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Simulating the impact of tax incentives using a type choice model for lease cars

Abstract

Tax incentives for hybrid and electric cars are one of the possible policy instruments to reduce the CO_2 emissions of cars. This paper looks at the impacts of this policy in the context of The Netherlands, where up to 2016 substantial tax incentives were provided to fuel efficient lease cars, especially for hybrid and electric lease cars. For this analysis this paper uses a new model of vehicle type choice. Existing models for the choice among car type alternatives either exclude electric and hybrid cars or are based on stated preference data. In both cases, the models usually focus on privately-owned cars. The car type choice model for lease cars, that is used in this paper, includes electric and hybrid alternatives and is estimated on revealed preference data from lease car users in The Netherlands. Simulations with this model show that the tax incentives provided over the period 2011-2016 have led to a reduction in CO_2 emissions of lease cars, but also to an increase in the share of diesel cars and local air pollution.

1. Introduction

The CO_2 emissions of passenger cars are one of the key issues in the current debate on reducing global warming. Furthermore, many cities in the world are facing severe local emission problems with negative impacts on the health of their citizens, which are also to a considerable extent caused by cars. The debate on these issues has further been fuelled by the discovery that several types of diesel cars contained equipment to detect test conditions and reduce the emissions under such test conditions, but not in practice (dieselgate). This is the context within which several authorities try to reduce the emissions from cars by several means, including financial incentives for relatively efficient cars.

1.1 Tax incentives for lease cars

In this paper, we look at the effectiveness of tax incentives, particularly for lease cars. By lease cars we mean cars owned by lease companies that are provided to employees by their employers and for which the employers pay the lease companies. Company cars (cars owned by a company, either a lease company or any other company) are nowadays mostly lease cars.

The above research question is studied in the context of The Netherlands, but where possible we will try to draw broader conclusions that could also apply in other countries. In The Netherlands there are about 900,000 company cars, of which two-thirds are lease cars (VNA, 2017). The total number of passenger cars in 2017 in The Netherlands was 8.2 mln (Statistics Netherlands, 2019).

Understanding the vehicle type choice in the lease/company car market is very important for determining and forecasting the total emissions of passenger cars in a country. In The Netherlands, company cars have a share of around 50% in the new passenger car sales of 400,000 cars per year in total (Bovag and Rai, 2019). To this, one might add that company cars have a higher annual mileage than privately-owned cars and that, through the second-hand car market, many company cars later in their life become privately owned cars. Also in other European countries about half of the new cars is a company car (Naess-Schmidt and Winiarczyk, 2010). In most countries in Europe, the annual cost of car ownership for the company car users are determined through the tax system, usually by adding a term to taxable income consisting of the purchase price times a rate determined by the tax authorities (Naess-Schmidt and Winiarczyk, 2010). In the UK for instance, in 2016 there were about 1 mln employees paying tax on their company car as a benefit in kind (in total, the UK had 31 mln passenger cars; Department for Transport Statistics, 2019). In some countries, such as France and the UK, the government attempts to promote efficient cars and the penetration of alternative sources of energy by letting this additional income component depend on the CO_2 emission rate of the vehicle (ACEA, 2018).

In the case of company/lease cars the person who chooses the car (usually the company car driver) is not the person who bears the costs for purchase and possession (usually the employer). In The Netherlands therefore tax incentives were directed at the lease car users. This was done by linking the benefit in kind (BIK), the percentage of the purchase price that a lease car user needs to add to his/her taxable income (so that it will be taxed), to the car's CO_2 emission rate. The goal of this policy was to reduce CO_2 emissions.

Until 2007, a BIK rate of 22 percent applied to all cars. In 2008 this uniform percentage was increased to 25 percent. For zero-emission cars, the BIK rate became 0 from 2010 onwards. This rate of 0 was extended in 2012 to ultra-efficient cars, to which most plug-in hybrids belong.

In 2015 it was decided to phase out the tax discounts. In 2016, the rate for plug-in hybrids (ultra-efficient cars) went up to 15 percent and the rate for fuel-efficient and very fuel-efficient cars increased to 21 percent. Since 2017, there are only two BIK rates: 4 percent for zero-emission cars (electric and hydrogen cars) and 22 percent for all cars with CO_2 emissions of at least 1 gram. Since 1 January 2019, expensive (over 50,000 euro) zero-emission cars no longer get the reduced BIK rate, but the less expensive ones still qualify..

In this paper we analyse the impacts of these tax incentives on the choice of vehicle type for lease cars, and through type choice on the emissions of CO_2 and local air pollutants. For reasons of data availability, we look at the tax incentives provided over the period 2011-2016. The tax incentive policy will be evaluated using a newly developed model for the type choice of lease cars in The Netherlands.

1.2 A type choice model for lease cars

The international literature on transport, economics and the environment contains quite a few vehicle type choice models, nowadays often with a focus on electric and hybrid cars. For an overview of papers on electric vehicle adoption, see Rezvani et al. (2015) or Liao et al. (2017) or Dimitropoulos et al. (2013) for a meta-analysis. Most of these models are fully or partly based on stated preference (SP) data, which is often unavoidable because of the still low market penetration rate of electric and hybrid cars in most countries. Moreover, a large majority of these existing models is restricted to privately-owned cars.

This paper forms an exception to these rules in that it is based on revealed preference (RP) data and specifically deals with cars that are provided by employers to private individuals, but owned by lease firms ('lease cars' for short). Vans and trucks are not studied in this paper; we restrict our attention to passenger cars. Although we use RP data, we also distinguish electric and (plug-in) hybrid cars in our lease car type choice model. This is possible because in the past few years the government of The Netherlands has been promoting the use of electric and plug-in hybrid lease cars by levying relatively low tax rates on the private use of such cars (see section 1.1 above). This policy has led to substantial market shares in the lease car sales for fully electric cars (approximately 1% in 2015) and plug-in hybrid cars (approximately 15% in 2015), much higher than their shares in the private car sales and high enough (given that we have a data set of several thousands of observations) for inclusion of these cars in a detailed type choice model on observed data. This in turn makes it possible to assess this policy with the help of the estimated type choice model, as well as other potential future policies for the lease car market.

