explicit information on the retirement of vehicles, we use the date of a vehicle attending a MOT test as evidence of its survival up to that point in time. As our data ends on 31st December 2022, we have a right-censoring issue. More precisely, for a vehicle that regularly attends MOT tests, we do not know the exact date of its death, but can conclude that it must have happened after the last MOT test is recorded in the data.

The use of MOT records allows us to infer that death occurred within a certain interval of time. A legal requirement is that if a vehicle is over three years old and still operating on British roads it must attend a MOT test every year. As our database contains all MOT tests taken within our sample period, if a vehicle is not recorded as having taken a test then it raises questions about the continued survival of that vehicle. If all vehicles strictly follow the legal requirement, we can confidently classify a vehicle as 'retired' if no test result is observed for a certain period (usually one year) after the last MOT test result recorded in the system. However, there are a number of practical reasons why a vehicle MOT test may be delayed so we allow for a 'buffer period' after the date the test should have been taken before concluding that a vehicle has been retired.[13]

Figure 2 gives an example of an MOT attendance pattern and illustrates the vehicle retirement assumptions used in the analysis. The top line shows that the vehicle regularly attended MOT tests at times t_1, t_2, and t_3. As the cutoff point of our data is the end of 2022, in this case, we do not observe the vehicle fate as the expected MOT t_4 has not yet happened and thus we conclude that the vehicle fails at some point after t_3, or in other words within the interval (t_3, ∞). On the other hand, the second line shows a vehicle that attended regular MOT tests up to t_2 but missed the MOT test that should have happened in t_3. To account for delays in taking the MOT in that

[13] For example, some drivers may be unaware of the importance of regular MOT testing or when their MOT is due, particularly if the vehicle recently changed ownership. The cost of an MOT test and any necessary repairs can also be a factor for some owners, particularly if they are facing financial difficulties. Vehicles that are not used frequently or have mechanical issues may be kept off the road until they can be repaired, which can also push back the eventual MOT date that is recorded in the system.

year, we allow a buffer Δt and search again. If we do not see the vehicle attending an MOT test within the designated buffer period we conclude that the vehicle no longer operates on British roads and classify it as retired between the interval $(t_2, t_3 + \Delta t)$.

[Figure 2 about here]

The selection of buffer time Δt is an empirical matter. One should note that if we allow for a long Δt, we may miss information on some real deaths of vehicles and lose useful information (i.e. classify an interval-censored death as a right-censored death). In contrast, if we assume too short a Δt, we may misclassify some surviving vehicles with late MOT attendance as retired. Our heuristic approach to selecting the appropriate buffer time is to analyse the distribution of the gaps between consecutive MOT test dates in our cleaned database (which includes more than 264 million tests). Our analysis suggests that around 50% of tests fall strictly within a year of the previous MOT test. Therefore, setting a buffer time to zero would classify any vehicle that misses an MOT test within one year as retired and would be too strong an assumption. In contrast, when we set the baseline buffer time to six months we capture 99% of tests since results show that less than 1% of tests occur more than six months after the original due date. As our baseline we classify as retired any vehicles that fail to attend a MOT test within 18 months of their last recorded test. As a sensitivity check our results also include estimates based on two alternative thresholds three months early and later than our 18 month baseline at 15 and 21 months.

4.2 Survival Analysis

To model the longevity of a vehicle we use survival analysis, a statistical technique that deals with the expected duration of time until an event occurs (Xie et al., 2019). More specifically, we are interested in a non-negative random variable T representing the lifetime of a vehicle, i.e., the duration until retirement (being scrapped or no longer driving on British roads). The distribution of T can be characterised by a survival function, $S(t) = P(T > t)$, which gives the probability that a vehicle will survive past a certain time t, and a hazard function, which specifies the probability for a vehicle to be scrapped in the next infinitely small period of time, Δt, conditional on the fact that the vehicle survives to time t.

$$h(t) = \lim_{\Delta t \to 0} \frac{P(t < T < t + \Delta t)}{\Delta t} = \frac{f(t)}{1 - F(t)} = \frac{f(t)}{S(t)} \tag{1}$$

In this equation, $f(t)$ and $F(t)$ are respectively the density function and the cumulative distribution function and the survival function can be expressed as $S(t) = 1 - F(t)$.

Adopting the proportional hazard function, a common approach to model hazard function $h(t)$, we assume that the hazard function of a vehicle is proportionate to a baseline hazard function, $h_{0k}(t)$, and is adjusted by a vector of time-invariant covariates, x_j, and a vector of coefficients, β_k. Here we use subscript k for the baseline hazard and vector of coefficients to highlight the fact that we model data separately for each powertrain: petrol, diesel, (P)HEVs and BEVs.

$$h_j(t) = h_{0k}(t) \exp(x_j \beta_k) \tag{2}$$

A range of covariates are included in the analysis: (1) we use the mileage rate recorded at the last test date as a proxy for the usage pattern of vehicles hypothesising that a vehicle driven more often will tend to retire earlier. (2) We include a cohort variable as a proxy for the technology available at the time the vehicle is first on the road. (3) For powertrains with internal combustion engines we include a vector of indicator variables for cylinder capacity to account for the variation in lifespan across engine sizes (1 litre and below, 1 - 2 litres, and 2 litres and above). (4) We include a vector to capture the colour of the vehicle as this choice may be correlated with some unobserved traits related to the choice of colour and the characteristics of drivers that may influence driving patterns (Lardelli-Claret et al. (2002); Newstead and D'Elia (2010) have suggested that the visibility of vehicles may affect their safety). (5) We use the region that the MOT test was taken to proxy regional driving and road conditions. (6) We include vehicle make dummies to explain the variation in vehicle popularity, demand for luxury or cost sensitivity and to capture the possibility that the make of a vehicle may also be correlated with driver characteristics.

Here, we do not explicitly model the impact of policies on the scrappage decisions of vehicle owners. Although there was a UK-wide, government-backed scrappage scheme introduced in the 2009 UK Budget (HM Treasury, 2009) it was terminated in March 2010 and did not target vehicles registered after 2005 (which is the first cohort included in our sample). More recent regional scrappage schemes, including Birmingham (2021), Bristol (2022), London (2023), and Scotland (2023) (Evans, Claire, 2023), had only a negligible effect on the vehicles in our dataset, given their proximity to the end of our study period (2022). As such, the longevity estimates are mainly driven by mechanical ageing, user behaviour, accidents, and market factors, rather than explicit policies.[14]

We further assume that the baseline hazard function is parametric and follows a Weibull distribution such that:

[14]Market factors may include various scrappage schemes run by car manufacturers, which typically offer financial incentives to trade in old vehicles for new.

$$h_j(t) = \rho_k t^{\rho_k - 1} \exp(x_j \beta_k) \quad (3)$$

The key implication of this parametric form is that the hazard rate is monotonic and increasing or decreasing over time, depending on whether the shape parameter ρ_k is greater or smaller than 1, respectively. If $\rho_k = 1$ the hazard rate is constant over time and the Weibull simplifies to an exponential distribution. The parameterization $\lambda_j = exp(x_j \beta_k)$, which is non-negative, time invariant, and covariate dependant, scales the baseline hazard rate up or down and is specific to each vehicle (Alberini et al., 2018). We use the Weibull proportional hazard model as the literature suggests that it is well-suited to model the retirement of vehicles with censored data (Rashidi and Mohammadian, 2011; Alberini et al., 2018). Again, the subscription k of ρ_k highlights the fact that our models permit distinct shape parameters across powertrains. Meanwhile, other observable covariates come into play, affecting the scale parameter of the Weibull distributions within each powertrain.

The vector of the coefficient β and the shape parameter ρ were estimated with maximum likelihood. As discussed above, the observations are either right-censored ($j \in RC$) or interval-censored ($j \in IC$). This means we do not observe t_j directly but instead have its lower bound t_{lj} (the last MOT test the vehicle attended) and the upper bound t_{uj} for some vehicles that missed a recent MOT test. The log-likelihood function for estimation can be written as follows:

$$\log L = \sum_{j \in RC} \log S_j(t_{lj}) + \sum_{j \in IC} \log[S_j(t_{lj}) - S_j(t_{uj})] \quad (4)$$

For each vehicle, and standard in the literature, we estimate the median lifetime as the point in time where the survival function reaches a value of 0.5:

$$\hat{l}_j = \{t : \hat{S}_j(t) = 0.5\} \quad (5)$$

The median lifetime mileage is then estimated as the product of the estimated median lifespan and the estimated mileage rate ($\hat{r}_j$) recorded in the last MOT test.

$$\hat{m}_j = \hat{l}_j \times \hat{r}_j \quad (6)$$

5 Results and Discussion

5.1 Summary Statistics

The data cleaning process outlined earlier gives us a final population of 30.2 million vehicles and over 264 million test results for the period 2005 to 2022 as summarised in Table 1. The majority of cars in our sample are petrol (15.1 million) or diesel (14.7 million) and a smaller number of (P)HEVs (371.3 thousand) and BEVs (41.7 thousand). This is consistent with official statistics trends in the UK where petrol and diesel cars still dominate the market despite growing EV sales (see Table VEH1103 (DfT and DVLA, 2023)).

