How to foster electric vehicle market penetration? – A model based assessment of policy measures and external factors

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Abstract
Electric vehicles (EVs) have the potential to reduce green house gas emissions from the transport sector. However, the future market evolution of EVs strongly depends on several influencing factors such as battery and oil prices as well as their future evolution. The effect of these and other influencing factors as well as the resulting future market evolution are uncertain, yet policy makers need an empirical basis to take decisions impacting the future market evolution. Here, we study the market evolution of EVs in Germany until 2020 and perform a model-based assessment of influencing factors and different monetary policy measures. We use an agent-based model with a utility maximising decision function for several thousand individual private and commercial vehicle owners.

Our results reveal a great deal of uncertainty in the market evolution of EVs due to external conditions and the users' willingness-to-pay for this new technology. Energy prices have a large impact on EV market evolution as a 25 % increase in fuel prices would double the number of EVs in stock by 2020 compared to a reference scenario. We find a special depreciation allowance for commercial vehicles and a subsidy of 1,000 Euro per vehicle to be the most effective and efficient monetary policy options. Furthermore, the high uncertainty of framework conditions and the EV market evolution implies that policies to foster market diffusion of EVs should be dynamically adaptable to react to changing framework conditions.

Introduction
The reduction of green house gases and the scarcity of conventional energy resources in combination with a drastic increase of mobility demand are important challenges of the mobility sector in the 21st century. Electric vehicles (EV) in combination with renewable energies are one possible solution for these challenges (Kalhammer 2007, Arar 2010). However, a successful market penetration of EVs depends on several technical factors like the advancement of battery technology, economical factors as the development of oil or electricity prices, organizational factors like the availability of charging infrastructure as well as user behavioural factors like consumer acceptance of this new technology or individual driving behaviour. Thus, the future market evolution of EVs is highly uncertain. Still, policy makers and car manufacturers require market diffusion estimates and an analysis of policy options.

In Germany, EV have also been identified as essential measures for a sustainable transport system in the National Development Plan electric mobility of Germany. Germany has set itself the goal to become the leading provider in international competition and leading market for electric vehicles in order to maintain its leadership in the automotive and supplier industries. As an intermediate goal, the federal government and the National Electric Mobility Platform pursue one million EV on German roads by 2020 and six million by 2030. Here, we analyse a selected number of policy measures integrated in the TCO calculation with regard to their effect on market penetration in Germany. The effect of potential support schemes, individually and in combination, were analysed, depending on the year of implementation, i.e. implementation in 2015 and then delayed from 2018. Furthermore, a qualitative assessment of the market diffusion of electric vehicles in Germany based on growth rates of comparable technologies is presented to estimate the potential and realistic achievable goals of this new technology.

For the following considerations, EV are defined as passenger cars and light commercial vehicles if they are fully or partially electrically driven and have an on-board charger. These include pure battery-powered vehicles (BEV), plug-in hybrid electric vehicles (PHEV) and range-extender vehicles (REEV). All data, assumptions and scenarios are based Plötz et al. (2014) as well as Gnann et al (2014) if not indicated otherwise.

The diffusion of new technologies and EVs in particular has received considerable attention in the literature (see (Al-Alawi and Bradley 2013) for a recent review of EV market diffusion models). A general classification of market diffusion models was given by Geroski (2000). He describes two groups of models for market diffusion of innovations: population and probit models. Since probit models are one classification of consumer choice models, we will refer to consumer choice models for the second group. The latter also includes the frequently used agent-based models.

Population models describe users or adopters not as individuals, but as groups. Population models assume for example that the rate of adoption is proportional to the number of adopters and the remaining population that has not adopted a technology yet. This leads to the well-known logistic differential equation and can be interpreted via the spread of information about a technology (Geroski 2000). Population models offer a simple structure and interpretation. They are usually applied by calibrating the market diffusion curve to existing market data or by assuming hypothetical growth rates. This procedure is rather sensitive in early market phases when little data is available. Furthermore, the heterogeneity of the individual buying decisions and preferences of users, for example reflected in the willingness to pay more for new technologies of some users as well as the individual economics of the driving behaviour, cannot be incorporated into these models.

The second group of market diffusion models, consumer choice and agent based models, studies adopters individually. These models are often applied when the purchase decision is more complex or the technologies to be adopted are rather expensive. For example, a simple probit model for EV adoption would calculate the average ownership cost difference between conventional and electric vehicles and estimate a EV market share based on this difference. As fuel and battery prices change over time, these cost differences change and with them the estimated EV market share. Thus, consumer choice models develop market diffusion bottom-up and acknowledge that individual users can be very different. This is particularly important to identify niche markets in early phases of market development. However, these models face the problem that consumer statements about their preferences for EVs are often inaccurate. Given the current market shares of EVs, the vast majority of users has never experienced a EV and can hardly judge its utility.