The choice alternatives in our model are combinations of brand/make (e.g. Ford), model (e.g. Fiesta), coupled with fuel type (petrol, diesel, hybrid-petrol, hybrid-diesel, plug-in-hybrid-petrol, plug-in-hybrid-diesel and fully electric). In the paper, we present both multinomial and mixed logit models explaining this choice. The explanatory variables are technical attributes of the car types such as engine size and weight, financial attributes of the car types such as fuel costs, lease price, purchase price and tax for private car use, and interactions with personal and household attributes such as income, age and household size.

After having estimated the model, we present the results of a policy simulation using the estimated model. The policy investigated concerns the reduction in the taxation on private car use of electric, hybrid and other low-emission lease cars that was in place in The Netherlands in the period 2011-2016. We investigate the impacts of this policy on car type choice and emissions, relative to a counterfactual in which there would have been the same high tax for all lease cars.

1.3 Structure of this paper

In section 2 of this paper, a short review of the literature on vehicle type choice, with a focus both on electric and hybrid cars and on lease cars, is provided. The model specification is presented in section 3, and the data used are discussed in section 4. Section 5 contains the results of the model estimation for a multinomial logit car type choice model and for mixed logit. The simulation of the impact of tax differentiation on the private use of lease cars is presented in section 6. Finally, section 7 contains a summary and conclusions.

2. A short review of the literature on vehicle type choice

Disaggregate vehicle type choice models have been developed since the seventies and eighties Existing reviews on models for car ownership include a specific section on vehicle type choice models (de Jong et al. (2004)) or discus these under the heading of exogenous static automobile ownership models (Anowar et al. (2014a)). Originally, these models used RP data on type choice, combined with external data on the technical and price attributes of the various car types (e.g. Manski and Sherman (1980), Berkovec (1985), Train (1986), Hensher et al. (1992)).

Later, the interest in car types that were not yet available on the market (such as hybrid and electric cars) became stronger, and researchers had to rely on SP choice data to include these new car type alternatives. Beggs et al. (1981) was a forerunner on studies on the demand for electric cars. Since the turn of the 21st century many more studies have investigated the potential demand for hybrid and electric cars using SP data (Achtnicht et al. (2012), Daziano et al. (2016), Dimitropoulos et al. (2013), Hess et al. (2012), Hoen and Koetse (2014)). Rezvani et al. (2015) and Liao et al. (2017) provide a review of the literature. Daziano et al. (2016) not only include electric cars, but also distinguish in the SP and the model analysis between no, full and some automation. A meta-analysis of such studies, focussing on the relative importance of driving range of the vehicle, has also been carried out (Dimitropoulos et al., 2013).

The key variables explaining car type choice according to the literature are: household income, car purchase cost, car running cost or fuel efficiency, car quality attributes and various socio-demographic attributes of the household/person (de Jong et al., 2004). Anowar et al. (2014a) lists 21 papers that include vehicle type choice as the choice studied or one of the choices studied (e.g. together with annual car use). The explanatory variables in these papers are: demographic attributes of households and of individuals, employment attributes, household life-cycle attributes, attributes of the built environment, transit attributes (as an alternative to the car) and policy variables. Some of the models also take account of unobserved heterogeneity in the preferences of the decision-makers, by using a mixed logit model (e.g. Daziano, 2012) or latent class model (e.g. Anowar et al., 2014b), but most type choice models are of the multinomial logit (MNL) form.

Vehicle type choice models on RP data often contain a large number of choice alternatives. For instance Brownstone et al. (2000) distinguished 689 make-model-vintage combinations (with estimation on a sample of 28 alternatives drawn from the 689). Birkeland and Jordal-Jørgenson (2001) had 1,500 vehicle alternatives (detailed make-model combinations) in their model and estimated on a sample of 50. De Jong (1996) used about 1,000 make-model-vintage alternatives (with an estimation sample of 20 alternatives). These large choice sets were not selected out of a desire to forecast by brand and model, but because these alternatives come close to the kind of choice alternatives consumers will have in mind when deciding about car purchase. Moreover, these alternatives can be aggregated in many different ways (e.g. by fuel type, vintage and/or weight) and also combined with specific emission factors to give all kind of policy-relevant outputs.

SP studies usually have a much more limited choice set, based on the specific alternatives that are presented on a card or screen in a choice experiment. Daziano et al. (2017) for instance distinguish between hybrid, plugin-electric, battery-electric and conventionally fuelled cars, with as attributes driving cost, purchase price, electric driving range, recharging time and degree of automation. Rezvani et al. (2015) in their review also show that in electric vehicle adoption research, SP surveys are prominent and that the most common attributes in the experiments are driving range, recharging time, performance, carbon emissions, the charging infrastructure, purchase costs and running cost. Liao et al. (2017) review studies on consumer preferences for electric vehicles. All the studies they found are based on SP data, 'due to lack of large-scale presence of electric vehicles in the market'. They show that these SP studies work with 2-4 vehicle alternatives (conventional fuel and 1-3 new alternatives) and that the attributes used often include: the purchase price, running costs, driving range, recharging time, performance, CO_2-emissions and the charging infrastructure. These models have been used to simulate policies including reductions in purchased tax, purchase price, annual car tax and tolls as well as free parking and access to high occupancy vehicle (HOV) lanes for electric cars. In their meta-regression of the willingness-to-pay for driving range, Dimitropoulos et al. (2013) found that a driving range of 100 miles is on average perceived to be as bad as a 17,000 $ higher purchase price.

None of these above studies separate out lease cars, but either exclude these cars or include these in the analysis together with the privately-owned cars.

Some researchers have studied the relation between ownership of company cars and attributes of firms and sectors that provide these cars to their employees (NEI, 1989). However, nowadays in The Netherlands and many other countries, the type choice for lease cars is usually made by the employee, possibly within restrictions imposed on the choice set by the employer. This calls for research studying the lease car from the perspective of the employee. Such studies have been quite scarce. Examples are Gutiérrez-i-Puigarnau and van Ommeren (2011), Shiftan et al. (2012), Koetse and Hoen (2014) and Dimitropoulos et al. (2016).

Gutiérrez-i-Puigarnau and van Ommeren (2011) use RP data for The Netherlands, but not on vehicle type choice, but on the (money) value of the most expensive car in the household and distance travelled by car, for which they do regression-type analyses, looking into the differential impact of company cars versus private cars. They find that the tax treatment of company cars leads to a shift to more expensive cars and more kilometres driven, which in turn leads to a welfare loss for society.