Looking at the cohort variable (the year of first registration) shows that the the average petrol car in our sample is slightly older (2010.7) than the average diesel car (2011.3) but also highlights that in contrast the (P)HEVs and BEVs in our sample are much newer, with an average cohort years of 2013.7 and 2015.1, respectively. In terms of mileage, unsurprisingly, diesel cars which tend to be used for longer trips have an average mileage of 28.8 miles per day compared to petrol cars which average 18.2 miles per day. Newer powertrains are somewhere in between these figures, with (P)HEVs covering approximately 26.5 miles per day, closer to diesel, and BEVs averaging around 18.9 miles per day, closer to petrol vehicles.

Table 1 also shows that in terms of colour, black followed by silver, then blue are the most popular choices for petrol vehicles while black then silver and white were more popular among diesel vehicles. For (P)HEVs, white and black were the most popular while white dominated the BEV sample with more than 33% being this colour. In terms of cylinder capacity, a medium engine between 1.0-2.0 litres was the most popular across all powertrains (except engine-less BEVs). South East England had the largest population of petrol, diesel and BEVs, while London had the largest fleets of (P)HEVs. There was a wide range of makes for petrol and diesel vehicles in the dataset, each occupying a small share of the market. However, as the choice for electric vehicles is more limited (P)HEVs were concentrated in the makes of Toyota (53%) and Lexus (21%), while Nissan (49%), Tesla (19%) and Renault (17%) were the three largest BEV makes.

5.2 Survival Analysis Results

Table 2 presents the results of the survival analysis for four different powertrain categories: Petrol (columns 1-3), Diesel (columns 4-6), (P)HEV (columns 7-9) and BEV (columns 10-12). Table 2 shows three specifications for each powertrain using different definitions of retirement for buffers 15, 18, and 21 months. To enhance interpretability, we present the coefficients in the exponentiated form, capturing hazard ratios. Our preferred specification utilises the coefficients corresponding to the 18-month cut-off point. Overall, the choice of buffer makes little difference to the sign and significance of the results.

Weibull parameter

The regressions in Table 2 use a parametric approach and assume a Weibull distribution for the baseline hazard. Estimates of Weibull parameters ρ for all powertrains are consistently greater than 1, indicating that the failure rate increases over time. When comparing the 18 month estimates of the ρ parameter, the ageing process appears to be more aggressive for petrol vehicles (4.06) which is greater than diesel (3.41), (P)HEVs (2.50) and BEVs (2.45). These ρ parameters are presented in Figure 3. The suggestion is that the differences can be attributed to the fact that internal combustion engines have more moving parts and are subject to more wear and tear than electric motors, which are simpler in design. In addition, the use of hybrid technology in HEVs is thought to help reduce wear and tear on a vehicle's mechanical components and improves fuel efficiency, slowing the failure rate over time. Over this period the BEV and Petrol survival functions cross almost exactly at the 0.5 level.

Usage patterns

It is reassuring that for all powertrains, usage patterns appear to be an important predictor of lifespan (significant at the 0.1% level). An increase of 1 mile per day increases the hazard rate by 8.4% for petrol vehicles, 6.4% for diesel, 4.5% for (P)HEVs, and 2.5% for BEVs. This confirms the hypothesis that the more intensively a vehicle is driven, the shorter is its longevity but that BEVs appear to be responding well increased intensity of use.

Technological improvement and product variety

Perhaps the most interesting results concern the coefficients for the cohort variable, which are statistically significant and are consistently smaller than 1 for the petrol, diesel, and BEV powertrains. A value below 1 implies that over this time period each of these powertrains has benefited to some extent from technological improvements and that newer models from the same manufacturers exhibit improved reliability over time. Of these three powertrains, BEVs demonstrate the most rapid improvement, with a 12% lower hazard rate for the cohort born one year later.[15] In contrast, petrol and diesel vehicles show more modest decreases in hazard rates of 6.3% and 1.9%, respectively. One explanation for these results is that both petrol and diesel powertrains are established technologies that only experience marginal improvements year on year while BEV manufacturers are still on a rapid learning curve.

However, there is a noteworthy reversal in this trend for the (P)HEV powertrain. It is important to note that based on make and even model information from the dataset, we were unable to distinguish between plug-in hybrid cars (PHEVs) and traditional hybrid electric vehicles (HEVs).[16] The decrease in reliability observed in this case may be attributed to the increasing prevalence of PHEVs in recent vehicle vintages, which represent a newer and less mature technology. An analysis of Consumer Reports (2023) using 330,000 vehicles spanning model years from 2000 to 2023 reveals that the integration of internal combustion engines with electric drives in PHEVs introduces added complexity, resulting in 146% more owner-reported problems compared to traditional ICEVs. Conversely, HEVs exhibit a noteworthy 26% reduction in problems when compared to their conventional counterparts. In addition, as HEVs gain popularity, newer cohorts include more affordable HEV models from the same manufacturers, which could potentially offset some of the loss in reliability. The inclusion of new makes of HEV with less manufacturing experience is also a possible cause of the reduced reliability of more recent cohorts.

Engine size

In terms of engine size, smaller engines are associated with lower hazards for petrol vehicles. Compared to the mid-size engine (1.0-2.0 litres), which is the most popular, a small petrol engine is 3.7% less hazardous, while a large engine above 2.0 litres is

[15]As a robustness check, in Appendix Table A1, we raise the thresholds for selecting major BEV manufacturers from 100 to 1,000, aligning with the criteria applied to other incumbent fuels. Consequently, only BMW, Nissan, Renault and Tesla BEVs are included in the regressions. The hazard rates of BEVs exhibit a slower reduction over time, yet they continue to outpace other powertrains, declining at a rate of 8% per year.

[16]For example, the Toyota Prius, initially a flagship HEV, has seen the PHEV version of this model become more popular over time.

6% more hazardous. The results are reversed for diesel, where a big engine above 2.0 litres is 20.9% less hazardous than the mid-size version. The difference in engine size hazards between petrol and diesel vehicles can be attributed to the way in which the engines operate and the design of the vehicles. Petrol engines tend to be more performance-oriented, thus smaller engines may be designed to be more efficient and reliable to meet the demands of high-performance driving. Conversely, diesel engines are often used in larger vehicles, such as vans and SUVs, and are designed to be more durable and efficient at higher speeds and for longer journeys. Finally, a larger engine may be associated with the luxury end of the product range, although there is not enough information in this dataset to control for the body type of vehicles. (P)HEVs with small engines (under 1 litre) are particularly reliable and 51% less hazardous than the mid-range.

Fixed effects parameters

In addition to the previously mentioned variables, MOT data offer a diverse set of details on factors influencing the longevity of vehicles, such as colour, make, and location. These categorical variables are incorporated into our model as fixed effects (FEs). The Wald χ^2- tests reported in Table 2 confirm that each set of FEs collectively significantly correlates with vehicle longevity at the 5% levels and beyond.

When selecting a colour for their car, consumers may have a variety of reasons. Colour choice may reflect the personal characteristics, gender, or preferences of the owners, and this choice could depend on culture and context (Heap and Talavera, 2019). As a matter of fashion, vehicle colour tastes vary over time. Using data at our disposal, it appears that vehicle owners of newer cohorts appear to have switched from colours such as black, blue, and silver to white, grey and red. While there may be little reason to believe in a direct link between colour and mechanical reliability, Lardelli-Claret et al. (2002) suggest that light colours may be more visible and thus less subject to passive accidents. However, the relationship between colour and crash tendency could also be confounded by driver traits if safe driving habits are correlated with certain colour preferences (Newstead and D'Elia, 2010). After controlling for other variables, our analysis suggests that colour may correlate with lifespan, although the effect varies across powertrains. The results are shown in Figure 4.

For petrol, all other colours tend to be more reliable than black, but the colour effect is small in magnitude. This finding is consistent with research using Australian data that suggests black vehicles have the highest crash risk during the daytime (Newstead and D'Elia, 2010). White vehicles have a much lower hazard rate than others for the diesel and (P)HEV powertrains. The BEV sample however shows another trend. Bright and vibrant colours such as red and blue appear statistically more reliable than black with coefficients lower than other monochrome colours (silver, white, and grey). Our analysis also reveals a significant variation in vehicle lifespan based on manufacturer. Figure 5 shows the coefficient of hazard ratio for major makes exceeding 100 unique vehicles for BEVs and 1,000 unique cars for other powertrains, relative to the reference make (Mitsubishi). Accordingly, all else equal, relative to the reference group Mitsubishi, the make with the lowest hazard ratio for each powertrain is Honda (petrol), Skoda (diesel), Toyota ((P)HEV) and Tesla (BEV). We only report the top 30 performing makes for petrol and diesel and all makes for (P)HEVs and BEVs. Results for all makes of ICEVs included in our sample are available from the authors upon request.

There are also some survival differences based on location. An analysis of the fixed effects coefficients presented in Figure 6 reveals a north-south divide for vehicle reliability. For all four powertrains, Scotland and the northern regions of England (the north-west and north-east) have relatively high hazard ratio coefficients. This observed pattern may be attributed to the comparatively rugged terrain of these areas, relatively poor road conditions as well as the prevailing cold and wet weather conditions. In addition, the presence of more salt used on the roads that accelerates corrosion and rust, coupled with a higher incidence of potholes (due to worse weather and potentially fewer repairs), means vehicles driven in these regions could explain the lower survival rate. Notably, London stands out negatively for diesel vehicles. The hazard rate in this region is surpassed only by Scotland. The high congestion, low average speeds, and frequent stop-and-go traffic patterns characteristic of London may contribute to the increased wear and tear on diesel powertrains.

