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Abstract

Many countries plan to ban the sale of new combustion engine vehicles. I examine the impact of introducing such a ban in Great Britain in 2023, estimating demand, and calculating the reduction in the carbon externality using data on vehicle emissions and individual mileages. This reveals issues with the ban's design, mainly due to hybrids' popularity: anticipation will not incentivise firms to develop electric vehicles, low-income households would be harmed most, and CO_2 emissions would not be substantially reduced. Using a revenue-neutral combination of sales taxes and subsidies delivers 50% of the ban's climate benefit at 15% of the cost.

1 Introduction

Climate change is the most significant externality facing the world and proposals to decarbonise the transport system are central to many countries' mitigation plans: road transport accounts for 15% of global emissions (Ritchie, 2020) and is subject to substantial regulation. The UK plans to ban the sale of new petrol and diesel cars powered only by internal combustion engines from 2030;[1] the European Union, People's Republic of China, and several US states plan to implement similar bans in 2035. The performance of these bans, particularly their consequences for consumers, firms, and emissions, are of first-order importance for the economy and the climate. I study the British market and examine the implications for firms' product innovation incentives, identify the households and firms that would currently be harmed by a ban, and consider the relative performance of less stringent policies. Answering these questions sheds light on the distributional consequences of maximally disruptive climate policy, which will influence the ban's political success, the climate benefit of banning internal combustion engine vehicles when hybrids can still be sold, and current factors blocking the transition to a decarbonised road transport system.

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[1] I refer to vehicles powered *only* by internal combustion engines as 'internal combustion engine vehicles' throughout. Self-charging hybrids with an internal combustion engine and an electric motor are 'hybrids'.

I find that under existing market conditions the popularity of hybrids, which are close substitutes to internal combustion engine cars and have similar emissions, means that the climate benefit is relatively muted. If firms expect these preferences to persist for a number of years then they have a clear incentive to introduce new hybrid models rather than battery electric vehicles: vehicles which will be on the roads, polluting, for years. There is evidence that they are already doing so. Low-income households and European firms would be harmed the most. Introducing a revenue-neutral combination of a sales tax on internal combustion engine vehicles with a subsidy for battery and plug-in hybrid electric vehicles would attain 50% of the reduction in emissions at 15% of the welfare cost by making battery electric vehicles more attractive relative to hybrids.

I combine market and micro data from Great Britain to estimate a utility model with random coefficients, based on Berry et al. (1995), and jointly estimate supply by assuming that firms play a static price-setting game each year. The market for battery and hybrid electric vehicles is sufficiently developed that consumer preferences are identified from variation in the choice set and micro data. Instruments are chosen systematically using Gandhi and Houde (2023)'s IIA test to reduce the risk of weak identification. Testing data on vehicle emissions and individual odometer data on mileages are used to measure the ban's impact on carbon emissions; this accounts for mileage heterogeneity across vehicles with different engine types. The individual odometer data are taken from Great Britain's MOT testing data, an annual roadworthiness test which provides complete usage information for all vehicles in the country over three years old.[2]

In the counterfactual where internal combustion engine cars are removed from the 2023 choice set, most households remaining in the market choose to purchase hybrids: their market share increases from 13% to 61%. This is a consequence of hybrids' similarity to internal combustion engine vehicles and the relative unpopularity of battery electric vehicles, due to both their high prices and non-price factors. Every make (brand) except for the relatively small Dacia and Tesla would make more profit under the ban from introducing a hybrid than a battery electric vehicle: anticipation of this may drive firms' product development in the coming years. The change in welfare is the within-year change in variable profits, consumer surplus, plus an upper bound on the value of the change in CO_2 emissions. European firms and low-income households would be harmed most, making implementing the policy politically challenging. The lowest income households lose six times more consumer surplus, relative to their income, than the highest income households do: they are made worse off due to their higher price sensitivity and preference for internal combustion engine vehicles. Combining data on emissions and vehicle mileages reveals that there is a limited reduction in emissions because of the popularity of hybrids: they fall by only 50%.

Banning internal combustion engine vehicles is equivalent to imposing an arbitrarily large sales

[2] MOT stands for Ministry of Transport, a government department which no longer exists.

tax. To test the performance of less extreme policies, I discretise the space of possible tax and subsidy rates and search for the combination which delivers the same fall in emissions as the ban at the lowest possible welfare cost: overall welfare falls by 75% as much as under the ban. Since this policy is prohibitively expensive, I also find the revenue-neutral policy which delivers the largest climate benefit: this can attain 50% of the ban's reduction in emissions at 15% of the cost. This demonstrates the importance of making battery electric vehicles more attractive relative to hybrids to lower emissions; the ICE ban does not achieve this.

This paper considers the short-term consequences of introducing the ban. Over a longer time horizon, preferences are not immutable and may change. However, even in a rapidly changing market these results have long-term implications: if firms choose to introduce hybrids rather than battery electric vehicles, anticipating substitution patterns similar to these, households may continue to purchase relatively unclean vehicles until 2035. As the sale of new hybrids will be banned in 2035 and the average model redesign occurs after five to eight years, firms introducing new hybrid models in the next few years can sell the vehicles for their typical lifetimes.

These results should be informative about climate policy and the transition towards electric vehicles in many countries' passenger vehicle markets. Table 1 takes new car registration data from the European Automobile Manufacturers' Association (ACEA) for some European countries, the EU, and the UK. Market conditions are similar in many European countries: hybrids are more popular than battery electric vehicles. Since this is the key mechanism behind issues with the ban's design, the conclusions drawn here may apply to these markets, especially since the EU plans to ban the sale of new hybrids and internal combustion engine vehicles in 2035.

The paper contributes to a nascent literature studying product bans: it is the first to estimate substitution patterns for a particular market and evaluate the impact of a ban on internal combustion engine cars. Holland et al. (2021) build a dynamic model, calibrated to US data, to investigate the timing of a ban on gasoline vehicles. They find that a ban performs well only if battery electric vehicles are good substitutes for conventional vehicles; this fits with my finding that current substitution patterns make a ban costly. I complement their work by estimating a model on observable data, comparing the performance of different policies at a particular point on the transition path, and go further by showing that substitution to hybrids mitigates the ban's climate benefit. This mirrors the larger literature on product entry in vehicle markets.[3] Petrin (2002) uses a similar model to measure the increase in welfare from the introduction of the minivan in the United States; Langford and Gillingham (2023) investigate the introduction of hybrids in California and, consistent with this

[3]For example, Feenstra (1988), Fershtman and Gandal (1998), and Sabal (2025). Armitage and Pinter (2022) and He and Hao (2023) look at battery electric vehicles while Bresnahan and Gordon (1997) discusses the broader implications of product entry.

Table 1: EU Vehicle Sales Composition

	2024				2023			
Country	BEV	PHEV	HEV	ICE	BEV	PHEV	HEV	ICE
France	17.5%	8.8%	35.5%	38.1%	17.5%	9.5%	25.3%	47.7%
Germany	13.6%	6.8%	27.0%	52.6%	18.5%	6.2%	23.5%	51.8%
Italy	4.6%	3.7%	44.2%	47.5%	4.7%	4.8%	39.8%	50.7%
Netherlands	34.9%	13.9%	28.3%	23.0%	31.0%	12.8%	24.5%	31.6%
Spain	5.8%	6.0%	39.9%	48.3%	5.6%	6.7%	32.8%	54.8%
European Union	14.0%	7.4%	31.9%	46.7%	15.0%	8.0%	26.6%	50.4%
United Kingdom	19.6%	8.6%	35.3%	36.5%	16.5%	7.4%	31.6%	44.5%

Note: This gives each engine's type share of total registrations, excluding cars with 'other' engines, from the ACEA new car registration data. Percentages may not sum to one hundred due to rounding. The UK figures do not align with those in section 3.1 because the ACEA data classifies 'mild hybrids' as 'hybrids', unlike the GB registration data which classifies them as ICEs.

paper, find a limited reduction in emissions and regressive gains in consumer surplus.

There is a very broad literature studying the impact of environmental regulation in the car market; this includes papers studying the impact of emissions standards,[4] subsidies and rebate programs,[5] taxes,[6] scrappage subsidies (Schiraldi, 2011), and quotas (Li, 2018). This paper contributes to this literature by comparing the efficacy of a product ban with taxes and subsidies and finding that taxes and subsidies are effective because they drive consumers to substitute towards battery electric vehicles rather than hybrids. This complements the finding by Durrmeyer and Samano (2018) that revenue-neutral feebates outperform fuel economy standards by showing that price interventions outperform command-and-control regulation in this setting.

It also contributes to the wider literature examining competition and trade in car (automobile) markets, recently surveyed by Van Biesebroeck and Verboven (2024).[7] Keiller et al. (2024a,b) examine wage growth from 1980-2018 and the change in markups from 1998-2018 in the UK car market. I find the same downward trend in markups, albeit at a lower level, and specify a more detailed model which allows for preference heterogeneity over several product characteristics. Unlike papers which study the market for battery electric vehicles and thereby provide insights into network

[4] Such as Goldberg (1998), Jacobsen (2013), Ito and Sallee (2018), Reynaert and Sallee (2021), Reynaert (2021), and Alé-Chilet et al. (2025).

[5] See Beresteanu and Li (2011), D'Haultfœuille et al. (2014), Huse and Lucinda (2014), Chen et al. (2021), Xing et al. (2021), Durrmeyer (2022), Muehlegger and Rapson (2022), Barwick et al. (2024), and Remmy (2025).

[6] Including Grigolon et al. (2018) and Miravete et al. (2018).

[7] Some early papers are Bresnahan (1987), Berry et al. (1995, 1999, 2004), Goldberg (1995), and Goldberg and Verboven (2001); Grieco et al. (2024) study changing competition in the US automobile market using a similar model.

effects (Li et al., 2017; Springel, 2021; Fournel, 2024) or innovation and industrial policy (Allcott et al., 2024; Barwick et al., 2025; Head et al., 2025), I consider the market for all passenger vehicles to estimate substitution patterns between vehicles with different engine types.

This paper uses the MOT testing data for Great Britain to measure vehicle mileage. Often, papers account for mileage heterogeneity by taking the distribution from survey data (Bento et al., 2009; Grigolon et al., 2018); some use odometer data to estimate driving elasticities (Gillingham, 2016; Gillingham and Munk-Nielsen, 2019). Knittel and Sandler (2018) evaluate gasoline taxes and use odometer data to account for heterogeneity. I also use odometer readings to account for heterogeneity in mileage, across engine types here: the data's complete national coverage means that it gives the most accurate possible picture of this heterogeneity.

Section 2 introduces the data. Section 3 provides an overview of Great Britain's new car market. I present the model in section 4 and the estimation procedure in section 5. Section 6 gives the parameter estimates and discusses the substitution patterns. The ban is evaluated in section 7, and alternative tax and subsidy policies are covered in section 8. Section 9 concludes.

2 Data

2.1 Market Data

Sales data for new vehicles in Great Britain come from the UK Department for Transport and Driver and Vehicle Licensing Agency. These run from 2001 to 2023 and provide the number of new vehicles registered each quarter by make (brand), model, and engine type: I aggregate this to the annual level and keep only cars and vans (henceforth 'vehicles'). The registration data slightly overestimates sales as it includes non-roadworthy vehicles restored by individuals.[8] There is a proliferation of these low-registration observations: 48.6% of model-year combinations have fewer than 10 registrations. I exclude these by dropping all models with a market share below 0.05%. The retained models represent over 90% of registrations in all years before 2020 and over 86% after that.

The market size is the number of households in Great Britain divided by five: this is all of the households who typically purchase a vehicle each year, whether new or used. I base this on the RAC's 'Car ownership in Great Britain' report (Leibling, 2008) which found that, on average, households owned 1.25 cars and kept a car for four years. The share of the outside good fluctuates between 48% and 66% before reaching 75% in the pandemic.

Data on product prices and characteristics are taken from the Parkers website. The website is scraped for data on vehicle model variants using the R package `rvest` (Wickham, 2024). These are

[8] For example, there are 30 Austin-Healey Sprites (produced 1958-71) registered in the sample.

aggregated to the year-make-model-engine level by taking the median of numeric variables. There are four engine types: battery electric (BEV), plug-in hybrid (PHEV), hybrid (HEV), and internal combustion engine (ICE).[9] The emissions figures are Worldwide Harmonised Light Vehicles Test Procedure (WLTP) values; I discuss this further in section 3.2. The data contains 3,391 model-year observations and 458 distinct models.

There are a small number of cases where Parkers is missing characteristics. I impute these by hand and add data on ownership and the attributes of electric vehicles. The cost of driving 100 miles, as in Fournel (2024), is calculated using ONS data on average unit electricity prices and RAC data on the price of petrol and diesel at the pump.[10] Data on the number of public charging points come from Zapmap. The price and cost of driving are deflated by UK CPI to be in 2015 GBP.

To instrument for price, I build a proxy for vehicle input costs (D'Haultfœuille et al., 2019): a model's weight multiplied by the raw material input cost per kilogram in the previous year. Using the previous year accounts for delays in planning and production. For BEVs the index includes some of the materials used in producing batteries which contribute to higher production costs.

2.2 Micro Moments and Demographics

Data on demographics and household purchases come from the Expenditure and Food Survey for 2001 to 2007 and the Living Costs and Food Survey for 2008 to 2023. Both are UK-wide household surveys that run throughout the year.[11] On average 5,571 households are surveyed each year.[12] The UK data proxies for Great Britain. The survey contains data on several important vehicle characteristics: price, engine type, and novelty. I supplement this with data from a survey of 848 PHEV and BEV drivers commissioned by the Department for Transport and run by BritainThinks in 2021. All price and income variables are deflated to be in 2015 GBP. Section 3.3 provides descriptive statistics on household purchases which motivate the choice of micro moments used to estimate the model. The transaction data groups HEVs and PHEVs.

When estimating the model, income is drawn from a log-normal distribution with parameters estimated from the survey data. Transactions from 2013 onwards are included as from this year both vehicles purchased outright and through a hire purchase agreement can be identified, not just the former. This better aligns the market and micro data. There is substantial cross-market variation in income: average real income goes from £29,000 to £37,000 and is above that for 14 years.

[9] Mild hybrids are classified as ICE vehicles; 'hybrids' are self-charging hybrids.
[10] Source: https://www.rac.co.uk/drive/advice/fuel-watch/.
[11] I treat household purchases as made in the surveyed year since the precise purchase date is unknown.
[12] Only 1,029 households are surveyed in 2023 as the most recent data release only includes the first quarter.

2.3 Mileage Data

Vehicle mileages come from the MOT testing data for Great Britain. This is an annual road safety test, mandatory after three years, during which an odometer reading is taken. The dataset contains an anonymised record of every test performed in the calendar year. I obtain each engine type's empirical mileage distribution by matching vehicles' unique identifiers across 2022 and 2023 and measuring the change in mileage; a mileage for each model is obtained from the relevant distribution and held fixed throughout. After cleaning the data and matching there are 1,010,599 observations.

Appendix A contains further details on the imputation of missing characteristics, construction of market size and the input cost index, the household surveys, and the matching of MOT records.

3 The British Market for New Vehicles

This section provides an overview of changing product prices and sales, differences between vehicles with different engine types, their emissions, and the demographics of different vehicle buyers.