SP data on the willingness to give up the company car or to receive a company car and on travel mode to and from the workplace were collected in Israel, and reported in Shiftan et al. (2012). The models estimated on these data were used to look at the impact of company car taxation. It was found that the taxation policy in Israel (where the employee pays a relatively low tax on the his or her benefits from the company car) leads to extra car use.

Koetse and Hoen (2014) is based on SP experiments among 940 company car drivers in The Netherlands. The respondents were asked to choose between three unlabelled alternatives., descibed in terms of the attributes fuel type (conventional fuel, hybrid, plug-in hybrid, fuel cell, electric and flexifuel), catalogue price, list price, tax rate on the benefit in kind, driving range, recharging/refuelling time, additional detour time, number of brands/models and a policy indicator (current, free parking, access to bus lanes). The data were used to estimate an MNL model for car type choice of company cars. They found that under the company car tax system of The Netherlands at that time (2011), hybrid and flexifuel cars are preferred to conventional cars.

Dimitropoulos et al. (2016) carried out an SP experiment in The Netherlands with four choice alternatives for the next company car: plugin-hybrid, fully electric with fixed battery, fully electric with swappable battery and a conventional car (internal combustion engine or hybrid car). The attributes were: official purchase price (list price), company-car tax rate, employee's annual net contribution paid to the employer for the provision of the company car, driving range, refuelling time at station, charging time at home/work and extra detour time to reach a fast-charging or battery-swapping station. The models used are multinomial logit and latent class models.

SP data can be quite valuable, especially for providing willingness to pay estimates, but they have the disadvantage that they originate from experiments (hypothetical choices) and therefore result in models that have a different unexplained variance than reality. As a result, models based on SP data only are not appropriate for forecasting studies and for calculating the impact of policies.

To our knowledge, there have been no RP studies into the vehicle type choice of company or lease cars so far, and more particularly on the adoption of electric and hybrid cars in the lease car market.

Unlike the previous literature, in our paper we study lease car type choice from the perspective of the employee (private household) and with a focus on electric and hybrid cars, using RP choice data. As in previous RP studies and as argued above, we distinguish a large number of vehicle type alternatives (brand, model and fuel type combinations). As explanatory variables, we use the variables that RP studies commonly use (as described above), with the exception that we also include a number of variables that are specific to the lease market, such as the lease costs and the share of the purchase price that a lease car user has to add to his or her taxable income. Attributes that are common in SP research on electric vehicles like driving range, recharging time and charging infrastructure are on the other hand not included in our RP data.

3. Model specification

The dependent variable in the models in this paper is the brand, model and fuel type of a lease car. Fuel type can be petrol, diesel, hybrid (either petrol-electric or diesel-electric), plug-in (as a hybrid with either petrol or diesel) and fully electric. In The Netherlands, there are also some cars on Liquid

Propane Gas (LPG), but the share of these among the leased cars is very small[1], and these cars were not included in the analysis. Vintage is not a relevant choice dimension, since we are estimating a model for the choice of new cars (in various years of the data set). In total we have 196 choice alternatives in our data.

The choice variable comes from the NZO survey, provided by the lease companies. This data source also yields the data that we use on person and household attributes.

The data on attributes of the 196 car type alternatives comes from other sources (see section 4), such as the car sales and ownership registers of The Netherlands and from Statistics Netherlands.

We explain lease car type choice both in a multinomial logit (MNL) framework (Ben-Akiva and Lerman, 1985) and in a mixed logit (Train, 2003) framework. The utility function in the MNL model is:

$$U_{ij} = \beta_1 . (1 + \alpha_1 . Z_{i1} + \alpha_2 . Z_{i2} + \dots + \alpha_z . Z_{iz}) . X_{j1} + \beta_2 . (1 + \gamma_1 . W_{i1} + \gamma_2 . W_{i2} + \dots + \gamma_w . W_{iw}) . X_{j2} + \dots$$

$$B_m . (1 + \lambda_1 . V_{i1} + \lambda_2 . V_{i2} + \dots + \lambda_v . V_{iv}) . X_{jm} + e_{ij} \qquad (1)$$

Where:

U_{ij}	:	utility from the choice of car type alternative j by person i;
Z_{iz}, W_{iw}, V_{iv}	:	the z-th, w-th or v-th characteristic of person i (or his/her household); these are the interaction variables
X_{jm}	:	the m-th attribute of car type alternative j;
B_m, α_z, γ_w, λ_v	:	coefficients to be estimated
e_{ij}	:	error term (which in the MNL we assume to be i.i.d. distributed according to the extreme value type I distribution).

In the mixed logit model, we allow various β coefficients to be a random variable, following a specific statistical distribution (for which we tested the Normal and Lognormal distribution). This is the random coefficients specification of the mixed logit model, in which one of more preference parameters, such as cost coefficients, vary stochastically over the population, so that the model can capture unobserved heterogeneity in preferences of the decision-makers. Observed heterogeneity among the decision-makers is already captured by the α, γ and λ coefficients for the person and household attribute interactions with the attributes of the choice alternatives.

In the specification search within the MNL model, we test the following attributes of the car type choice alternatives:

- Fuel cost;
- Purchase price;
- Car purchase tax BPM;
- Lease cost;
- Absolute amount of euros to be added to taxable income for private car use
- % of the purchase price to be added to taxable income for private car use;

[1] A few decades ago, the share of LPG cars in The Netherlands was more substantial, but the international car manufacturers have concentrated on diesel cars first and more recently on electric cars, as a result of which there is hardly any supply of new LPG cars left.

- Engine size;
- Horse power;
- Maximum speed;
- Weight;
- Horse power/weight ratio;
- Segment according to the classification (called PRC) used by the car manufacturing sector
- Brand dummy;
- Fuel type dummy.

The tax on the private use of the lease car is only relevant for respondents who drive more than 500 private kilometres with the car in a year. For respondents who drove fewer private kilometres in some year, we did not include the income tax on private car use.

Furthermore, a number of characteristics of the person-, household and firm are tested as interaction variables:

- Age class interacting with engine size, weight, horsepower/weight, purchase price and PRC segment;
- Household size interacting with weight and PRC segment;
- Gross annual income interacting with fuel cost, car purchase tax, lease cost, purchase price, absolute and relative tax on private car use and PRC segment;
- Firm size class interacting with fuel cost, lease cost, purchase price and PRC segment;
- Sector of the firm interacting with fuel cost, lease cost, purchase price and PRC segment;
- The availability of alternative modes interacting with weight, horsepower/weight and PRC segment.