5.3 Vehicle longevity analysis

Having considered the other covariates we now estimate the lifespan of vehicles which is important for planning fleet replacement and the treatment for the end-of-life of vehicles (for example, organising scrapping and recycling facilities and hiring skilled labours for these facilities). From a life cycle perspective, the total distance travelled during a vehicles lifetime is perhaps more relevant for assessing the emissions of vehicles to provide more information on how driving an EV can help to 'save the planet'.

Table 3 presents the estimated median longevity and lifetime mileage for the entire fleet, broken down by powertrain, region, and the five most popular makes of vehicle. The 18-month specification remains our preferred estimates with the 15 and 21-month results being thought of as providing upper and lower bound estimates.

When all powertrains are combined, Panel A shows that the average vehicle lifetime is 17.9 years and travels 138,000 miles during this lifetime (columns 2 and 5). This lifetime mileage is close to the 130,000 miles/200,000 km widely used in the LCA literature (Hutchinson et al., 2014). A decrease in the buffer time for our assumption of a vehicle's death leads to a slightly reduced estimate. The 15-month specification suggests an average lifespan of 17.2 years and 134,000 miles travelled, while the 21-month buffer time suggests an average lifespan of 18 years and 140,000 miles travelled.

Our lifetime estimates are higher than the average age of a vehicle at scrappage, which was reported as 13.9 years in 2015 (SMMT, 2023). There are several reasons for this disparity. First, we provide lifetime estimates for almost every car that has ever joined the fleet, including a large number that are still in operation, rather than conditioning our estimates on those that have already been scrapped.[17] The selection bias means that scrapped cars would have a lower estimated lifetime than surviving cars. Second, our updated analysis focuses on cars registered between 2005 and 2017, with an average registration year of 2011. These are newer models compared to those scrapped in 2015, most of which were likely registered in the early 2000s. Technological advances over the last two decades have contributed to prolong lifespan, as indicated for the majority of vehicles in Table 2. Furthermore, these relatively newer vehicles in our samples are also less susceptible to the major scrappage scheme that was introduced in the 2009 United Kingdom Budget (HM Treasury, 2009) and concluded in March 2010, which incentivised the scrappage of cars over 10 years old.[18] Finally, reduced vehicle usage, as measured by miles travelled per year has also contributed to a longer overall lifetime.

Panel B reveals significant disparities in the lifespan and mileage performance across different powertrains. When comparing petrol and diesel, our baseline estimates indicate that a petrol vehicle survives for 1.9 more years, but covers 44,000 miles less compared to a diesel vehicle. Notably, (P)HEVs demonstrate substantially improved longevity and mileage performance and exhibit an average lifespan of 25 years and are expected to travel over 210,000 miles on average. Given that (P)HEVs outlast petrol vehicles by more than 50% in both longevity and mileage, their adoption promises sub-

[17]However, we do exclude cars that are scrapped early, for example, due to accidents within the first few years, preventing them from undergoing their first MOT test at three years old.

[18]Our analysis however does not model future national scrappage schemes.

stantial environmental benefits. The less technologically mature BEVs do not match the durability of (P)HEVs. Nevertheless, they still offer promising characteristics, with an average lifespan of 18.4 years, which approximates that of an average petrol vehicle. Importantly, BEVs surpass petrol cars in terms of lifetime mileage, covering 124,000 miles across their lifetime. Panel C provides a breakdown of lifetime mileage estimates for the leading five brands within each powertrain category. The top-performing BEV make is Tesla while the best performing (P)HEV is Toyota followed by Honda. Skoda and Audi lead the way for diesel and petrol, respectively. While intuitive these present some of the first such results on reliability for the new powertrains.

Finally, Panel D shows the discrepancies in expected durability of vehicles across regions. These average numbers are mainly driven by ICEVs, as their fleet size outweighs newer powertrains such as (P)HEVs and BEVs. According to the baseline specification, the average lifespan varies between 16.3 years (Scotland) and 18.9 years (South West England). Meanwhile, the average mileage varies between 128,000 miles (Scotland) and 145,000 miles (East England).

5.4 Trends in Vehicles Use and Longevity

The next stage is to look at the evolution of the patterns of vehicles use by different powertrains, their expected longevity and miles travelled throughout their life cycle using the predictions generated from our preferred 18-month specifications from Table 2 and odometer information recorded at the last test of each vehicle. The aggregate trend in Figure 7 captures several factors, including shifts in technology, driver preferences, behavior, and the range of products available in the market.

Panel A shows a fairly flat or even declining trend in vehicle usage, measured as miles travelled per year across the entire sample. This decline aligns with a broader reduction in travel demand, as reported in the National Travel Survey, which has a particularly pronounced impact on newer models (Department for Transport, 2023). A declining trend is seen most clearly for (P)HEVs, which could be impacted by the growing share of new plug-in versions. Conversely, BEVs show a substantial increase in usage, with mileage rates increasing from approximately 2,200 miles per year for the 2010 cohort to 7,800 miles per year for the 2017 cohort. This result can be attributed to the diffusion of BEVs into various segments, including those with higher travel demands, and improvements in technology that have reduced range anxiety. For example, the average range of a typical BEV has increased from 79 miles to 151 miles between 2010 and 2017 (IEA, 2023), making BEVs a viable and attractive choice for individuals who require longer travel distances on a regular basis.

Panel B aligns with our survival analysis results presented in Section 5.2, highlighting an increase in the expected median lifespan for all powertrains, except for (P)HEVs. Panel C reveals analogous trends in the expected median lifetime mileage. Despite the declining trends observed for (P)HEVs, this powertrain remains the most reliable option in 2017, whether evaluated in terms of expected years of service or the total distance travelled over their lifetime. Meanwhile, BEVs have experienced rapid improvements and surpassed the average fleet lifetime mileage in 2017.

6 Conclusions

Technological advances, supportive policies, and increasing concern for the environment have driven the shift from traditional internal combustion engines towards cleaner powertrains, paving the way towards a net-zero carbon future. To effectively plan for fleet replacement and properly handle retired vehicles in an environmentally friendly manner, a better understanding of vehicle longevity is critical. In light of the shortage of accessible detailed data on vehicle retirement, we propose the use of compulsory MOT test data to track vehicle operation, infer information on its end-of-life, and associate it with a wealth of vehicle characteristics recorded during MOT tests.

Our analysis of over 30 million vehicles and 300 million MOT test results uses a Weibull proportional hazard model to identify key predictors of a vehicle's longevity, including driving intensity, engine size, colour, make, and location. The freely accessible data enabled us to conduct a timely evaluation and compare the impact of each determinant among different powertrains, including traditional petrol and diesel engines against newer powertrains such as (P)HEVs vehicles and BEVs.

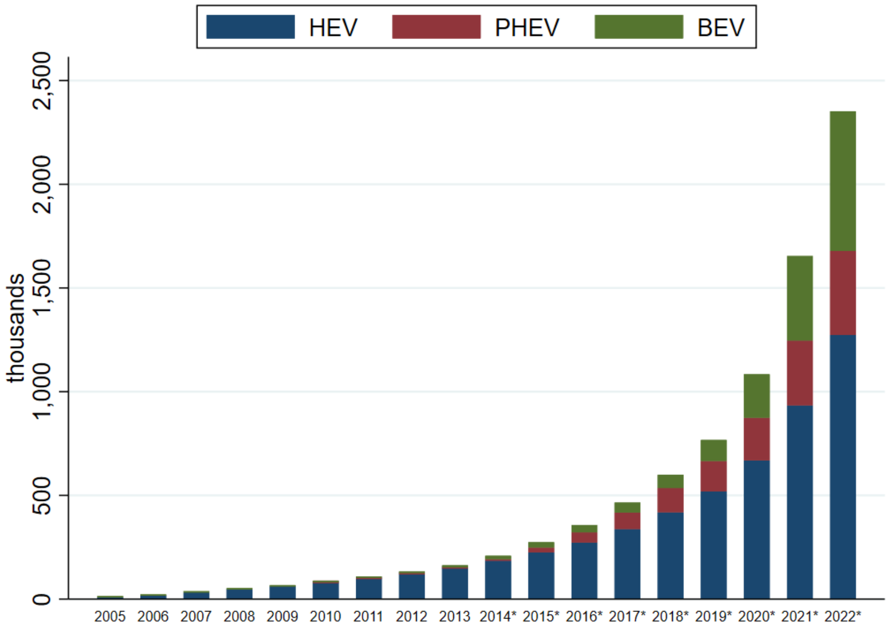
Our analysis highlights the advantages of (P)HEVs due to their extended service life in addition to their positive impact on the environmental and climate-friendliness. While BEVs represent a newer technology that was traditionally less reliable, they have rapidly evolved, with the latest BEVs expected to outlast the average ICEVs within the same cohort. When accounting for differences in the usage phase, EVs, in general, offer greater environmental benefits than life cycle estimates that assume a common functional unit for all powertrains. Hence, considering our predicted extended lifespan, the implication is that EVs would have a lower total cost of ownership that previous studies have suggested.