Consumer choice and agent-based models were used to model EV market diffusion in (Eppstein al. 2011, Zhang et al. 2011, Shafiei et al. 2012) where the detailed modelling approaches range from determining user shares by stated preference experiments to agent-based models. Some models are based on driving behaviour of conventional vehicles (Eppstein et al. 2011). This would in principle allow to analyse user behaviour in more detail. However, the latter models use driving profiles of only one day which can cause severe inaccuracies on the individual level as a single day might not show the individual's typical driving as is crucial for EVs due to their limited range. In summary, agent-based models offer the possibility to include several aspects of great relevance for the market diffusion of EVs in the current market development phase: individual purchase preferences, individual driving behaviour (to account for the limited range of EVs and the vehicle kilometres travelled (VKT) related usage costs), the need for frequent recharging and infrastructure as well as the limited choice of EV brands and models.

Methods and data

METHODS

We use a market diffusion model to simulate the market penetration of electric vehicles (EVs) based on a broad data set of user behaviour and has been comprehensively described in Plötz et al. (2014). The model consists of two steps: (1) every vehicle is simulated individually as PHEV and BEV based on the existing charging infrastructure. (2) Based on the battery simulation, the best vehicle option is determined for each driving profile and in case of PEV they are added to the PEV stock. Figure 1 gives an overview of the model showing the main parts in three columns: the inclusion of user behaviour in the first column, the model steps in the second and the parameters necessary in the third column.

The battery simulation for every driving profile is as follows: The battery is discharged when the vehicle is driven according to the driving profile. After each trip we determine whether to charge or not and if yes, the vehicle is recharged until the next trip. The decision to charge depends on the location where the vehicle is parked which derives from the driving profiles and on the availability of infrastructure at this location: Vehicles that are privately used can always be recharged at domestic stops if charging infrastructure is available there. The same holds for stops at work if work charging is permitted in the charging scenario. Commercial fleet vehicles can charge at their company or organisation as a pendant to domestic charging facilities. If vehicles stop at a public charging spot (stop is not a domestic, commercial or work location), the PEV-type and the charging spot necessity determine the possibility to recharge: If the battery state of charge (SOC) is below 50 %, i. e. in case the vehicle was charged completely before the last trip, the way back to the last charging facility would not be possible, and the charging spot density at the stopping point is high enough, a BEV will be charged. For a PHEV the SOC has to be lower than 50 %, the charging spot density must be high enough and the cost for driving in charge depleting mode must be lower than for driving in charge sustaining mode. Otherwise a PHEV could also use its internal combustion engine. The charging point density will be introduced and discussed in the first part of the results. With these decision rules, we can determine what shares of electricity every PEV would need at which location and include this in the buying decision. Also the ability of BEVs to perform the whole profile as well as the share of electric driving for PHEV are outputs of this step. Apart from the driving profiles as main input, we also need several vehicle parameters, such

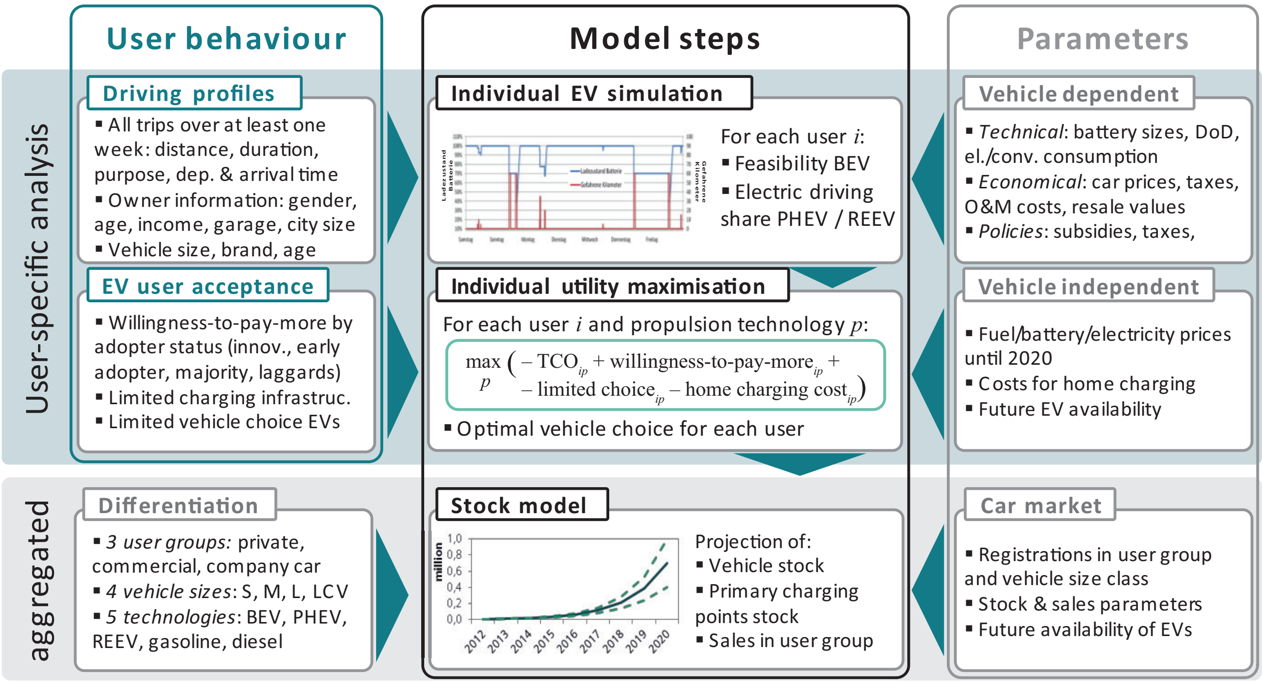

Figure 1. Model overview.

as electricity or fuel consumptions, scenarios where charging is permitted as well as the initial charging infrastructure stock.