4. The data used

The data used consist of survey data among lease car users (the NZO data), but also data on attributes of cars from the car register (RDW data) and on fuel and car prices from Statistics Netherlands (CBS). Below, we discuss these sources one by one.

4.1. NZO data

On behalf of The 'Vereniging van Nederlandse Autolease-maatschappijen (VNA)' (Association of Dutch car lease companies) VMS Insight annually collects survey data among lease car drivers and representatives of firms leasing cars. If email addresses are available, the respondents are approached by email using personalised invitations. Other respondents are recruited through anonymised hyperlinks in relevant email news messages and on websites. The survey itself took place by means of the internet (computer-assisted web interviewing, CAWI). In this paper, we focus on the data on the users of lease cars. VNA has given PBL Netherlands Environmental Assessment Agency access to microdata from this survey, called 'Nationaal Zakenauto Onderzoek (NZO)' (National Company car Survey) for the years 2013 to 2016. This includes more than 2,500 completed interviews with lease car users per year. VNA reports that the response rate is 'high', but does not report the rate itself (VNA et al., 2016).

This is the main source of data used in this paper. We model the vehicle type choice of lease car users on disaggregate RP data from these users. In this model, we try to include the various costs and taxes that exist for lease cars and we specifically include various types of electric and hybrid cars as separate choice alternatives, so that we can investigate the penetration of such cars in the lease car market and the impact of the tax rules on this.

For model estimation, microdata from the National Company car Survey NZO are used (VNA et al., 2016). In the NZO survey, users of lease cars answered a number of questions about the lease car they are using, as well as about themselves, their household and the firm where they are working. Table 1 describes the variables from this survey that were used in estimation (including specification testing).

The general setup of the NZO survey is similar for the different years, but the questionnaire was not exactly the same in each year. In 2013, fuel type was not asked, and because of the absence of this key variable (for us), we could not use the 2013 data in estimating the model. All models were estimated on the data for 2014, 2015 and 2016, for which all the information that is described in Table 1 could be obtained.

The NZO survey also includes a number of variables on the restrictions that the employers have set on the choice of car types (e.g. only certain brands are made available to their employees). In section 5 we will describe how we tried to include this information in estimation, also showing why these variables were not be used in the final models.

Table 1 - Variables in the NZO dataset

NZO data	**Category**	**Count**	**Percentage**
Age	< 36 years	1047	13.3%
	36- 50 years	3385	43.0%
	> 50 years	2092	26.6%
	unknown	1346	17.1%
Household size	1-2 persons	2266	28.8%
	3-4 persons	3320	42.2%
	>4 persons	938	11.9%
	unknown	1346	17.1%
Gross annual income	< €40.000	610	7.8%
	€40.000 - €80.000	3356	42.6%
	> €80.000	1537	19.5%
	unknown	2367	30.1%
Firm size	< 10 employees	358	4.5%
	10-200 employees	2700	34.3%
	> 200 employees	1411	17.9%
	unknown	3401	43.2%
Firm sector	agriculture	39	0.5%
	industry	547	7.0%
	construction	358	4.5%
	health care, education and government	340	4.3%
	retail and services	4705	59.8%
	other sector	1881	23.9%
Kilometres per year	< 500 km	6	0.1%
	1501-5125 km	12	0.2%
	5126-11250 km	45	0.6%
	11251-20000 km	447	5.7%
	20001-30000 km	1164	14.8%
	30001-40000 km	3739	47.5%
	40001-52500 km	1253	15.9%
	52501-67500 km	1046	13.3%

	> 67500 km	158	2.0%
Lease contract duration	<15 months	94	1.2%
	15-25 months	128	1.6%
	26-36 months	796	10.1%
	37-48 months	5661	71.9%
	> 48 months	1191	15.1%
Lease year	2011	994	12.6%
	2012	1946	24.7%
	2013	1979	25.1%
	2014	1613	20.5%
	2015	1129	14.3%
	2016	209	2.7%

4.2 RDW data

For the attribute values of the available car types we use data from registers of the Rijksdienst Wegverkeer RDW (the national car registration office). These data consist of separate files for each quarter of the years 2011 to 2016. It includes the number of cars sold per model as well as a number of characteristics of each car. Using these quarterly files, we derived annual averages for car attributes by car choice alternative, weighted by the number of cars purchased. The variables we used from this source are in Table 2. We also received data from PBL to translate the test emissions and fuel use to real world emissions and fuel use, and to determine the percentage of the purchase price that needs to be added for private car use to taxable income.

Table 2 – Variables in the car file

RDW data	**Minimum**	**Maximum**	**Average**	**Standard deviation**
Fuel costs (€/100 km)	1.35	14.37	8.32	2.12
Purchase price (€)	11680	111230	35923	14651
Lease costs (€/month)	350	1760	862	261
Share of purchase price added to taxable income	0.04	0.25	0.23	0.03
Weight (kg)	780	2072	1341	233
Horse power/weight ratio (kW/kg*1000)	38.60	110.53	71.24	12.04

RDW data	**Category**	**Count**	**Percentage**
Car segment	segment A	9	4.6%
	segment B	30	15.3%
	segment C	76	38.8%
	segment D	69	35.2%
	segment E	12	6.1%

On the basis of the RDW data, we constructed a ‘car file’ that includes the attributes of the chosen and the unchosen car type choice alternatives in the NZO survey. We are using car attribute data on cars that were built since 2010. Respondents with cars that were built earlier were removed from the NZO data.

4.3 CBS data

The RDW data described above does not contain information on lease costs and fuel prices. These items were obtained from Statistics Netherlands (CBS).

Lease prices

For determining the lease prices that the employers pay to the lease car companies, we started with CBS data for 2015 on the lease prices including fuel costs for a large number of brand-model-fuel type combinations. These prices were available per quarter and had originally been provided by several car lease companies. This data was used to calculate a monthly average lease cost for each car alternative in the CBS data. This data however only had information on lease prices for 117 of the 196 alternatives. Lease prices for another 54 car alternatives were added from the website www.leasevergelijker.nl. (an internet tool for comparing lease contracts). For the 25 remaining alternatives we had to denote the lease price as 'unknown' in the model estimation (so, these alternatives were not dropped from the estimation data).

