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ORIGINAL PAPER

A generic discrete choice model of automobile purchase

Vegard Østli[1] · Lasse Fridstrøm[1] · Kjell Werner Johansen[1] · Yin-Yen Tseng[2,3]

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Abstract
Purpose The introduction of novel fuel and propulsion technologies, such as battery, (plug-in) hybrid and fuel cell electric vehicles, and the need to combat the exhaust emission of local and global pollutants from the passenger car fleet have enhanced the political interest in the vehicle purchase choices made by private households and firms, and in how these choices can be influenced through fiscal and regulatory penalties and incentives.
Methods As a tool to understand and analyse such questions, we have developed a generic nested logit model of automobile choice, based on complete disaggregate vehicle sales data for Norway for the period ranging from January 1996 until July 2011. The data set contains 1.6 million vehicle transactions.
Results Being sensitive to changes in the vehicle purchase tax and the fuel tax, the model discriminates well between various fiscal policy scenarios. In using the model for such purposes, one is greatly helped by the fact that the model distinguishes between price changes due to taxation and those originating from the manufacturing or marketing side.
Conclusions The strongly CO_2 graduated vehicle purchase tax, with exemptions granted for battery electric vehicles, is shown to have a major impact on the average type approval rate of CO_2 emissions from new passenger cars registered in Norway. The fuel tax also helps induce car customers to buy low emission vehicles.

Keywords Nested logit · Passenger cars · Purchase tax · Fiscal incentives · CO_2 emissions

✉ Lasse Fridstrøm
lef@toi.no

1 Institute of Transport Economics (TØI), Gaustadalléen 21, 0349 Oslo, Norway

2 VU University Amsterdam, De Boelelaan 1105, 1081 HV Amsterdam, Netherlands

3 Southwestern University of Finance and Economics, 555, Liutai Avenue, Wenjiang District, Chengdu, Sichuan 611130, People's Republic of China

1 Introduction

Since the seminal papers by Lave and Train [24] and Manski and Sherman [25], automobile demand and vehicle choice have been the subjects of multiple studies by transport researchers. Most studies (e. g., [3, 4, 8, 10, 21, 34]) are based on disaggregate discrete choice modelling of household behaviour. But some are also based on aggregate sales data, whereby one estimates total demand or market shares held by various vehicle models (e.g., [1, 5, 14, 20, 22]). Common to most of these studies is that their data sets and methodology are too crude or too incomplete to allow for reliable predictions of the car fleet composition under varying fiscal and regulatory policy options. Some recent studies have, however, come a long way towards modelling the complex, joint decision processes of vehicle choice and usage [6, 9, 18, 19, 28].

The introduction of novel fuel and propulsion technologies, such as battery, (plug-in) hybrid and fuel cell electric vehicles, and the need to combat the exhaust emission of local and global pollutants from the passenger car fleet have enhanced the political interest in the vehicle purchase choices made by private households and firms, and in how these choices can be influenced through fiscal and regulatory penalties and incentives. In Norway, a large number of incentives have been implemented over the last 10–12 years, most importantly a steeply CO_2-graduated vehicle purchase tax. These incite a growing number of car buyers to prefer low and zero emission vehicles [13, 16]. In 2015, no less than 17% of all new automobiles registered in Norway were zero emission cars, almost all of them battery electric vehicles (BEVs).

The Norwegian Parliament has adopted a non-binding target for the average type approval CO_2 exhaust emission rate of new passenger cars to be registered in Norway in 2020. The target has been set at 85 gCO_2/km, i. e. 10 gCO_2/km lower than the EU mandated target, which commits car manufacturers not to exceed 95 gCO_2/km as averaged over all cars sold in 2020/2021.

How can the continued use of fiscal incentives ensure that this and subsequent – possibly sharpened – targets are reached? Is it possible to fine-tune the vehicle purchase tax so as to obtain desired market shares for certain, more environmentally friendly vehicle types? If and when the fiscal privileges currently enjoyed by BEVs are abolished, how much will their market share drop? What kind of tax incentives are needed in order for plug-in hybrid vehicles (PHEVs) to obtain a certain share? How will the environmental attributes of petrol and diesel driven cars develop under the present tax regime, or under some stiffer or laxer alternative? Will the environmentally oriented taxes eventually erode their own basis, as consumers respond to the incentives by buying cars with steadily lower exhaust emission rates and lower tax? How can the government maintain the level of revenue from vehicle purchase taxes?

In order to answer these questions, a detailed and comprehensive behavioural model of demand for new passenger cars is needed.

2 Approach and method

We have developed a nested logit model of automobile choice, based on complete vehicle sales data for Norway for the period ranging from January 1996 until July 2011.

For each year, more than 2000 different vehicle model variants have been identified and their annual sales recorded. Obviously, few – if any – of these model variants are available on the market throughout the period. Only a certain subset of variants enters the choice set in a given year.

In the nested logit model every single car sale is regarded as a discrete choice where, in principle, every model variant available in the market at that time is included in the buyers' choice set. There are a total of approximately 1.6 million transactions, or choice situations, registered in the new car sales database. For each vehicle model variant, the database includes information such as the vehicle's make, list price, purchase tax amount, type of fuel, calculated kilometre cost of fuel, curb weight, engine power, drivetrain, and number of seats and doors. The nested logit model uses these individual vehicle characteristics as explanatory variables in the indirect utility function.

Since the model is supposed to predict the market share of potential new car model variants with known or assumed attributes, care was taken to specify the model as a generic one. There are no alternative specific coefficients, other than the dummies capturing the vehicle's make.

Extensive testing was done in order to find the appropriate nest structure. At first, we tried a structure in which the upper nests were defined by such segments as 'mini', 'small', 'compact', 'medium', 'fullsize', 'luxury', 'minivan', 'off-road' or 'sport-utility vehicle' (SUV). Secondly, we examined structures based on more objective size categories, such as kilogram curb weight intervals. Nesting based on fuel or propulsion technology was also tried. We found, however, that the only nest structure compatible with a priori assumptions under the utility maximization paradigm (scale parameters larger than unity) was one in which each vehicle make forms one nest. Thus, there are 21 such nests in the model, the last one being a residual nest assembling 'all other makes'. Fig. 1 illustrates the model's nest structure.

According to this structure, the probability of choosing a given vehicle model variant i of make j is the product of the probability of choosing make j and the conditional probability of choosing model variant i given the set available within make j. The mathematical formula for calculating the choice probability in year t can be stated as:

$$P_t(\text{variant} = i) = P_t(\text{variant} = i | \text{make} = j) \cdot P_t(\text{make} = j) \tag{1}$$

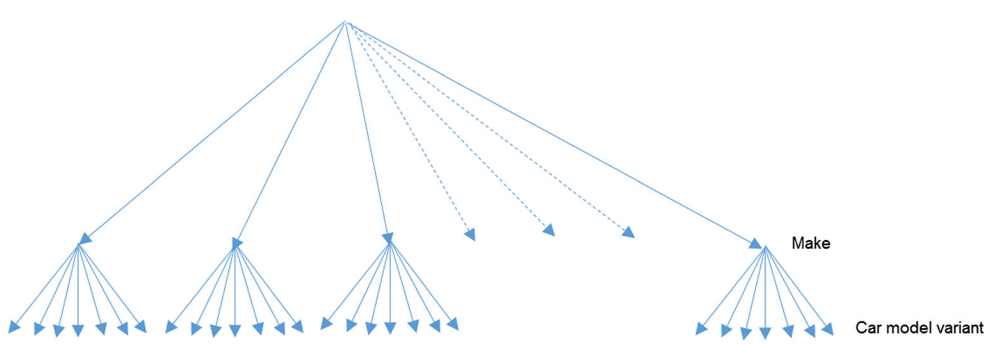

Fig. 1 Nest structure in automobile purchase model

If we denote by M_{tj} the set of model variants of make j available in year t, the two factors in Eq. (1) can be specified as

$$P_t(\text{variant} = i|\text{make} = j) = \frac{\exp\left(\mu_j V_{ij}\right)}{\sum_{h \in M_{tj}} \exp\left(\mu_j V_{hj}\right)}, \quad (t = 1996, 1997, \ldots, 2011) \quad (2)$$

$$P_t(\text{make} = j) = \frac{\exp^{\frac{1}{\mu_j}\ln\left[\sum_{i \in M_{tj}} \exp\left(\mu_j V_{ij}\right)\right]}}{\sum_{k=1}^{21} \exp^{\frac{1}{\mu_k}\ln\left[\sum_{i \in M_{tk}} \exp\left(\mu_k V_{ik}\right)\right]}} \quad (t = 1996, 1997, \ldots, 2011). \quad (13)$$

In these two expressions μ_j denotes the estimated scale parameter for each make in the lower nest. When normalizing the upper scale parameter to unity, these lower scale parameters are restricted to be larger than unity. The indirect utility function specified for each individual vehicle model variant i of make j, denoted V_{ij}, is specified as a linear combination of coefficients and explanatory variables:

$$V_{ij} = \sum_k \beta_k x_{ijk} + \gamma_j. \quad (4)$$

Here, the explanatory variables x_{ijk} are vehicle attributes. The γ_j are make-specific constants, estimated as the coefficients of a set of dummy variables – z_{ij}, say – equal to one if and only if model variant i belongs to make j (see Table 1 below for details). Note that the β_k coefficients are not indexed by i or j – they are generic, i. e. identical across vehicle model variants and makes.

As analysts, we do not have full information about the indirect utility generated by each vehicle model variant. Following common practice [2], we assume that the observable utility U_{ij} (say) consists of the systematic term V_{ij} and some random disturbance term e_{ij}, i. e.

$$U_{ij} = V_{ij} + e_{ij}, \quad (5)$$

where the e_{ij} are independent and identically Gumbel distributed random variables with scale parameters μ_j.

3 Estimation results

3.1 Model coefficients

Maximum likelihood estimates were derived using the Biogeme Python software [7]. All coefficient estimates are shown in Table 1.

Most coefficients are significantly different from zero at the 1% level. They also have the anticipated sign, whenever a priori expectations apply.

The *Price* coefficient is negative, as expected. Other things being equal, a higher price reduces a vehicle's market share.