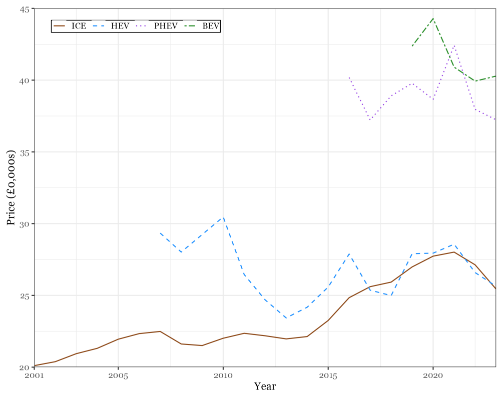
3.1 Vehicle Sales and Characteristics

Vehicle prices (in 2015 GBP) were relatively static from 2001 to 2015, increased until 2021, then fell slightly. Figure 1a shows that this is partially driven by a composition effect as expensive battery electric models (BEVs) enter the market, but also by an increase in the price of hybrids (HEVs) and cars with only internal combustion engines (ICEs). The post-pandemic fall in prices is seen everywhere except for BEVs. The Herfindahl-Hirschman Index is just over 1,000 for most of the period: There is little change from 2019 to 2023 despite a large increase in non-ICE vehicle sales visible: the market is characterised by incumbents expanding their product lines, not by high levels of firm entry. The total number of models offered, shown in Figure 1b, has risen even as fewer internal combustion engine models are sold. Since this is the number of models with a market share weakly greater than 0.05%, demand has become more dispersed as manufacturers have diversified their product lines towards electric vehicles, possibly driven by anticipation of the ban.

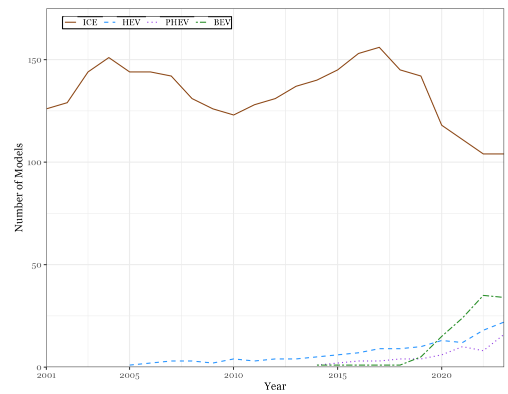
Figure 1c shows a substantial fall in sales from 2020: the same period saw rising real prices so the reduction cannot be driven entirely by falling demand. Alongside the pandemic reducing consumer demand as households delayed their purchases, there was strong anecdotal evidence of significant supply chain issues as carmakers struggled to secure parts.[13] The non-ICE market is well developed with a collective market share of over a third in 2023: see Figure 1d. The BEV share of the inside

[13] For example: https://www.ft.com/content/c6fb3706-4ee8-47a5-bfdd-fc6d5252c62e.

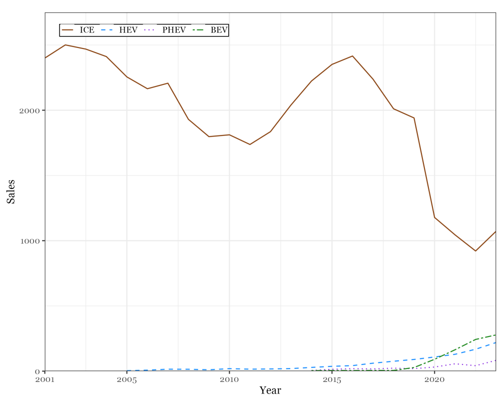
Figure 1: Market Overview 2001-2023



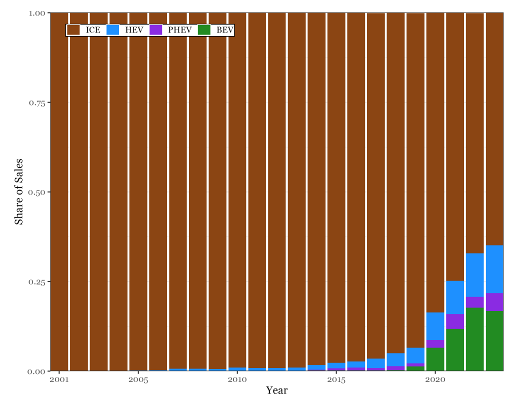
(a) Real prices



(b) Number of models



(c) Total Sales



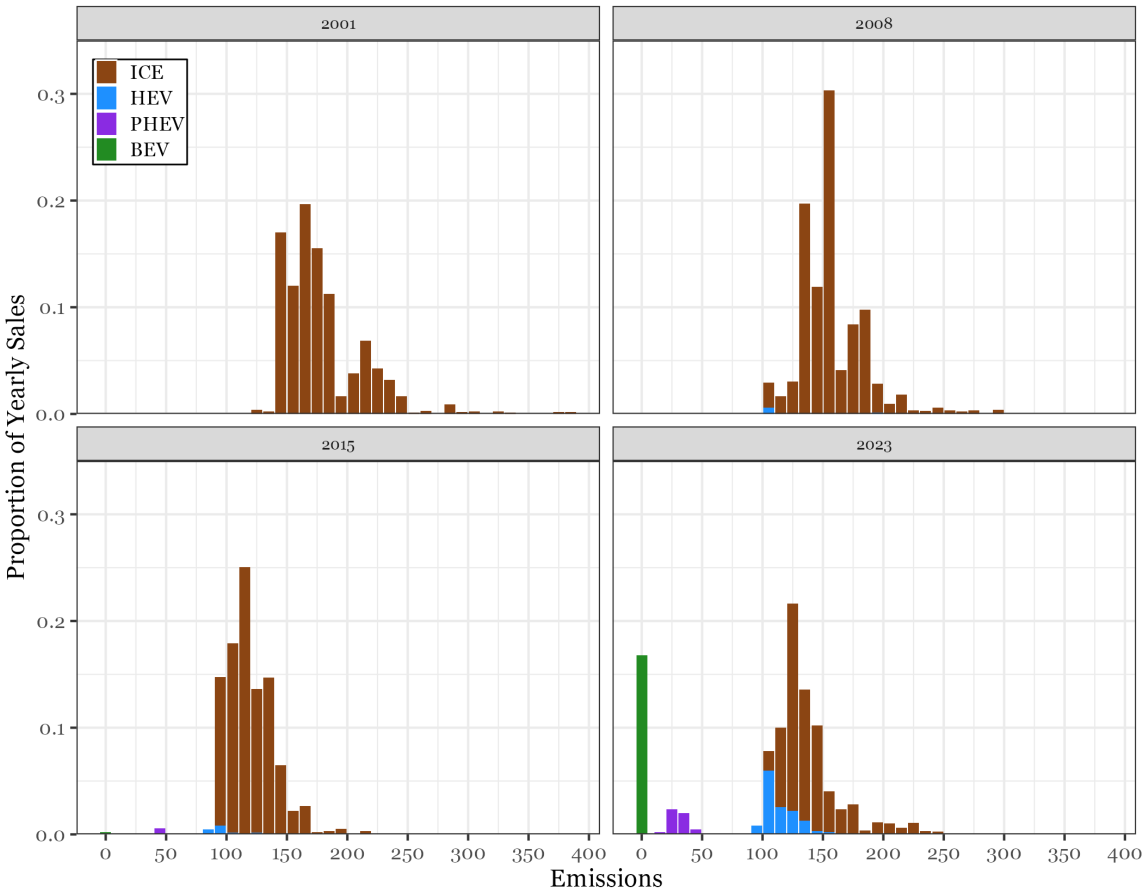
(d) Engine type share of sales

Note: Panels (a) contains the share-weighted mean price in thousands of 2015 GBP; engine types are only included when they have at least three distinct models. Panel (b) gives the number of models sold in a year after filtering on share. In panel (c), total annual sales are in thousands and calculated after filtering on share. Panel (d) gives each engine's type share of total sales.

goods is 17%, the HEV share is 13% and the PHEV share is 5%. The presence of a developed market for alternative engine types makes it possible to observe rich substitution patterns and estimate consumer preferences over different engine types. There is some evidence that growth in demand for battery electric vehicles has begun to slow, with their market share plateauing in 2023.

Battery electric vehicles differ systematically in their observable characteristics, particularly price. Figure 1a shows that BEVs and plug-in hybrids (PHEVs) are substantially more expensive: the average real price of a BEV was nearly £15,000 higher than that of an ICE vehicle in 2023. Figure A.1 shows that they have higher horsepower, while BEVs are cheaper to drive but have a lower range. PHEVs are more similar to BEVs than HEVs in their price, horsepower, and size; HEVs are similar to ICEs in all their observable characteristics. Table A.5 contains some descriptive statistics on how characteristics changed from 2001 to 2023.

Figure 2: Distribution of Vehicle Emissions



Note: Each panel plots the distribution of emissions in a given year. The bar's height gives the proportion of yearly sales in that emissions bin.

3.2 Emissions

Vehicle emissions have fallen steadily since 2001 due to cleaner ICE cars and the increasing popularity of battery electric vehicles; substantial gains have been made from technological improvement.

The share-weighted mean level of CO_2 emissions has fallen from 180g/km in 2000 to 108g/km in 2023, as shown in Table A.5. This matches the trend found by the National Audit Office, who attribute the temporary increase from 2015 to 2019 to increased SUV sales.[14] Figure 2 decomposes this change by plotting the distribution of emissions: it gives the proportion of yearly sales in each emissions bin for 2001, 2008, 2015, and 2023. There is a clear trend towards cleaner ICE vehicles from 2001 to 2015 but a limited change in the distribution of their emissions after 2015. This reflects a fall in the rate of technological change as innovation has focused on electric vehicles.[15] Even

[14]See page 9 of report at `https://www.nao.org.uk/reports/reducing-carbon-emissions-from-cars/`.

[15]Barwick et al. (2025) find a large increase in EV-related inventions, especially from 2008, which surpass the number

if vehicles with cleaner internal combustion engines proved to be popular, there are now only a limited number of years in which firms can profit from their success. The fall in emissions from 2019 is driven by the higher share of zero-emission BEVs. The figure makes clear how similar HEV emissions are to those of clean ICE vehicles.

Since the emissions data are taken from the WLTP values for each vehicle, the tailpipe emissions for battery electric vehicles are zero. This makes the unrealistic assumption that there are no emissions from charging.[16] I proceed on the basis of this assumption, treating the electricity system as decarbonised, since it provides an upper bound on the climate impact of the ban and avoids making detailed assumptions about the electricity system. This means that the welfare analysis undertaken in section 7 can be treated as a *best case* measure of the reduction in the carbon externality: the figure would be scaled down if emissions from charging were included.

3.3 Micro Data

The transaction data contains 5,764 transactions from 2013 onward: 4,833 are for used vehicles, 931 for new vehicles, 97 for hybrids, and 23 for battery electric vehicles. The relative size of the last three groups are all slightly at odds with the aggregate data, probably due to survey timing.[17]

Table 2 summarises the demographics of different vehicle buyers. New car buyers are wealthier and older than the average household and wealthier than used car buyers; the buyers of hybrids are wealthier still. The small sample size makes the mean income of BEV buyers sensitive to outliers: I therefore use the data on new BEV and PHEV buyers from the BritainThinks survey, not the transaction data, to build a micro moment for their average income. This is higher than the average income of new ICE buyers. I account for these trends when including demographic interactions in the model.

The survey data do not align perfectly with the market data. The outside share in the micro data is 82% in 2013, compared to 60% in the aggregate data, while the mean price paid is £17,700 in the micro data and £22,000 in the aggregate data. I account for this in section 5 when choosing micro moments. Table A.6 presents these statistics for a subset of years.

of yearly ICE-related inventions from 2013. They also present suggestive evidence that ICE and EV-focused patents might crowd out innovation in the other market segment.

[16] In reality, Mehlig et al. (2022) find that the average emissions of a BEV in the UK in 2019 was 41g/km of CO_2.

[17] Battery electric vehicle sales only start to take off in 2020 and the most recent survey data area from the first quarter of 2023 (for purchases in the previous 12 months) so there is limited overlap.

Table 2: Demographics of Different Vehicle Buyers

	Income			Age		Size		
Group	Mean	Median	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	N
All households	38.9	31.9	2.65	53.13	16.76	2.36	1.27	50,277
All car buyers	46.3	39.8	2.71	49.79	15.10	2.73	1.30	5,764
New car buyers	50.1	43.0	2.93	57.67	14.41	2.41	1.10	931
New HEV buyers	55.7	46.4	3.57	60.83	13.19	2.45	1.09	37
New BEV buyers	44.6	54.2	2.52	64.03	14.86	2.17	0.85	13

Note: Income is in thousands of 2015 pounds. Age is the age of the household's head and size is the total number of household members. The data are from 2013 to 2023.

4 Model

4.1 Demand

I use the discrete choice demand model for a differentiated products market from Berry et al. (1995) and follow the canonical treatment closely (Berry and Haile, 2021; Gandhi and Nevo, 2021).

There are $t \in \{1, 2, ..., T\}$ markets (years). In market t consumer i picks product $j \in \mathcal{J}_t \cup \{0\}$ to maximise their indirect utility. The outside good $j = 0$ represents the decision to purchase a used car or make no purchase at all.

Consumer i's conditional indirect utility from $j \in \mathcal{J}_t$ is given by:

$$u_{ijt} = x_{jt}\beta_{it} + \alpha_{it}p_{jt} + \xi_{jt} + \epsilon_{ijt} \tag{1}$$

where $x_{jt} \in \mathbb{R}^K$ is a vector of observed product characteristics, p_{jt} is the price, ξ_{jt} is a product-specific demand shock, and ϵ_{ijt} captures the consumer's idiosyncratic valuation for the good. Market and make fixed effects are included, so $\xi_{jt} = \xi_t + \xi_m + \Delta\xi_{jt}$ where m indexes make, e.g. Audi. The econometric error, $\Delta\xi_{jt}$, is observed by agents but not by the researcher.

The vector $\beta_{it} \in \mathbb{R}^K$ captures consumer i's tastes for different observed characteristics. To allow for heterogeneity across individuals, component $\beta_{it}^{(k)} \in \beta_{it}, \forall k = 1, ..., K$, takes the form:

$$\beta_{it}^{(k)} = \beta_0^{(k)} + \sigma^{(k)}\nu_{it}^{(k)} + \beta_y^{(k)} y_{it}. \tag{2}$$

The coefficient on price, α_{it}, takes the same form:

$$\alpha_{it} = \alpha_0 + \sigma\nu_{it}^{(0)} + \alpha_y y_{it} + \alpha_{y^2} y_{it}^2. \tag{3}$$

The first term is a common taste for the characteristic while the others capture preference heterogeneity. The unobserved taste of consumer i for characteristic k is given by the random variable $\nu_{it}^{(k)}$ which is drawn from a standard normal distribution; $\sigma^{(k)}$ gives the extent to which tastes for k vary with these unobserved preferences across consumers. Income, y_{it}, is drawn from a log-normal distribution each year with parameters taken from the national survey data. For some characteristics, $\sigma^{(k)} = \beta_y^{(k)} = 0$. The indirect utility from the outside good is normalised to $u_{i0t} = \epsilon_{i0t}$.