However, there are a number of caveats. The extended lifespan of EVs may require battery replacements if the original batteries deteriorate prematurely. Lithium-ion batteries remain the dominant technology for powering EVs and the longevity of these batteries is uncertain (Noel et al., 2019). Most new EVs come with warranties of eight years and 100,000 miles for their batteries (RAC, 2021) and most research anticipates a lifespan of approximately 8 to 10 years (Skeete et al., 2020). Industrial sources tend to be more optimistic about their products, with Tesla claiming that their batteries are designed to outlast the vehicle (Tesla, 2021), and Nissan reporting that almost all of the batteries they have ever produced are still in use in the EVs they sold over the last 12 years (Forbes, 2022). To fully realise the benefits of a longer BEV lifespan, replacement batteries, if necessary, must be affordable relative to the residual value of BEVs without their original batteries. The establishment of a robust circular economy for batteries is imperative to effectively support the dynamics of this technological advancement. Moreover, the widespread adoption of EVs may give rise to new business models such as car leasing and car-hailing. To prevent potential environmental issues, regulation is crucial, as exemplified by the emergence of EV graveyards in China (Bloomberg News, 2023), where a significant number of EVs are left unused before reaching the end of their mechanical lifespan as the new businesses fail.

It is important to note that our analysis is dependent on the assumption that vehicle owners comply with compulsory MOT tests, and the robustness of our findings can be strengthened by presenting results under different assumptions. Users are advised to use their institutional knowledge to select the results that best suit their analytical purposes. Currently, information on the export pattern of used EVs from Great Britain, which leaves the British road in a manner that is different from scrappage, is not available. Further research is thus needed in this area to understand its impact.

Figures

Figure 1: Licensed Electric Vehicles in Great Britain (2005-2013) and United Kingdom(2014-2022)



Notes: This figure shows the number of licensed electric cars and light goods vehicles by fuel types: hybrid electric vehicles (HEV), plugin electric vehicles (PHEV) and battery electric vehicles (BEV) as recorded in Table 1103 by Department for Transport (Dft) and Driver and Vehicle Licensing Agency (DVLA). A negligible number of range-extended electric and fuel cell electric are excluded. Data for the United Kingdom is available from 2014. Data from earlier years is for Great Britain.

Figure 2: Schema of Interval-Censored Data and the Heuristic of Death Definition

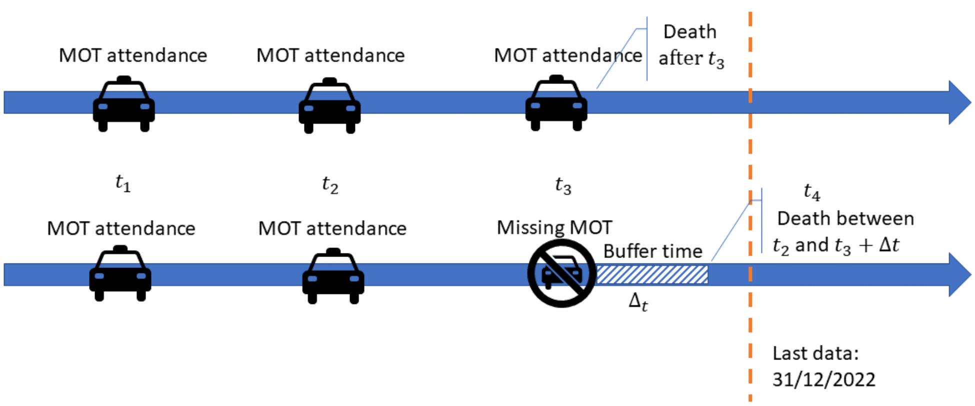
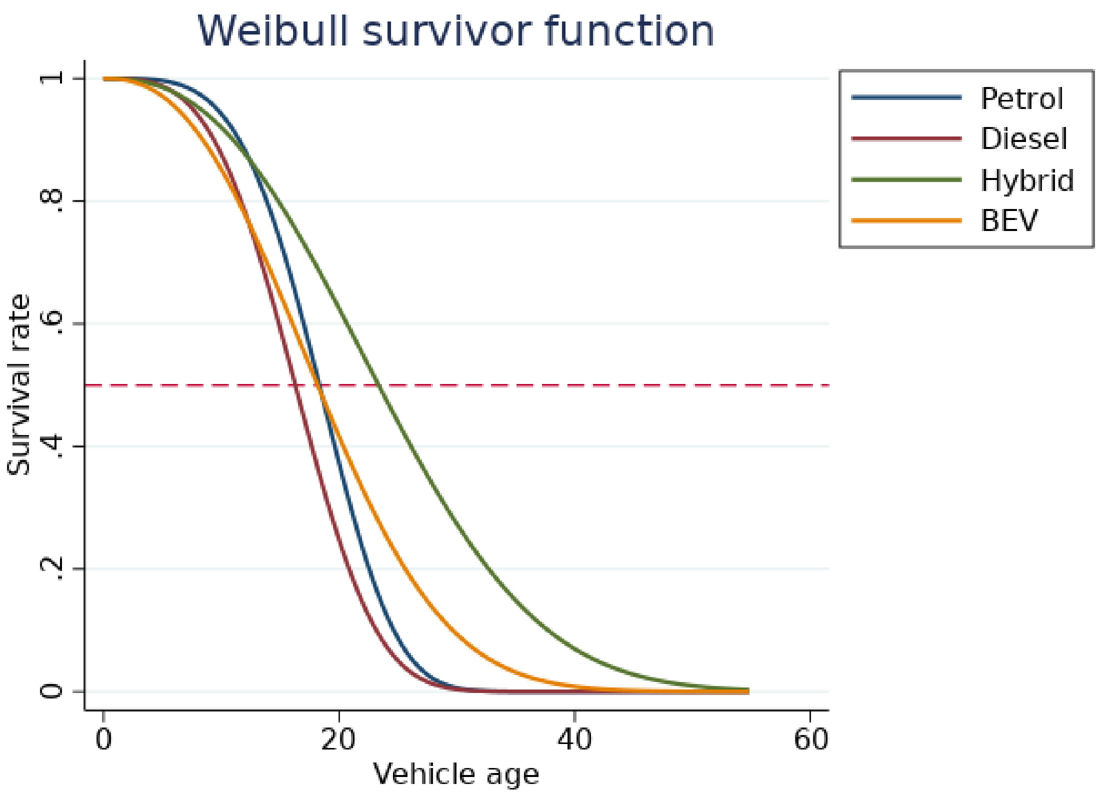


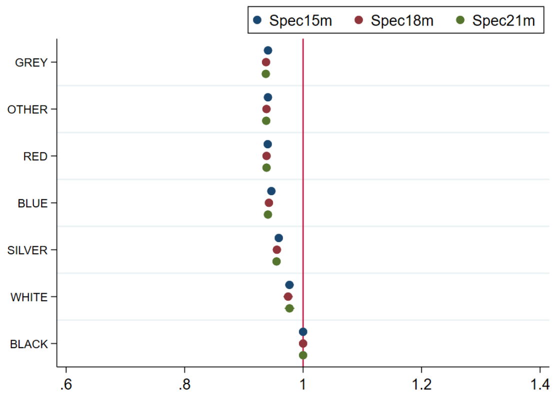
Figure 3: Survival function



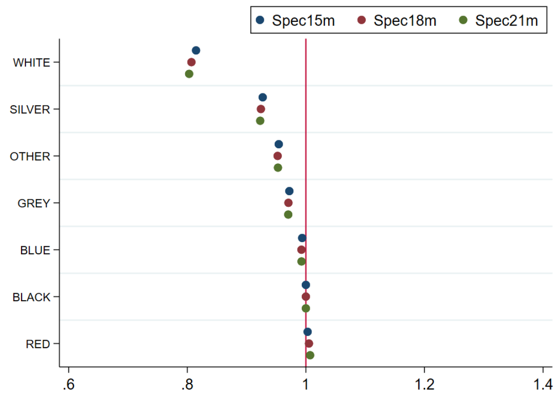
Notes: This figure illustrates the survival function, using the parametric survival estimates from the preferred specifications (18 months) in Table 2, along with the covariate means for four samples: Petrol, Diesel, (P)HEV, and BEV.