The *Resourcecostshare* variable, being constrained between zero and one, is defined as the share of the vehicle's retail price that is not made up by purchase tax or value added tax (VAT), i. e. as the price net of tax divided by the price including tax. As expected, its coefficient comes out positive, suggesting that, other things (including the price) being equal, buyers are more reluctant to choose a heavily taxed car than one that is subject to zero or little tax. The *Resourcecostshare* variable allows us to distinguish the effect of a tax increase from that of a higher manufacturing or marketing cost.

The variable *Fuelcost*, defined as the relevant per litre real fuel price (in NOK 2010) times the type approval rate of fuel consumption per 10 km, captures the expected fuel cost per unit of driving distance. Its coefficient is negative, as expected. For BEVs, zero fuel cost is assumed.

Bigger is better. The *Size* variable, defined by the log-transformed product of the vehicle's length and width, as measured in square metres, comes out with a positive coefficient.

The *Acceleration* variable, defined by the amount of engine power in relation the vehicle's weight, comes out with a positive sign, but the coefficient is not statistically significant. To reflect the decreasing marginal utility of acceleration, the variable is not entered linearly, but specified as the negative of the inverse, squared ratio of engine power to weight, corresponding to a Box-Cox transformation with parameter minus two.

Load measures the log-transformed, maximum utility load of the vehicle (passengers and luggage, not including 75 kg driver) relative to its size in square metres. It has the expected positive sign, and is statistically significant at the 5% level.

The *Dieseltrend* variable captures the gradual improvement of diesel vehicle technology as compared to petrol driven cars. It is specified as a diesel vehicle dummy multiplied by the natural logarithm of years passed since 1996. The starting point of the diesel trend effect is determined by the dummy *C_Diesel*, estimated at −0.803, which translates into a significant disadvantage as compared to petrol cars in 1996.

Dummy variables *C_Electric* and *C_Hybrid* capture the effect of propulsion systems other than the petrol engine, which acts as our reference category. The hybrid class includes plug-ins as well as ordinary hybrids. These coefficients are both positive, but not highly significant.

Another set of dummy variables – *C_Fourwheeldrive* and *C_Frontwheeldrive* – capture the quality differences with respect to the standard rear-wheel drivetrain. 4-wheel drive is highly valued by Norwegian consumers, but front-wheel drive does not stand out as preferable to rear-wheel drive.

The dummy *C_Fiveormoredoors* typically captures station wagons and multi-purpose vehicles (MPV) as opposed to

Table 1 Estimation results from generic automobile choice model. Norway 1996–2011

Variable description	Variable name	Estimate	Robust t-statistic
Continuous variables			
Real retail price measured in 100,000 NOK 2010	*Price*	-0.153	-6.44
Share of retail price that is not purchase tax or VAT	*Resourcecostshare*	1.310	5.15
Operating cost: fuel price x fuel consumption per 10 km	*Fuelcost*	-0.063	-5.60
Log of vehicle length times width (square metres)	*Size*	1.560	6.32
Log of allowed load divided by Size (kg/sq m)	*Load*	0.187	2.18
Diesel dummy x log of years passed since 1996	*Dieseltrend*	0.309	3.84
Engine power (kW) per 100 kg curb weight, raised to the power of −2, with sign reversed	*Acceleration*	0.519	0.87
Dummies for vehicle attributes			
Diesel engine	*C_Diesel*	-0.803	-3.99
Hybrid vehicle	*C_Hybrid*	0.133	1.80
Battery electric vehicle	*C_Electric*	0.660	1.99
4-wheel drive	*C_Fourwheeldrive*	0.352	6.04
Frontwheel drive	*C_Frontwheeldrive*	0.024	0.89
5 seats	*C_Fiveseats*	0.071	3.27
6 or more seats	*C_Sixormoreseats*	0.023	0.42
5 or more doors	*C_Fiveormoredoors*	0.228	4.90
Dummies for vehicle make			
Toyota	*Ctoyota*	3.12	8.66
Volkswagen	*Cvolkswagen*	3.10	8.87
Ford	*Cford*	2.46	7.81
Opel	*Copel*	1.75	5.76
Peugeot	*Cpeugeot*	2.31	6.41
Volvo	*Cvolvo*	2.39	5.03
Audi	*Caudi*	1.84	5.24
Nissan	*Cnissan*	2.06	5.17
Mitsubishi	*Cmitsubishi*	1.86	4.46
Mazda	*Cmazda*	2.15	5.04
Hyundai	*Chyundai*	1.46	4.37
Skoda	*Cskoda*	1.77	4.79
BMW	*Cbmw*	1.53	4.03
Mercedes-Benz	*Cmercedes*	0.07	0.21
Renault	*Crenault*	1.62	5.00
Honda	*Chonda*	1.78	4.31
Suzuki	*Csuzuki*	1.89	5.19
Citroën	*Ccitroen*	1.30	3.80
Saab	*Csaab*	1.90	4.91
Subaru	*Csubaru*	1.32	3.00
Scale parameters			
Toyota	*mutoyota*	3.96	6.01
Volkswagen	*muvolkswagen*	4.52	5.87
Ford	*muford*	3.86	5.74
Opel	*muopel*	2.65	6.23
Peugeot	*mupeugeot*	3.89	5.79
Volvo	*muvolvo*	3.91	8.68
Audi	*muaudi*	3.07	7.51
Nissan	*munissan*	3.79	5.78
Mitsubishi	*mumitsubishi*	3.53	5.31

Table 1 (continued)

Variable description	Variable name	Estimate	Robust t-statistic
Mazda	*mumazda*	5.43	5.49
Hyundai	*muhyundai*	2.81	3.74
Skoda	*muskoda*	4.17	5.28
BMW	*mubmw*	2.83	6.18
Mercedes-Benz	*mumercedes*	1.63	7.73
Renault	*murenault*	4.37	3.81
Honda	*muhonda*	3.84	5.22
Suzuki	*musuzuki*	4.50	4.96
Citroën	*mucitroen*	3.26	4.36
Saab	*musaab*	5.10	5.03
Subaru	*musubaru*	3.55	6.31
All other makes	*muother*	1.59	6.43
General statistics			
Number of parameters estimated			56
Sample size (number of vehicles)			1,617,303
Initial log-likelihood			12,549,628.19
Final log-likelihood			11,866,231.32
Likelihood ratio test			1,366,793.7
Goodness-of-fit	Rho bar		0.054

ordinary sedans, while the variables *C_Fiveseats* and *C_Sixormoreseats* measure differences with respect to cars with four seats or less.

The dummies capturing vehicle make are all positive and, with one exception, significantly different from zero, suggesting a higher choice probability than the reference category 'all other makes'. These dummy variables are, however, hard to interpret. On the one hand, they reflect the popularity of each make as measured by their market share. On the other hand, they are also affected, and negatively so, by the number of different model variants offered by each manufacturer. The larger the number of similar vehicles the consumer can choose from, the smaller will be the market share of each particular model variant – confer the famous 'red bus – blue bus' example ([2]: 51–55). This explains why the prestigious Mercedes-Benz (MB) make comes out with the smallest coefficient of all makes. While, in our data set, the average number of model variants offered annually by each manufacturer is 45 (disregarding 'all other makes'), MB have split their sales among, on average, 206 different model variants, with a mean sale of only 15 cars per model variant per year. While their aggregate market share is only 3.1%, they represent 8.6% of all the model variants entering the market (Table 2).

3.2 Model predictions vs. observed outcomes

In Fig. 2 we show observed and predicted annual market shares, at the most disaggregate level.

As can be expected in a data set where all choice probabilities are quite small, the fit is rather poor, as measured by the adjusted likelihood ratio index $\overline{\rho}^2 = 0.054$. One notes that for model variants with a very low market share, some of the predicted values are widely off the mark. Certain variants sell only one or two units in a given year, corresponding to an observed market share between 0.0008 and 0.003%. On account, however, precisely of these variants' infinitesimal market shares, their weak fit is of little consequence to the model's predictive power. For variants with a higher market share, the correspondence between observed and fitted values is stronger.

The differences between the various vehicle model variants making up our data set are, in many cases, miniscule. To fix ideas we show, in the Appendix, data lines pertaining to the 2010 assortment of Volkswagen Golf model variants. There are 73 such variants in the market, no two of them being exactly equal in terms of the attributes entering the discrete choice model: engine power, curb weight, utility load, cylinder volume, fuel, no. of seats, no. of doors, length, width, body style, or traction.

Obviously, the prediction of market share for each of these individual variants is of limited commercial or political relevance. Comparing observed and fitted market shares at the somewhat more aggregate levels carries more interest. In Fig. 3 we have grouped observations into segments defined by energy carrier and/or curb weight.

Again, the predictive power is comparatively weak for segments with very low market shares. Within the more popular

Table 2 Aggregate number of new automobiles sold, mean number of model variants offered per year, and average number of vehicles sold annually per model variant, by make. Norway January 1996–July 2011

Make	Vehicles sold 1996–2011	Mean # of variants offered per year	Vehicles sold annually per model variant
Toyota	221,167	140	99
Volkswagen	206,839	246	53
Ford	131,789	168	49
Opel	109,885	172	40
Volvo	92,587	109	53
Peugeot	87,958	141	39
Audi	83,115	196	27
Nissan	65,850	68	60
Mitsubishi	58,401	63	58
Mazda	49,072	45	68
Hyundai	48,325	49	62
Skoda	53,435	88	38
BMW	53,076	163	20
Mercedes-Benz	50,188	206	15
Renault	43,199	79	34
Honda	42,088	36	74
Suzuki	45,587	33	86
Citroën	37,304	61	38
Saab	31,287	57	35
Subaru	33,692	39	54
All other makes	72,514	247	18
Total	1,617,358	2406	42

vehicle segments, however, the fit seems quite satisfactory. A case in point is the 1000–1199 kg class of petrol driven cars, exhibiting a 40% observed and predicted market share in 1996, declining to a 7% observed and predicted market share in 2011.

The model is somewhat less accurate in predicting the respective market shares of different vehicle makes (Fig. 4), but fairly precise in terms of the distribution between CO_2 emission intervals (Fig. 5).