Furthermore, the lease prices in this data source had been calculated assuming a fixed contract period and a fixed number of kilometres per year. This means that we cannot relate this lease price to the contract period and the annual kilometrage that the respondents to the NZO survey provide.

For this reason we added lease prices to the CBS data from the website www.leasevergelijker.nl, for various combinations of lease contract period (30 to 54 months) and kilometrage per year (15,000 to 55,000). On the resulting prices we estimated a regression equation with contract period and kilometrage as explanatory factors. The estimated relation was then applied to the contract period and annual kilometrage of the NZO respondents to determine an individualised lease price for each car alternative.

Lease price data for other years than 2015 were not available to us. We constructed the data for the other years from the 2015 data by correcting for the changes over time in the general price index for operational car lease over the years 2010-2016 (from the CBS Statline website of Statistics Netherlands). All car lease prices were expressed in euros of 2016.

Fuel prices

Fuel prices for the period 2010-2016 were taken from CBS Statline. To calculate the fuel cost of plug-in-hybrids we assumed that 30% of all kilometres were driven in electric mode and 70% on conventional fuel.

Price level

The fuel prices are also all expressed in 2016 euros (on the basis of the consumer price index on CBS Statline). This was not only done for lease and fuel costs, but also for BPM and purchase price.

5. Model estimation

Multinomial logit (MNL) models were estimated in ALOGIT and mixed logit models in Biogeme. In this section, we first describe the estimation data, then discuss how we treated availability of alternatives and finally present and discuss the estimation results.

5.1 Estimation data

After having selected the brand-model-fuel type alternatives that were chosen at least five times in the NZO data, we have 196 choice alternatives left. Respondents that choose any of the other cars were removed from the estimation data. In total we have 41 brands, 112 unique models and 8 fuel types (LPG is not part of the choice set). The estimation data file has 7870 records (lease car users). We assume that when a lease starts, the car will be new, and the vehicle type choice is made at this specific time from a choice set of new car types. So we link the attributes of chosen and non-chosen car alternatives (that differ from year to year) to the year of manufacture provided by the respondent in the NZO for his or her actual lease car.

5.2 Availability of alternatives

The NZO data also contains a number of variables that are meant to provide a picture of the constraints that employers formulate for the choice of a lease car by their employees. We had hoped that these variables would have allowed us to define an appropriate individual-specific choice set (full, or limited in some way) for every respondent in the NZO, but this proved impossible. The first reason for this is that the question in the NZO whether a specific brand was allowed as an alternative often was not answered. Especially in the years after 2014 the share of respondents that answered this question is very small (2014: 59%; 2015: 10%; and 2016: 19%)[3]. Furthermore, for those that did provide answers on brand availability, 21% actually chose a brand that was reported as not allowed. This led us to the conclusion that these responses on brand restrictions were not sufficiently reliable to be used at the individual level.

There also were questions in the NZO on choice restrictions in terms of budget, model, energy label and type of propulsion. But these were simply yes/no questions, which do not provide us with insight in the exact nature of the constraints.

It was decided to use only the RDW as source for non-availability of car alternatives. If there were no data for an alternative in a year in the RDW data (e.g. because the car type had not yet been introduced on the market), that alternative was set to be non-available in the estimation. In our main model estimation, we use no data whatsoever on car type restrictions from the NZO: all cars in the RDW data for the relevant year are available. We checked this assumption of free choice by also estimating a model on the NZO respondents that had indicated that they were not facing any restrictions on their car type choice (see section 5.3).

5.3 Estimation results for the MNL model

The MNL model estimation results are in Table 3. Model A reports the results for a model estimated on all 7870 respondents that are in the estimation data set. Model B was estimated only on the subset of 3774 respondents that replied they had no restrictions imposed by their employers on their choice set. We find that this does not change the coefficients in any big way, and continue with models on all 7870 observations.

Table 3 – Estimation results for MNL models of lease car type choice

Model	Model A	Model B
Observations	7870	3774
Final log (L)	-36199.6	-17319.3
D.O.F.	54	54

[3] The owner of the NZO data, VNA, explained this decline from the fact that the questions on availability of a specific brand were only asked from a subset of the respondents from 2015 onwards.