The estimation procedure is clearer if the utility function is rewritten as:

$$u_{ijt} = \underbrace{x_{jt}\beta_0 + \alpha_0 p_{jt} + \xi_{jt}}_{\delta_{jt}} + \underbrace{(p_{jt}, x_{jt}) \cdot (\Pi D_{it} + \Sigma\nu_{it})}_{\mu_{ijt}} + \epsilon_{ijt} \tag{4}$$

where δ_{jt} is product j's mean utility, and $\mu_{ijt} + \epsilon_{ijt}$ gives i's deviation from that mean. The deviation given by i's taste for characteristics, μ_{ijt}, depends on Σ, a diagonal matrix with elements $(\sigma, \sigma^{(1)}, ..., \sigma^{(K)})$, and Π, which collects the demographic coefficients in (2) and (3); D_{it} contains income and squared income.

Consumers are utility maximisers who purchase a single good, a natural assumption in the market for new vehicles. The problem facing consumer i in market t is $\max_j\{u_{ijt}\ \forall j \in \mathcal{J}_t \cup \{0\}\}$. The market share of product j is obtained by integrating the choice probability that a consumer picks product j over the mixing distribution of consumers. The idiosyncratic valuations, ϵ_{ijt}, are drawn independently from a Type I extreme value distribution.

The market share of product j in market t is:

$$s_{jt} = \int_{\nu,D} \frac{\exp(x_{jt}\beta_{it} + \alpha_{it}p_{jt} + \xi_{jt})}{1 + \sum_{k=1}^{J_t} \exp(x_{kt}\beta_{it} + \alpha_{it}p_{kt} + \xi_{kt})} dF(\nu)dF(D). \tag{5}$$

4.2 Supply

Firms play a static game each year by simultaneously setting prices to maximise profits. I abstract away from the presence of retailers: firms set the prices which consumers pay at the level of corporate ownership, internalising cross-make effects. The marginal cost of producing a product is constant in each year. Each firm f produces a subset of the choice set, $J_{ft} \subset \mathcal{J}_t$. Their profit is:

$$\pi_{ft} = \sum_{j \in J_{ft}} (p_{jt} - c_{jt}) s_{jt}. \tag{6}$$

The system of first-order conditions is:

$$p_t - c_t = [\Delta_t(\mathcal{H}_t)]^{-1} s_t \tag{7}$$

where $\mathcal{H}_t$ is the ownership matrix and Δ_t is the matrix of price elasticities. The marginal cost of producing a product is log-linear in observed cost shifters, w_{jt}, and an unobserved cost shifter, ω_{jt}:

$$\ln(c_{jt}) = w_{jt}\gamma + \omega_{jt}. \tag{8}$$

Make fixed effects are included: $\omega_{jt} = \omega_m + \Delta\omega_{jt}$. Firms face no capacity constraints: this exposes current issues with the implementation of the ban which might persist into the future.

The prices in the data are assumed to form a Nash equilibrium each year. These and the elasticities implied by the demand system are used to obtain estimates of c_{jt} from (7). Estimating demand and supply jointly delivers more precise estimates at the cost of assuming that firms are not colluding. In section 7 I restrict the choice set by excluding internal combustion engine vehicles and use (7) to solve for the new equilibrium prices.

5 Estimation and Identification

All demand and supply parameters are estimated using the `PyBLP` package in line with best practices (Conlon and Gortmaker, 2020, 2025). This implements Berry et al. (1995)'s Nested Fixed Point algorithm. The GMM objective function is constructed by inverting market shares and stacking the sample aggregate and micro moments. The solver then searches over $\theta_2 = (\Pi, \Sigma, \alpha_0)$ until the solution converges. The linear parameters, $\theta_1 = (\beta_0, \gamma)$, are concentrated out. This section describes the estimation procedure, identification conditions, and the choice of instruments.

Estimation. The GMM estimator is:

$$\hat{\theta}_2 = \arg\min_{\theta_2} \hat{g}(\theta_2)'\hat{W}\hat{g}(\theta_2) \tag{9}$$

where $\hat{W}$ is a positive definite weighting matrix and $\hat{g}(\theta_2) = (\hat{g}_A(\theta_2), \hat{g}_M(\theta_2))'$ stacks the sample moments. The aggregate moments, g_A, are constructed from moment conditions $\mathbb{E}[\Delta\xi_{jt}z^D_{jt}] = 0$ and $\mathbb{E}[\Delta\omega_{jt}z^S_{jt}] = 0$, where $(\Delta\xi_{jt}, \Delta\omega_{jt})$ are the econometric errors and $z_{jt} = (z^D_{jt}, z^S_{jt})$ are the exogenous instruments. The micro moments, g_M, minimise the difference between observed summary statistics and their model analogues; including them means that the classical two-stage least squares weighting matrix cannot be used. Instead, $\hat{W}$ is the inverse of the variance-covariance matrix of all moments computed at an initial guess θ_0 as recommended in Conlon and Gortmaker (2020). Ten random starting values are tested; the solution that converges to an optimum and has the best objective value and model fit is chosen.

The market share integrals are approximated by taking 1,000 scrambled Halton draws along each dimension of heterogeneity and the system of market shares are inverted using the `SQUAREM` algorithm with a convergence threshold of 1×10^{-14}. This implements an accelerated version of the Berry et al. (1995) contraction mapping.[18] All linear parameters in θ_1 except for α_0 are concentrated out and recovered by a linear IV regression. I impose a tolerance threshold of 1×10^{-6} on the objective function in (9) and use SciPy's optimisation algorithm `trust-constr`. The parameters are estimated with a two-step routine.

Micro Moments. Including micro moments helps to identify the nonlinear parameters, Σ and Π. Due to the discrepancies between the aggregate and micro data shown in Table A.6 micro moments are defined relatively; this avoids imposing levels inconsistent with the equilibrium prices and market shares.

Income is discretised into five quintiles and micro moments match the average purchase probability and price for each quintile relative to the bottom. There is also a micro moment matching the relative average income of hybrid buyers (both conventional and plug-in) and electric vehicle buyers (battery and plug-in hybrids). The list is available in Table 5. Micro moments are pooled across all years from 2013 to 2023, except for the electric vehicle driver survey which was undertaken in 2021. This increases the estimator's variance but reduces the risk of asymptotic bias from using too many moment conditions (Han and Phillips, 2006). Pooling can be problematic if different markets are incompatible; the national market means that this should not be a problem.

5.1 Identification

The demand system is identified by the use of valid instruments, underpinned by cross-market variation in the choice set, and micro moments. Berry and Haile (2014) show that the demand system is nonparametrically identified from aggregate data if at least one of the product characteristics does not have a random coefficient, the demand system satisfies a connected substitutes condition, and the instruments used are exogenous and relevant. All three assumptions are satisfied here. The first is satisfied since only the constant, price, and engine type dummies have random coefficients. The second is satisfied for this demand system by Berry et al. (2013). Identification therefore depends upon the use of valid instruments; the next section addresses this.

Using micro data helps to identify the nonlinear parameters by imposing additional structure on the model; the higher price paid by richer households will require a positive interaction between

[18] Further details are available in Conlon and Gortmaker (2020). Fixed effects are absorbed using the LSMR method of Fong and Saunders (2011); PyBLP handles this by calling the `PyHDFE` package.

price and income. Each micro moment in Table 5 targets a specific demographic interaction. Micro data can also help to identify the coefficients on the random draws (Petrin, 2002; Berry et al., 2004).[19]

Cross-market variation in the choice set is informative about mean tastes and substitution patterns. The four years in which battery and hybrid electric vehicles make up a substantial share of models and sales make it possible to identify consumer preferences for these newer products.

If demand is identified then marginal cost estimates can be obtained using the pricing first-order conditions. Once these values are obtained the marginal cost function (8) is identified so long as the instrumental variables, z_{jt}^{S}, are valid.

5.2 Instruments

The instrumental variables are used to estimate the nonlinear parameters, Σ and Π, which govern consumer substitution patterns. The parameters in Σ are identified by a set of market structure instruments, built from observed product characteristics, which measure product differentiation. Micro moments also identify both Σ and Π while cross-market variation in the choice set is informative about mean tastes, β_0. The input cost index described in section 2 instruments for prices.

The market structure instruments are exogenous if the mean independence conditions hold:

$$\mathbb{E}[\Delta\xi_{jt}|x_{jt}] = 0 \text{ and } \mathbb{E}[\Delta\omega_{jt}|x_{jt}] = 0.$$

This seems plausible: vehicles' observed characteristics are determined in prior years and are unlikely to be adjusted in response to unanticipated shocks. The input cost instrument is exogenous so long as changes in international commodity prices are uncorrelated with the unobserved demand shocks. Including make and year fixed effects controls for much of the variation in unobserved quality (and costs); this also makes the optimal instruments easier to compute.

The market structure instruments are differentiation instruments which measure the isolation of a product in characteristics space. I choose which instruments to include by testing systematically for weak instruments, using the IIA test proposed by Gandhi and Houde (2023). This involves regressing inverse demand in the simple logit model on the observable characteristics and instruments: the null hypothesis is that the differentiation instruments do not matter for demand. This corresponds to a setting where preferences satisfy the IIA property. These tests reveal that classical BLP instruments suffer from a weak instruments problem here, but that the differentiation instruments can reject the null hypothesis of IIA preferences. Appendix B defines the instruments,

[19] Berry and Haile (2024) show that the use of micro data relaxes the instrumental variables requirement so that only cost shifters are needed. Due to the limited extent of the survey data I continue to make use of a set of market structure instruments to identify substitution patterns.

explains the testing procedure in more detail, and provides the test results.

On the demand side, differentiation instruments for price, emissions, their interaction, and the engine type instrument are included. The BLP constant instrument is also included. On the supply side, the instruments are differentiation instruments in horsepower and size (logged), their interaction, the engine type instrument, and the excluded characteristics. Random coefficients are estimated on the constant, price, and engine type dummies. These capture the key dimensions along which preferences vary and which will drive consumer behaviour under a ban.

In the second step, an approximation to the optimal instruments based on Chamberlain (1987) and Reynaert and Verboven (2014), as implemented by PyBLP, are used. The residuals are generated by replacing them with their expectations (Berry et al., 1999). This is computationally cheap and works well since the inclusion of make and year fixed effects means that the unobserved residuals are small. The excluded characteristics and input cost index are also included.

6 Results

This section presents the parameter estimates, model fit, and estimated substitution patterns.

Parameter Estimates. Table 3 contains the demand side parameter estimates. The constant's large random coefficient reflects substantial heterogeneity in the valuation of a new vehicle, with higher income households preferring them. All the price coefficients are statistically significant and have the expected signs. There is some unobserved heterogeneity in price sensitivity and higher income households are less price sensitive (at a decreasing rate). All linear coefficients have the expected sign except cost; all except range and the HEV and PHEV dummies are statistically significantly different from zero. Cost could be capturing 'luxury', for which there is no observable characteristic.

The mean distaste for battery electric vehicles is high but this is partially offset by BEVs rating highly on many desirable observable characteristics. The counterfactual in section 7 shows that BEVs are not as unpopular as this makes them appear. There is more heterogeneity in tastes towards BEVs, observed and unobserved, than the other engine types. The non-price distaste for BEVs may be due to omitted variables, such as repair costs and the depreciation rate, which do not appear in the price but impact the amount which households spend on a vehicle in its lifetime and can recoup from selling it later.[20] There may also be anxiety about new technology that will fade with exposure. Both the linear and random coefficients on the HEV dummy are close to zero. This reflects their similarity

[20] High repair costs are driven by a limited number of qualified mechanics, while the high depreciation rates may be driven by an immature secondary market. These translate into higher insurance costs. The EDFE report Electrifying the UK discusses the high depreciation rates of BEVs and the difficulty of obtaining financing.

Table 3: Demand Parameter Estimates

Variable	β_0	σ	Demographic Interactions: Income	Demographic Interactions: Income Sq.
Constant	-	9.21	0.329	
		(3.7)	(0.141)	
Price	-4.25	0.578	0.253	-0.0143
	(0.544)	(0.0881)	(0.046)	(0.0032)
Horsepower	3.91			
	(0.502)			
Size	0.649			
	(0.104)			
Driving Cost	1.16			
	(0.521)			
Emissions	-1.43			
	(0.548)			
Range	0.0358			
	(0.091)			
Chargers	3.81			
	(1.65)			
BEV	-49.6	7.19	0.35	
	(21.3)	(2.27)	(0.183)	
HEV	-0.676	1.18	0.083	
	(1.74)	(1.75)	(0.052)	
PHEV	-9.84	4.87		
	(5.11)	(2.51)		

Note: Income and price are given in tens of thousands of 2015 pounds. Size is length $\times$ width in square metres. Horsepower is in 100bhp, emissions is 100g/km, driving cost is the cost of driving 100 miles in tens of 2015 pounds. Range is in hundreds of miles, chargers is the logged number of chargers nationally and is zero for non-BEVs. Make and year fixed effects are included. Standard errors are clustered by product.

to ICE vehicles, as seen in Figure A.1. PHEVs are clearly perceived as somewhere in between BEVs and HEVs, although both the linear and random coefficient are imprecisely estimated here. The relatively small magnitude of the demographic interactions means that most of the heterogeneity is due to unobserved characteristics.

The estimated parameters for the supply side are given in Table 4. Larger vehicles with higher horsepower are more expensive to produce, as are battery electric vehicles. Strangely, the input cost instrument is estimated to reduce marginal costs. Given that higher input costs are strongly correlated with larger size and horsepower this is not particularly worrying; most of the effect is through those variables.

Table 4: Supply Parameter Estimates

Variable	γ
log(HP)	0.776
	(0.0325)
log(Size)	0.914
	(0.0703)
Trend	-0.000297
	(0.000812)
Input Cost Instrument	-0.39
	(0.137)
BEV	0.141
	(0.0283)
HEV	0.0886
	(0.0348)
PHEV	-0.113
	(0.0356)

Note: Horsepower is in 100bhp, size is in square metres. Both are logged. Make fixed effects are included.

Model Fit. Table 5 contains the observed values of the micro moments used to estimate the model and the values of their model analogues. The demographic interactions in Table 3 all had the expected sign, so the overall patterns are reproduced. The model slightly underestimates the relationship between income and both price and purchase probability of the inside good.