In Fig. 6, we show how well the model explains the trend towards lower average type approval exhaust emission rates during 1996–2011. The model picks up the trend reasonably well.

3.3 Willingness-to-pay for vehicle attributes

Following common practice in hedonic demand modelling [30], we derive the willingness-to-pay for a certain attribute by taking the ratio of its coefficient estimate to the price coefficient. Table 3 summarizes the calculated willingness-to-pay for selected vehicle attributes.

Our nested logit model implies a value of NOK 8600 for a one percentage point increase in the non-tax share of the vehicle retail price. By extrapolation, the willingness-to-pay for a non-taxed vehicle is NOK 430000 higher than for a vehicle whose price consists of 50% tax.

The willingness-to-pay for a reduction in petrol or diesel consumption by one litre per 100 km is estimated at NOK 41,400. For a vehicle running 240,000 km during its lifetime[1], the energy saving is 2400 l, at a cost of roughly NOK 30,000–35,000 (= appr. € 4000). Hence, when car buyers make their choice, they may seem to take more than full account of future energy costs, while also not applying a discount rate much higher than zero. The estimate may be affected by the fact that the type approval rates of fuel consumption entering our data set are typically 10 to 30% lower than the actual consumption on-the-road [27]. It may seem as if consumers are well aware of this. Also, the estimate may reflect concern about future energy prices and a desire to minimize such risk.

Norwegians love four-wheel drive, which provides superior traction on snow and ice as well as enhanced accessibility on the rough road to their mountain or seaside cottage. The willingness-to-pay for four-wheel relative to rear-wheel drive is calculated at NOK 230,000, while front-wheel drive is valued at NOK 15,900.

A vehicle model variant with five seats rather than four or less seats has an added value to the consumer of NOK 46,500. A station wagon or 5-door multi-purpose vehicle (MPV) is valued at NOK 149,000 more than the otherwise similar sedan.

The willingness-to-pay for a hybrid vehicle rather than a petrol car is approximately NOK 87,000 (2010 prices) (Fig. 7). This indicates that consumers assign an extra value to this type of vehicle compared to petrol driven ones, ceteris paribus.

The estimated willingness-to-pay for diesel vehicles, rather than petrol cars, shifts from negative to positive in 2008, amounting to approximately NOK 35,000 in 2011.

The added willingness-to-pay for battery electric vehicles comes out at no less than NOK 431,000 = € 51,000. At first sight, this may seem exaggerated. However, the estimate must be interpreted in light of the fact that the *Fuelcost* variable is set to zero for BEVs. The estimate includes, in other words, the perceived advantage of having zero fuel cost throughout a vehicle's lifetime. When we adjust for this, applying an average *Fuelcost* value of NOK 8.91 per 10 km, the

[1] Travelling, on average, 14,000 km annually, Norwegian registered automobiles have a life expectancy of 17 years [15].

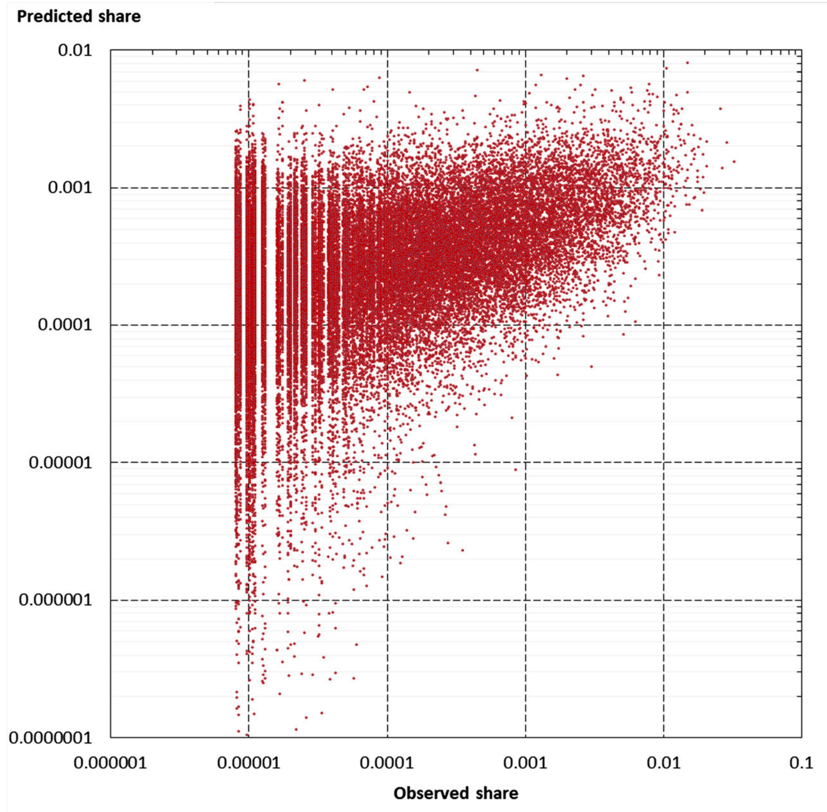

Fig. 2 Observed and fitted annual market shares of individual vehicle model variants 1996–2011. Logarithmic scale

BEVs' market advantage is reduced to around NOK 66,000 = € 7800. This estimate reflects the fact that, in Norway, BEVs enjoy a large number of privileges, such as access to the bus lane, exemption from road tolls and public parking charges, strongly reduced ferry fares, and free recharging in many public parking lots. Among BEV owners in Norway as of March 2016, the median value of these benefits has been estimated at NOK 10,000 = € 1200 per year [13]. In certain parts of the country, the value of the toll exemption alone can exceed € 4000 per year for a motorist using a long bridge or subsea tunnel on his daily commute.

4 Policy analysis

There are several ways in which our nested logit model can be used as a policy support tool.

By simulating hypothetical changes in certain vehicle attributes, we can calculate policy or marketing relevant response surfaces at more or less aggregate levels. Thanks to the generic character of the model, we can predict the market shares of these hypothetical vehicles as well as the change in demand for every other passenger car in the market. Fridstrøm et al. [15] show how, by integrating the discrete choice model into a dynamic stock-flow model of the car fleet, one can assess the long-term consequences of changes in vehicle technology or in the fiscal incentives.

In this paper, we report on three other policy relevant applications of the model. In Section 4.1, we present a short-term analysis of potential changes in the Norwegian vehicle purchase tax. In Section 4.2, we present model simulations of changes in the fuel cost. In Section 4.3, we present the results of a counterfactual back-casting exercise, in which one simulates the market development during 2007–2014 under the hypothetical assumption that the strongly CO_2-graduated purchase tax and/or the tax exemptions for BEVs had never been introduced.

4.1 Simulated changes to the vehicle purchase tax

The Norwegian automobile purchase tax, payable upon first registration of a vehicle, is a sum of four independent components, calculated on the basis of curb weight, ICE power, and type approval CO_2 and NO_X exhaust emission rates, respectively (Fig. 8). All but the NO_X component are convex, exhibiting increasing marginal tax rates. The CO_2 component is negative (as of 2014) for vehicles emitting less than 105 gCO_2/km by the type approval test. That is, for these cars there is a deduction applicable to the

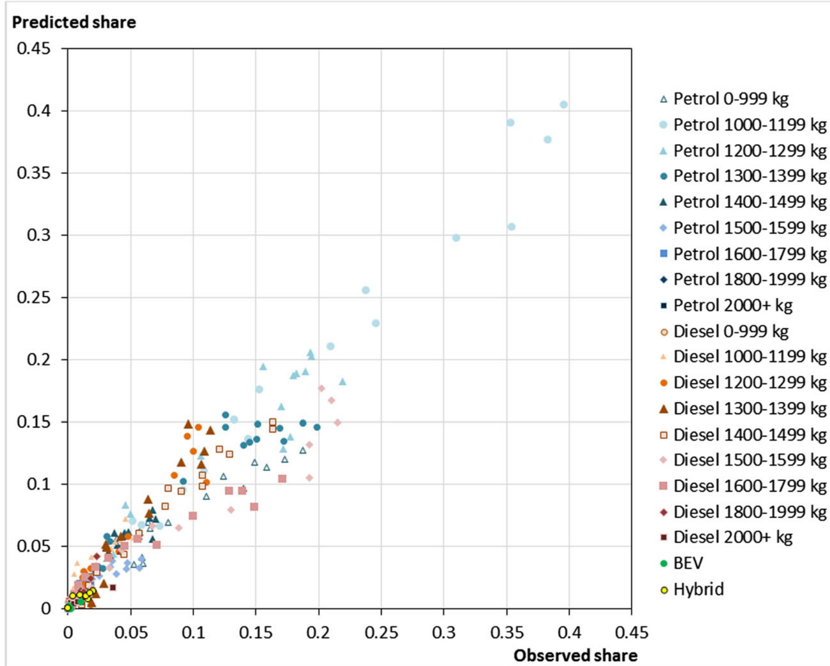

Fig. 3 Observed and fitted annual market shares 1996–2011, by energy carrier and/or curb weight. Linear scale

sum of the weight, power and NO_X components. The total purchase tax cannot, however, become negative, as in a feebate system.

For PHEVs, the electric motor does not count towards the tax on engine power, only the combustion engine does, and the weight component is reduced by a benchmark 15% (as of 2014), so as to leave the weight of the battery pack out of the tax base. As noted above, BEVs and FCEVs are altogether exempt of purchase tax, as well as of the standard 25% value added tax (VAT).

Relying on the discrete choice model shown in Table 1, we have simulated six different policy options bearing on the automobile purchase tax:

1. A 10% increase in all purchase tax components.
2. A 10% increase in the CO_2 component
3. A 10% increase in the curb weight component
4. A 10% increase in the engine power component
5. Introduction of purchase tax on BEVs, according to same rules as for PHEVs.