The second model step is the determination of the PEV stock. Since the buying decision of a vehicle is based on a variety of factors, we determine the best vehicle option by utility maximisation:

$$u_{im} = -TCO_{im}^{veh} - TCO_{im}^{CI} + wtpm_{im}$$

The utility function includes the vehicle's total cost of ownership (TCO_{im}^{veh}), the cost for individual charging points (TCO_{im}^{CI}) as a hampering factor and the willingness to pay more (WTPM, $wtpm_{im}$) for an electric vehicle as a favouring factor symbolizing the enthusiasm for a new technology (Plötz et al. 2014, Gnann et al. 2014). Based on this equation the utility maximizing drive train is chosen. The limited number of makes and models of electric vehicles is another obstructing factor integrated in the PEV registration: Profiles with the highest use as electric vehicles are registered to the PEV stock up to this limited amount of vehicles deriving from diffusion curves of PEVs (see section 2.3.2 in (Plötz et al. 2014) for details). Commercial electric vehicles in the PEV stock that are older than their first registration horizon (=investment horizon) are replaced by private electric vehicles (second hand car market). The electric driving share deriving from the previous model step as well as the location-specific energy consumption serve as input to the vehicle's TCO. Vehicle-specific assumptions like the cost for operations and maintenance or vehicle tax are shown in Table 3.

Since driving varies noteworthy between drivers, we consider driving profiles to be appropriate for the representation of individual driving behaviour. Here we differentiate between three different user groups: (1) Users of private vehicles: These vehicles are licensed to a private person and are used for private purposes. (2) Users of fleet vehicles: Those vehicles are licensed to a company and are only used for business purposes. (3) Users of company cars: The third group of vehicles is licensed to the company, but may be used commercially and privately by its driver. We will also distinguish between (a) four vehicle size classes according to typical cubic capacities in German car segments: small (cubic capacity 1,400 ccm), medium (1,400 ccm < cubic capacity 2,000 ccm), large (2,000 ccm < cubic capacity) and for fleet vehicles also light commercial vehicles (LCV, with a weight less than 3.5 tons) (b) and five propulsion technologies: internal combustion engine vehicles (ICEV) fuelled with gasoline (in the following referred to as Gasoline vehicles), ICEV fuelled with diesel (Diesel vehicles), plug-in hybrid electric vehicles (PHEV), range-extended electric vehicles (REEV) and battery electric vehicles (BEV). This distinction is important as we use different driving profile data sets for the user groups. For private and company cars we use the German Mobility Panel (MOP 2010) which is an annual household travel survey. We chose this data set since it contains the trips of people in the household for one week instead of one day which is crucial for the determination of a realistic electric driving share. The same holds for fleet vehicles where our own collection of commercial driving profiles (REM 2030 driving profiles (Fraunhofer ISI 2014)) is, to the best of our knowledge, the only data set of commercial driving profiles of more than one day observation period for Germany.

As MOP is a household travel survey which focuses on people and their trips, we have to assign trips to vehicles if unambiguously possible, e.g. when only one vehicle is available in the households but used by several household members (see Kley 2011 and Gnann et al. 2012). By using all data from 1994 until 2010, we obtain 6,339 vehicle driving profiles with 172,978 trips in total. 6,177 profiles belong to private vehicles and 162 to company cars. Besides the driving, the profiles contain socio-economic information of the driver (e. g. age, sex, occupation, household income, education) and the vehicle (e. g. vehicle size, vehicle owner, garage availability). The

REM2030 driving profiles are collected via GPS-trackers which are sent to companies willing to let their vehicle trips be collected for at least three weeks. There are 435 vehicles in the data set with 60,203 trips in total.

Apart from the driving profiles, we use two data sets for the willingness to pay more (WTPM) for electric vehicles which we include as a favouring aspect representing the appreciation of users for a new technology (see Plötz et al. 2014 for a detailed description and discussion of the WTPM). Users are grouped according to Roger's adoption groups innovators, early adopter, early and late majority (as one group here) and laggards (Rogers 1962). The assignment of the WTPM to driving profiles is done via a cluster analysis of socio-demographic attributes. For commercial users the WTPM we assign is 7 % of a comparable conventional car to vehicles of companies with more than 50 employees based on (Dataforce 2011). As hampering effect we integrate the cost for every primary charging point of each vehicle to its TCO using the information about its usual overnight parking spot. All other modelling steps are motivated and explained in more detail in Plötz et al. (2014)

DATA AND PARAMETER

The market diffusion of electric vehicles is influenced by both the framework conditions in general and the parameters depending on the vehicles. All data and parameters are described in detail in Plötz et al. (2014) and Gnann et al. (2014). We only summarise the main assumptions here.