Although not a formal measure of model fit, the own-price elasticities of demand help to assess the estimates' plausibility. Table 6 shows that none of the demands are inelastic. The share-weighted mean own-price elasticity has decreased over the period, from -6.9 in 2001 to -9.2 in 2022. Most of

Table 5: Model Fit: Micro Moments

Moment	Model	Data	$\frac{\text{Model}}{\text{Data}}$
$\mathbb{E}[\mathbb{1}\{j \neq 0\}\vert Q_5]/\mathbb{E}[\mathbb{1}\{j \neq 0\}\vert Q_1]$	1.503	1.682	89.4
$\mathbb{E}[\mathbb{1}\{j \neq 0\}\vert Q_4]/\mathbb{E}[\mathbb{1}\{j \neq 0\}\vert Q_1]$	1.241	1.241	100.0
$\mathbb{E}[\mathbb{1}\{j \neq 0\}\vert Q_3]/\mathbb{E}[\mathbb{1}\{j \neq 0\}\vert Q_1]$	1.120	1.421	78.8
$\mathbb{E}[\mathbb{1}\{j \neq 0\}\vert Q_2]/\mathbb{E}[\mathbb{1}\{j \neq 0\}\vert Q_1]$	1.021	1.192	85.7
$\mathbb{E}[p_{jt}\vert Q_5] - \mathbb{E}[p_{jt}\vert Q_1]$	0.604	0.698	86.6
$\mathbb{E}[p_{jt}\vert Q_4] - \mathbb{E}[p_{jt}\vert Q_1]$	0.366	0.382	95.7
$\mathbb{E}[p_{jt}\vert Q_3] - \mathbb{E}[p_{jt}\vert Q_1]$	0.210	0.312	67.4
$\mathbb{E}[p_{jt}\vert Q_2] - \mathbb{E}[p_{jt}\vert Q_1]$	0.078	0.300	26.1
$\mathbb{E}[y_{it}\vert HEV == 1 \vee PHEV == 1] - \mathbb{E}[y_{it}\vert ICE == 1]$	0.616	0.585	105.3
$\mathbb{E}[y_{it}\vert BEV == 1 \vee PHEV == 1]$	5.853	5.445	107.5

Note: The first eight micro moments condition on income quintile, with Q_5 containing the top 20% of households by income. All moments except the last are pooled from 2013 to 2023. Price and income are in tens of thousands of 2015 GBP.

the fall occurs after 2015, matching the observed increase in prices seen in Figure 1a. This is slightly higher than the average elasticity found by Grieco et al. (2024) for the US auto industry.[21] Figure A.2 shows the change in the estimated marginal costs and markups, as measured by the Lerner index ($\frac{p-c}{p}$), over the sample. The average markup fell from 15% to 12.5% from 2015 to 2021; markups are lowest on the more expensive battery electric vehicles and plug-in hybrids due to their higher marginal costs. Both the average price and marginal cost rose by roughly £8,000 from 2014 to 2021: markups fell because the competitive constraint stopped firms from increasing prices further.[22]

Table 6: Own-Price Elasticities

Min.	Max.	Median	Mean	Std. Dev.	10th Percentile	90th Percentile
-20.01	-3.02	-8.23	-7.77	2.79	-12.35	-5.02

Note: Summary statistics are taken across all years; the mean is weighted by market share.

[21] It is also somewhat above the typical average in the literature for the automobile industry, but is consistent with several other studies (Beresteanu and Li, 2011; Li, 2018; Guo and Xiao, 2023).

[22] Keiller et al. (2024b) estimate a nested logit model of demand in the UK new car market, with four nests based on model horsepower and weight, and also find that domestic markups fell sharply from 2015 to 2020. Their estimated level is much higher, however, at 39% in 2020. This may be due to them using different weights (revenue rather sales) or estimating much less elastic demand.

Table 7: Sample of 2023 Price Elasticities

Model	MG ZS	Cooper	3008	GLC	Prius	Kona	Austral	X-Trail	Corsa	Enyaq	C40	iX
ICEs												
MG ZS	-5.892	0.148	0.036	0.023	0.036	0.024	0.017	0.022	0.004	0.010	0.004	0.013
Mini Cooper	0.076	-7.758	0.036	0.034	0.032	0.023	0.018	0.025	0.003	0.011	0.005	0.021
Peugeot 3008	0.063	0.126	-9.202	0.045	0.030	0.022	0.018	0.028	0.003	0.012	0.006	0.029
Mercedes GLC	0.029	0.081	0.031	-13.068	0.020	0.018	0.018	0.035	0.002	0.011	0.007	0.062
HEVs												
Toyota Prius	0.061	0.109	0.029	0.027	-7.569	0.054	0.042	0.060	0.003	0.011	0.005	0.017
Hyundai Kona	0.054	0.102	0.028	0.033	0.071	-8.424	0.043	0.064	0.003	0.011	0.005	0.020
Renault Austral	0.047	0.095	0.028	0.040	0.066	0.051	-9.336	0.070	0.003	0.011	0.005	0.023
Nissan X-Trail	0.038	0.085	0.027	0.049	0.060	0.049	0.045	-10.346	0.002	0.011	0.005	0.027
BEVs												
Vauxhall Corsa	0.013	0.023	0.006	0.005	0.007	0.005	0.004	0.005	-9.460	0.318	0.125	0.299
Skoda Enyaq	0.009	0.020	0.006	0.008	0.006	0.005	0.004	0.006	0.085	-12.223	0.129	0.464
Volvo C40	0.008	0.019	0.006	0.011	0.005	0.004	0.004	0.006	0.071	0.276	-13.688	0.568
BMW iX	0.005	0.016	0.006	0.020	0.004	0.003	0.003	0.006	0.034	0.195	0.111	-16.285

Note: Cell (i, j) contains the percentage change in share for i when j increases in price by 1%.

6.1 Substitution Patterns

The model generates rich substitution patterns with clear implications for climate policy: the market is partially segmented by engine type, but with consumers happy to substitute between HEV and ICE vehicles, and most consumers buying new vehicles are unlikely to substitute to the outside good.

Table 7 presents the price elasticities of demand for twelve products: the four products from each of the three main engine types with prices closest to the 10th, 40th, 60th, and 90th percentiles within that type. The entry for the i'th row and j'th column contains the elasticity $\varepsilon_{ij} = \frac{p_{jt}}{s_{it}} \frac{\partial s_{it}}{\partial p_{jt}}$. This gives the percentage change in good i's share when j's price increases by 1%.

Two results are apparent. The market is clearly segmented by engine type: buyers of ICEs and HEVs substitute within this group, to similar priced products, while the buyers of battery electric vehicles are loath to substitute away. The own-price elasticity of demand is also increasing in price.

The diversion ratio from good i to j is the proportion of households who purchase product j after substituting away from i: $\mathcal{D}_{ij} = -\frac{\partial s_{jt}}{\partial p_{it}} / \frac{\partial s_{it}}{\partial p_{it}}$. Table 8, inspired by a similar table in Berry et al. (2004), gives the proportion of households who substitute towards the outside good and the two most preferred alternatives. The degree to which the market is segmented by engine type is even more apparent; the most popular alternatives are all vehicles within the same segment.

Purchasers of more expensive vehicles are more likely to stay within the market following a price increase. Their more elastic demands indicate that price competition is fierce within a segment, with customers willing to pay for their desired product but shopping around for the best deal, not that these consumers are making marginal decisions between buying a new vehicle or not.

These substitution patterns have clear implications for climate policy. Households currently

Table 8: Sample of 2023 Diversion Ratios

Model	First Alternative	% Movers	Second Alt.	% Movers	% Outside Good
ICEs					
MG ZS	Vauxhall Corsa	3.44	Ford Puma	3.19	14.23
Mini Cooper	Ford Puma	3.42	Vauxhall Corsa	2.84	13.39
Peugeot 3008	Ford Puma	3.30	Toyota Yaris	2.51	12.48
Mercedes GLC	LR Defender	2.72	VW Tiguan	2.12	9.63
HEVs					
Toyota Prius	Toyota Yaris	5.50	Ford Puma	2.71	12.32
Hyundai Kona	Toyota Yaris	5.37	Ford Puma	2.65	11.89
Renault Austral	Toyota Yaris	5.21	Ford Puma	2.57	11.37
Nissan X-Trail	Toyota Yaris	5.04	Ford Puma	2.47	10.71
BEVs					
Vauxhall Corsa	MG 4	9.39	Tesla Model Y	8.34	10.83
Skoda Enyaq	Tesla Model Y	8.98	MG 4	6.85	10.23
Volvo C40	Tesla Model Y	10.21	Audi Q4	5.83	8.28
BMW iX	Tesla Model Y	10.17	Porsche Taycan	6.56	5.40

Note: The third, fifth, and sixth columns give the percentage of households who substitute to the listed good out of those who no longer buy the row good after a 1% increase in price

purchasing ICE vehicles are most likely to substitute towards HEVs if they become more expensive or are no longer sold, although there may be more movement towards BEVs at the top of the price distribution. Households currently purchasing new vehicles are more likely to stay within the market, even if conditions change, than turn to the outside good.

Although these substitution patterns capture the heterogeneity in preferences for vehicles of different engine types, there are some limitations. There is no indicator for the body type of a vehicle, e.g. SUV, which is an important dimension of preference heterogeneity. The specification also sets the off-diagonal elements in the random coefficients matrix, Σ, to zero. In reality, unobserved preferences for different engine types may be correlated due to environmental preferences.

7 The Impact of an ICE Ban

This section explores the impact of the proposed ban on the sale of new vehicles with internal combustion engines by estimating the counterfactual equilibrium prices and shares. Households who stay in the market overwhelmingly prefer hybrids, giving firms little incentive to develop new battery electric vehicles. European firms and low-income households are badly affected. The benefit from lower carbon emissions compensates for the fall in profits but not the fall in consumer surplus.

Estimating the Counterfactual. The impact of the proposed ban is modelled by removing all ICE vehicles from the 2023 choice set, leaving hybrids, plug-in hybrids, and battery electric vehicles, and re-estimating equilibrium prices and shares.[23] There are 72 vehicles remaining in the choice set.[24] I assume throughout that there is no change to the utility of the outside good, with its mean utility still normalised by $u_{i0t} = \epsilon_{i0t}$. Abstracting from the secondary market is necessary given data constraints but restrictive: it is possible that the ban would lead to changes in the secondary market, such as a change in prices, leading to a change in δ_{0t}. For example, if prices were to increase in the secondary market due to the fall in supply of used ICE cars then there might also be disruption and a reduction in consumer surplus there, leading to an underestimate of the fall in welfare.

Product Shares. The combined market share of all inside goods falls from 30% to 24%. The balance of sales between different vehicle types also changes dramatically. Table 9 shows that the major beneficiaries of the ban are HEVs while battery electric vehicles - previously the most popular of the alternative engine types - increase their share by a much smaller proportion, as do the similar plug-in hybrids. The gain in BEV share is not that much lower than the gain in PHEV share, despite the large differences in mean tastes in Table 3, due to the larger heterogeneity in tastes and high BEV quality on other attributes.

Table 9: Change in Sales Composition

Fuel Type	Pre Ban (%)	Post Ban (%)	Ratio
HEV	13.28	61.24	4.61
BEV	16.81	26.78	1.59
PHEV	5.02	11.99	2.39
ICE	64.89	0.00	0.00

Note: These are each engine type's percentage share of total sales.

Industry concentration increases by relatively little given the substantial change in market conditions: the largest firm's share of the inside goods is unchanged and the combined share of the six largest firms increases from 68.4% to 74%. The market is still an oligopolistic market with several

[23] These are estimated using Conlon and Gortmaker (2020)'s implementation of the Morrow and Skerlos (2011) fixed point iteration.

[24] 105 vehicles are removed. The UK's proposed ICE ban would exempt vans: this implementation is equivalent to banning only ICE cars as no vans appear in the 2023 choice set after filtering on market share.

large firms and a long tail of smaller manufacturers: the ICE ban merely squeezes some firms. Table A.7 compares a variety of measures of industry concentration.

The five vehicles with the largest absolute gains in market share are HEVs, while the smallest five are all battery electric vehicles. These increases are strongly correlated with existing share. East Asian companies, such as Toyota, with a pre-existing competitive range of hybrids are the biggest beneficiaries: the Yaris and Corolla were the most popular hybrids pre-ban and have the first and fourth largest increases in market share. All of these hybrids emit more than 100g/km of CO_2, a level comparable to the most environmentally friendly ICEs: the environmental benefits of any ban which leaves hybrids available to purchase will clearly be limited.

Product Prices. When setting prices, firms trade off changes on the intensive and extensive margins. The ban on ICE vehicles leads to a diverse range of price changes by altering this trade-off differently for different products: 27 products cut their prices and 45 increase them. The vehicles with the largest increases in market share, all HEVs, take advantage of the reduced number of substitutes, as similarly priced ICE vehicles are removed, to raise their prices. This is the most important change from a consumer perspective: the share-weighted average price increases by £230 (in 2015 GBP). Prices do not change more despite the significant change to market conditions because the outside good serves as a competitive constraint on firms: price-sensitive households always retain the option of not purchasing a new vehicle.

All of the models which cut their prices are BEVs and PHEVs. Some of these firms have lost many of their infra-marginal consumers who previously purchased internal combustion engine cars and are competing for marginal consumers to recover their lost business. The higher mean distaste for battery electric vehicles means that the exclusion of ICE cars does not substantially alter their close substitutes; there is still tough competition for potential customers.

Costs are held constant in the counterfactual, so markups change one-to-one with prices. The share-weighted mean increase in markups on non-ICE cars is 0.6 percentage points, a more moderate change than the size of the counterfactual might suggest. The average level is lower than it was before ICE vehicles were removed. Maintaining the same level of marginal costs abstracts away from the possibility of capacity constraints and economies of scale. In reality, capacity constraints would bite for some of the hybrid models faced with particularly large increases in demand.

7.1 Firms' Innovation Incentives

One reason for announcing a ban on internal combustion engine cars is to incentivise a change in firm behaviour. Changing the expected profits of different models, by reducing the years for which

ICEs can be sold, should encourage the development of new hybrid and battery electric models.

In order to understand the possible impact on firm behaviour, I examine the impact of each make (brand, e.g. Audi) introducing a new product to the market before and after the ban is imposed. Two new products are considered: a median HEV and a BEV. These have characteristics equal to the median of observed characteristics for that engine type. All products also have an unobserved quality and cost, ξ_{jt} and ω_{jt}, which consist of the make and year fixed effects and a deviation. I take the estimated effects for 2023, the particular make, and the average $\Delta\xi_{jt}$ and $\Delta\omega_{jt}$ from the empirical distribution of unobserved residuals in 2023: the only difference in unobserved quality comes from the make. New equilibrium prices and shares are computed with the product added to the choice set; firms set prices optimally to account for their different costs.

Table 10 examines a subset of firms and gives the change in each firm's total market share and variable profits from introducing the product before and after a ban is imposed. Banning the sale of new ICE cars increases the gain in profit from introducing a hybrid vehicle by a factor of four for most firms. The cross-firm variation is explained by different make effects and current penetration into the hybrid market. For hybrids, Land Rover gain the most despite setting a high price due to their high quality. Toyota, which already has a large range of hybrids, gains very little as they cannibalise share from their existing products. Vauxhall, which is particularly badly affected by the ban, experiences the opposite: their market share increases almost one-to-one with their product's. These are the change within-year variable profits, so they show that firms' short-run incentive is to try and quickly introduce new HEV models to the market.

The introduction of the ban has a much smaller impact on the incentives of firms to introduce battery electric vehicles: there is a limited pool of new customers due to consumers' large mean distaste. The pattern of firm heterogeneity is similar. Only two of the thirty makes in the market, Dacia and Tesla, would find it more profitable to introduce a battery electric vehicle than a hybrid under the ban. Across makes, the sales-weighted average increase in profit from introducing the median HEV is £132 million compared to £95 million for the BEV.[25]

This analysis studies firms' unilateral incentives. Since each firm introduces their new vehicle once at a time it produces an upper bound on the increase in a firm's variable profits; if multiple firms expanded their product lines at once then there would be smaller gains in market share.