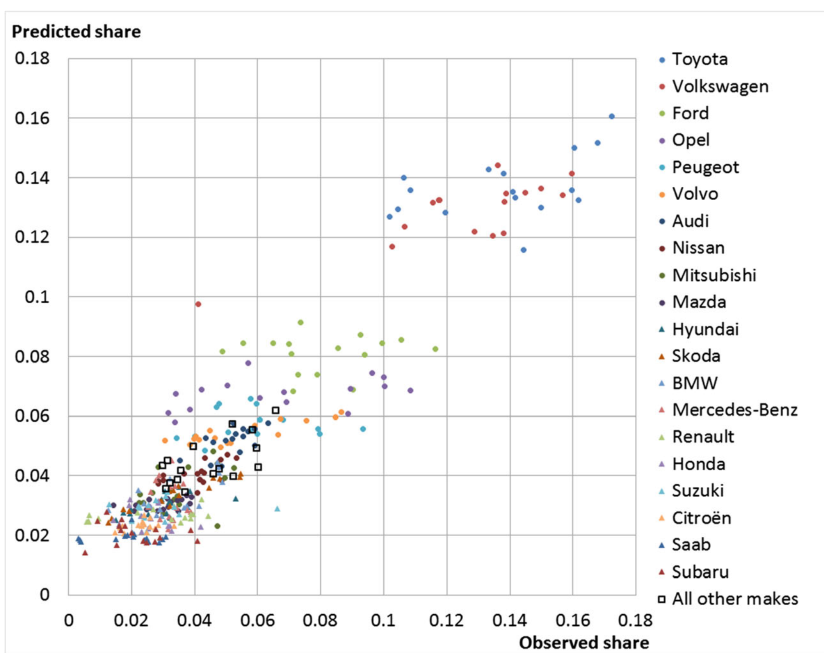

Fig. 4 Observed and fitted annual market shares 1996–2011, by vehicle make. Linear scale

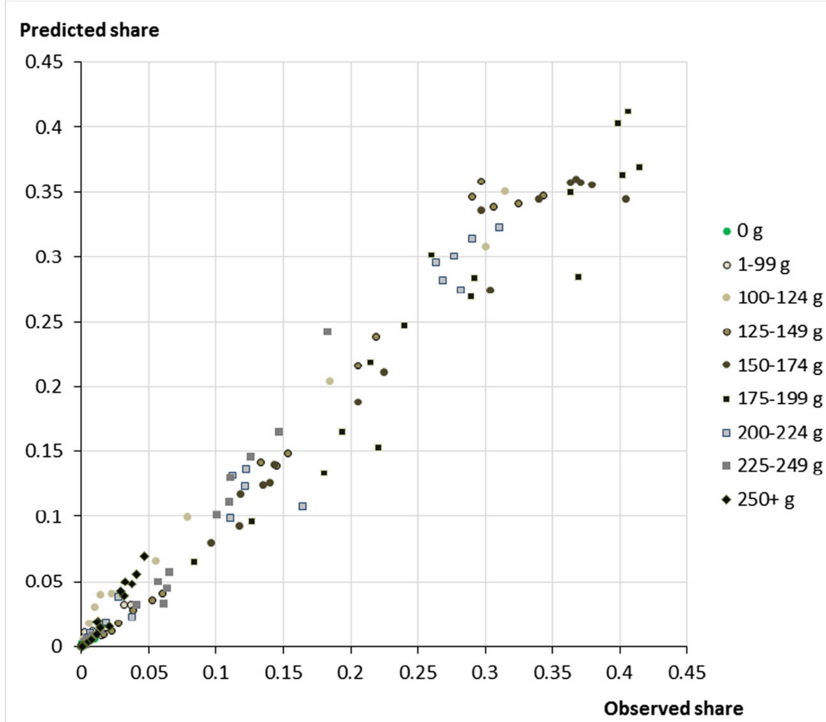

Fig. 5 Observed and fitted annual market shares 1996–2011, by type approval CO_2 exhaust emission bracket (gCO_2/km). Linear scale

6. Introduction of VAT and purchase tax on BEVs, according to same rules as for PHEVs.

Simulations were made on the basis of a benchmark calculated for 2014. As seen from Fig. 9, more than half the passenger cars sold in 2014 had type approval CO_2 exhaust emission rates between 100 and 149 gCO_2/km. BEVs had a market share of 12.5% in Norway 2014.

By adjusting the constant terms, we calibrated the model as of 2014 so as to yield correct aggregate market shares for battery electric, hybrid electric, petrol and diesel driven cars, as well as for the Tesla make of BEVs. Since the Teslas stand out as rather more expensive than other BEVs, it was considered necessary to account for these most expensive BEVs as accurately as possible. In all of the simulations, it has been assumed that tax changes are passed on 100% to the buyers, through corresponding changes in the retail price.

Figure 10 shows changes in the market shares of vehicles within different CO_2 emission brackets. As shown by the left-

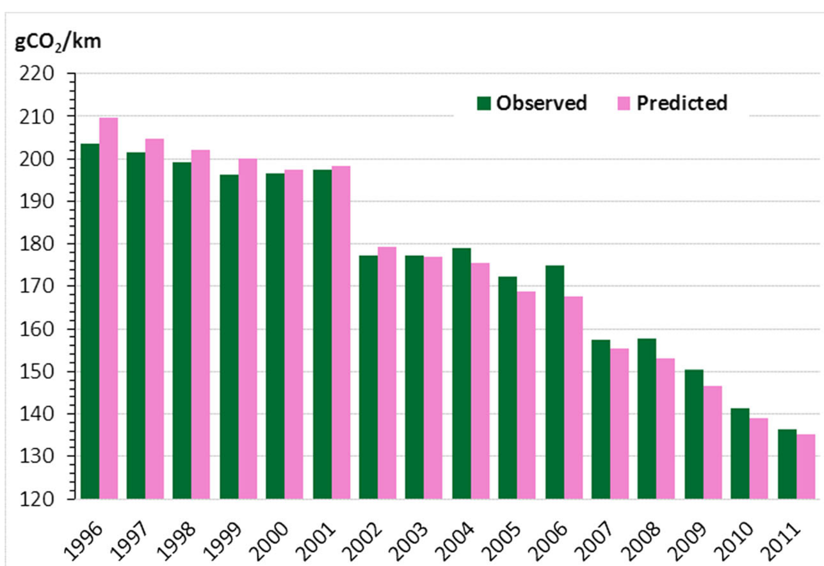

Fig. 6 Mean observed and predicted type approval CO_2 exhaust emission rates of new Norwegian registered automobiles 1996–2011

Table 3 Willingness-to-pay for selected vehicle attributes

Attribute	Willingness-to-pay (NOK[a] 2010)	Explanation
Resource cost share	8600	Value of 1 percentage point increased *Resourcecostshare*
Fuel cost per 10 km	41,400	Per litre decrease in consumption per 100 km
Four-wheel drive	230,000	Measured relative to rear wheel drive
Front-wheel drive	15,900	Measured relative to rear wheel drive
Five seats	46,500	Measured relative to four seats or less
Six or more seats	15,300	Measured relative to four seats or less
Five or more doors	149,000	Measured relative to four doors or less

[a] NOK = Norwegian kroner. As of 1 July 2014, € 1 = NOK 8.43

most cluster of bars (alt. 1), a 10% increase in every purchase tax component would, when passed on entirely to the buyers, translate into a 24% lower market share for the most extreme ‘fuel guzzlers’, but an almost 10% increase in the sales of zero emission vehicles, i. e. BEVs.

Obviously, when only one tax component changes (alt. 2 through 4), the resulting impact is smaller. If only the CO_2 component is increased, low emission cars (emitting 1–99 gCO_2/km) will gain market shares. Even the weight and power components are seen to have some effect on the market shares of low vs. high emission vehicles. An increased weight component will benefit zero emission vehicles only.

The introduction of purchase tax on BEVs (alt. 5) will have rather moderate effects, assuming BEVs would then be subject to the same tax rules as PHEVs. For most BEVs, the negative CO_2 component would in such a case more than outweigh the positive weight component, resulting in zero purchase tax.

But if both exemptions – from VAT and purchase tax – were to be revoked (alt. 6), the BEV market share would drop by an estimated 24%, while the fuel guzzlers would see their market grow by around 10%.

The overall changes in average type approval CO_2 exhaust emissions from new passenger cars, under the six different policy scenarios, are shown in Fig. 11.

A uniformly 10% higher purchase tax will reduce the mean exhaust emission level by 2.4 gCO_2/km, or about 2.2% compared to the reference level of 113 gCO_2/km. Increasing the CO_2 or weight component leads to a 1.1 gCO_2/km decrease in average exhaust emissions, while an increase in the power component will have very little effect on the CO_2 level.

Introducing a purchase tax for BEVs, identical to the one in effect for PHEVs, will lead to a moderate, 0.56 gCO_2/km increase in the average exhaust emission level of new cars.

If, however, both the VAT and the purchase tax exemptions are lifted, the result will be an estimated 3.85 gCO_2/km higher level of exhaust emissions. The VAT effect alone can be calculated as 3.85–0.56 = 3.3 gCO_2/km by the type approval test.