Rho²(0)	0.12	0.12
Scaling	1	1
Fuel costs (€/100 km)	-0.2732 (-11.6)	-0.2750 (-7.1)
Dummy for gross annual income €40.000-€80.000	0.1168 (4.9)	0.1091 (2.8)
Dummy for gross annual income > €80.000	0.2254 (9.0)	0.2199 (5.3)
Dummy for dross annual income unknown	0.1426 (5.8)	0.1303 (3.3)
Lease costs (€/quarter)	-0.00313 (-6.5)	-0.00234 (-3.1)
Dummy for lease costs from www.leasevergelijker.nl	-0.3659 (-10.1)	-0.3968 (-7.5)
Dummy for lease costs unknown	-3.892 (-7.7)	-3.320 (-4.1)
Dummy for gross annual income > €40.000	0.00248 (5.1)	0.00193 (2.6)
Dummy for gross annual income unknown	0.00202 (4.0)	0.00127 (1.7)
Dummy for lease costs unknown, gross annual income > €40.000	2.402 (4.7)	2.057 (2.5)
Dummy for lease costs unknown, gross annual income unknown	1.801 (3.4)	1.264 (1.5)
Horsepower/weight ratio (W/kg)	0.01300 (7.5)	0.01684 (6.8)
Weight (kg)	-0.00447 (-16.3)	-0.00422 (-10.7)
Dummy for age 36-50 years	0.00200 (9.6)	0.00159 (5.2)
Dummy for zge > 50 years	0.00290 (13.3)	0.00288 (9.0)
Dummy for age unknown	0.00170 (6.1)	0.00185 (5.0)
Dummy for household size 3-4 persons	0.00102 (6.7)	0.00111 (4.8)
Dummy for household size unknown	0.00215 (9.9)	0.00231 (7.1)
Purchase price	-8.04e-5 (-7.7)	-9.36e-5 (-5.7)
Dummy for gross annual income > €40.000	7.28e-5 (7.1)	8.20e-5 (5.0)
Dummy for gross annual income unknown	7.54e-5 (7.1)	8.51e-5 (5.2)
Share of purchase price added to taxable income	-17.52 (-40.5)	-18.34 (-29.4)
Dummy for PRC segment B	1.375 (13.9)	1.163 (8.9)
Dummy for PRC segment C	3.409 (30.3)	2.986 (20.0)
Dummy for PRC segment D	4.288 (33.4)	3.829 (21.9)
Dummy for PRC segment E	4.433 (26.2)	4.014 (16.9)
(Semi-) electric car dummy	-1.614 (-15.5)	-1.385 (-9.6)
Audi dummy	1.278 (8.6)	1.340 (5.9)
BMW dummy	1.177 (7.7)	1.266 (5.5)
Chevrolet dummy	-1.401 (-3.2)	-1.720 (-2.3)
Citroën dummy	0.2929 (1.9)	0.3725 (1.6)
Dacia dummy	-1.649 (-3.5)	-1.189 (-1.9)
Fiat dummy	-0.1575 (-0.6)	0.05557 (0.2)
Ford dummy	0.8578 (5.7)	0.7708 (3.4)
Honda dummy	-0.5637 (-2.2)	-0.6935 (-1.7)
Hyundai dummy	0.1145 (0.6)	0.3585 (1.3)
Jaguar dummy	0.02157 (0.1)	0.4939 (1.1)
Kia dummy	0.1032 (0.6)	0.4189 (1.7)
Landrover dummy	-0.01640 (-0.0)	-0.2181 (-0.2)
Lexus dummy	1.187 (6.6)	1.304 (4.8)
Mazda dummy	-0.01979 (-0.1)	0.00566 (0.0)
Mercedes dummy	0.6268 (3.8)	0.7770 (3.2)
Mini dummy	0.3535 (1.5)	0.3008 (0.8)
Mitsubishi dummy	1.489 (9.0)	1.746 (7.1)
Nissan dummy	-1.327 (-6.3)	-1.770 (-5.3)
Opel dummy	0.7547 (4.9)	0.8496 (3.6)
Peugeot dummy	1.219 (8.3)	1.295 (5.8)
Renault dummy	1.325 (9.0)	1.426 (6.4)
Seat dummy	0.5688 (3.6)	0.7131 (3.0)
Skoda dummy	1.241 (8.2)	1.342 (5.9)
Tesla dummy	-1.623 (-4.5)	-1.921 (-3.8)
Toyota dummy	0.3053 (2.0)	0.4008 (1.7)

Volkswagen dummy	1.498 (10.2)	1.614 (7.3)
Volvo dummy	1.136 (7.7)	1.133 (5.1)

For all cost attributes (fuel cost, lease cost, purchase price and the % of the purchase price that should be added to taxable income a negative and significant coefficient is found. We also tested the absolute amount of money that should be added to taxable income (the BIK rate times the purchase price), but this led to a positive (wrong) sign and this specification is therefore not presented in Table 3. This is probably due to the fact that some expensive cars had relative low BIK rates (e.g. hybrid and electric cars). When we include the BIK rate and the purchase price as separate explanatory variables in the model, both get the correct sign.

The model also includes interaction variables of gross income with fuel cost, lease price and purchase price. The interaction coefficients (for example 0.1168 for gross annual income between 40,000 and 80,000 euro and fuel cost in model A) should be added to the base coefficients (for -0.2732 for fuel cost in Model A) that are always presented above them. This shows that these costs weight less heavy for those with a higher gross income (as expected).

We tested whether power, maximum speed, engine size or power/weight worked best in estimation, and found that power/weight yielded the most significant coefficient. In the final model, this specification is used. Power/weight has a positive effect on the choice for a car type. Mass on the other hand gets a negative sign. For higher age classes as well as for higher income classes this impact becomes smaller. The dummy for plug-ins (hybrid and fully electric) is negative: these car types are seen as less attractive, controlling for all the other factors. For the PRC class, the consumer appreciation increases if we go from segment A to E (from small to large cars).

On the basis of the cost coefficients we calculate that, at a monthly kilometrage of about 8700 km, the consumer is indifferent between a 1 euro increase in the lease price and a 1 euro increase in fuel costs (-0.2732/-0.00313). Furthermore, he/she is indifferent between a 1 euro increase in the lease price (per month) and a 1 euro increase in the purchase price for a car lifetime of 39 months (-0.0000804/-0.00313=0.026). So on average, the car purchase price (which co-determines how much the users will be taxed) is relatively important for the lease car users, more so than the employer's lease cost and much more than the fuel cost.

5.4 Estimation results for Mixed Logit model

The estimated MNL model might be improved by taking into account random (unobserved) variation between persons, through the estimation of mixed logit models with random coefficients.

Starting from the best MNL model (model A from Table 3), we estimated several random coefficients models, by trying out random variation in several combinations of the of the estimated behavioural coefficients. Furthermore we tested several statistical distributions from which these coefficients values are drawn (uniform, log-uniform, normal, log-normal). The mixed logit models could only be estimated by leaving out the interaction coefficients for observed heterogeneity.

For all the financial variables (fuel price, lease price, purchase price and percentage added to income), the estimated standard deviations of the random coefficients were far from significant (this did not change with the statistical distributions tested) and the loglikelihoods of those models did not improve compared to MNL (this is because in the mixed logit we dropped significant interaction variables).

The mixed logit models that performed best were models with random coefficients for either PRC segment or mass and horsepower/weight. However, even here the standard deviations are not significant at the 95% confidence level. We therefore prefer MNL model A from Table 3, and this model specification was used to investigate the effects of lease car market policies.

6. Simulating the impacts of different taxed on private car use of lease cars

On the basis of the estimated MNL model for lease car choice, a spreadsheet tool was programmed to allow simulations of the effects of exogenous influencing factors and policies (e.g. tax policies) on the choice of car type on the lease market. The estimation data (NZO) is not necessarily fully representative of the Dutch lease car market. Therefore, the estimated model was first made representative for the lease car market by calibrating new constants for each brand-model, so that the application on the NZO sample for the reference situation matches the distribution in the RDW register data on lease cars.