The limited increase in profits from introducing a new battery electric vehicle reveals that the ban will not open up the market to new entrants, even if these companies are producing high quality cars, because of consumer preferences. In the short term there is a limit to how much government

[25] The BEV average is distorted by Dacia and falls to £49 million when they are excluded. Their low cost fixed effect allows them to set a price of £22,678 and enjoy a large market share. I do not regard this as particularly plausible since it is estimated from a small number of cheap ICEs: they never have more than three models in a year and the highest price of any model is £16,224. It does, however, show that a sufficiently cheap BEV can attract consumers.

Table 10: Impact of Introducing a New Product

	Product				Company Gain			
	Price		Share		Share		Profit	
Make	Pre-Ban	Post-	Pre-Ban	Post-	Pre-Ban	Post-	Pre-Ban	Post-
HEV								
Land Rover	33,923	34,035	0.588	2.081	0.548	2.045	106.67	406.39
Vauxhall	25,118	24,880	0.195	0.867	0.164	0.862	32.47	142.81
Ford	24,937	24,880	0.204	0.857	0.175	0.777	33.87	138.85
Audi	29,485	28,935	0.142	0.689	0.084	0.653	20.99	115.46
Mercedes	31,755	31,686	0.152	0.623	0.132	0.623	25.40	109.08
Tesla	19,369	19,381	0.093	0.403	0.074	0.394	10.32	60.88
Toyota	29,102	29,918	0.065	0.205	0.058	0.105	12.25	33.45
BEV								
Ford	35,922	35,901	0.410	0.526	0.392	0.508	71.70	90.86
Vauxhall	36,201	36,152	0.381	0.494	0.339	0.450	66.39	85.09
Land Rover	49,237	49,261	0.314	0.406	0.301	0.390	58.71	76.53
Tesla	28,395	28,378	0.364	0.473	0.253	0.349	55.22	75.73
Audi	42,752	42,705	0.143	0.187	0.072	0.111	21.45	30.37
Mercedes	46,230	46,253	0.105	0.135	0.082	0.122	17.48	23.55
Toyota	41,632	41,743	0.082	0.102	0.089	0.100	15.49	17.62

Note: Price is in 2015 pounds. Share is the percentage share of the total market, including the outside good. Profit is in millions. The product is identical across makes except for price and make fixed effects. It has the median observed characteristics of cars of that engine type and an unobserved quality computed from the fixed effects and the average from the empirical distribution of the residuals.

policy can change this, but lower repair costs, higher resale values, or longer exposure to the new technology could lead to preferences changing over time. Regardless, these results matter now for long-term environmental outcomes. If firms anticipate these potential profits by introducing new hybrid models to the market in the coming years, these vehicles will be in the product mix for many years. Qualitative evidence provides some external validation that this is already motivating firms to introduce new hybrid models: S&P Global Mobility found that the number of hybrid models offered by carmakers was increasing by 43% from 2024 to 2025, the most of any engine type.[26]

Given the limited environmental impact of switching to hybrids, visible below in Figure 3, the transition to net zero could be materially slowed by a delay in the development of high-quality zero-emission vehicles as firms focus on the provision of relatively unclean HEVs.

[26]Source: `https://www.ft.com/content/e1f3cfd3-770a-4b75-946b-4fc2a09c302c`. This article states that Porsche, BMW, and Mercedes-Benz have all promised to develop new hybrid models. So have Ford, Stellantis, e.g. for their Vauxhall make, and Volkswagen. Jaguar Land Rover are shifting from BEVs to PHEVs.

7.2 Welfare

I measure the within-year change in consumer surplus, variable profits, and carbon emissions in the market for new vehicles following the ban on ICEs. The impact on both variable profits and consumer surplus is highly heterogeneous. Firms with popular hybrids, such as Toyota and Honda, more than triple their profits, and lower income households are the most adversely affected. The fall in emissions is muted due to the popularity of HEVs.

Producer Surplus. Industry variable profits fall by £800 million, 13 percent, following a ban. They fall by less than demand as firms use their strengthened market power to increase prices. This masks a significant redistribution of market share and profits between firms; a natural consequence of firms choosing different adjustment paths in expectation of the future ban.

Producer surplus is measured by variable profits: $\pi_{ft} = \sum_{j \in J_{ft}} (p_{jt} - c_{jt}) q_{jt}$ where $q_{jt} = s_{jt} \mathcal{M}_t$ and $\mathcal{M}_t$ is the size of market t. This abstracts away from changes to fixed costs. Table 11 presents the change in company shares and variable profits for the seven firms with the largest shares post-ban.

The big winners are Honda, Renault, and Toyota, who increase their share of profits and sales at the expense of European firms focused on ICEs. Toyota has a relatively small range of products but seven of their eight models are hybrids including cars with relatively low prices, e.g. the Yaris costs £21,345 (in 2015 pounds) in 2023. Volkswagen, whose profits fall to a third of their pre-ban level, have a range of ICE cars, and some BEVs and PHEVs, but no HEVs. Tesla fails to capitalise on the change in market conditions due to their lack of a hybrid product line.

Changes to firm profits have a significant international dimension. Japanese and Korean manufacturers gain while European firms suffer: Czech, German, and Spanish makes (brands) lose more than £900 million. German losses are the largest.[27] Tata, who own the British company Jaguar Land Rover, see their profits halve. In particular, the ban threatens to hollow out European manufacturing: the profits made by models produced in Germany and Spain will fall by £3 billion in each country. They increase most in Japan, Turkey, and the UK (due to the presence of Honda, Nissan, and Toyota factories). This may explain Germany's 2023 opposition to the EU's proposed ban.[28]

These poor returns are a consequence of European firms being behind the curve, mainly selling ICEs and beginning to develop BEVs without using hybrids as a bridging technology. For this approach to work, and for the transition to not be prohibitively costly for many companies, governments and firms will have to make battery electric vehicles more attractive relative to hybrids.

[27] This takes the make's national association, not place of financial listing. e.g, the German makes sold in 2023 are Audi, BMW, Mercedes, Mini, Porsche, and Volkswagen.

[28] See https://www.ft.com/content/23e1fb1c-c34a-4aaa-adc6-e71853befb36.

Table 11: Company Shares and Profits

	Shares			Variable Profits		
Company	Pre Ban (%)	Post Ban (%)	Change	Pre Ban	Post Ban	Ratio
Honda	0.39	1.61	1.22	63	273	4.32
Toyota	2.11	5.73	3.62	378	1,306	3.46
Renault	0.65	1.76	1.11	102	297	2.91
Nissan	1.51	2.35	0.84	251	428	1.70
Hyundai	3.14	3.89	0.75	542	739	1.36
Ford	2.46	1.13	-1.33	416	197	0.47
Volkswagen	7.17	2.52	-4.65	1,507	548	0.36
Others	12.54	5.16	-7.37	2,271	1,006	0.44
Overall	29.97	24.16	-5.81	5,531	4,793	0.87

Note: Shares are given in percentage terms, with the change being in percentage points. Profits are in millions of 2015 pounds. The other companies are Avtovaz, BMW, Daimler, Geely, Mazda, SAIC, Stellantis, Suzuki, Tata, and Tesla. Neither Avtovaz nor Suzuki offer any battery or hybrid electric vehicles so their share and profits are zero after the ban.

Consumer Surplus. The change in consumer surplus from the introduction of a ban is measured by using compensating variation. The baseline case, market t, is 2023 as observed. I compare this to market t', where a ban is introduced in 2023, and find the amount of money required to make the consumer indifferent between the baseline and counterfactual. For an individual i the change in consumer surplus is:

$$CS_{it'} - CS_{it} = \mathbb{E}[u_{ijt'}] - \mathbb{E}[u_{ijt}] = -\frac{1}{\alpha_{it}}[\log(\frac{\sum_{j\in J_t'} \exp(V_{ijt'})}{\sum_{j\in J_t} \exp(V_{ijt})})] \text{ where } V_{ijt} = \delta_{jt} + \mu_{ijt} \quad (10)$$

and the total change in consumer surplus is found by integrating over all consumer types. As with profits, the change in consumer surplus is measured for the year in which the ban is imposed.

The last column in Table 12 divides the average change in consumer surplus for each quintile by the quintile's average gross income to measure how households are affected relative to their resources. Lower income households would be disproportionately affected. Households in the lowest quintile obtain consumer surplus worth 32.8% of their gross income before the ban. This is high but not surprising: a car is a major household purchase which lasts for several years. Introducing the ban reduces their consumer surplus by almost 10% of their annual income; richest households experience a reduction worth only 1.5% of their annual income, one-sixth as much. The relationship between income and lost consumer surplus, relative to purchasing power, is monotonic.

Table 12: Consumer Surplus

	Consumer Surplus			Consumer Surplus / Income		
Income Quintile	Pre Ban	Post Ban	Change	Pre Ban	Post Ban	$\frac{\Delta CS}{Income}$
Q1	3,743	2,692	-1,051	0.328	0.236	-0.092
Q2	4,157	3,080	-1,077	0.201	0.149	-0.052
Q3	5,109	3,796	-1,313	0.168	0.125	-0.043
Q4	7,215	5,525	-1,690	0.172	0.132	-0.040
Q5	8,189	6,949	-1,240	0.101	0.086	-0.015

Note: The consumer surplus figures are the average consumer surplus for each income quintile in 2015 pounds. The final three columns divide the first three by the average income of that quintile.

These consumer surplus figures are a static measure of the within-year change, albeit for households who come to the market every five years; they provide a sense of the policy's heterogeneous impact and possible deficiencies. Beyond the normative issues this poses, the proposed ban may struggle to secure long-term political support without policy changes to make battery electric vehicles cheaper or support for low-income households to transition.

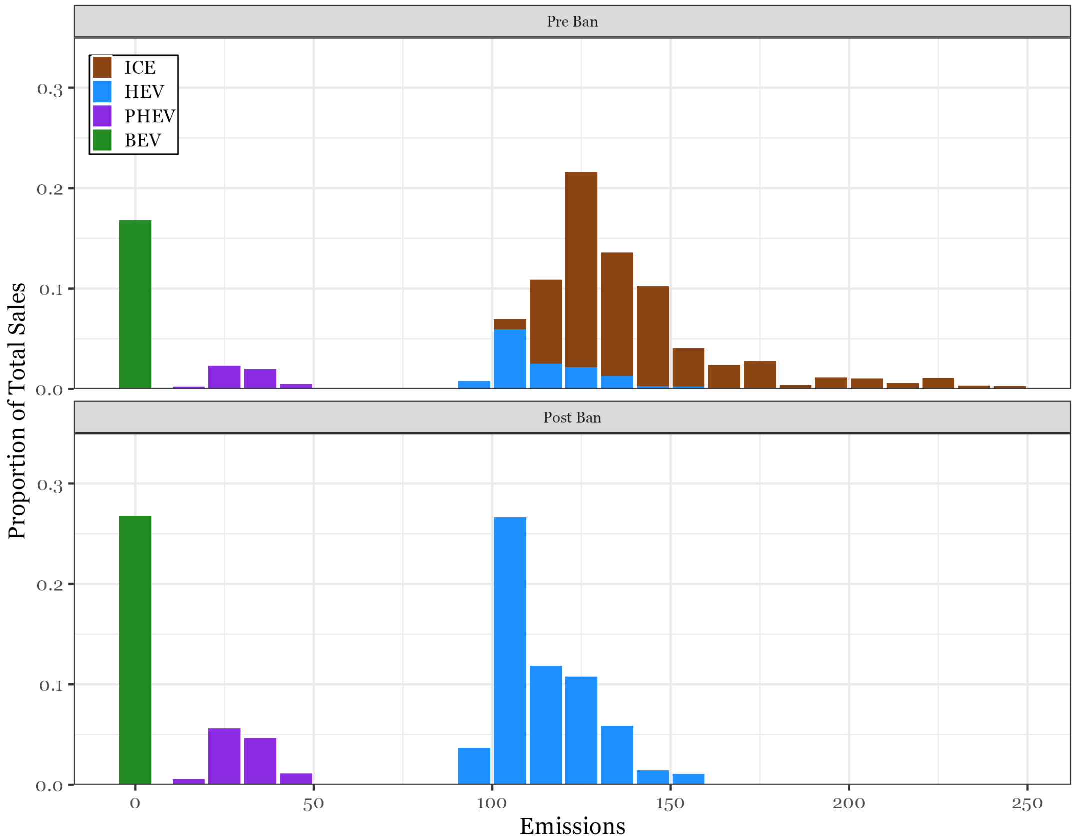
Climate Impact. To complete the welfare analysis, I obtain an upper bound for the expected fall in carbon emissions and increase in welfare. This captures the benefit to the climate from lower greenhouse gas emissions; it does not measure the change in any other externalities, such as the health benefits of lower air pollution. Figure 3 shows the muted climate impact of the ban. The distribution of sales across emissions bins shifts slightly to the left, but not dramatically; more than than half of the vehicles sold are hybrids that emit more than 100g/km of CO_2.

I combine vehicle CO_2 emissions, mileages, and the social cost of carbon to measure the increase in welfare from a fall in the emissions of new cars purchased in 2023.[29] This abstracts from the carbon cost of production, other measures of air pollution, and different vehicle lifespans to reduce the number of assumptions made. I assume that households who switch from purchasing an ICE to a non-ICE do not adjust their mileage; i.e. that there is no 'rebound effect' where households increase their mileage in response to a lower cost of driving. The evidence indicates that there is a partial rebound effect in many settings – Stapleton et al. (2016) estimate a mean rebound effect for vehicle mileage in Great Britain of 19% – so this will slightly overstate the climate benefit.[30] I check the

[29] Households substituting to the outside good leads to a fall in emissions. While they may purchase a used car, these vehicles were already being driven before changing hands on the secondary market. As the stock of new cars falls, I treat this as a reduction. This fits with the interpretation of these results as an upper bound on the ban's climate benefit.

[30] See Gillingham et al. (2016) for a discussion of the difficulties with estimating the rebound effect and a survey of

Figure 3: Changing Emissions Distribution



Note: The top panel is the distribution of emissions in 2023. The bottom panel is the distribution after a ban is imposed and counterfactual shares and prices are calculated. The bar's height gives the proportion of yearly sales in that emissions bin.

estimate's sensitivity to this assumption later. Recall from section 3.2 that we have made the (false) assumption that the electricity system is fully decarbonised so that BEVs have zero emissions: this, assuming no rebound effect, and ignoring the carbon cost of production, means that the result is an *upper bound* on the policy's climate benefit.

As discussed in section 2, vehicle emissions are given by WLTP values. Each model has a mileage obtained from the their fuel type's mileage distribution (estimated from the MOT data). Households switching from ICEs to a given model all have the same mileage, again obtained from the ICE mileage distribution; the details are in appendix A. I assume that the empirical distribution of mileage does not change with the ban. The change in emissions is multiplied by the social cost of carbon: £252/tonne in 2020 prices.[31] This figure is multiplied by five to match the assumption on market size and ownership length: the change in welfare from lower emissions is therefore compa-

several estimates. Since households cannot be tracked across vehicles there is no way to estimate the effect here.