Since, for the 2014 cohort of passenger cars in Europe, exhaust emissions on the road are roughly 40% higher than according to the NEDC laboratory testing cycle [33], the 3.85 gCO_2/km type approval differential corresponds to 5.4 gCO_2/km in real traffic. For a car running 240,000 km before scrapping, accumulated CO_2 savings over the car’s lifetime amount

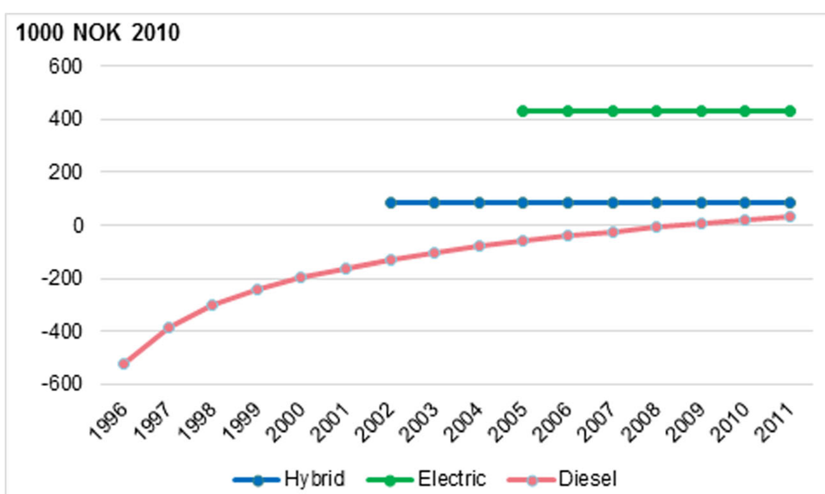

Fig. 7 Willingness-to-pay for hybrid, electric and diesel powered vehicles relative to petrol driven model variants

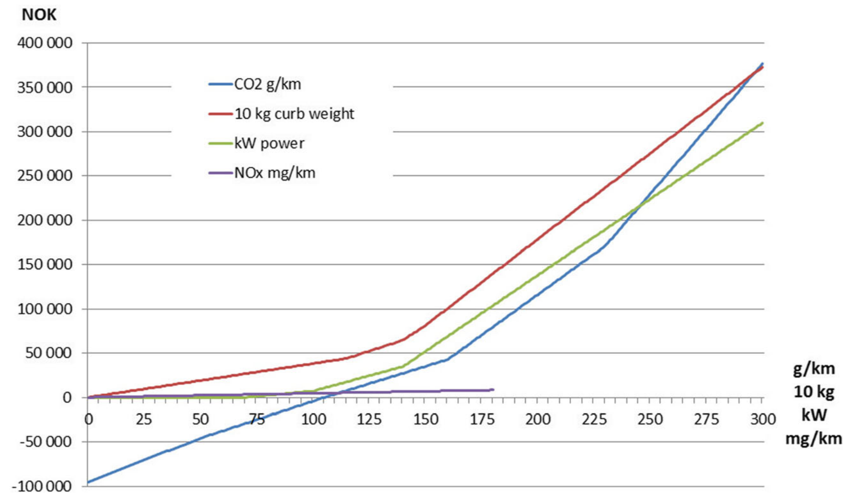

Fig. 8 Vehicle purchase tax as a function of curb weight, engine power, and type approval CO_2 and NO_X exhaust emission rates, in Norway 2014
Source: Fridstrøm et al. [17]

to 1300 $kgCO_2$. For the whole 2014 cohort of Norwegian registered cars (144,202 vehicles), lifetime CO_2 savings amount to around 190,000 t.

The fiscal revenue impact of the six policy options is also calculable from the model (Fig. 12).

Increasing all purchase tax components by 10% generates an extra NOK 742 million per annum for the public treasury, according to the model. Note, however, that the possible rebound effect in the form of lower aggregate car sales is not taken into account here, nor in any of the other scenarios studied.

Increasing the CO_2 component by 10% will have comparatively small effects on the purchase tax revenue. The same is true of the engine power component. The weight component, however, is a potent one. Most of the revenue increase obtained by a uniform 10% increase in all tax components is due to the weight component.

Interestingly, the purchase tax exemption for BEVs reduces public revenue by only NOK 200 million – a small amount compared to the large numbers featured in multiple media announcements on the 'cost' of the electric vehicle incentives. Note, however, that our point of reference is a tax regime in which low and zero emission vehicles in general and PHEVs in particular enjoy very much lower tax rates than do fuel guzzlers.

A much larger increase in public revenue would take place if the VAT exemption were lifted as well. In such a case, some car buyers would shift from BEVs to ICE vehicles, whereby the purchase tax revenue would increase, not by NOK 200 million, but by more than NOK 500 million. A more than twice as large revenue increase would come from the VAT system[2].

In the long run, reduced exhaust emissions from cars will go along with a proportional decrease in fossil fuel consumption and hence in fuel tax revenue. This effect is not included in our revenue calculations. For a car running 240,000 km before scrapping, a 3.85 gCO_2/km difference in type approval exhaust emissions corresponds to fuel savings of roughly 500 l over the vehicle's lifetime, with a NOK 2500–3000 (= € 300–350) reduced fuel tax bill. As applied to the entire 2014 cohort of new cars, the lifetime fuel tax revenue differential is around NOK 350–400 million.

There is thus an inherent contradiction between the fiscal and environmental policy goals. An effective environmental tax may erode its own base. The consequences could be wide-reaching, since fuel taxes are probably the most important market correction mechanism currently in place in Europe. According to Thune-Larsen et al. [32], the Norwegian petrol tax is just about high enough to balance the vehicles' average marginal external cost. The per litre diesel tax, however, falls around NOK 3 (= appr. € 0.35) short of the associated external cost. BEVs are subject to only a small electricity tax, despite giving rising to an external cost that is only 30% lower than for petrol cars.

If and when BEVs make up a major share of the car fleet, the need for an alternative market correction mechanism, such as generalised marginal cost road pricing, will come to the fore. Satellite based road pricing was studied extensively in the Netherlands [26], but not implemented. Interestingly, the proposed Dutch scheme appears to have solved the privacy problem, in that the detailed information on the vehicle's movements would be stored nowhere but in the vehicle owner's own on-board unit.

4.2 Simulated changes to the fuel cost

To assess the impact on car purchases of changes in the price of fuel, as brought about e. g. by a higher fuel

[2] In Norway 2014, 47.4% of new cars were registered to commercial businesses (source: www.ofv.no). Most of these firms are VAT registered. With the exception of taxi companies, however, corporate buyers are not allowed to deduct input VAT on automobiles in their VAT account. We have therefore included the full amount of VAT on automobiles in our revenue calculations.

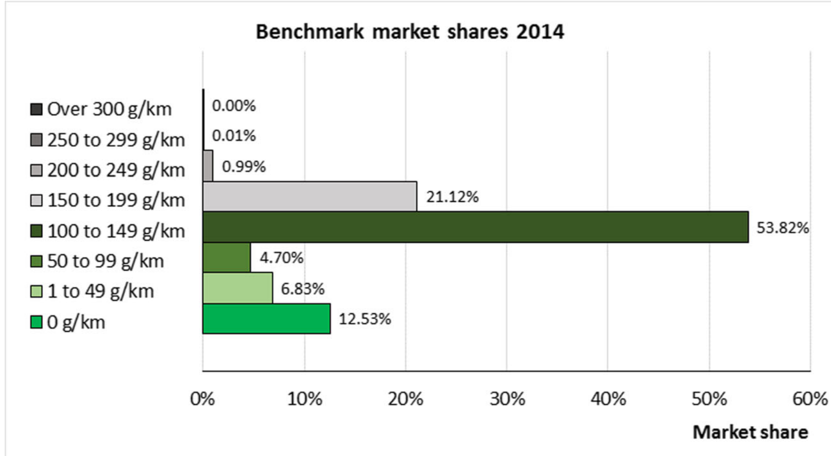

Fig. 9 Calculated automobile market shares for 2014, by type approval CO_2 exhaust emission bracket

tax, we have simulated 10 and 50% increases in the *Fuelcost* variable. A generally increased fuel price would lead to proportional changes in the fuel cost of every car model in the sample. Response in terms of fuel consumption would translate into proportional changes in CO_2 emissions. The results are shown in Fig. 13.

In the hypothetical event of a 10% higher fuel price in 2010, the mean type approval CO_2 exhaust emission rate is predicted to fall from 138.91 to 138.22 gCO_2/km, i. e. by 0.5%, implying an elasticity of −0.05. In the case of a 50% price rise, the predicted effect is just about five times stronger: 2.43%, suggesting an almost constant elasticity.

By comparison, estimates of the price elasticity of demand for fuel, as measured in terms of short term car travel and fuel demand responses, generally range between −0.25 and −0.1 [12]. The indirect effect channelled through vehicle choice adds, in other words, an extra 20 to 50% on top of the direct fuel demand response, when assessed in a long-term perspective. The indirect effect works only in the long run, i. e. over the vehicle's lifetime.

Underlying the indirect vehicle choice response to fuel price increases is, of course, a reallocation from higher to lower emission car models. This is shown explicitly in Figs. 14 and 15. As in Fig. 13, simulations are done as of 2010 – our last full year of sales data.

A higher fuel cost would induce car customers to buy fewer large cars and more small ones (Fig. 15). Also, since the diesel engine is generally more energy efficient than the petrol engine, a higher fuel price would, in general, boost demand for diesel cars at the expense of petrol cars.

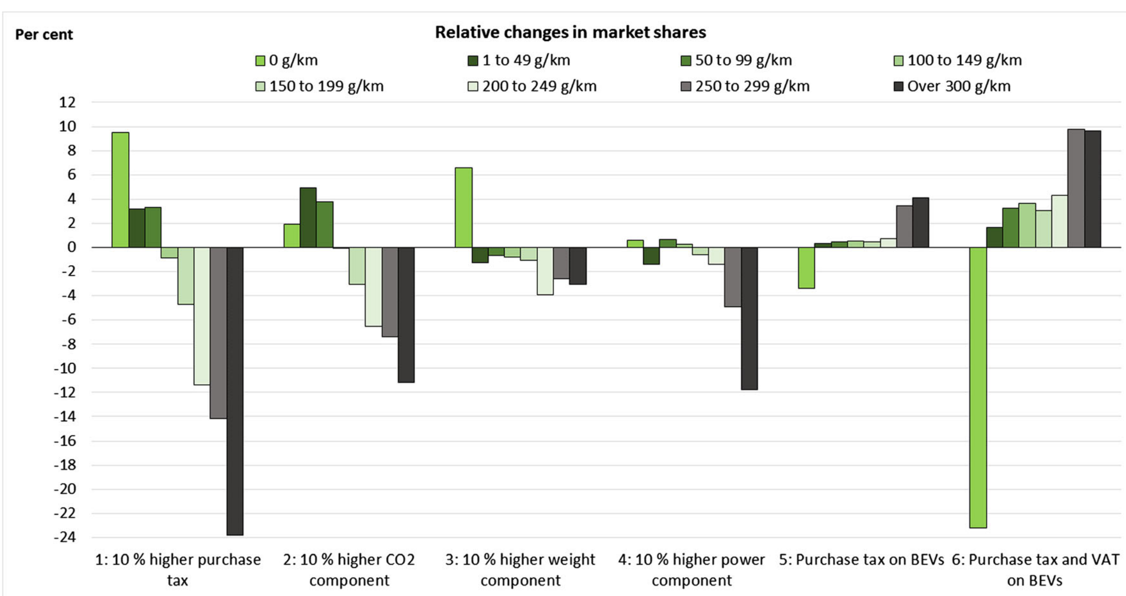

Fig. 10 Relative changes in market shares under six fiscal policy scenarios as of 2014, by CO_2 exhaust emission interval, assuming that tax increases are passed on 100% to buyers