Figure 4: Colour fixed effects

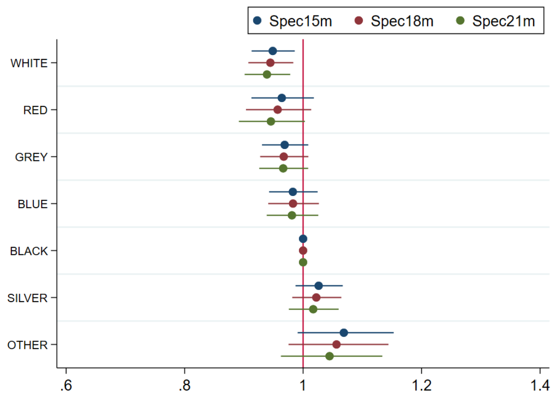
(a) Panel A: Petrol



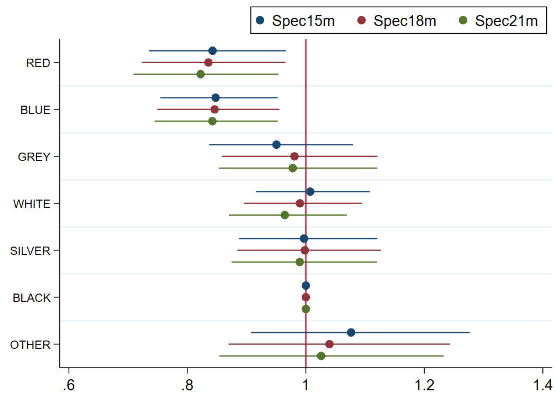
(b) Panel B: Diesel



(c) Panel C: (P)HEV



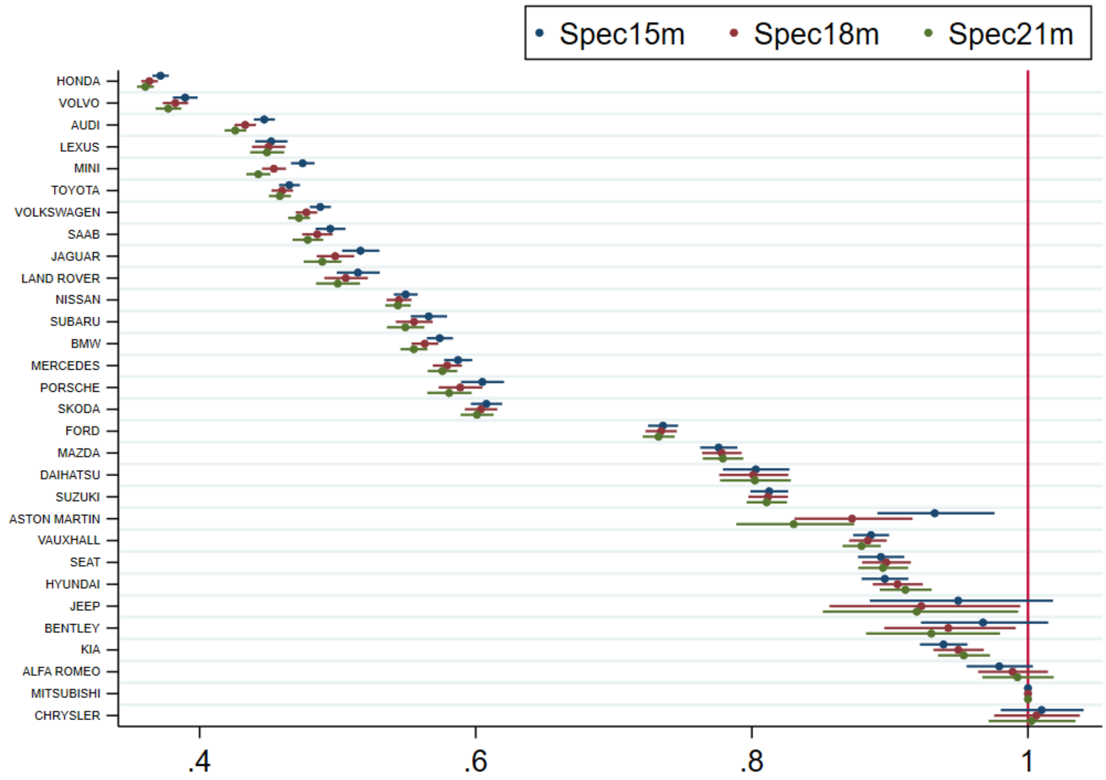
(d) Panel D: BEV



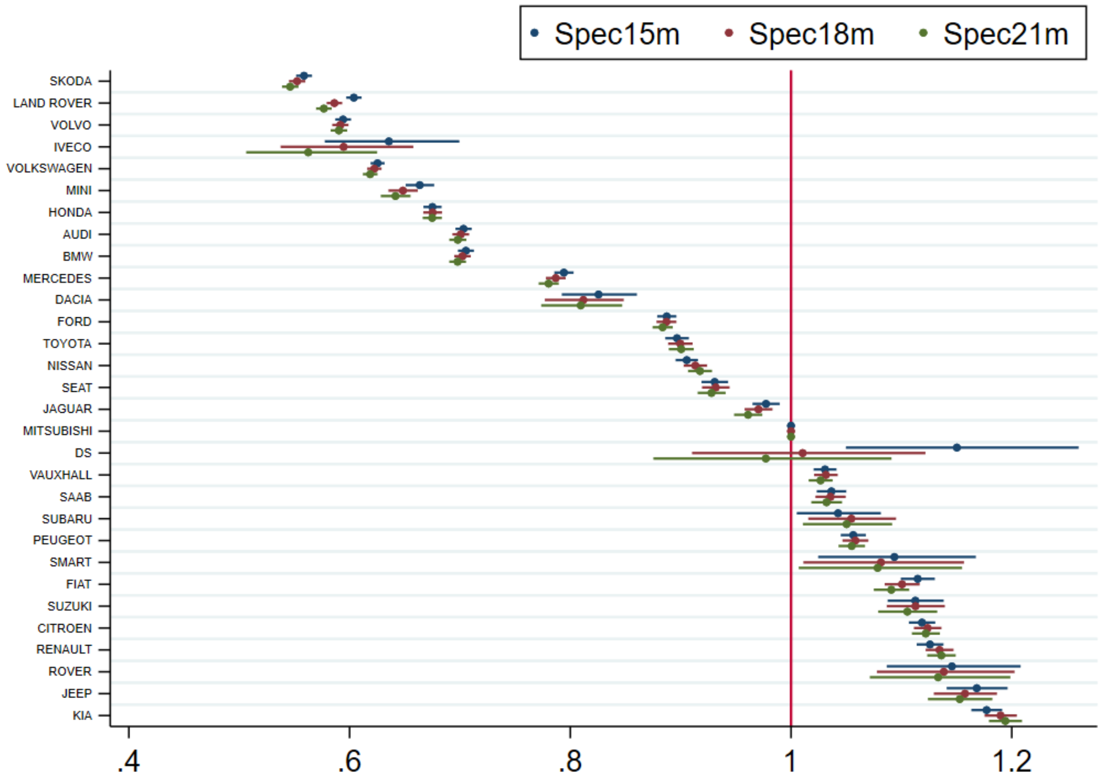
Notes: These figures illustrate the exponentiated coefficients and 95% confidence intervals of colour fixed effects in Table 2 for four samples and three thresholds 15 months, 18 months (preferred) and 21 months. Coefficients smaller than one (positioned to the left of the red vertical lines) indicate colours with lower hazard rates than the reference group (black colour).