[31] This is the government's 2023 carbon value for policy appraisal; see the policy paper on valuing carbon emissions.

Table 13: Change in Emissions

	Emissions (Mt)			Social Cost of Carbon (£mn)		
Type	Pre Ban	Post Ban	Difference	Pre Ban	Post Ban	Difference
BEV	0.00	0.00	0.00	0	0	0
PHEV	0.23	0.39	0.16	53	90	36
HEV	2.28	6.94	4.66	529	1,609	1,080
ICE	10.47	0.00	-10.47	2,427	0	-2,427
Overall	12.98	7.33	-5.65	3,008	1,698	-1,310

Note: The emissions columns are in million tonnes of CO2. The cost columns are in millions of 2015 pounds. They are obtained by multiplying the change in emissions by the social cost of carbon for 2023 and by a factor of five to match the market size assumptions on average ownership length.

rable to the within-market welfare measures.

Imposing the ban on ICE vehicles leads to new vehicle emissions in 2023 falling from 12.98Mt of CO_2 to 7.33Mt, 56% of the pre-ban level. The climate benefit of the policy is bounded above by £1,310 million. In 2022, the latest year for which data area available, the total emissions of CO_2 from UK cars was 60 million tonnes, so these figures imply that new cars accounted for just over 20% of this figure.[32] These results are not particularly sensitive to assuming that there is no rebound effect: a rebound effect of 19% leads to emissions falling to 7.63Mt and a climate benefit of £1,239 million.[33]

Household-Level Impact. The overall cost of the policy, even after accounting for the benefits from reducing pollution, is large. Table 14 divides the changes in consumer surplus, variable profits, and the carbon externality by the 2023 market size. This gives the welfare change at the level of the prospective buyer: the fall in welfare is £1,175 per prospective buyer, or £235 per household. The gain from lower carbon emissions more than offsets the fall in variable profits but there is a substantial fall in consumer surplus from higher prices and households exiting the market.[34] Each reduction in the social cost of carbon of £1 costs £6 in consumer surplus and variable profits.

Obviously forcing households to substitute away from their preferred products will be costly: the distributional impact of the policy is of primary interest. The negative impact on European firms

[32]See https://www.gov.uk/government/statistics/transport-and-environment-statistics-2024/.

[33]To account for the rebound effect, I increase the mileage of all new customers by the difference between the given model's mileage and the mileage of the new customers, who previously bought ICEs, multiplied by 0.19.

[34]Including demographic interactions and micro data avoids the logit error term inflating the change in consumer surplus, a problem identified by Petrin (2002).

Table 14: Household-Level Welfare Change: ICE Ban

Consumer Surplus	Variable Profits	Climate Benefit	Overall
-1,278	-134	237	-1,175

Note: All columns give the overall change (in 2015 pounds) divided by the market size.

and low-income households suggest that the ban may face serious political opposition without a change in market conditions. The limited climate benefit is due to the current popularity of HEVs.

7.3 Further Analysis

Alternative Product Bans. The emissions benefit of the proposed ICE ban is muted due to the popularity of hybrids. To test if restricting consumers to zero-emissions vehicles helps, I re-estimate the counterfactual with only BEVs included in the choice set.[35] This trivially rebalances firms' product innovation incentives. Most households exit the market; low income households are harmed the most while only Tesla increase their profits. There is a large reduction in emissions but the fall in consumer surplus means that the welfare loss is three times larger than under the ICE ban. This is a large counterfactual but highlights the relative popularity, and affordability, of HEVs.

I also decompose the ban on ICEs into three stages based on the tailpipe emissions of the vehicle. Banning only the sale of ICE models with emissions of 150g/km or greater, one third of the ICEs available in 2023, realises 21.1% of the complete ICE ban's climate benefit at 16.6% of the cost to consumer surplus. Targetting dirty ICEs has a fairly limited impact, despite the ability to target models with lower carbon emissions, because consumers tend to substitute towards only slightly cleaner ICEs. This less stringent ban has a slightly different distributional pattern: luxury manufacturers lose out while some firms with traditional product offerings, such as Stellantis and Ford, see their profits increase. Households in the fourth highest income quintile are hurt most. Alongside the limited benefits from directly targeting emissions with the ban, governments may be hesitant to introduce emissions-based bans since they incentivise gaming of emissions tests (e.g. Tanaka (2020) and Reynaert and Sallee (2021) document evidence of gaming in Japan and Europe). Appendix C contains further details on these counterfactuals.

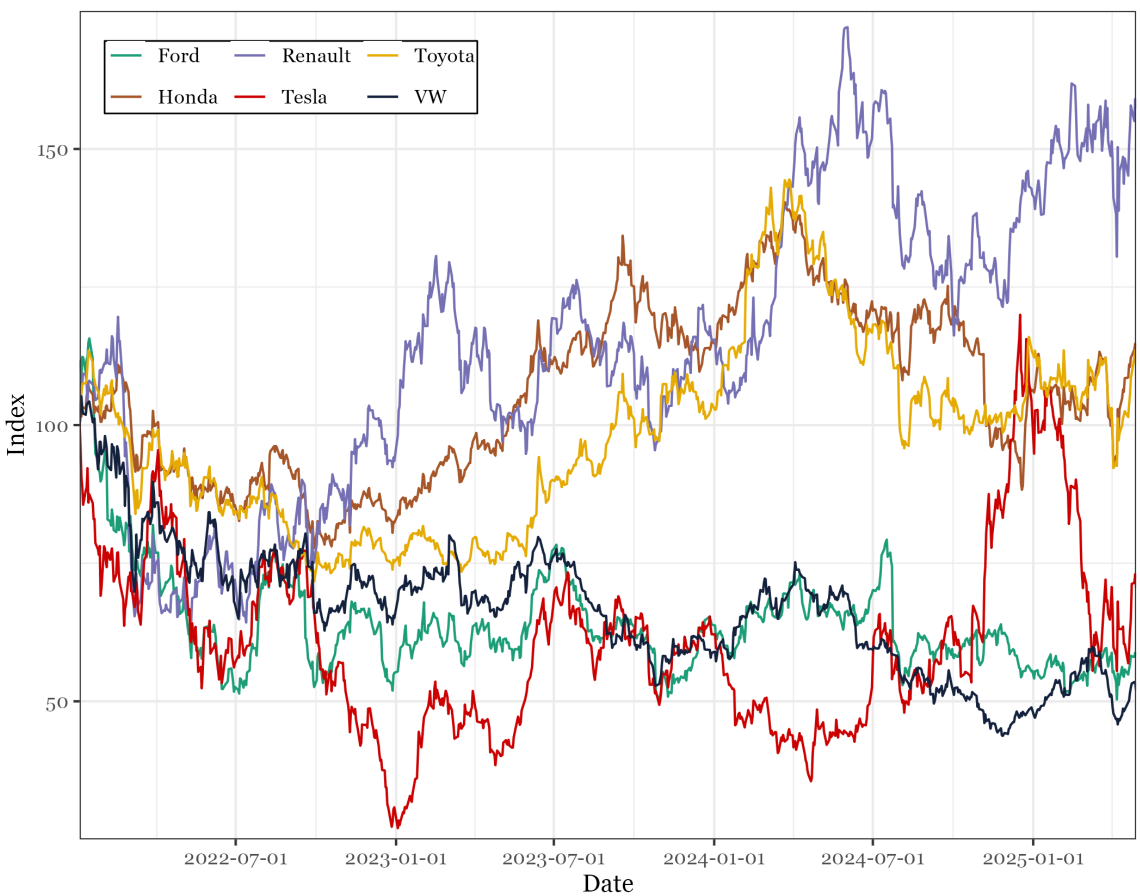
External Evidence. Alongside the evidence that firms are beginning to introduce more hybrid models, changes in company stock prices provide external support for the model's predictions about the popularity of hybrids, firms' innovation incentives, and cross-firm heterogeneity. Figure 4 shows

[35] Both the EU and the UK plan to ban the sale of all new emitting vehicles in 2035.

the change in the stock prices of the firms in Table 11 with the largest changes in profit, and Tesla, from the 3rd January 2022 to the 1st May 2025. If the model's findings are correct then anticipation of future demand for hybrids ought to be priced into companies' stock market performance.

The changes in stock prices align with the model's predictions. Firms with large hybrid offerings – Honda, Renault, and Toyota – have all performed strongly relative to other manufacturers. Volkswagen and Ford, which do not offer many HEVs, have struggled. This reproduces the pattern in Table 11, suggesting that market participants increasingly anticipate the estimated substitution patterns persisting in the coming years. Tesla has, absent volatility in 2024 and 2025 for political reasons, seen a fall in price. This may be because investors have adjusted their expectations for future earnings downwards as they anticipate consumer preferences for hybrids over battery electric vehicles persisting. The gradual widening of the gap may reflect the increasing credibility of the ban as 2030 approaches.

Figure 4: Company Stock Prices



Note: Stock price data are pulled from Yahoo Finance. The graph runs from 3rd January 2022 to 1st May 2025. The index has a value of 100 for all firms on 3rd January 2022.

8 Taxes and Subsidies

Introducing a ban on ICE vehicles effectively applies a sales tax rate of infinity to these vehicles. In this section I consider a set of more mild sales tax and subsidy policies. Implementing an appropriately chosen combination of taxes and subsidies would deliver the same climate benefit as the ban at 75% of the cost, while a revenue-neutral policy delivers over 50% of the ban's climate benefit at 15% of the welfare cost. Both of these policies incentivise the majority of firms to introduce new battery electric vehicle models, unlike the ban.

Combining taxes on ICE vehicles and subsidies on low-emissions cars reduces the absolute price of BEVs, attracting buyers who otherwise would have purchased hybrids or exited the market, at a smaller revenue cost for the government. Combining these as a revenue-neutral policy may make implementation less politically difficult. Measuring the impact of these policies requires accurately estimating the level of pass-through, which depends on the curvature of demand (Weyl and Fabinger, 2013). Miravete et al. (2025) show that common functional form assumptions made when estimating discrete choice demand models can artificially constrain curvature. Interacting price with both income and income squared helps provide the necessary flexibility here.

Generally, an optimal response to a negative externality is to tax the externality's source (Pigou, 1932; Baumol, 1972). The sales tax does not do this as well as two alternatives which target emissions more directly. One is to tax vehicles based on their emissions; this risks incentivising gaming. Another is to increase fuel taxes. This is likely to be infeasible for political reasons: fuel duty has been frozen in the UK from 2011, with regularly planned increases delayed, while fuel taxes motivated the *gilets jaunes* protests in France.[36] These problems motivate the focus on sales taxes. The theoretical literature does not provide a justification for subsidising a good which is neutral with respect to the externality, as BEVs are. I include subsidies due to their positive short-term impact: they allow HEVs to function as a bridging technology while incentivising substitution to BEVs. The results show that they help considerably to reduce emissions at a lower welfare cost; they could be phased out as BEVs improve in quality.

To estimate the impact of these tax and subsidy policies, $p_{jt}(1 + \tau_{jt})$ replaces p_{jt} in the utility specification. The value of τ_{jt} is τ_T if the vehicle is an ICE car and τ_S if it is a BEV or PHEV. I test 5%, 10%, and 15% tax, subsidy, and joint tax-subsidy programs. I then discretise the grid of values of (τ_T, τ_S) and search for two 'optimal' policies. First, the policy that delivers the same climate benefit as the ban for the smallest fall in total welfare. Second, the policy that maximises the climate benefit

[36] There are also fairness considerations: households who have bought ICEs before the taxes were implemented are now 'trapped' into paying taxes which they did not expect.

Table 15: Household-Level Welfare Changes: Taxes and Subsidies

(τ_T, τ_S)	Mean PT	CS	Var. Profits	Climate Benefit	Revenue	Overall
Taxes						
(5%, 0%)	87.3%	-214	-57	36	210	-25
(10%, 0%)	86.8%	-388	-100	68	357	-63
(15%, 0%)	86.4%	-536	-132	95	454	-119
Subsidies						
(0%, 5%)	93.1%	123	29	13	-156	9
(0%, 10%)	93.6%	285	69	30	-380	4
(0%, 15%)	93.9%	482	125	48	-698	-43
Taxes & Subsidies						
(5%, 5%)	89%	-74	-25	50	39	-10
(10%, 10%)	89.4%	-64	-19	96	-85	-72
(15%, 15%)	90.1%	22	19	139	-387	-207
(32%, 25%)	92.1%	359	217	237	-1710	-897
(16%, 10%)	89.7%	-223	-51	127	-2	-149

Note: All columns give the overall change (in 2015 pounds) divided by the market size. Mean PT gives the average passthrough weighted by counterfactual market share. Passthrough is calculated as $\frac{|\tilde{p}_{jt}+\tau_{jt}-p_{jt}|}{p_{jt}}$ where $\tilde{p}_{jt}$ is the counterfactual price and p_{jt} is the observed price

while being close to revenue neutral.[37] Table 15 gives the changes in welfare at the prospective buyer level; the last two rows contain the solutions to these constrained optimisation problems.

Both of these policies incentivise the majority of firms to develop BEVs rather than HEVs, reversing Table 10's pattern: their long-term impact on product innovation should be superior to that of the ICE ban. Under the first, all makes (brands) except Porsche make more profit from introducing a BEV: the average increase in profit is £95 million versus £60 million from an HEV. Under the revenue-neutral policy only five are better off introducing an HEV and the average increases in profit are £82 million versus £54 million.[38]

Taxing ICE cars has a similar impact to the ban, with the added benefit of raising revenue. Subsidising battery and plug-in hybrid electric vehicles boosts consumer surplus and variable profits, as households are persuaded to substitute from the outside good to existing models, but becomes very costly for the government. Subsidies lower the absolute price of BEVs and, importantly, make them more attractive relative to HEVs and the outside good; taxation only makes them more attractive relative to ICEs. Both interventions are almost completely passed on to the consumer. The inter-

[37] The revenue shortfall is constrained to be no greater than £5 per prospective buyer.

[38] When Dacia is excluded the average increase in profit from introducing a BEV falls to £84 million under the first policy and £55 million under the second. The average increase from introducing an HEV is almost unchanged.

ventions are complements, as taxes reduce the cost to the government of using subsidies to increase welfare in all other areas, and combining the two can deliver the same climate benefit as the ban at three-quarters of the cost. This avoids the ban's problems but is prohibitively expensive for the government, at a cost of over £1,700 per prospective buyer, and is clearly not implementable.

The more realistic revenue-neutral policy, which involves a tax of 16% on ICEs and a subsidy of 10% on BEVs and PHEVs, delivers over 50% of the ban's climate benefit at 15% of the overall cost. Reducing the social cost of carbon by £1 costs £2.17 in consumer surplus, variable profits, and revenue: this ratio is more than twice as good as that of the least costly ban considered in appendix C. Consumers are still harmed, with the same distributional pattern as before, but are dramatically better off than under the ban. Both policies lead to a substantial increase in variable profits for companies with larger BEV and PHEV product lines, such as BMW, Geely, Tata, and Tesla. The revenue-neutral policy attains a larger climate benefit than the more stringent emissions-based ICE ban shown in Table A.4 at a lower welfare cost and without incentivising the gaming of emissions tests. The much smaller cost of the revenue-neutral policy indicates that the last mile in reducing emissions may be very expensive if achieved via taxes and subsidies, with a segment of households very reluctant to switch away from ICEs, but that substantial gains can be realised cheaply. This suggests that combining taxes and subsidies with a product ban may be an effective policy. Using some form of ban might be desirable due to the ability for governments to constrain future policymakers: a product ban would be difficult to reverse after several years.