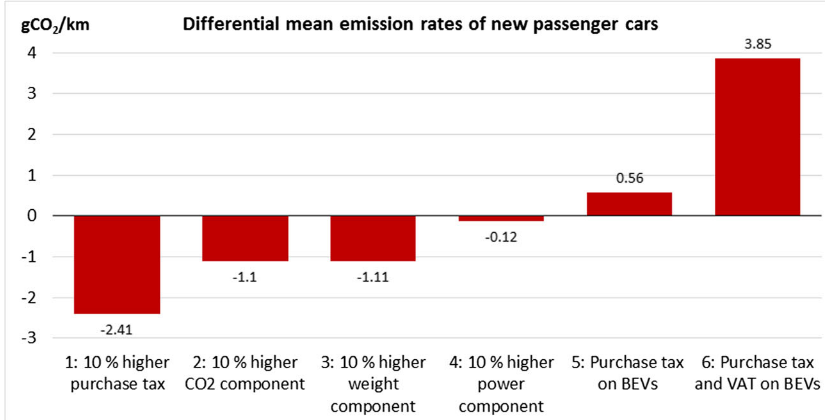

Fig. 11 Absolute changes in mean type approval CO_2 exhaust emission rates of new passenger cars, compared to reference case, under six fiscal policy scenarios as of 2014

4.3 A counterfactual back-casting

The CO_2 component of the vehicle purchase tax was first introduced in 2007 and has since become gradually steeper. In Fig. 16 we show the outcome of a back-casting exercise with five alternatives. The reference scenario (A) mirrors more or less the actual history of the purchase and value added taxes applicable to passenger cars since 2007. In scenario B, we imagine that the CO_2 component of the purchase tax was never introduced, but the remaining tax components apply as in the reference path. One notes that already in 2007, there is a marked difference between the two developments, as car buyers in the reference scenario are induced to choose more energy efficient cars with lower CO_2 emissions. This shift has also been observed in reality [16].

Note, however, that since our model does not predict aggregate automobile sales, only how it is distributed among model variants, the rebound effect due to generally cheaper cars in scenario B is not taken into account. D'Haultfoeuille et al. [11] show that such rebound effects are potentially important.

Under alternative C, the removal of the CO_2 component is compensated by a 15.5% increase in the weight and power components, sufficient to uphold the government's total purchase tax revenue during 2007–2014. This scenario is, in other words, fiscal revenue neutral compared to the reference path.

In scenario D, the tax exemptions for BEVs are abolished. Since there are few BEVs on the market in 2007, this policy measure does not take much effect until the last couple of years.

In the most radical scenario E, where neither the CO_2 component nor the tax exemptions for BEVs are assumed to come true, the predicted mean type approval rate of CO_2 exhaust emissions from new cars in 2014 is 136 gCO_2/km, versus 113 gCO_2/km under the reference path[3]. Apparently, the fiscal policy pursued by the Norwegian government since 2007 has been successful in lowering the average CO_2 emissions from new cars registered. As of 2014, the CO_2 component and the purchase tax and VAT exemptions for BEVs together account for an estimated 23 gCO_2/km reduction in the type approval emission rate of new cars.

Note, however, that this estimate does not include the effects of numerous other incentives benefiting zero and low emission cars in Norway, such as the 15% 'rebate' in the weight tax component of PHEVs, the zero purchase tax on electric motor power, the BEVs' access to the bus lane, their strongly reduced ferry fares and annual circulation tax, their exemption from road tolls and public parking charges, and their free recharging in many public parking lots.

Scenario E is not fiscal revenue neutral. A certain rebound effect, of uncertain direction, would have to be expected if this scenario had come true. The removal of the CO_2 component would tend to increase aggregate automobile demand, while the imposition of VAT on BEVs would work in the opposite direction.

[3] The real, observed rates in 2007 and 2014 were 159 and 110 gCO_2/km, respectively. Being a stylized instrument, the model does not produce perfectly accurate predictions.

5 Discussion

Although the issue of GHG abatement through vehicle fleet renewal and electrification receives considerable attention from scientists [23, 29, 31], extensive literature reviews have shown no example of another approach to automobile market forecasting equivalent to ours. It appears to be unique in combining the following three features: (i) Nested logit modelling is applied to a disaggregate set of complete nationwide new vehicle sales data over an extended period. (ii) We specify and estimate an entirely generic model, which can be used to predict the market shares of hitherto non-existent vehicle model variants with certain characteristics. (iii) The model relies exclusively on objective vehicle registration data, requiring no input on household characteristics or

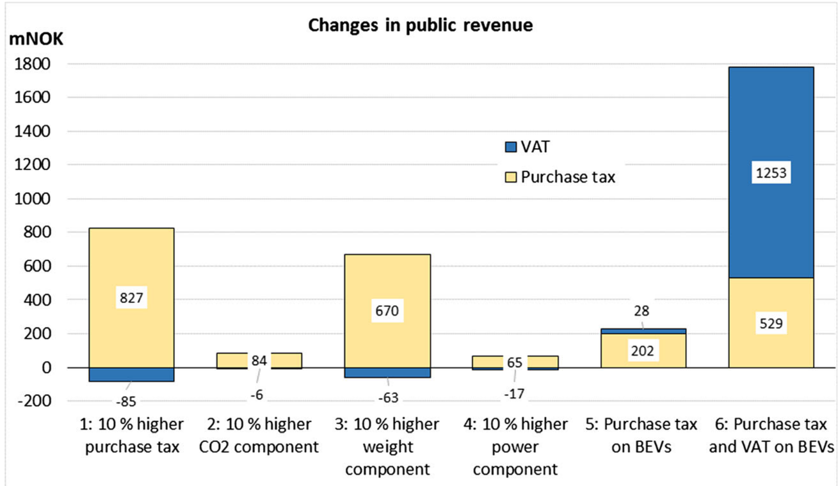

Fig. 12 Differential annual VAT and purchase tax revenue under six fiscal policy scenarios as of 2014

preferences. Since our model keeps track of a five-digit number of different passenger car model variants sold in Norway during 16 years, with an average annual sale of about 40 vehicles per model variant, it is as detailed as any disaggregate approach, capturing differences between all the vehicles available in the market.

The generic character of the model does, however, come at a price. The model does not predict automobile sales at the level of the individual vehicle model variant with any degree of precision. Nor is this the intention. Some vehicle model variants are very similar – indeed, in some cases deciding whether two cars represent two different model variants or two versions of the same model variant may seem like a matter of fine judgment. Hence the prediction of demand at the level of the individual vehicle model variant carries less political interest than forecasting at the somewhat more aggregate level, whereby cars are grouped according to, e. g., their make, size, fuel economy or exhaust emissions. At this level, the model appears to discriminate well between various policy scenarios, as demonstrated by the simulation exercise described in Section 4 above. When fed into a dynamic stock-flow cohort model of the car fleet, it becomes a powerful policy support tool [15, 16].

There is at least one big advantage to this kind of disaggregate specification. Precisely because it does not involve averaging across type approved model variants, except that vehicles belonging to the same variant may be differently equipped and styled, aggregation bias is minimized.

But since the model contains no information on the human decision makers, it cannot predict trends rooted in changes occurring to these individuals – such as their income, education, family structure, residence pattern, employment, or travel demand.

The logic of forecasting by means of our model may appear intriguing. The future demand for automobiles will depend, in the aggregate as well as by make and model variant, on what car model variants manufacturers bring to the market. The suppliers determine the assortment of automobiles available. Obviously, our model cannot predict these changes in the choice set. Instead, future choice sets must be formed by assuming that (most) model variants available in our last year(s) of observation continue to be offered in the market, albeit possibly with certain alterations and improvements, such as a steadily improved fuel efficiency. When it is known – or assumed – that new vehicle

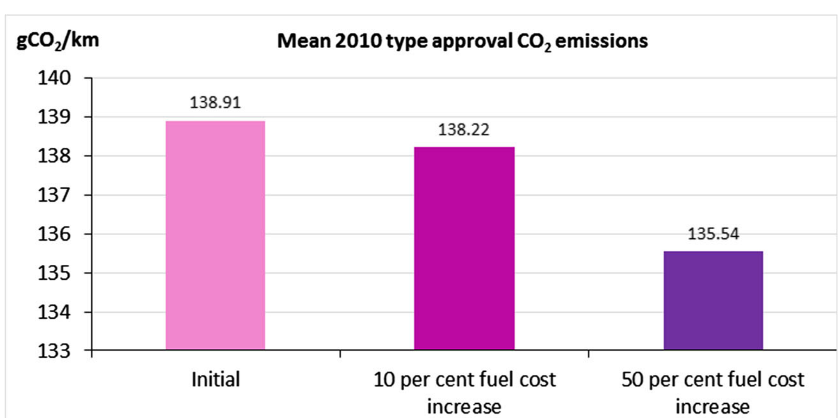

Fig. 13 Mean type approval CO_2 exhaust emissions from new automobiles, as simulated for 2010

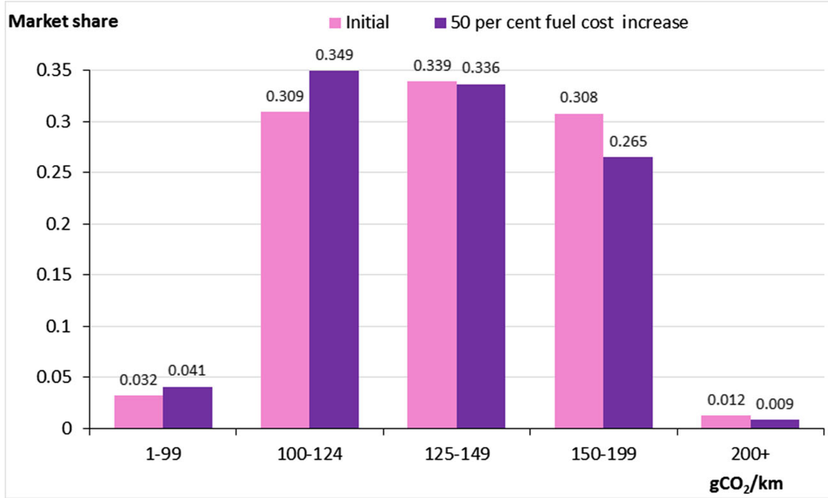

Fig. 14 Predicted vehicle market shares, by type approval CO_2 exhaust emission bracket, under actual 2010 and simulated 50% higher fuel cost

technology will enter the market, the model user can specify any number of such model variants and include them in the choice set for future years. For the most part, however, forecasts must be based on the concrete model variants already observed in the past or present. In the forecast, these model variants play the role of abstract representatives of the future vehicle assortment.