The framework conditions include the number of new car purchases divided into segments and user groups forming the general potential for electric cars. Vehicle dependent parameters such as purchase price or fuel consumption on the other side are the base for the TCO calculation for each segment and user group. Due to a relatively constant number of new registrations in the past five to seven years, this input factor is assumed constant at 3.1 million cars per year until 2020. The shares of different vehicle sizes within the new registrations are also assumed constant.

The TCO-gap between electric and conventional vehicles is significantly driven by the differences in purchase prices of the technologies. The purchase price of electric vehicles consists of two parts: a relative constant price for the chassis and drive train and a price for the battery system. The battery size determines the total purchase price and in combination with the depth of discharge (DoD) limits the range of the vehicle. Battery sizes are assumed to be 24 kWh (BEV), 16 kWh (REEV) and 10 kWh (PHEV) for medium size vehicles with a DoD of 90 % (BEV), 80 % (REEV) and 75 % (PHEV)[1]. Fuel costs are the second most important component of the TCO. All values for fuel consumptions are based on Helms et al. (2011), where the major assumption for future development of consumption is a decline in fuel consumption (diesel, gasoline) of at least 1.5 % per year to meet the 2009 announced EU emission targets. Compared to past efficiency developments, these assumptions seem moderate. Note that the values represent real consumption and not driving cycle values. We compared our assumptions to the 2014 EPA ratings of actual vehicles (as compared to our prototype vehicle assumptions – see EPA (2014)) and find our assumptions for average vehicles to be consistent with actual BEV and PHEV on the market. Maintenance costs also differ among technologies.

Vehicle taxes are calculated based on the current German tax legislation with complete tax exemption for BEV owners. Variations of the tax legislation are considered within the framework of different policy measures (see below). As mentioned before, we distinguish between three user groups from two data sets. In the EV simulation we assume that private and company cars can charge with 3.7 kW whenever they are at home, the trip purpose "home trip" is used to decide about the parking spot of the vehicle. For fleet vehicles, we do not know the trip purposes but the GPS-location which we use to let the vehicles charge with 3.7 kW during the day when they are not further than 500 m away from their main company location. They can additionally charge overnight, assuming that the vehicle can be plugged in, no matter whether it is parked at a private household or at the company site.

As we know where private and company cars from our driving profile database are usually parked overnight, we distinguish between vehicles with and without garage. Users of vehicles that are parked in a garage are assumed to buy a wallbox for charging, while non-garage-owners do have to pay for a simple public charging facility. For the latter, we choose the cheapest charging facility available – a charging point integrated into a lantern – and split up the investment and running cost between two users, assuming they could share one charging point. Investment and running cost for both solutions as well as investment horizons are given in Table 4. Since we do know the common charging facility overnight for just a few fleet users, we assume that fleet users buy a simple wallbox like private users with garages.

For battery prices, as well as electricity and fuel prices, we define three scenarios, which are summarised below. The first scenario makes rather optimistic assumptions with regard to the market success of electric vehicles (pro-EV scenario); the second more pessimistic assumptions (contra-EV scenario) and the assumptions made in the third scenario for Germany up to 2020 lie in-between these two (medium scenario). The battery prices for all three scenarios decrease exponentially from values up to 900 EUR/kWh in 2011 (pro-EV, medium, contra-EV) to below one third in 2020 (all values without VAT). Prices for diesel and gasoline are based on the New Policy Scenario of the world energy outlook 2013 for the medium scenario with an additional increase of 20 % in the pro-EV scenario and a decrease of 20 % in the contra-EV scenario. Finally the electricity prices are equal in 2011 and change linearly until 2020 with a slight increase in the medium and pro-EV scenario and a greater rise in the contra-EV scenario. We will use the medium scenario as reference case below.

POLICY MEASURES

In this study, a series of policy measures is considered. The following values of monetary policy actions are carried out on the market run-up in terms of their influence:

1. a special depreciation for commercial vehicles held from 2015,

1. The expected near-future reduction of battery prices could lead to cheaper EVs if battery sizes are fixed or to EVs with langer ranges if battery sizes were increased. For the present work, all battery cost reductions go into EV cost reductions. Preliminary calculations with increasing battery sizes show no qualitative difference to the results presented below.

Table 1. Scenarios and framework conditions.

(all prices including VAT)	Year	Pro-EV	Medium scenario	Contra-EV
Diesel price	2013		1,45	
[Euro/Litre]	2020	1,73	1,58	1,43
Gasoline price	2013		1,57	
[Euro/Litre]	2020	1,79	1,65	1,54
Electricity price private	2013		0,265	
[Euro/kWh]	2020	0,29	0,29	0,33
Electricity price commercial	2013		0,20	
[Euro/kWh]	2020	0,215	0,215	0,25
Battery price EVs	2013	470	520	575
[Euro/kWh]	2020	300	335	370

2. a special depreciation for commercial vehicles held from 2018,
3. a low-interest KfW loan for private electric vehicles from 2015 (leading to a reduction of the interest rate from 5 % to 4 % in the discounted cash flow calculation),
4. a low-interest KfW loan for private electric vehicles from 2018,
5. a price subsidy for private and commercial electric vehicles from 2015,
6. a price subsidy for residential and commercial electric vehicles from 2018,
7. a special depreciation commercial electric vehicles and a price subsidy for residential and commercial electric vehicles from 2018,
8. a special depreciation commercial electric vehicles and a purchase price subsidy for residential and commercial electric vehicles from 2018 to reach the one million target in 2020.