Figure 5: Make fixed effects

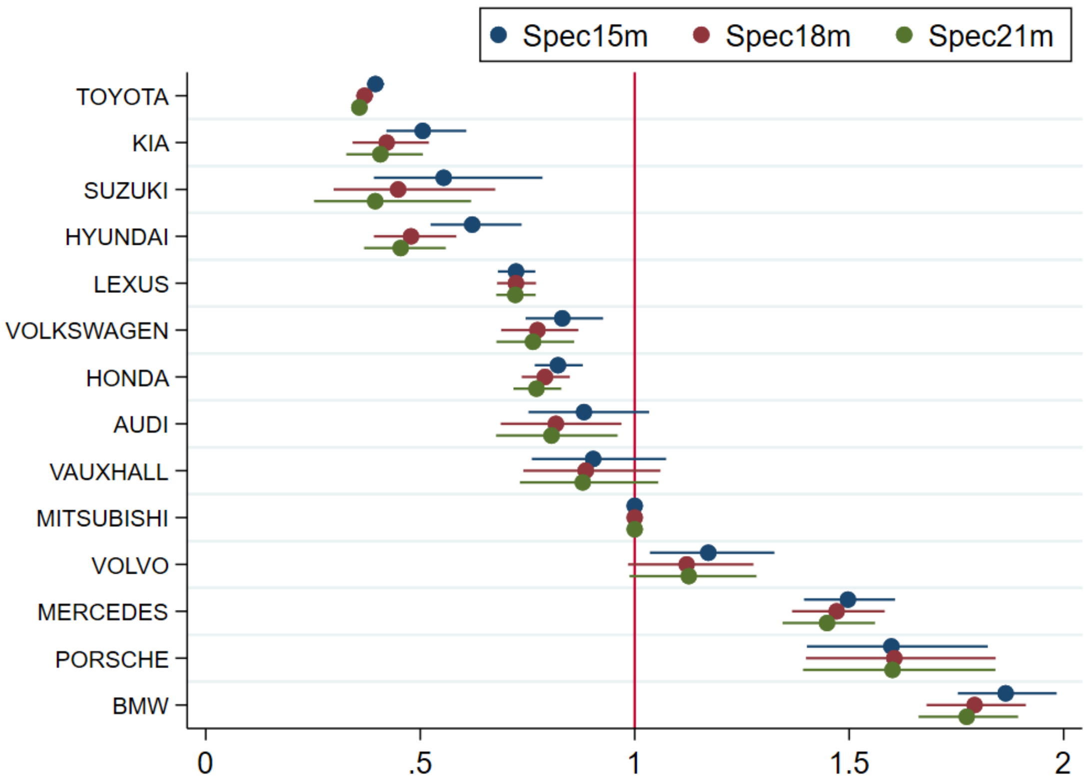
(a) Panel A: Petrol



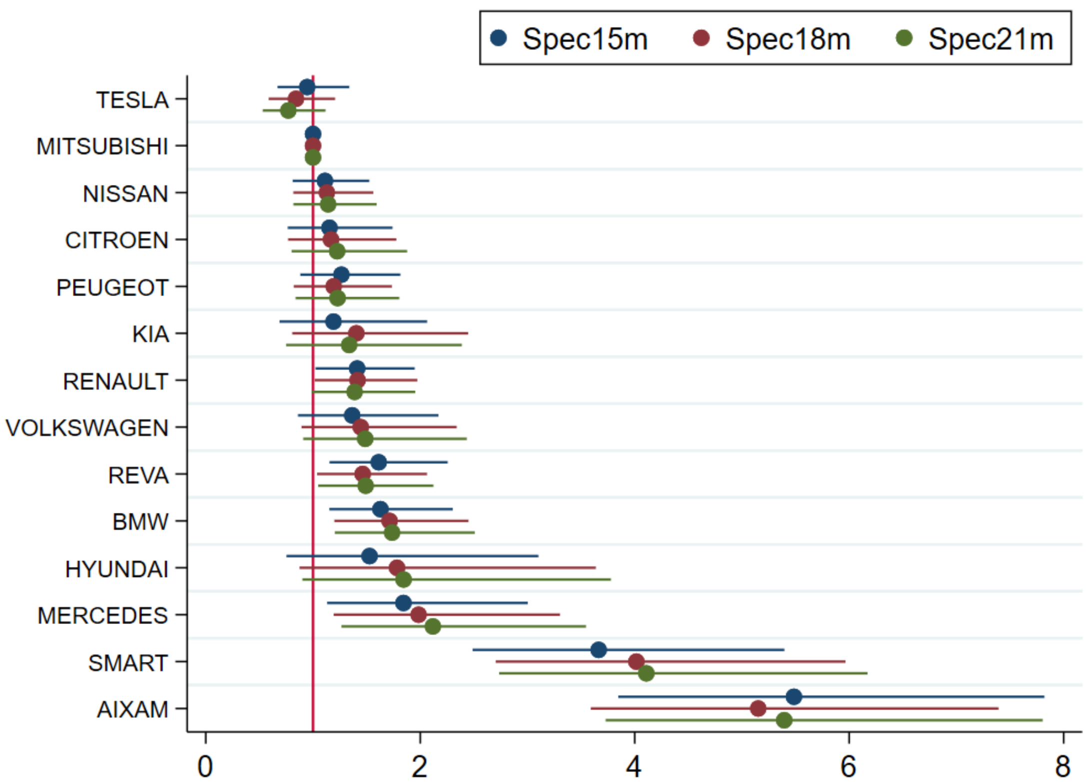
(b) Panel B: Diesel



(c) Panel C: (P)HEV



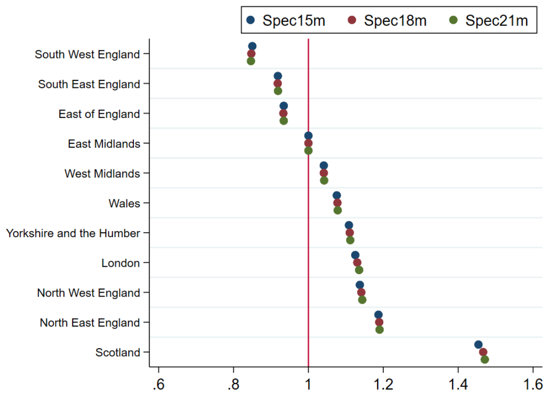
(d) Panel D: BEV



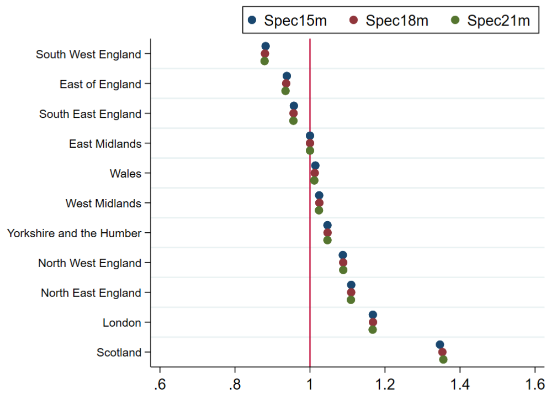
Notes: These figures illustrate the exponentiated coefficients and 95% confidence intervals of make fixed effects in Table 2 for four samples and three thresholds 15 months, 18 months (preferred) and 21 months. Coefficients smaller than one (positioned to the left of the red vertical lines) indicate brands with lower hazard rates than the reference group (Mitsubishi). For illustrative purposes, panels A (petrol) and B (dieselO only show the top 30 brands in terms of reliability (with the lowest hazard ratios) while panels C ((P)HEV) and D (BEV) show all brands included in the regressions.

Figure 6: Regional fixed effects

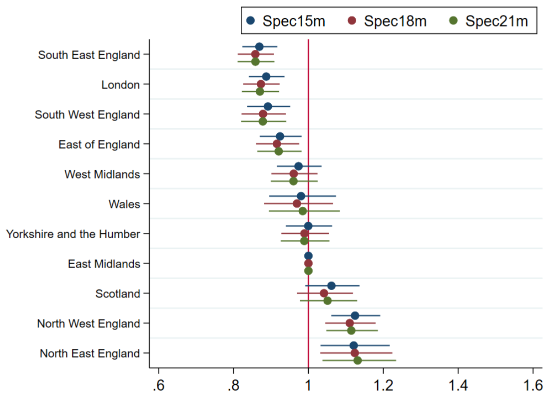
(a) Panel A: Petrol



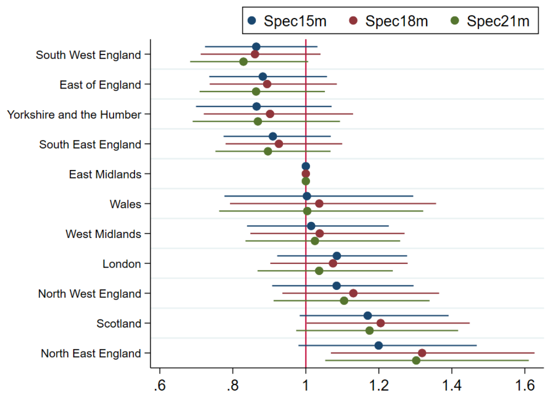
(b) Panel B: Diesel



(c) Panel C: (P)HEV



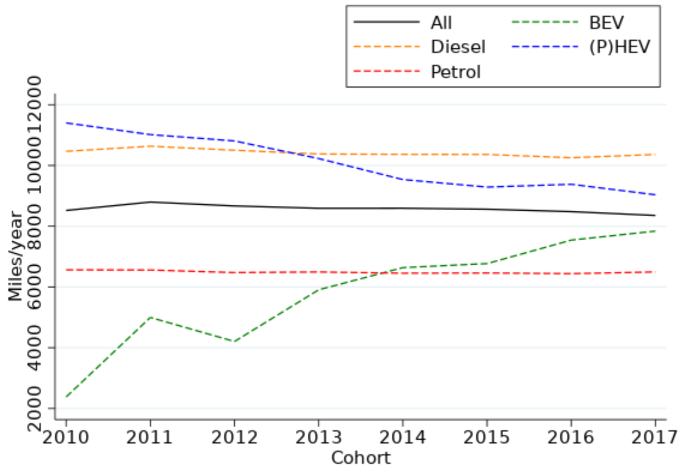
(d) Panel D: BEV



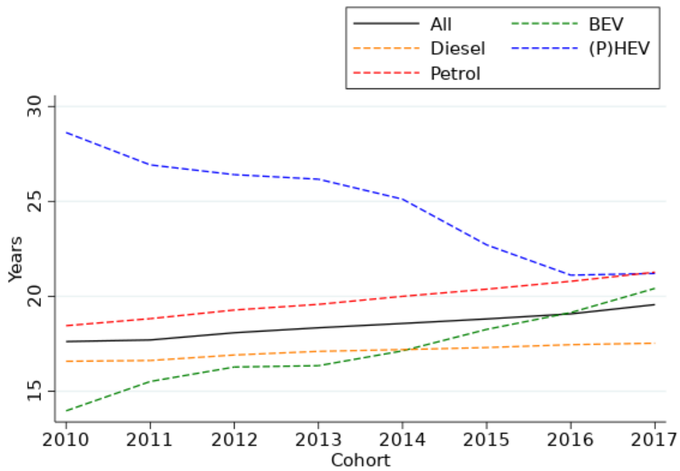
Notes: These figures illustrate the exponentiated coefficients and 95% confidence intervals of regional fixed effects in Table 2 for four samples and three thresholds 15 months, 18 months (preferred) and 21 months. Coefficients smaller than one (positioned to the left of the red vertical lines) indicate regions with lower hazard rates than the reference group (East Midlands).

Figure 7: Electric Vehicle Revolution

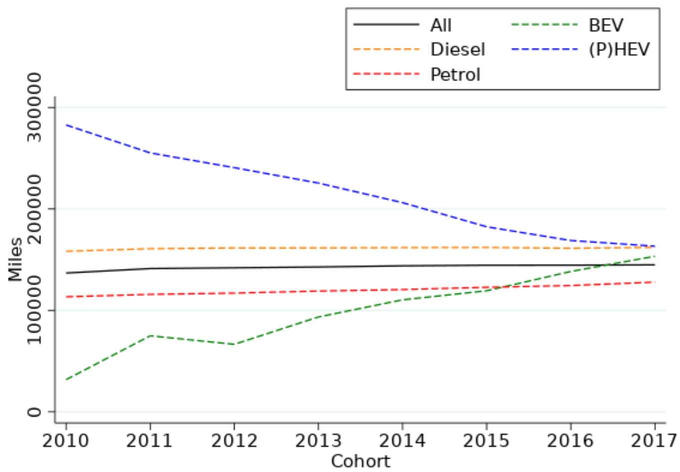
(a) Panel A: Average (Observed) Mileage rate



(b) Panel B: Average (Expected) Median Life time



(c) Panel C: Average (Expected) Median Life Mileage



This figure aggregates the mileage rate (at the last test), the median lifetime predicted by the 18-month specification illustrated in Table 2, and the lifetime mileage as predicted by the two variables mentioned above, categorised by cohort and powertrain.