In econometric models of demand for heterogeneous products, such as ours, an important source of omitted variable bias may be present if the product quality is positively related to its manufacturing cost and hence to its price. Unless the regression model succeeds in capturing all the quality aspects of the product through the inclusion of appropriate independent variables, the numerical value of the price coefficient will be underestimated, since the price embodies certain quality factors not otherwise accounted for. Such a pitfall could apply even to our model. Although our model does include several important quality attributes such as make, size, utility load, engine power, drivetrain, energy carrier, fuel mileage, seat capacity, and number of doors, the attributes *not* explicitly accounted for are even more numerous – suffice it to mention automatic shift, automatic cruise control, electronic stability control, anti-lock braking systems, airbags, power steering, power windows, leather upholstery, metallic paint, or the innumerable design features which distinguish model variants visibly from one another.

We may, however, have avoided – and perhaps even reversed – this type of bias through the inclusion of the *Resourcecostshare* variable, defined as the share of the retail price that is not made up by tax. Since it is positively related to the manufacturing and marketing cost of the vehicle, one possible interpretation of the *Resourcecostshare* variable could be as a residual measure of quality, over and above the quality attributes already included in the regression. It could, on the other hand, also reflect circumstances such as the manufacturer's

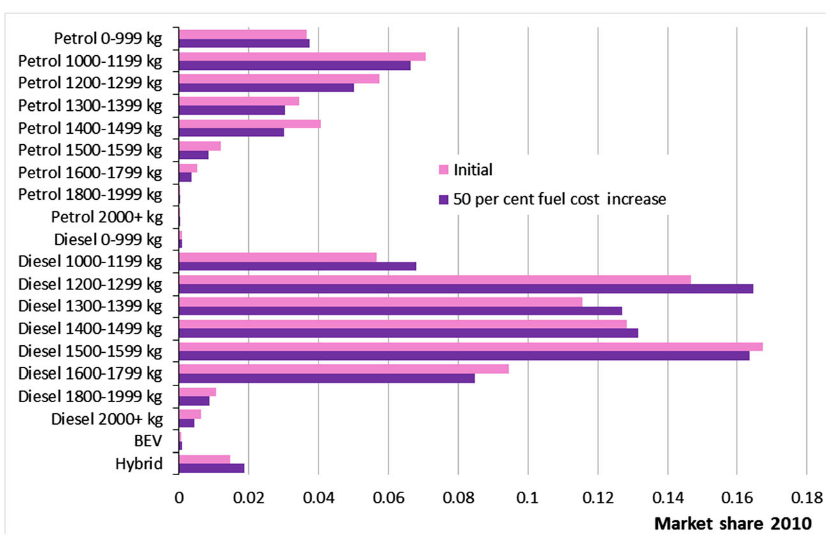

Fig. 15 Predicted vehicle market shares, by energy carrier and/or curb weight, under actual 2010 and simulated 50% higher fuel cost

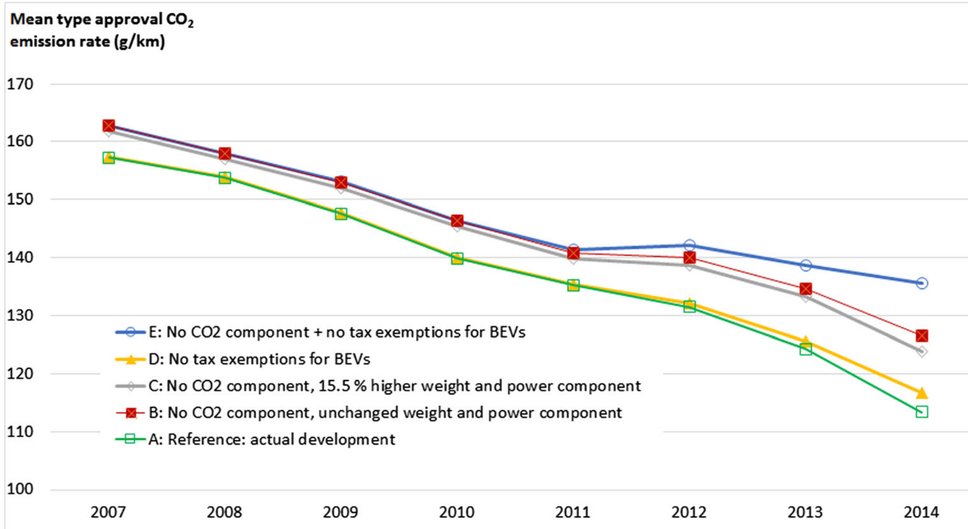

Fig. 16 Counterfactual backcasting simulating the non-introduction of CO_2-graduated purchase tax and/or tax exemptions for battery electric cars

market power, profitability or production inefficiency, or simply the vehicle customers' psychological aversion against taxpaying. Being inversely related to the amount of purchase tax payable, it tends to decrease with the vehicle's weight, engine power and rate of CO_2 emissions. It must, in other words, be interpreted with some caution.

One possible way of acquiring independent information on vehicle quality could be to exploit the many Internet surveys published on how owners perceive the properties of their car. Further research would be needed to ascertain the validity and practicality of such an approach.

6 Summary and conclusions

We have estimated a nested discrete choice model for new passenger cars registered in Norway. The model is based on exhaustive, disaggregate vehicle sales data covering almost 16 years. More than 1.6 million individual vehicle transactions make up the data set.

Since the model was intended to predict the market share of potential future car model variants with known or assumed attributes, care was taken to specify the model as a generic one. Model coefficients have the expected sign, almost all of them being highly significant by the robust t-test. The per kilometre fuel cost coefficient is compatible with car buyers taking full account of future energy cost savings, while also not applying a discount rate much higher than zero.

It was found that the only permissible nest structure is one that assigns all cars of a given make to one nest. There are 21 such nests in the model, the last one being a residual nest assembling 'all other makes'.

At the disaggregate – i. e., single vehicle model variant – level, estimated response surfaces must be interpreted with great caution. At the more aggregate level, however, the model appears to discriminate well between various policy scenarios, differentiated, e. g., by the size and structure of fiscal penalties and incentives. In using the model for such purposes, one is greatly helped by the fact the model distinguishes between price changes due to taxation and those originating from the manufacturing or marketing side.

Our vehicle choice model differs from most models reported in the literature in that it contains no information on the vehicle owners or their households. Hence the model cannot predict the effect of changes occurring to the car owners rather than to the vehicles themselves. The benefit of this approach is one of considerable simplification, leaving room for a maximally detailed, exhaustive and disaggregate representation of the passenger car market. Also, it means that no input is required on such variables as household structure, population and income growth, or on transport infrastructure and prices, in order for the model to produce a policy dependent forecast.

Automobile choice models are important climate policy decision support tools, since the acquisition of a new car affects GHG emissions for the coming 15–20 years, regardless of whether the new vehicle remains at the hands of its first owner, or is traded second hand.

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Appendix: Example data file excerpt

Table 4 Example model variants entering data set in 2010: VW Golf

Make	Model variant	Engine power (kW)	Curb weight (kg)	Cylinder volume (ccm)	Fuel	Seats	Length (cm)	Width (cm)	Body style	Doors	Traction	Total weight (kg)	Utility load (kg)	Fuel use (cl/km)	CO_2 emissions (g/km)	Gearbox	Units sold 2010
Volkswagen	GOLF PLUS 1.2–105	77	1281	1197	Petrol	5	420	176	MPV	5	Front	1920	554	5.9	139	Manual	12
Volkswagen	GOLF PLUS 1.2–105	77	1325	1197	Petrol	5	420	176	MPV	5	Front	1970	570	5.9	139	Automatic	38
Volkswagen	GOLF PLUS 1.4–122	90	1341	1390	Petrol	5	420	176	MPV	5	Front	1970	554	6.5	152	Manual	1
Volkswagen	GOLF PLUS 1.4–122	90	1363	1390	Petrol	5	420	176	MPV	5	Front	1990	552	6.3	146	Automatic	11
Volkswagen	GOLF PLUS 1.4–122	90	1384	1390	Petrol	5	422	178	MPV	5	Front	1990	531	6.5	152	Automatic	1
Volkswagen	GOLF PLUS 1.4–80	59	1262	1390	Petrol	5	420	176	MPV	5	Front	1890	553	6.6	154	Manual	7
Volkswagen	GOLF PLUS 1.6–105 D	77	1371	1598	Diesel	5	420	176	MPV	5	Front	2010	564	4.8	126	Manual	181
Volkswagen	GOLF PLUS 1.6–105 D	77	1375	1598	Diesel	5	421	176	MPV	5	Front	1970	520	4.3	114	Manual	105
Volkswagen	GOLF PLUS 1.6–105 D	77	1392	1598	Diesel	5	420	176	MPV	5	Front	2030	563	4.9	129	Automatic	381
Volkswagen	GOLF PLUS 1.6–105 D	77	1396	1598	Diesel	5	420	176	MPV	5	Front	1990	519	4.4	115	Automatic	245
Volkswagen	GOLF PLUS 1.6–90 D	66	1365	1598	Diesel	5	420	176	MPV	5	Front	2000	560	4.7	125	Manual	106
Volkswagen	GOLF PLUS 2.0–140 D	103	1426	1968	Diesel	5	420	176	MPV	5	Front	2070	569	5.5	144	Automatic	1
Volkswagen	GOLF 1.2–105	77	1158	1197	Petrol	5	420	179	COM	5	Front	1790	557	5.7	134	Manual	33
Volkswagen	GOLF 1.2–105	77	1189	1197	Petrol	5	420	179	COM	5	Front	1820	556	5.8	134	Automatic	27
Volkswagen	GOLF 1.2–105	77	1293	1197	Petrol	5	453	178	STV	5	Front	1910	542	5.8	136	Manual	10
Volkswagen	GOLF 1.2–105	77	1334	1197	Petrol	5	453	178	STV	5	Front	1950	541	5.9	136	Automatic	6
Volkswagen	GOLF 1.2–86	63	1154	1197	Petrol	5	420	179	COM	5	Front	1780	551	5.5	129	Manual	223
Volkswagen	GOLF 1.2–86	63	1185	1197	Petrol	5	420	179	COM	5	Front	1810	550	5.8	134	Automatic	31
Volkswagen	GOLF 1.4–122	90	1215	1390	Petrol	5	420	178	COM	5	Front	1820	530	6.2	144	Manual	3
Volkswagen	GOLF 1.4–122	90	1215	1390	Petrol	5	420	179	COM	5	Front	1820	530	6.2	144	Manual	109
Volkswagen	GOLF 1.4–122	90	1241	1390	Petrol	5	420	178	COM	5	Front	1850	534	6	138	Automatic	2
Volkswagen	GOLF 1.4–122	90	1241	1390	Petrol	5	420	179	COM	5	Front	1850	534	6	138	Automatic	143
Volkswagen	GOLF 1.4–122	90	1319	1390	Petrol	5	453	178	STV	5	Front	1940	546	6.3	146	Manual	36
Volkswagen	GOLF 1.4–122	90	1351	1390	Petrol	5	453	178	STV	5	Front	1970	544	6	139	Automatic	50
Volkswagen	GOLF 1.4–160	118	1271	1390	Petrol	5	420	179	COM	5	Front	1840	494	6.3	145	Manual	20