These measures are among the measures currently being discussed in German political forums. The evaluation of these measures is due to their monetary effect for the individual purchaser by means of integration into the TCO calculation. Other non-monetary or indirectly support measures were not considered.

Results

THE EFFECT OF POLICY MEASURES

The future market evolution of EV stock in Germany under the different scenario assumptions are shown with 10 %, 30 %, 50 %, 70 % and 90 % confidence intervals in Figure 1 (Gnann et al. 2014 and Plötz et al. 2014). The EV stock in 2020 strongly depends on the external conditions such as oil, electricity and battery price. Although the changes in the scenario assumptions are minor, they lead to noteworthy differences in the potential stock evolution. Thus energy and battery prices have a major impact on the future market evolution of EV in Germany.

We now take the medium scenario from Table 1 as reference scenario and analyse the effect of different policy measures on the EV stock in Germany in 2020. Figure 2 shows the results from model calculation for the policy measures explained above.

It is clearly visible that all policy measures have a significant promoting effect on the market up of electric vehicles. You can identify three groups with similar results:

- The measures introduced in 2018 (No. 2, 4 and 6), constitute the group with the lowest market up numbers (from 700,000 to 800,000 electric vehicles). They increase the number of EV registrations only from 2018 onwards. According to our model calculations, the growth rates in the years 2018–2020 would rise to about 40 % per year.
- The group of measures active from 2015 onwards (No. 1, 3 and 5) show a higher increase in EV sales and stock (850,000–970,000 electric vehicles). Although support as early as 2015 comes into force, the largest increases are obtained in later years when EVs become attractive for more buyers.
- The third group is formed by the combined measures of special depreciation and purchase price subsidy (No. 7 and 8), which fulfil the one million EV goal of the federal government. The growth in registrations as from 2018 with over 60 % per year is estimated as extreme and is discussed in the following section.
- The policy measures lead to no significant shifts between electric drive trains (BEV, PHEV, REEV) or vehicle sizes.

In addition to the effect of a policy measure the cost and efficiency of a measure have to be taken into account. For this purpose, the funding were calculated, which are spend for policy measures, as well as the deadweight effect arising from the fact

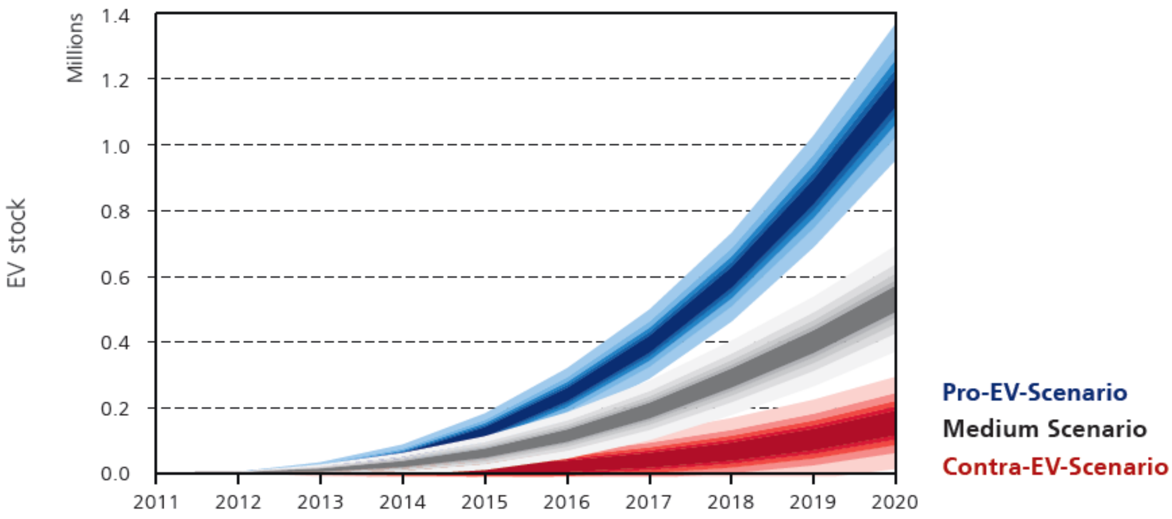

Figure 2. EV stock evolution in Germany in three scenarios.