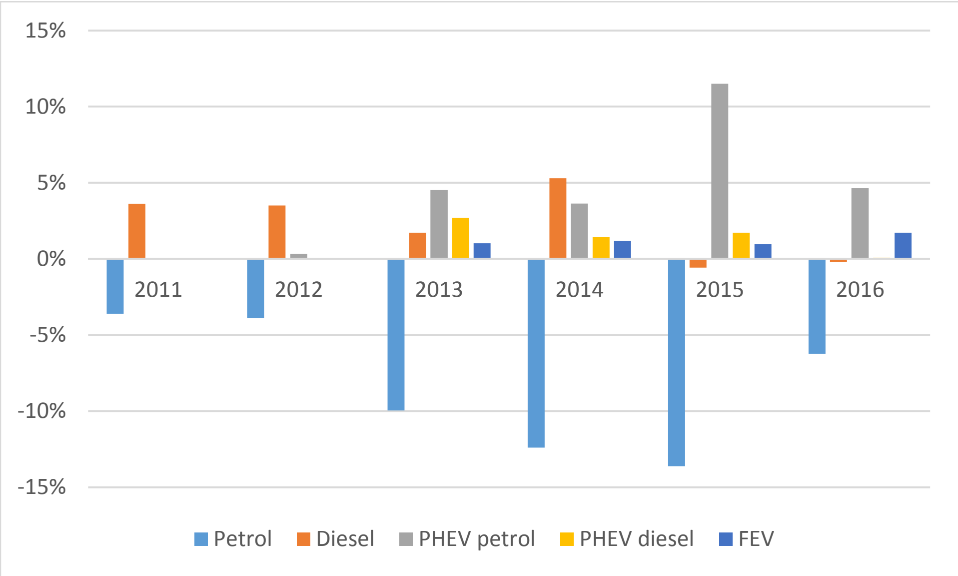
In this paper, we report about the impacts that we calculated for the reduction that was in place in the years 2011-2016 in the percentage of the purchase price that a lease car user needed to add to his taxable income (the BIK rate). During these years, users of lease cars with low CO_2 emissions, and especially hybrid and fully electric cars, could add a much lower percentage of the purchase price to their taxable income, and in this way reduce their tax payments. We compare this policy that was actually carried out with a hypothetical situation in which for all lease cars the BIK rate would have been equal to the general lease car tax rate in the period 2008-2016 of 25%.[4] Given that this policy was actually implemented in the past, one might argue that an evaluation of its effects could take place by simply measuring what happened in these years, without recourse to a model. However, the problem with this approach is that it does not tell us what would have happened without the policy measure (the 'counterfactual' or 'reference situation'). Several other things also changed during these years, such as the further introduction of hybrid and electric cars on the world market. The benefit of using a model for policy evaluation is that it allows us to compare two situations that only differ in terms of the implementation of the tax policy on lease cars, to produce the isolated effect of this policy on car type choice and CO_2 emissions. The impacts of the CO_2-reduction of the BIK rate on the composition of new lease car sales can be seen in Figure 1.

The measure that was implemented clearly has a large impact on the composition of the sales of lease cars. We observe a substantial reduction in the sales of petrol cars over the period 2011-2016 compared to a situation where the percentage would have been 25%. The sales of diesel, hybrid, plug-in-hybrid and fully electric cars on the other hand increased as a result of the tax incentives. 2015 is the year in which the impacts were the largest. In this year, the share of plug-in-hybrid-petrol cars in lease car sales was 12 percentage points (almost 30,000 cars) larger than what it would have been otherwise. In 2016, the BIK rate for plug-in-hybrids was increased from 7 to 15%. This also seems to have contributed to the spike in plug-in sales among lease cars in 2015 (anticipation effect). It is a striking result that the extra sales of plug-in-hybrids and fully electric cars in the period studied mainly replaced petrol cars and not diesel cars. Car manufacturers in this period offered diesel cars that had CO_2 emissions just below the CO_2 upper bound of the category where a BIK rate of 14% applied. This trend towards diesel cars leads to a deterioration of the local air quality in The Netherlands (e.g. higher emissions of particulate matter and NO_x).

[4] We assume that this policy only has an impact on lease car type choice. Effects on the number of cars owned or on annual car use are not included.

The tax differentiation was an incentive for car manufacturers to offer cars with official test CO_2-emisions just below the cut-off points for different tax addition percentages. This could be regarded as a success of the fiscal policies, but it leads to car sales that are only marginally greener than the cars just above these thresholds. The model simulations also show that the differentiation led to a shift to the smaller car segments.

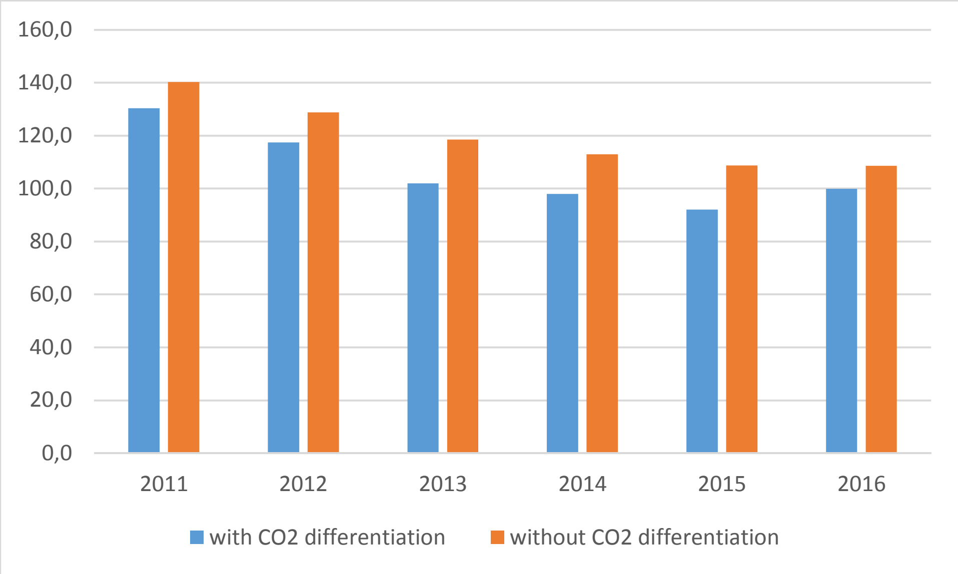
Figure 1 - Impacts of the tax incentives on the composition of the new lease car sales (in percentage points of the total lease car sales).