Table 4 (continued)

Make	Model variant	Engine power (kW)	Curb weight (kg)	Cylinder volume (ccm)	Fuel	Seats	Length (cm)	Width (cm)	Body style	Doors	Traction	Total weight (kg)	Utility load (kg)	Fuel use (cl/km)	CO_2 emissions (g/km)	Gearbox	Units sold 2010
Volkswagen	GOLF 1.4–160	118	1286	1390	Petrol	5	420	179	COM	5	Front	1860	499	6	139	Automatic	35
Volkswagen	GOLF 1.4–160	118	1373	1390	Petrol	5	453	178	STV	5	Front	1960	512	6.4	149	Manual	9
Volkswagen	GOLF 1.4–160	118	1385	1390	Petrol	5	453	178	STV	5	Front	1970	510	6.1	143	Automatic	5
Volkswagen	GOLF 1.4–80	59	1142	1390	Petrol	5	420	178	COM	5	Front	1750	533	6.4	149	Manual	16
Volkswagen	GOLF 1.4–80	59	1142	1390	Petrol	5	420	179	COM	5	Front	1750	533	6.4	149	Manual	52
Volkswagen	GOLF 1.4–80	59	1256	1390	Petrol	5	453	178	STV	5	Front	1870	539	6.4	149	Manual	4
Volkswagen	GOLF 1.6–105 D	77	1239	1598	Diesel	5	420	178	COM	5	Front	1870	556	4.5	119	Manual	27
Volkswagen	GOLF 1.6–105 D	77	1239	1598	Diesel	5	420	179	COM	5	Front	1750	436	3.8	99	Manual	1049
Volkswagen	GOLF 1.6–105 D	77	1239	1598	Diesel	5	420	179	COM	5	Front	1870	556	4.5	119	Manual	405
Volkswagen	GOLF 1.6–105 D	77	1243	1598	Diesel	5	420	178	COM	5	Front	1840	522	4.1	107	Manual	28
Volkswagen	GOLF 1.6–105 D	77	1243	1598	Diesel	5	420	179	COM	5	Front	1840	522	4.1	107	Manual	609
Volkswagen	GOLF 1.6–105 D	77	1262	1598	Diesel	5	420	178	COM	5	Front	1890	553	4.7	123	Automatic	6
Volkswagen	GOLF 1.6–105 D	77	1262	1598	Diesel	5	420	179	COM	5	Front	1890	553	4.7	123	Automatic	295
Volkswagen	GOLF 1.6–105 D	77	1265	1598	Diesel	5	420	179	COM	5	Front	1860	520	4.2	109	Automatic	356
Volkswagen	GOLF 1.6–105 D	77	1370	1598	Diesel	5	453	178	STV	5	Front	1980	535	4.5	119	Manual	191
Volkswagen	GOLF 1.6–105 D	77	1377	1598	Diesel	5	453	178	STV	5	Front	1960	508	4.2	109	Manual	473
Volkswagen	GOLF 1.6–105 D	77	1391	1598	Diesel	5	453	178	STV	5	Front	2000	534	4.8	125	Automatic	148
Volkswagen	GOLF 1.6–105 D	77	1398	1598	Diesel	5	453	178	STV	5	Front	1980	507	4.3	113	Automatic	92
Volkswagen	GOLF 1.6–105 D 4M	77	1496	1598	Diesel	5	453	178	STV	5	4-wheel	2100	529	5.5	143	Manual	230
Volkswagen	GOLF 1.6–90 D	66	1239	1598	Diesel	5	420	178	COM	5	Front	1860	546	4.5	118	Manual	72
Volkswagen	GOLF 1.6–90 D	66	1239	1598	Diesel	5	420	179	COM	5	Front	1860	546	4.5	118	Manual	1391
Volkswagen	GOLF 1.6–90 D	66	1370	1598	Diesel	5	453	178	STV	5	Front	1980	535	4.5	119	Manual	35
Volkswagen	GOLF 1.9–105 D	77	1357	1896	Diesel	5	456	178	STV	5	Front	1970	538	4.6	122	Manual	1
Volkswagen	GOLF 1.9–105 D	77	1361	1896	Diesel	5	456	178	STV	5	Front	1990	554	5.2	137	Manual	1
Volkswagen	GOLF 1.9–105 D	77	1376	1896	Diesel	5	456	178	STV	5	Front	2010	559	5.3	139	Automatic	1
Volkswagen	GOLF 1.9–105 D 4M	77	1474	1896	Diesel	5	456	178	STV	5	4-wheel	2100	551	6	158	Manual	1
Volkswagen	GOLF 2.0–110 D	81	1264	1968	Diesel	5	420	179	COM	5	Front	1870	531	4.9	128	Manual	1
Volkswagen	GOLF 2.0–140 D	103	1276	1968	Diesel	5	420	179	COM	5	Front	1920	569	4.8	126	Manual	154
Volkswagen	GOLF 2.0–140 D	103	1297	1968	Diesel	5	420	179	COM	5	Front	1940	568	5.3	138	Automatic	141
Volkswagen	GOLF 2.0–140 D	103	1299	1968	Diesel	5	420	178	COM	5	Front	1910	536	4.9	129	Manual	5
Volkswagen	GOLF 2.0–140 D	103	1299	1968	Diesel	5	420	179	COM	5	Front	1910	536	4.9	129	Manual	1
Volkswagen	GOLF 2.0–140 D	103	1322	1968	Diesel	5	420	178	COM	5	Front	1930	533	5.4	142	Automatic	1
Volkswagen	GOLF 2.0–140 D	103	1420	1968	Diesel	5	453	178	STV	5	Front	2030	535	4.9	128	Manual	8

Table 4 (continued)

Make	Model variant	Engine power (kW)	Curb weight (kg)	Cylinder volume (ccm)	Fuel	Seats	Length (cm)	Width (cm)	Body style	Doors	Traction	Total weight (kg)	Utility load (kg)	Fuel use (cl/km)	CO_2 emissions (g/km)	Gearbox	Units sold 2010
Volkswagen	GOLF 2.0–140 D	103	1420	1968	Diesel	5	453	178	STV	5	Front	2030	535	5	132	Manual	17
Volkswagen	GOLF 2.0–140 D	103	1446	1968	Diesel	5	453	178	STV	5	Front	2050	529	5.4	139	Automatic	14
Volkswagen	GOLF 2.0–140 D	103	1446	1968	Diesel	5	453	178	STV	5	Front	2050	529	5.5	144	Automatic	27
Volkswagen	GOLF 2.0–140 D 4M	103	1376	1968	Diesel	5	420	179	COM	5	4-wheel	2020	569	5.5	143	Manual	446
Volkswagen	GOLF 2.0–140 D 4M	103	1399	1968	Diesel	5	420	178	COM	5	4-wheel	2000	526	5.5	145	Manual	5
Volkswagen	GOLF 2.0–170 D	125	1329	1968	Diesel	5	420	178	COM	5	Front	1880	476	5.3	139	Manual	1
Volkswagen	GOLF 2.0–170 D	125	1329	1968	Diesel	5	420	179	COM	5	Front	1880	476	5.3	139	Manual	12
Volkswagen	GOLF 2.0–170 D	125	1334	1968	Diesel	5	420	179	COM	5	Front	1890	481	5.1	134	Manual	7
Volkswagen	GOLF 2.0–170 D	125	1351	1968	Diesel	5	420	178	COM	5	Front	1910	484	5.6	147	Automatic	2
Volkswagen	GOLF 2.0–170 D	125	1351	1968	Diesel	5	420	179	COM	5	Front	1910	484	5.6	147	Automatic	23
Volkswagen	GOLF 2.0–170 D	125	1356	1968	Diesel	5	420	179	COM	5	Front	1910	479	5.4	142	Automatic	25
Volkswagen	GOLF 2.0–211	155	1318	1984	Petrol	5	420	179	COM	5	Front	1870	477	7.3	170	Manual	5
Volkswagen	GOLF 2.0–211	155	1339	1984	Petrol	5	420	178	COM	5	Front	1890	476	7.4	173	Automatic	1
Volkswagen	GOLF 2.0–211	155	1339	1984	Petrol	5	420	179	COM	5	Front	1890	476	7.4	173	Automatic	15
Volkswagen	GOLF 2.0–271 4M	199	1466	1984	Petrol	5	420	179	COM	5	4-wheel	2030	489	8.4	195	Automatic	4

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