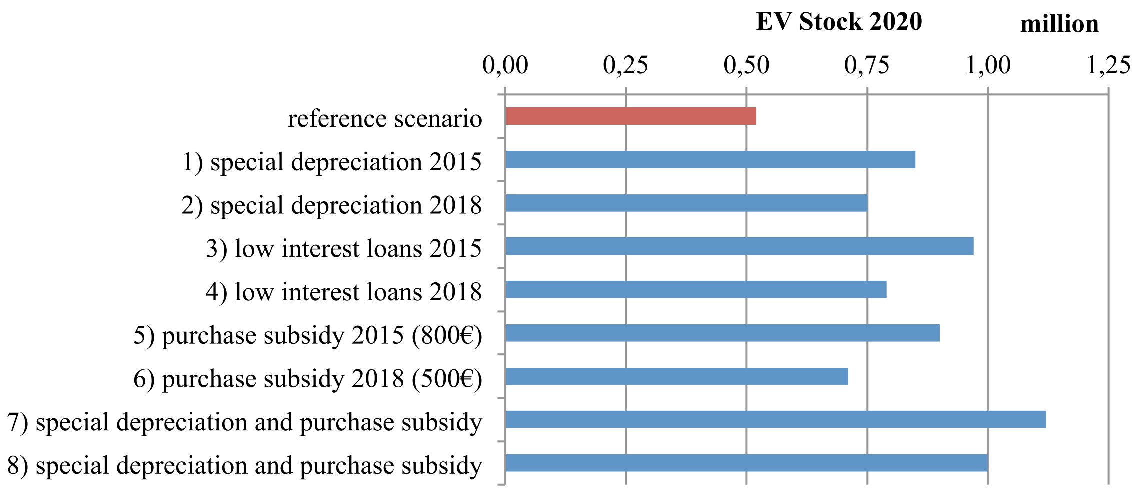

Figure 3. EV stock 2020 in Germany under different policy measures.

that vehicles which would (without funding measure) bought in the base case, in addition receive this subsidy (windfall gains). Putting the promotion in relation to additional electric vehicles, we analyse the cost effectiveness of the policy measure. The required government aids have been calculated for every year and have been discounted to 2014 values with an assumed governmental interest rate of 2 % (a variation of this interest rate between 0 and 5 % led to quantitative but no qualitative differences). These values are shown in Table 2.

The comparison of the promotion of individual policy measures differs significantly from the increase of the number of EV. However, comparing the funding of the respective policy measures for each additional passenger car, so we can distinguish three other groups: A group with a funding to €1,000 per electric vehicle (purchase price subsidies No. 5 and 6), a group with funding of about €1,600 per additional EV (No. 1, 2, 7, and 8) and a group with significantly larger funding per additional electric vehicle of over €3,500 per additional electric vehicle (KfW loans No. 5 and 6). Furthermore, one has to note that not all user groups benefit equally from the policy measures. While special depreciation rules are beneficial for commercial holder, the low interest loan has been modelled exclusively for private users. The purchase price subsidy targets all user groups.

COMPARISON TO HISTORICAL TECHNOLOGY EVOLUTION

In the previous section the effect of various policy measures on the potential market diffusion of electric vehicles in Germany has been analysed. Different measures as well as the evolution of general framework conditions have an impact on the future EV stock in Germany. In this section, the growth rates corresponding to the stock evolution are compared to the historical diffusion of comparable new technologies.

The market share of new technologies analysed over a time follows an s-shaped diffusion curve. In the early market phase after product implementation the increase in market share shows an exponential growth and slows down in the continu-

Table 2. Results and cost of policy measures.

Scenario	Stock EV 2020	government aid [Mio. €]	windfall gain [Mio. €]	government aid per EV [€]	windfall gain
reference scenario	520,000	–	–	–	–
1) special depreciation 2015*	850,000	529	195	1,600	37 %
2) special depreciation 2018*	750,000	383	143	1,670	37 %
3) low interest loan 2015	970,000	1,610	936	3,580	58 %
4) low interest loan 2018	790,000	1,047	608	3,880	58 %
5) purchase subsidy from 2015 (€800)	900,000	391	245	1,030	63 %
6) purchase subsidy from 2018 (€500)	710,000	196	137	1,030	70 %
7) special depreciation 2018 plus incentives from 2018 (€500)	1,120,000	961	267	1,600	28 %
8) special depreciation 2018 plus incentives from 2018 (€275)	1,000,000	749	227	1,560	30 %

Table 3. Historical growth rates in the automotive sector.

Technology (Country Code)	historical CAGR	period of record (years)	Source
Diesel (DE)	9 % p.a.	20	Hacker et al. (2011)
Natural gas (DE)	19 % p.a.	15	Hacker et al. (2011)
Hybrid (DE)	25–40 % p.a.	8	Own calculation
Natural gas (IT)	30–85 % p.a.	12	Own calculation
Battery electric (NO)	80–100 % p.a.	6	Own calculation
automatic transmission (USA)	15 % p.a.	20	Hacker et al. (2011)
front wheel drive (US)	17 % p.a.	20	Hacker et al. (2011)

ing market phase to reach a plateau when the market is saturated. For the early market phase the mean growth rates can be determined and allow us a projection for the later market phase. Therefore, the compound annual growth rate (CAGR), which is the average annual growth rate, will be analysed in the following:

$$\mathrm{CAGR}(t,t') = [N(t')/N(t)]^{1/(t-t')} - 1$$

where ***N(t)*** is the annual new registrations. Average growth rates of new technologies in the automotive sector can be compared with the possible growth of new registrations of electric vehicles in Germany. In Table 3 historical growth rates of new technologies in the automotive sector are shown.