Tables

Table 1: Summary Statistics

	Petrol	Diesel	(P)HEV	BEV	All vehicles			
	mean	mean	mean	mean	mean	sd	min	max
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mileage rate (last)	18.2	28.8	26.5	18.9	23.4	12.1	0.00016	100
Cohort	2010.7	2011.3	2013.7	2015.1	2011.0	3.82	2005	2017
First colour								
- BLACK	0.20	0.22	0.19	0.18	0.21	0.41	0	1
- BLUE	0.18	0.14	0.15	0.12	0.16	0.37	0	1
- GREY	0.12	0.16	0.15	0.11	0.14	0.35	0	1
- OTHER	0.053	0.042	0.035	0.024	0.047	0.21	0	1
- RED	0.13	0.069	0.095	0.12	0.098	0.30	0	1
- SILVER	0.19	0.19	0.17	0.11	0.19	0.39	0	1
- WHITE	0.13	0.19	0.22	0.33	0.16	0.37	0	1
Cylinder Capacity								
- Zero/Missing	0	0	0	1	0.0014	0.037	0	1
- Under 1.0 l	0.13	0.00048	0.019	0	0.067	0.25	0	1
- 1.0-2.0 l	0.81	0.76	0.78	0	0.78	0.41	0	1
- Above 2.0 l	0.052	0.24	0.20	0	0.15	0.35	0	1
First region								
- East Midlands	0.062	0.070	0.064	0.064	0.066	0.25	0	1
- East of England	0.096	0.096	0.093	0.091	0.096	0.29	0	1
- London	0.081	0.068	0.21	0.16	0.076	0.27	0	1
- North East England	0.047	0.047	0.028	0.043	0.047	0.21	0	1
- North West England	0.13	0.12	0.10	0.093	0.13	0.33	0	1
- Scotland	0.11	0.11	0.054	0.088	0.11	0.31	0	1
- South East England	0.16	0.16	0.19	0.20	0.16	0.37	0	1
- South West England	0.082	0.090	0.076	0.11	0.086	0.28	0	1
- Wales	0.047	0.049	0.025	0.024	0.047	0.21	0	1
- West Midlands	0.092	0.095	0.083	0.070	0.093	0.29	0	1
- Yorkshire and the Humber	0.091	0.099	0.081	0.058	0.094	0.29	0	1
Make								
- ABARTH	0.0011	0	0	0	0.00056	0.024	0	1
- AIXAM	0	0	0	0.0043	0.0000059	0.0024	0	1
- ALFA ROMEO	0.0031	0.0026	0	0	0.0028	0.053	0	1
- ASTON MARTIN	0.0011	0	0	0	0.00055	0.023	0	1
- AUDI	0.033	0.066	0.0063	0	0.049	0.22	0	1
- BENTLEY	0.0011	0	0	0	0.00054	0.023	0	1
- BMW	0.028	0.077	0.053	0.056	0.052	0.22	0	1
- CATERHAM	0.00013	0	0	0	0.000064	0.0080	0	1
- CF MOTO	0.000073	0	0	0	0.000036	0.0060	0	1
- CHEVROLET	0.0076	0.0013	0	0	0.0044	0.066	0	1
- CHRYSLER	0.0013	0.0024	0	0	0.0018	0.042	0	1
- CI MOTORHOME	0	0.000082	0	0	0.000040	0.0063	0	1
- CITROEN	0.032	0.046	0	0.0073	0.038	0.19	0	1
- DACIA	0.0034	0.0036	0	0	0.0035	0.059	0	1
- DAEWOO	0.00017	0	0	0	0.000084	0.0092	0	1
- DAIHATSU	0.0014	0	0	0	0.00068	0.026	0	1
- DODGE	0.00043	0.00053	0	0	0.00048	0.022	0	1
- DS	0.0011	0.00086	0	0	0.00098	0.031	0	1
- FERRARI	0.00054	0	0	0	0.00027	0.016	0	1
- FIAT	0.039	0.015	0	0	0.027	0.16	0	1
- FORD	0.16	0.14	0	0	0.15	0.35	0	1
- GREAT WALL	0	0.00013	0	0	0.000061	0.0078	0	1

Table 1: Summary Statistics

	Petrol	Diesel	(P)HEV	BEV	All vehicles			
	mean	mean	mean	mean	mean	sd	min	max
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
- HONDA	0.040	0.016	0.038	0	0.028	0.17	0	1
- HYUNDAI	0.032	0.017	0.010	0.0046	0.024	0.15	0	1
- INFINITI	0.00010	0.00047	0	0	0.00028	0.017	0	1
- ISUZU	0	0.0025	0	0	0.0012	0.035	0	1
- IVECO	0	0.00018	0	0	0.000086	0.0092	0	1
- JAGUAR	0.0037	0.014	0	0	0.0087	0.093	0	1
- JEEP	0.00091	0.0029	0	0	0.0019	0.043	0	1
- KIA	0.024	0.024	0.013	0.011	0.024	0.15	0	1
- LAMBORGHINI	0.00014	0	0	0	0.000070	0.0084	0	1
- LAND ROVER	0.0017	0.044	0	0	0.022	0.15	0	1
- LDV	0	0.00044	0	0	0.00021	0.015	0	1
- LEXUS	0.0022	0.0011	0.21	0	0.0042	0.065	0	1
- LOTUS	0.00034	0	0	0	0.00017	0.013	0	1
- MASERATI	0.00036	0.00021	0	0	0.00028	0.017	0	1
- MAZDA	0.025	0.0093	0	0	0.017	0.13	0	1
- MCLAREN	0.000088	0	0	0	0.000044	0.0066	0	1
- MERCEDES	0.022	0.063	0.023	0.0099	0.042	0.20	0	1
- MG	0.0018	0.00020	0	0	0.0010	0.032	0	1
- MICROCAR	0.00012	0	0	0	0.000060	0.0077	0	1
- MINI	0.031	0.010	0	0	0.021	0.14	0	1
- MITSUBISHI	0.0055	0.012	0.073	0.0045	0.0095	0.097	0	1
- MORGAN	0.00019	0	0	0	0.000096	0.0098	0	1
- NISSAN	0.053	0.040	0	0.49	0.047	0.21	0	1
- PERODUA	0.00030	0	0	0	0.00015	0.012	0	1
- PEUGEOT	0.051	0.053	0	0.016	0.052	0.22	0	1
- PORSCHE	0.0052	0.0016	0.0063	0	0.0034	0.059	0	1
- PROTON	0.00071	0	0	0	0.00036	0.019	0	1
- QUADZILLA	0.000085	0	0	0	0.000042	0.0065	0	1
- RENAULT	0.042	0.039	0	0.17	0.041	0.20	0	1
- REVA	0	0	0	0.018	0.000025	0.0050	0	1
- ROLLS ROYCE	0.00016	0	0	0	0.000079	0.0089	0	1
- ROVER	0.00083	0.00028	0	0	0.00055	0.024	0	1
- SAAB	0.0026	0.0046	0	0	0.0035	0.059	0	1
- SEAT	0.017	0.013	0	0	0.015	0.12	0	1
- SKODA	0.020	0.022	0	0	0.021	0.14	0	1
- SMART	0.0053	0.00048	0	0.0097	0.0029	0.054	0	1
- SMC	0.00015	0	0	0	0.000077	0.0088	0	1
- SSANGYONG	0.00014	0.0012	0	0	0.00064	0.025	0	1
- SUBARU	0.0029	0.00087	0	0	0.0019	0.043	0	1
- SUZUKI	0.023	0.0018	0.0058	0	0.012	0.11	0	1
- TESLA	0	0	0	0.19	0.00026	0.016	0	1
- TOYOTA	0.049	0.022	0.53	0	0.042	0.20	0	1
- VAUXHALL	0.15	0.093	0.0035	0	0.12	0.32	0	1
- VOLKSWAGEN	0.068	0.11	0.017	0.0096	0.086	0.28	0	1
- VOLVO	0.0046	0.025	0.0083	0	0.015	0.12	0	1
- YAMAHA	0.00012	0	0	0	0.000059	0.0077	0	1
Observations	15125166	14681350	371328	41663	30219507			

Notes: This table provides summary statistics of the key variables associated with different types of powertrains: petrol, diesel, (plugin) hybrid electric vehicles ((P)HEVs) and battery electric vehicles (BEVs). We have assumed that BEVs are the same as HEVs, but with zero or missing cylinder capacity and validated by a list of BEV generic models by DVSA. We have only included make-by-powertrain data that exceed 1,000 unique vehicles in the original dataset for petrol, diesel and HEVs, while the threshold is lowered to 100 for BEVs, as they are still new and less popular. To deal with potential discrepancies in the data, we rely on the first test for region, colour and first use time information, and the majority of tests for cylinder capacity and make information. We then use the odometer information and test date from the last test in our dataset to infer the average mileage of each car across its lifetime.