9 Conclusion

This paper studies the proposed ban on new cars with only internal combustion engines in Great Britain by estimating a model of demand and supply for new vehicles and simulating the impact of introducing this ban in 2023, along with a set of tax and subsidy policies. I provide suggestive evidence about which products firms have an incentive to introduce, identify the market participants not ready for the transition, and measure the relative performance of different climate policies. This is informative about the political economy of maximally disruptive climate policy, the emissions reductions achieved when hybrids are still available for sale, and the current factors inhibiting a smooth transition to a decarbonised road transport system.

I find that hybrids are currently much closer substitutes to ICE cars than other electric vehicles. Accordingly, the ban has a limited climate benefit as most households would purchase HEVs with relatively similar emissions to ICE vehicles: this has serious long-term implications if firms introduce hybrids to the market rather than working to improve the quality of battery electric vehicles.

There is evidence that this is beginning to occur. The worst affected groups are low income households and European manufacturers; the ban's heterogenous impact suggests that, without government intervention, it will be unpopular and difficult to implement politically. Finally, combining sales taxes and subsidies can reduce emissions at a much lower welfare cost by making battery electric vehicles more attractive relative to hybrids. Using a revenue-neutral policy dominates a partial ban on dirty ICEs. Although the paper does not study the government's zero emissions vehicle mandate, which fines firms for selling too large a proportion of internal combustion engine cars, these estimates suggest that firms may find these quotas difficult to satisfy as 2030 approaches.

These results are not a firm prediction about what will happen in 2030; they instead shed light on current market dynamics, how anticipation of the ban may change firm behaviour, and the emissions impact of including hybrids in the product mix after a combustion engine ban. It is possible that preferences may change quickly if battery electric vehicles substantially improve in quality and price. Even if they do, they will need to become much more attractive than hybrids, not just cars with only internal combustion engines, for the ban to have a larger impact on carbon emissions.

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A Appendix: Data

A.1 Market Size

The Office for National Statistics (ONS) publishes annual data on the number of UK households. The Northern Irish Statistics and Research Agency report the number of NI households in 2001, 2011, and 2021 in the Census. I interpolate values for the interior years linearly and extrapolate to 2023 by assuming that the household growth rate from 2021-2023 is the same as the average annualised growth rate from 2011-2021. This series is subtracted from the ONS estimates. This is a small adjustment; in 2021 the Northern Irish population made up 2.8% of the UK.

A.2 Data Imputation

There are a number of cases where Parkers is missing non-price characteristics for models. To impute the data on characteristics I take the following steps:

1. Locate the model from the previous year. If not available, use the model from the next year.
2. If there is minimal change in all non-missing characteristics and Parkers indicates that both are part of the same generation, then assume that the missing characteristics are unchanged.
3. If these conditions are not met, obtain the data from other online car comparison websites.

Data on other variables of interest come from a range of sources, mainly the online repositories Electric Vehicle Database[39] and Encycarpedia[40]. The combustion engine range for non-EVs is computed by multiplying the vehicle's fuel efficiency by its fuel capacity. When calculating the cost of driving 100 miles there are different costs to purchasing petrol or diesel, and to charging at day or night; the mean of both average annual prices is used.

A.3 Input Costs Index

For non-BEVs the index uses a weighted average of steel, aluminium, plastic, and rubber prices. The weights are 0.73 for steel, 0.12 for aluminium, 0.09 for plastic, and 0.06 for rubber. For BEVs it also includes graphite, copper, and nickel. The weights are 0.65 for steel, 0.11 for aluminium, 0.08 for plastics, 0.06 for rubber, 0.04 for graphite, 0.03 for copper, and 0.03 for nickel. These reflect the average contribution of different materials to a vehicle's weight. I abstract from materials which

[39] See https://ev-database.org/uk/.
[40] See https://www.encycarpedia.com/.

appear in small proportions and adjust the weights to sum to one. These weights are based on European statistics on average weight (ICCT Pocketbook 21/22), plastics (CBI), aluminium (European Aluminium), and steel content (Eurometal) along with IEA statistics on minerals used in battery electric vehicles.

The data on annual prices for aluminium, copper, nickel, and rubber are taken from the IMF's Primary Commodity Price System. The data on steel, plastics, and graphite are taken from exchange data: the MEPS Carbon Steel Products World Price for steel, the China Flake Graphite -194 EXW price for graphite, and the NEXANT Western Europe polypropylene price for plastics.

A.4 Survey Data

Several variables in the survey data are top-coded in later years. To avoid inconsistencies, all variables are trimmed to match the most restrictive top-coding. Income is deflated to be in 2015 GBP. The best available income variable is each individual's gross weekly income. I sum this across all members of the household and multiply by 52 to obtain a household's annual income. The data is trimmed by dropping the bottom percentile and, for non-top-coded years, limiting all incomes to a maximum of the 96th percentile. This leaves 2,601 households with an annual income of zero in 2018 which are dropped. Table A.1 shows that this fits the pattern from other years better.

Table A.1: Demographics With and Without Zero Incomes

Year	Mean Income	Std. Dev.	Mean Age	Std. Dev.	Mean Size	Std. Dev.
Including Zero Incomes						
2016	37.88	26.73	52.87	16.88	2.35	1.24
2017	38.91	27.43	53.34	16.74	2.41	1.29
2018	19.33	27.15	53.38	16.73	2.37	1.27
2019	40.83	27.05	53.33	16.82	2.37	1.28
2020	42.26	26.60	53.19	16.84	2.37	1.29
Excluding Zero Incomes						
2016	37.88	26.73	52.87	16.88	2.35	1.24
2017	38.91	27.43	53.34	16.74	2.41	1.29
2018	38.88	26.88	53.53	16.69	2.37	1.26
2019	40.83	27.05	53.33	16.82	2.37	1.28
2020	42.26	26.60	53.19	16.84	2.37	1.29

Note: The first panel gives demographic summary statistics after trimming the data but before excluding households with an annual income of zero. The second panel excludes these households. Income is in thousands of 2015 pounds.

The Living Costs Food Survey (LCFS) contains a set of questions about the price, novelty, and engine type of vehicles owned by households. In every year those vehicles which were bought outright within the last twelve months, i.e. without a loan or hire purchase agreement, can be identified. From 2013 it is also possible to identify which of these vehicles were bought through a hire purchase agreement. For these years, I match cases where the household has a single such vehicle and a single vehicle mentioned in the separate set of hire purchase questions, keeping transactions that occurred within the last twelve months. There are insufficient data to match accurately when there is more than one vehicle on each side. Prices are adjusted for road tax and insurance payments when possible and only transactions for cars and vans, and those with positive prices, are kept. If a household makes multiple purchases in a single year then the most expensive one is kept. Household purchases are treated as if made in the surveyed year. Respondents who own conventional and plug-in hybrids are grouped together; I account for this when building micro moments.

The cross-tabs from the BritainThinks survey of EV and PHEV drivers are publicly available on the government website.[41] These include data on the household income band of new EV and PHEV owners (Table 208). I take the midpoint of every band except the top, which has no upper limit, and calculate the average real income of the respondents. To avoid underestimating the income of the fifth of respondents who list an income in the top band, I use the weighted average income of the 2021 LCFS respondents who have incomes in the same range as the midpoint.

A.5 MOT Data

The anonymised MOT data includes all tests performed in Great Britain: vehicles are given a unique identification number which persists across years. I drop all vehicles with duplicate ID numbers and those without a test class of '4' to keep only cars, vans, and other vehicles with up to twelve seats. Since newer vehicles tend to have higher mileages, as high-usage households replace their vehicles more often, I keep only vehicles registered from 1st January 2019: this is as close to new as it is possible to get while still being able to match vehicles across years. All observations with negative mileages, missing engine types, and fewer than ninety days between tests are dropped. The bottom and top percentiles are also dropped. To draw vehicle mileages I group tests by engine type, assume that plug-in hybrids have the same mileage as hybrids, and treat mileage as log-normally distributed. For each model, I take the average of 100 draws from the distribution. When it comes to calculating the climate impact in section 7, I also take the average of 100 draws from the ICE mileage distribution for each non-ICE vehicle. This gives the mileage for the consumers who previously drove ICEs and have substituted to that product following the ban.

[41] See the electric vehicle drivers: attitudes and behaviours page.

B Appendix: Instrument Testing

To identify the random coefficients which govern consumer substitution patterns I use a set of market structure instruments which measure the distance of a given product from the rest of the market in characteristics space. To reduce the risk of the model being weakly identified I test the ability of both classical BLP instruments, which count characteristics, and differentiation instruments from Gandhi and Houde (2023) to satisfy a 'weak instruments' testing procedure. The differentiation instruments used, detailed below, satisfy this test.

The product's differentiation in a continuous characteristic is measured by the Euclidean distance of the product from those owned by rival firms. For characteristic k:

$$z_{jt}^k = \sum_{l \notin J_{ft}} (d_{jl,t}^k)^2 \text{ where } d_{jl,t}^k = x_{lt}^k - x_{jt}^k.$$

Since engine type is a discrete variable, the number of vehicles with the same engine type captures how crowded a market segment is:

$$z_{jt}^{eng} = \sum_{l \in \mathcal{J}_t} \mathbb{1}(x_{lt}^{eng} = x_{jt}^{eng}).$$

To measure price differentiation, predicted prices are obtained by regressing price on the exogenous variables to obtain $\hat{p}_{jt} = \mathbb{E}[p_{jt} | x_{jt}, z_{jt}^{IC}, \text{Year FE}, \text{Make FE}]$ where z_{jt}^{IC} is the input cost instrument.

If the instruments are not relevant then the model might be weakly identified, with the moment conditions satisfied away from the true parameter values. Relevance cannot be tested traditionally since the model's reduced form depends upon the parameters.[42] Instead, I employ the Gandhi and Houde (2023) test for weak instruments: approximate the reduced form and attempt to reject IIA preferences. The reduced form is approximated by regressing the inverse demand function in a simple logit model, where $\mu_{ijt} = 0$, on observable characteristics, prices, the differentiation instruments, and the fixed effects. Price is instrumented for by z_{jt}^{IC}. The regression equation is:

$$\ln(\frac{s_{jt}}{s_{0t}}) = x_{jt}\gamma_x + \gamma_p p_{jt} + z_{jt}^{diffn}\gamma_z + \text{Make } \gamma_m + \text{Year } \gamma_t + e_{jt}$$

where $\gamma_x, \gamma_z, \gamma_m$, and γ_t are parameter vectors. The null is $H_0 : \gamma_z = 0$, since under IIA preferences substitution is only determined by market shares. In reality more isolated products ought to enjoy higher market shares if $\mu_{ijt} \neq 0$. Instruments are weak if the null cannot be rejected.[43] Negative coefficients on the differentiation instruments imply higher demand when products are less isolated

[42] The reduced form is the expectation of the inverse demand function conditional on observables.

[43] Alternatively, there might genuinely be IIA preferences. This seems exceedingly unlikely in this market.

and do not fit with the random coefficients model; these instruments will not be used and random coefficients will not be estimated on the characteristics.

Table A.2: Testing for IIA Preferences (Differentiation IVs)

	(1)	(2)	(3)	(4)	(5)
Predicted Price Inst.	4.576	0.834*	0.725	0.726*	0.811*
	(2.410)	(0.404)	(0.370)	(0.363)	(0.355)
Engine Type Inst.	-1.704	5.971	5.877	5.849	
	(7.339)	(3.347)	(3.176)	(3.115)	
Emissions Inst.	-3.170	2.678*	1.782*	1.775*	
	(3.809)	(1.363)	(0.869)	(0.859)	
Size Inst.	-0.159	0.008	-0.007		
	(0.150)	(0.108)	(0.101)		
User Cost Inst.	-3.178	-2.095			
	(5.239)	(2.460)			
Horsepower Inst.	-7.977*				
	(4.064)				
Range Inst.	-0.910***				
	(0.227)				
Test Stat.	25.7	19.7	20.3	17.8	5.21
P-Value	0.0006	0.001	0.0004	0.0005	0.02
No. Obs.	3391	3391	3391	3391	3391

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Each regression also includes make and year fixed effects and all of the observable characteristics which appear in Table 3. Price is instrumented for by the input cost instrument. All instruments have been rescaled by 1,000. The standard errors are heteroskedasticity-robust. The test statistic and p-value correspond to the null hypothesis that all displayed coefficients equalling zero.

Table A.2 contains the estimated parameters for a range of specifications, varying the different instruments included in z_{jt}^{diffn}, and the results from a Chi-squared test of $H_0 : \gamma_z = 0$. In all cases, we can reject the null of IIA preferences at the 5% level: this suggests that weak identification will not be an issue. Both the horsepower and range instruments have statistically significant negative coefficients. The price and emissions instruments are positive and statistically significant at the 5% level in most specifications. These two and their interaction are included. The engine type instrument is also included: the coefficient is positive, albeit imprecisely estimated, and it will help identify a key element of preference heterogeneity. Table A.3 shows that BLP instruments (Berry et al., 1995) fail to reject IIA preferences, justifying the use of differentiation instruments and the systematic approach to instrument selection. Further testing reveals that both local instruments, where differences are only computed for products with similar characteristics, and 'own firm' instruments perform worse. The BLP constant instrument is included to help identify the random coefficient on the constant: there is no differentiation instrument which can be used as a natural analogue.

On the supply side, I use differentiation instruments computed from the included supply-shifters, along with excluded characteristics which are included in the utility function. Concerns about rationalising random coefficients do not apply here.

Table A.3: Testing for IIA Preferences (BLP IVs)

	(1)	(2)	(3)	(4)	(5)
Constant Inst.	-0.204	0.082*	0.079*	0.042	0.042
	(0.190)	(0.037)	(0.035)	(0.038)	(0.036)
Predicted Price Inst.	0.009	0.045	0.044	0.022	-0.009
	(0.030)	(0.026)	(0.026)	(0.026)	(0.007)
Horsepower Inst.	-0.044	-0.098*	-0.097*	-0.056	
	(0.046)	(0.048)	(0.049)	(0.051)	
Emissions Inst.	-0.007	-0.029	-0.026		
	(0.033)	(0.017)	(0.019)		
Engine Type Inst.	-0.008	-0.009			
	(0.016)	(0.014)			
Size Inst.	0.023				
	(0.017)				
User Cost Inst.	-0.015				
	(0.032)				
Range Inst.	0.019				
	(0.020)				
Test Stat.	7.93	7.69	6.67	2.35	1.70
P-Value	0.440	0.174	0.154	0.504	0.427
No. Obs.	3391	3391	3391	3391	3391

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Each regression also includes make and year fixed effects and all of the observable characteristics which appear in Table 3. Price is instrumented for by the input cost instrument. All instruments have been rescaled by 1,000. The standard errors are heteroskedasticity-robust. The test statistic and p-value correspond to the null hypothesis that all displayed coefficients equalling zero.