The average growth rates of new technologies in the automotive market are in the range of 10–30 % per year. In short observation periods and for alternative drive trains partially higher growth rates are possible. However, the growth rates decrease over time (i.e. with increasing observation period) according to the s-shaped diffusion curve. The exact rate of growth in sense of CAGR(t, t') depends on both the specific market development as well as the selected starting and ending years t and t' of the observation period, as market shares do not develop completely continuous, but often show leaps or irregularities.

Where ranges of growth rates are given in Table 3, they include the central 50 % of growth rates obtained by varying the initial and final year. The growth rates for hybrid cars in Germany, natural gas car in Italy and electric vehicles in Norway in Table 4.

As electric vehicles in series-production became commercially available in the years 2012/2013, the 8 years to 2020 are a relevant period of observation for the analysis of the development of new car registrations of electric vehicles. Table 3 shows that in the field of drive train technology growth rates of more than 50 % of the new car registration per year are feasible for a short observation period of 6–12 years. The comparison with the diffusion of new technologies in the energy sector shows similar growth rates (see Table 4). The average growth rates of new technologies in the energy sector are in the range of 10–30 % per year as also observable in the automotive sector. Within short observation periods higher growth rates are possible here as well.

Generally speaking, the determination of average growth rates is subjected to considerable uncertainty, mainly due to the discontinuous development of markets and fluctuating conditions. In particular, the observed growth rates decrease with the length of the observation period and the size of the market share of the technology.

Table 4. Historical growth rates in the energy sector (Lund 2006).

Technology (Country Code)	historical CAGR	periond of record (years)
Biomass (FI)	15 % p.a.	33
heat pump (AT)	8 % p.a.	30
heat pump (SE)	11 % p.a.	29
HF ballasts (SE)	45 % p.a.	15
nuclear (global)	8 % p.a.	39
nuclear (FR)	15 % p.a.	39
photovoltaic (global)	22 % p.a.	28
solar heating (AU)	15 % p.a.	29
wind (global)	26 % p.a.	16
wind (DE)	31 % p.a.	16

Based on the previously observed new registrations of electric vehicles in Germany it is possible to predict future scenarios for the stock evolution of EV in Germany with assumed growth rates for new registrations. Therefore the new registrations of EV between January and October 2014 were projected for the whole year 2014 (12,412 electric vehicles) and a constant growth of new registrations until 2020 has been assumed.

The EV stock is derived from the accumulation of new registrations additionally the 12,156 electric vehicles that were in stock on 1.1.2014. The development of the electric vehicle stock for different assumed growth rates is presented in Figure 3. Here the electric vehicle stock at the end of the year is shown.

Figure 4 reveals that, starting from the current new registrations in 2014, the new registrations from 2015 to 2020 need to grow about 80 % per year on average to marginally reach the goal of one million EV in Germany. With an average growth rate of 60 % per year for new registrations half a million electric vehicles in stock could be achieved by the end of 2020. In comparison to historical growth rates an average growth of over 60 % per year appears to be rather ambitious. Since the time horizon until 2020 is a relatively short period of time and the new registrations of electric vehicles in recent years (2011–2014) in Germany have increased by 100 % per year, the goal of one million electric vehicles appears ambitious but possible. However, the actual market development also depends on a number of other conditions, such as the precise development of crude oil, electricity and battery prices.

The influence of selected policy measures on the development of new registrations is illustrated in Figure 5. In recent years the new registrations displayed a growth of about 100 % per year, as described previously. In the reference scenario without policy measures a growth of about 40 % per year from 2014 to 2020 can be expected. The suggested policy measures could lead to an increase of new registrations; associated with an approximate growth of 50 % per year as seen in the simulation. Regarding the entire period from 2011 to 2020 this would imply an increase of nearly 70 % per year for new registrations. However, it should be noted that only the start- and end value are considered and not the exact path of new registrations. The latter can lead to significant differences in stock development: The simulation reveals that the implementation of a special depreciation from 2015 until the end of 2020 could yield approximately 850,000 electric vehicles in stock, but with the implementation of a favourable low interest loan in 2015 approximately 970,000 EV are possible in 2020.

Therefore, relatively high growth rates are possible until the end of 2020. The implementation of well selected policy measures could create an significant positive influence on the average annual growth rate, although other (economic) frame conditions and the exact path of new registrations play a role in the development of the electric car population in Germany.

Discussion

We use a market diffusion model for EV which simulates the purchase decisions of potential EV users to analyse the effect of different policy measures on EV market evolution. A detailed discussion of the development and background of model can be found in Plötz et al. (2013 and 2014). Here, we focused on the medium scenario, yet the framework conditions have a decisive influence and their development is uncertain. This may lead to a lower or higher diffusion of EV under different policy measures than estimated here. Similarly, the integrated promoting and inhibiting factors have a relevant influence and their future development is difficult to estimate. Because of the uncertain framework conditions, any policy measure should be dynamically adaptable to be able to respond quickly to changes.

Furthermore, the selection of policy measures, which can be integrated without massive adjustment in the model, is limited to monetary measures since the decision to buy is mapped with a full cost accounting in the model. Thus, the impact of measures such as the expansion of public charging infrastructure or the possibility to use bus lanes or the effect of a special marking of electric vehicles and information-campaigns for electric mobility have not been analysed here. Furthermore, the potential effect of future CO_2 emission targets is not included.