The impacts on the CO_2-emissions[5] of the newly purchased lease cars (in Figure 2) show that as a result of increased sales of more fuel-efficient petrol and diesel cars and more plug-in-hybrids and fully electric cars, the CO_2-emissions were clearly lower than would have been the case without the differentiation. In the years 2013-2016 the average CO_2-emission was 13 g/km lower (11%) as a result of the BIK rate differentiation policy. However, if we would use the real-world CO_2-emission values, the relative reduction that is caused by the tax differentiation is 45% smaller for the period 2011-2016 than reported above. This gives a real-world reduction in CO_2 by 7 g/km or 6%.

[5] In these calculations of the CO_2-emissions, we used the test fuel consumption rates, as laid down for the European type approval. The real-world emissions are higher. The difference between the two has been increasing over the years and this gap becomes bigger for more fuel-efficient cars (Ligterink and Smokers, 2016).

Figure 2 - Simulated mean CO_2-emission factor of new lease cars (in g/km)



7. Summary and conclusions

In the Netherlands, a policy was in place in recent years to promote the choice of energy-efficient cars within the lease car market. The policy instrument was a reduction in the amount of money that car users have to add to their taxable income for the private use of the lease car. To simulate the impact of the policy, a model of the lease car market was developed.

This model represents the choice among 196 brand, model and fuel type alternatives as made by employees concerning the lease cars that are offered to them by their employers. What differentiates this type car choice model from the models in the literature is that it was estimated on RP data instead of SP data, while at the same time including hybrid and electric cars as choice alternatives.

The model was estimated on individual car user data supplied by the lease companies in The Netherlands, combined with data on attributes of the choice alternatives from the car register data and Statistics Netherlands.

In estimation, mixed logit models that try to account for unobserved variation in the behavioural coefficients did not outperform multinomial logit models. The latter models had the expected signs for the influencing factors, including interactions with socio-economic characteristics of the car users, and the important coefficients were all significant.

The estimated model was implemented to investigate the impact of the reduction that was given in The Netherlands to users of fuel efficient cars (including hybrid and electric cars, but also relatively efficient cars on conventional fuel) over the period 2011-2016 in the percentage of the purchase price that needs to be added to taxable income (the BIK rate). This policy, led on the one hand to a decline in tax income for the government and on the other hand turned out to have a large impact on the composition of the lease car sales: fewer petrol cars and more diesel, hybrid, plug-in-hybrid and fully electric cars were sold on the lease car market over this period than would have been the case with a uniformly high BIK rate. This policy-induced change in fuel type went hand-in-hand with a shift to smaller cars and a reduction in the CO_2 emissions of lease cars. The latter reduction however is smaller when based on real-world emissions than when based on official type-approval test rates. Also, the increase in the share of diesel cars led to an increase in the emission of local air pollutants. The goal of the BIK differentiation policy was to reduce CO_2 emissions from lease cars, so we can conclude that this policy was effective, though not necessarily efficient, since the costs in terms of foregone tax revenues were also substantial. Moreover, the tax incentives had unintended negative consequences in the form of local air pollution, which had not been taken into account when formulating and implementing the policy.

We conclude that fiscal policy can influence the choice of vehicle type on the lease car market quite substantially. Large impacts of fiscal incentives on type choice for new cars have also been found (van Meerkerk et al., 2014) on the private car market. Given that we have a situation here where policy can be very effective (unlike some other areas in transport, such as modal split and travel distances, which are often difficult to influence in a major way by policy instruments, see de Jong and van de Riet, 2008, Wardman et al., 2018), it is of the utmost importance that the right incentives are provided. Subsidising hybrid cars, which can also be used with conventional fuels, then may not be a good choice of incentive, especially if many of these vehicle types are relatively heavy. Incentives that are strictly based on fuel-efficiency can turn out to be an implicit subsidy for diesel cars, which is an undesired effect from a health perspective. The current incentives for lease cars in The Netherlands, that only favour the smaller fully electric cars seem to be more in line with societal objectives, with much smaller unwanted side-effects. It is important that policies should not only be evaluated on their effect on CO_2 reduction, but that a full social cost-benefit analysis of the effects of the policy should be carried out, looking at other benefits as well as at the costs of the policy.

The above also contains the policy lesson that might be learnt from this for other countries. It is possible for tax incentive policies to have a large effect on the composition of the car market, but this could be a mixed blessing if the tax incentives are designed such that there is not only a reduction in CO_2 but also an increase in local emissions. Instead of targeting cars with low CO_2 emissions (which could encompass diesel cars), a policy that specifically targets (small) electric cars would not have these perverse side-effects.

The model that was used in this study has a number of limitations. One of these is that attributes that are specific to electric cars, such as the driving range and the recharging time and opportunities, were not included in any of the RP data bases used. These attributes are usually included in SP studies on electric cars. SP data also is a solution when attributes are highly correlated with each other, as we experienced with some of the RP-based data. Other limitations are that the study only looked at the lease car market, not the private car market and that car use was not modelled.

A potential direction for future research would be to develop a joint type choice model of the entire Dutch car market focussing on hybrid, plug-in-hybrid and fully electric cars, based on SP and RP data for private cars (probably with a focus on SP) and SP and RP data (probably with a focus on RP) for lease cars. This model could then be used to simulate the impact of various kinds of taxes and subsidies on lease and private cars on all car sales in the country. This joint model could also be extended to include car use (annual kilometrage). This would make it possible to study the impact of the BIK rate not only on car type choice but also on car use.

Another promising avenue for further research would be analysing the impact of the choice of vehicle type for the lease car on the vehicle type choice (and car use) of the second car in the same household, which will probably be a private car.

Finally, it would be good to include the time dimension in the car market models. Even if many consumers would select an electric car at their next purchase (private market) or as their next lease car, it will take several years before all these consumers will have implemented this choice. The reason for this simply is that lease car users hold on to their car for several years (often three years) and private car owners on average have even longer ownership durations, and some much longer. Moreover, it can take a long time before private car owners that want to purchase their car on the second hand car market will have a sufficient supply of electric cars to choose from. Because of these time lags, the long-term effects of fiscal incentives and other car market policies will be larger than the short-term effects. Furthermore, policies such as fiscal incentives for green cars can reduce the average life of cars and lead to an increase in car production. Research on vehicle holding duration and transactions and whether these can be influenced by policy is therefore also very useful, as is the analysis of lifecycle emissions.

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