C Appendix: Alternative Product Bans

This section presents the results from simulating the impact of alternative product bans: a ban on all non BEVs, on all ICEs with emissions of at least 150g/km, and on all ICEs with emissions of at least 130g/km. The changes in welfare at the level of the prospective buyer are collated in Table A.4.

Only BEVs Counterfactual. To simulate the impact of a ban on all vehicles which emit carbon at the tailpipe, which has been proposed for 2035 in the UK, I remove all non-BEVs from the choice set and re-estimate equilibrium prices and shares. This is a large counterfactual: 143 products are removed and 34 remain. The combined share of the inside goods falls from 30% to 11.5%. The innovation incentives are clearly rebalanced as firms cannot introduce HEVs. The cross-firm profit distribution differs from that under the ICE ban: only Tesla are made better off while SAIC, Geely, BMW and Daimler are harmed the least, making more than 60% of their previous profits. Firms focused on manufacturing hybrids lose out. There is the same monotonic relationship between income and the fall in consumer surplus; the lowest income quintile now loses an average of 20% of their average income. The emissions benefit is as its maximum value due to the assumption that BEVs emit no carbon. The final row in Table A.4 shows that while the climate benefit increases, it grows by a smaller proportion than the losses in consumer surplus and variable profits. The overall welfare loss is nearly three times larger than under the ICE ban: reducing the social cost of carbon by £1 now costs £7.50 in consumer surplus and variable profits.

Less Stringent ICE Bans. Banning a subset of ICEs might deliver large reductions in carbon emissions at a lower welfare cost by targeting dirty vehicles. I test a set of ICE bans based on vehicle tailpipe emissions; focusing only on ICEs decomposes the changes in welfare from the overall ICE ban given in Table 14. Targetting high emissions ICEs performs slightly better, with a marginally lower welfare cost to reducing emissions, but the difference is small.

First, I remove all ICE vehicles with emissions of 150g/km or greater from the choice set. This excludes 34 products. The combined market share of the inside goods falls a small amount to 29.3%. The share of ICEs sold barely changes, falling from 65% to 61%. Some manufacturers with large HEV product lines, such as Nissan and Toyota, do well, as do Stellantis and Ford. Profit is redistributed away from the manufacturers of luxury ICEs like Land Rover. Consumer surplus falls, as the first row of Table A.4 shows, but the impact is more even across the income distribution than the more radical bans: households in the fourth highest income quintile are made worst off relative to their income. The balance between costs and benefits is only marginally better than under the complete ban: the climate benefit is £50 per prospective buyer, 21.1% of its level under the complete ban,

Table A.4: Household-Level Welfare Changes: Alternative Product Bans

Banned Products	Consumer Surplus	Variable Profits	Climate Benefit	Overall
ICEs with $CO_2 \geq 150$g/km	-212	-26	50	-188
ICEs with $CO_2 \geq 130$g/km	-543	-55	116	-482
All ICEs	-1,278	-134	237	-1,175
All non-BEVs	-3,467	-596	545	-3,518

Note: All columns give the overall change (in 2015 pounds) divided by the market size.

while the loss in consumer surplus is proportionately lower at 16.6%. It costs £4.76 in consumer surplus and variable profits to reduce the social cost of carbon by £1. This is the best ratio of any ban.

Second, I exclude all ICE vehicles with emissions of 130g/km or greater. This excludes 71 products; 106 remain. The share of the inside goods falls to 27.9%. There is a similar profit pattern to the least stringent ban: Toyota and Hyundai do well, as do Stellantis and Ford. BMW, Daimler, and Volkswagen all experience large falls in their profits. Consumer surplus losses are not too large, with households in the first income quintile losing 2.75% of their average income, and are monotonic with income except for the fourth quintile. Again, focusing on the dirtier ICEs only delivers a slight improvement in the ratio of benefits to costs: the climate benefit is at 49% of its level under the complete ban while the consumer surplus falls by 42.5% as much as it does under the complete ban. This corresponds to a cost of £5.16 for each £1 reduction in the social cost of carbon.

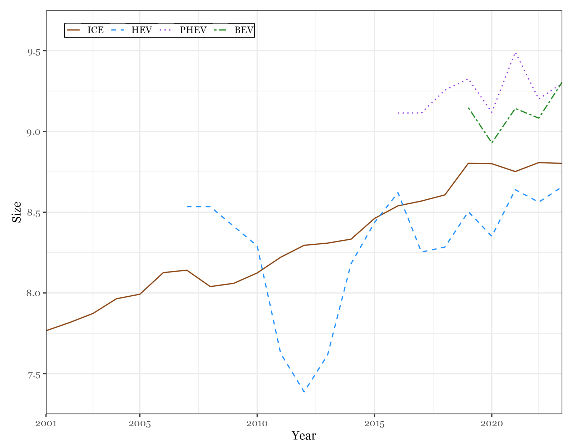
The final row of Table A.4 reproduces the changes in welfare when all ICEs are removed from the choice set. There are slightly diminishing welfare gains from removing the remainder of the ICEs: the climate benefit doubles compared to the previous ban while the fall in consumer surplus and variable profits more than doubles (they increase by 2.35x and 2.44x respectively).

These alternative product bans highlight the importance of hybrids to the climate impact of any ban on dirty ICEs. The similar emissions of HEVs to ICEs, and their relative popularity when compared to BEVs, means that banning the sale of all ICEs delivers a fairly muted climate benefit. Targetting the ban at more dissimilar ICEs – with higher emissions and higher prices – offers a slightly better method of balancing benefits and costs, but the difference is limited. Removing HEVs from the choice set avoids this problem and lowers emissions substantially but is very damaging to consumer surplus: current preferences make this policy costly.

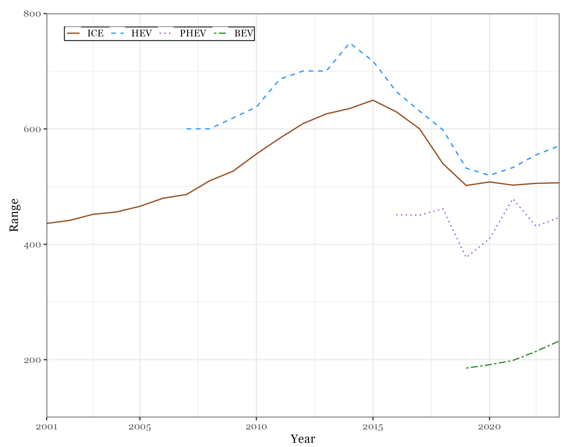
D Appendix: Additional Tables and Figures

Figure A.1: Change in Vehicle Characteristics 2001-2023

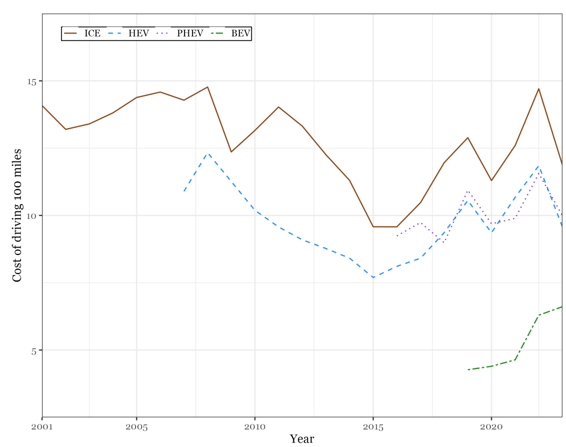
(a) Horsepower



(b) Size



(c) Range



(d) Cost of Driving

Note: All panels plot the share-weighted average value of the characteristic for each year. In all panels, engine types are only included when they have at least three distinct models. Horsepower is in bhp, size is length × width and given in square metres, range is in miles, and panel (d) gives the cost of driving 100 miles in 2015 pounds.

Table A.5: Industry Descriptive Statistics

Year	Sales	Models	Price	HP	Emissions	Engine Size	Size	Range	Driving Cost
2001	2,399	126	20.1	108	180	1,723	7.66	452	12.72
2002	2,500	129	20.4	110	177	1,742	7.76	460	11.98
2003	2,468	144	20.9	112	175	1,763	7.83	469	12.08
2004	2,411	151	21.3	113	174	1,755	7.91	476	12.41
2005	2,259	145	22.0	117	172	1,771	8.01	486	13.11
2006	2,172	146	22.4	122	170	1,803	8.05	489	13.34
2007	2,222	145	22.5	125	166	1,806	8.11	498	13.04
2008	1,944	134	21.7	121	158	1,733	8.06	517	13.94
2009	1,808	128	21.6	117	149	1,693	8.04	529	11.70
2010	1,830	127	22.1	120	144	1,686	8.15	560	12.60
2011	1,752	131	22.4	125	139	1,665	8.19	583	13.44
2012	1,852	135	22.2	125	131	1,653	8.22	612	12.55
2013	2,059	141	22.0	123	127	1,621	8.23	622	11.74
2014	2,261	147	22.2	123	123	1,610	8.27	632	10.73
2015	2,407	154	23.4	126	121	1,618	8.35	642	9.15
2016	2,481	164	25.0	134	123	1,638	8.48	628	9.09
2017	2,321	169	25.7	139	126	1,631	8.52	594	10.05
2018	2,115	159	26.0	140	131	1,610	8.55	540	11.46
2019	2,077	161	27.3	147	138	1,596	8.65	496	12.19
2020	1,408	152	29.1	156	130	1,465	8.63	487	10.24
2021	1,394	157	30.2	162	119	1,378	8.63	465	10.95
2022	1,373	165	29.7	171	110	1,256	8.65	454	12.34
2023	1,652	176	28.6	176	108	1,246	8.66	459	10.23

Note: This gives the sales-weighted mean for columns 4 through 10. Price and cost are in 2015 pounds. Both price and sales are in thousands HP stands for horsepower and is in bhp, emissions are in g/km. Engine size is in cc, size is length $\times$ width in square metres, range is in miles, and driving cost is the cost of driving 100 miles.

Table A.6: Aggregate and Micro Data Compatibility

					Outside Share		Mean Price	
Year	New	Used	Total	Demand	Micro Data	Market Data	Micro Data	Market Data
2013	112	509	621	0.12	0.82	0.60	17.72	21.98
2014	136	541	677	0.13	0.80	0.57	17.36	22.20
2015	120	557	677	0.13	0.82	0.54	17.36	23.40
2016	112	537	649	0.13	0.83	0.53	19.29	25.02
2017	98	533	631	0.12	0.84	0.56	19.95	25.70
2018	50	311	361	0.13	0.86	0.61	18.31	26.04
2019	81	516	597	0.11	0.86	0.62	19.72	27.35
2020	76	419	495	0.09	0.85	0.74	20.13	29.06
2021	82	434	516	0.10	0.84	0.75	22.37	30.17
2022	50	401	451	0.09	0.89	0.75	19.44	29.66
2023	14	75	89	0.09	0.84	0.70	20.33	28.55

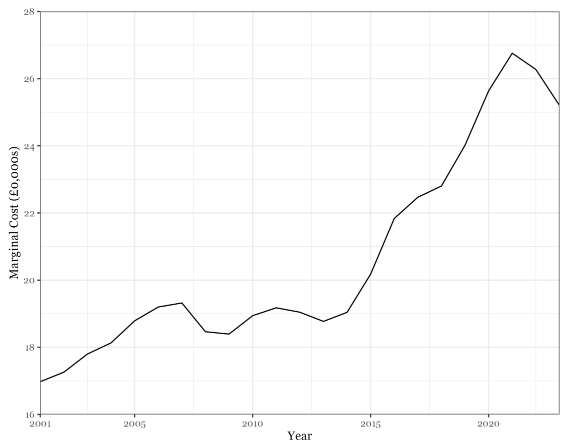
Note: The first three columns are the number of transactions in the survey data. The demand column gives the number of transactions divided by respondents to control for yearly variation in sample size. Price is in thousands of 2015 pounds, the market average is sales-weighted.

Table A.7: Industry Concentration

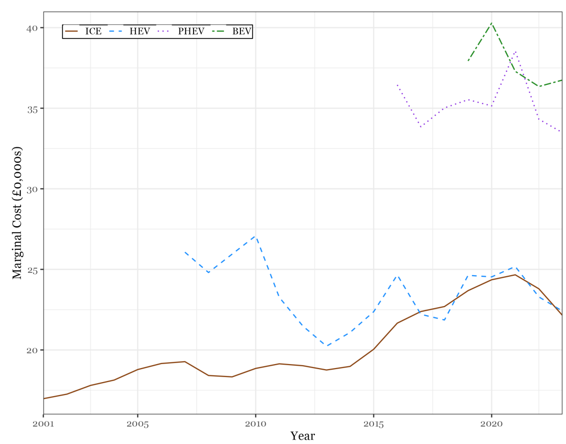
	HHI	CR1	CR2	CR3	CR4	CR5	CR6
Pre Ban	0.109	0.239	0.349	0.454	0.536	0.613	0.684
Post Ban	0.122	0.237	0.398	0.503	0.600	0.673	0.740

Note: HHI is the Herfindahl-Hirschman index. CRX is the market share of the top X firms, where market share is the share of sales of the inside good.

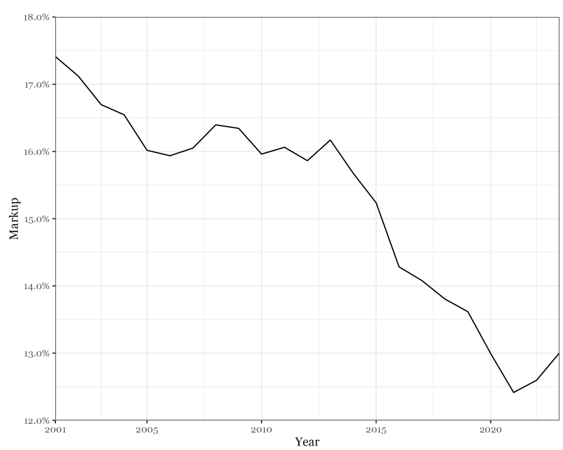
Figure A.2: Market Evolution 2001-2023



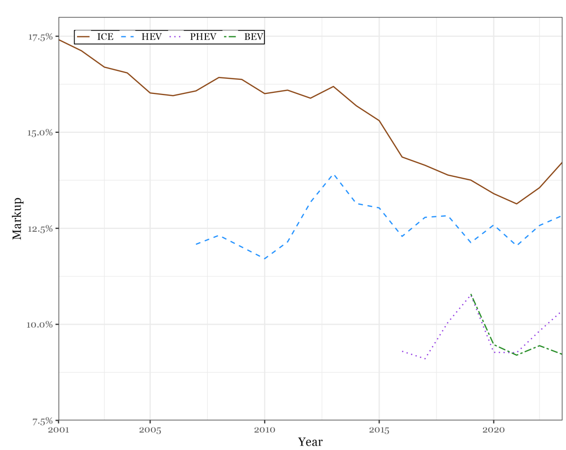
(a) Marginal Costs



(b) Costs by Engine Type



(c) Markups



(d) Markups by Engine Type

Notes: Each panel plots the share-weighted average for a year. In panels (b) and (d), engine types are only included when they have at least three distinct models. Marginal costs are obtained from the pricing first-order conditions and given in thousands of 2015 pounds. Markups are given by the Lerner index, $(p - c)/p$.