Table 2: Survival regression

	Petrol			Diesel			(P)HEVs			BEV		
	15m	18m	21m	15m	18m	21m	15m	18m	21m	15m	18m	21m
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Mileage rate (last)	1.083***	1.084***	1.085***	1.063***	1.064***	1.065***	1.043***	1.045***	1.046***	1.021***	1.025***	1.028***
	(0.0003)	(0.0003)	(0.0003)	(0.00006)	(0.00007)	(0.00007)	(0.0003)	(0.0004)	(0.0004)	(0.002)	(0.002)	(0.002)
Cohort	0.952***	0.933***	0.930***	0.990***	0.981***	0.982***	1.143***	1.129***	1.133***	0.914***	0.880***	0.879***
	(0.0003)	(0.0003)	(0.0004)	(0.0002)	(0.0002)	(0.0002)	(0.003)	(0.003)	(0.004)	(0.01)	(0.01)	(0.01)
Under 1.0 l	0.974***	0.963***	0.961***	1.341***	1.354***	1.368***	0.494***	0.494***	0.480***			
	(0.004)	(0.004)	(0.004)	(0.05)	(0.05)	(0.06)	(0.03)	(0.03)	(0.03)			
1.0-2.0 l	1	1	1	1	1	1	1	1	1			
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)			
Above 2.0 l	1.067***	1.060***	1.055***	0.798***	0.791***	0.786***	1.118***	1.093***	1.088**			
	(0.004)	(0.004)	(0.004)	(0.001)	(0.001)	(0.001)	(0.03)	(0.03)	(0.03)			
Weibull shape	4.072***	4.059***	4.113***	3.406***	3.411***	3.468***	2.541***	2.502***	2.571***	2.507***	2.453***	2.503***
parameter (ρ)	(0.003)	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)	(0.01)	(0.01)	(0.01)	(0.03)	(0.03)	(0.03)
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Color FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Make FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
pvalue (χ^2: Region FE)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
pvalue (χ^2: Color FE)	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.003	0.003	0.006	0.018	0.024
pvalue (χ^2: Make FE)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Observations	15125160	15125160	15125160	14681337	14681337	14681337	371328	371328	371328	41663	41663	41663
- # right-censored obs	11981198	12169091	12273685	11126162	11314626	11422244	345223	347538	348508	37768	38135	38289
- # interval-censored obs	3143962	2956069	2851475	3555175	3366711	3259093	26105	23790	22820	3895	3528	3374

Notes: This table reports the exponentiated coefficients and standard errors (in parentheses) of baseline survival regressions for Petrol (columns 1-3, Diesel (columns 4-6), (P)HEV (columns 7-9), and BEVs (columns 10-12). These regressions include petrol/diesel/(P)HEV makes with a minimum of 1,000 vehicles or BEV makes with a minimum of 100 vehicles. Column titles specify the buffer time used to determine the "death" of vehicles, ranging from 15 months, 18 months (preferred), to 21 months. *,**, and *** respectively indicate significance at 0.05, 0.01, and 0.001 levels.

Table 3: Estimated median lifetime and mileage by powertrain and region

	Median lifetime (years)			Median life mileage (miles)			Obs
	15m	18m	21m	15m	18m	21m	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				PANEL A: ALL VEHICLES			
Average	17.2	17.9	18	133834	138429	139852	30219508
				PANEL B: AVERAGE BY POWERTRAIN			
Petrol	18	18.7	18.9	111654	116016	117428	15125166
Diesel	16.3	16.8	16.9	155153	159758	161254	14681350
(P)HEV	23.3	25	24.9	196631	209638	208679	371328
BEV	16.8	18.4	18.6	113632	124156	125045	41663
				PANEL C: AVERAGE OF TOP FIVE MAKES BY POWERTRAIN			
				Petrol			
AUDI PE	19.9	20.9	21.2	135975	143074	145145	493332
VOLVO PE	19.7	20.5	20.7	137337	142339	144053	70283
LAND ROVER PE	18	18.7	18.9	130266	134894	136652	25748
LEXUS PE	18	18.4	18.6	130457	133273	134516	33309
SAAB PE	17.2	17.6	17.8	130271	132745	134240	38574
				Diesel			
SKODA DI	17.2	17.7	17.9	176379	181836	183555	316534
VOLVO DI	18.1	18.6	18.8	174806	180177	181445	371746
LAND ROVER DI	19.6	20.4	20.6	169193	176201	178139	653005
VOLKSWAGEN DI	17.1	17.6	17.8	170754	175629	177125	1571721
HONDA DI	17.7	18.2	18.4	170562	175122	176486	238243
				(P)HEV			
TOYOTA (P)HEV	27.2	29.4	29.2	229244	245316	244273	197827
HONDA (P)HEV	24.2	25.5	25.5	181437	190148	190154	14177
HYUNDAI (P)HEV	18.1	21.5	21.5	160687	189030	189723	3822
KIA (P)HEV	21.2	24.4	24.3	163829	187569	186636	4802
LEXUS (P)HEV	21.5	22.6	22.4	174498	182985	181423	77459
				BEV			
TESLA BEV	17.7	20.3	20.8	179751	203855	208543	7815
HYUNDAI BEV	15.1	15.7	15.5	135732	139295	136875	193
NISSAN BEV	17.4	18.8	18.8	113276	121786	121345	20461
KIA BEV	17.9	18.5	18.9	113386	116610	118962	438
BMW BEV	15.3	16.5	16.5	85261	91105	91114	2347
				PANEL D: AVERAGE BY REGIONS			
East Midlands	17.1	17.8	18	138492	143219	144676	1979983
East of England	17.5	18.2	18.4	140183	145097	146576	2895609
London	17.8	18.5	18.6	126453	131004	132305	2298969
North East England	16.6	17.2	17.4	130656	135060	136511	1412180
North West England	17	17.6	17.8	130059	134475	135870	3838499
Scotland	15.8	16.3	16.5	123965	127997	129396	3297217
South East England	17.9	18.5	18.7	138807	143683	145116	4810973
South West England	18.2	18.9	19	139944	144848	146288	2592338
Wales	17	17.6	17.7	133234	137701	139133	1427189
West Midlands	17.2	17.8	18	134421	139020	140469	2811173
Yorkshire and the Humber	17	17.6	17.8	133943	138449	139880	2855377

Notes: This table presents the estimated median lifetimes of all vehicles included in the regression sample, using the results reported in Table 2 and a breakdown by powertrain, make, and region. The median life mileages have been estimated from the median lifetime and the mileage rate calculated at the final test of each vehicle, then averaged over the sample or subsamples. We prefer the 18-month specification and use the 15-month and 21-month as the lower and upper bounds of our estimates.

A Appendix A: Appendix Tables

Table A1: Robustness check: BEV selection

	BEVs with at least					
	100 vehicles (baseline)			1000 vehicles		
	15m	18m	21m	15m	18m	21m
Mileage rate (last)	1.021***	1.025***	1.028***	1.018***	1.022***	1.024***
	(0.0022)	(0.0023)	(0.0023)	(0.0024)	(0.0026)	(0.0026)
Cohort	0.914***	0.880***	0.879***	0.958**	0.920***	0.920***
	(0.012)	(0.012)	(0.012)	(0.014)	(0.014)	(0.014)
AIXAM	5.799***	6.125***	7.009***			
	(0.82)	(0.91)	(1.06)			
BMW	1.722***	2.037***	2.257***	1.644***	1.946***	2.159***
	(0.17)	(0.21)	(0.24)	(0.16)	(0.20)	(0.23)
CITROEN	1.220	1.388	1.592**			
	(0.20)	(0.24)	(0.28)			
HYUNDAI	1.615	2.120*	2.397**			
	(0.52)	(0.68)	(0.77)			
KIA	1.259	1.670*	1.737*			
	(0.29)	(0.39)	(0.43)			
MERCEDES	1.949***	2.360***	2.752***			
	(0.38)	(0.49)	(0.57)			
MITSUBISHI	1.057	1.189	1.299			
	(0.19)	(0.22)	(0.25)			
NISSAN	1.175*	1.342***	1.482***	1.197**	1.377***	1.524***
	(0.080)	(0.10)	(0.12)	(0.083)	(0.10)	(0.12)
PEUGEOT	1.337*	1.418*	1.597***			
	(0.17)	(0.19)	(0.22)			
RENAULT	1.493***	1.683***	1.804***	1.487***	1.685***	1.810***
	(0.12)	(0.15)	(0.16)	(0.12)	(0.15)	(0.17)
REVA	1.705***	1.739***	1.937***			
	(0.23)	(0.24)	(0.28)			
SMART	3.874***	4.774***	5.338***			
	(0.51)	(0.66)	(0.76)			
TESLA	1	1	1	1	1	1
	(.)	(.)	(.)	(.)	(.)	(.)
VOLKSWAGEN	1.444	1.718**	1.932**			
	(0.27)	(0.34)	(0.39)			
Weibull shape	2.507***	2.453***	2.503***	2.557***	2.460***	2.512***
parameter (*rho*)	(0.027)	(0.026)	(0.026)	(0.032)	(0.029)	(0.029)
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Color FE	Yes	Yes	Yes	Yes	Yes	Yes
pvalue (χ^2: Region FE)	0.000	0.000	0.000	0.000	0.000	0.000
pvalue (χ^2: Color FE)	0.006	0.018	0.024	0.001	0.005	0.005
Observations	41663	41663	41663	37719	37719	37719
right-censored obs	37768	38135	38289	34882	35212	35347
interval-censored obs	3895	3528	3374	2837	2507	2372

Notes: Columns (1) - (3) in this table report the exponentiated coefficients and standard errors (in parentheses) of baseline survival regressions for Battery Electric Vehicles (BEVs), corresponding to columns (9)-(12) in Table 2. These regressions include BEV makes with a minimum of 100 vehicles. Columns (4) - (6) raise the threshold, retaining only major makes with at least 1000 vehicles, similar to incumbent ICEVs and (P)HEV in column (1)-(8) of Table 2. Column titles specify the buffer time used to determine the "death" of vehicles, ranging from 15 months, 18 months (preferred), to 21 months. *,**, and *** respectively indicate significance at 0.05, 0.01, and 0.001 levels.

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