The analysis of growth curves as presented here is also subject to a high degree of uncertainty. While the selection of an appropriate method of calculation depends on the technology and its intended use, the calculation of an average annual

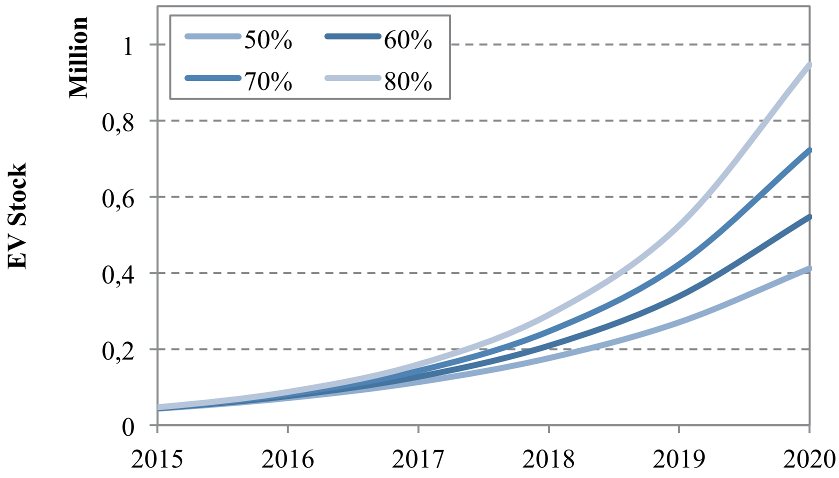

Figure 4. EV stock evolution at different growth rates.

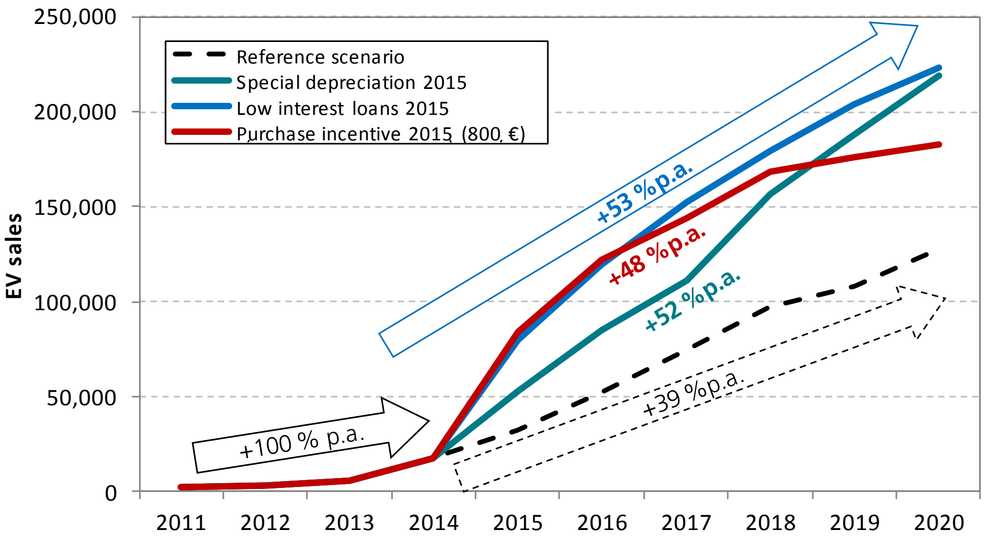

Figure 5. New registrations and growth rates of electric vehicles for selected policy measures in Germany.

growth rate (CAGR) is not subject to assumptions about the growth function. However, in particular, the reference period lead to significantly different growth rates. These uncertainties should be considered in the Interpretation of results.

Conclusions

The main question of the present paper has been: "What effects have different monetary policy measures on the market evolution of EV in Germany until 2020?" To answer this question we used a bottom-up market diffusion model and incorporated different policy measures via the total cost of ownership of EV.

The main results of this study are:

- The market diffusion of EV is highly uncertain and depends on framework conditions, in particular energy and battery prices. Here, we focused on a single scenario is considered that assumed neither strong promotional nor strong inhibitory framework conditions for EV.
- Starting from the assumption that at least one of the examined funding instruments (low interest loans for private electric vehicles, special depreciation for commercial electric vehicles and a purchase price subsidy for all users) is introduced in 2015, the gaol of one million EV can be achieved.
- The comparison of the market growth rates under the policy measures to historical growth rates of similar technologies in the automotive and energy sector, the potential future growth rates seem ambitious but possible.

References

Al-Alawi, B.M. and Bradley, T.H. (2013), Review of hybrid, plug-in hybrid, and electric vehicle market modeling studies. Renewable and Sustainable Energy Reviews, 21 (0): 190–203.

Arar, J.I. (2010), New directions: The electric car and carbon emissions in the US. Atmospheric environment 44, 733–734, doi: 10.1016/j.atmosenv.2009.09.042.

Bundesregierung (2009): Nationaler Entwicklungsplan Elektromobilität der Bundesregierung. Berlin.

Dataforce (2011): Elektrofahrzeuge in deutschen Fuhrparks – Zur künftigen Bedeutung von Elektrofahrzeugen in deutschen Flotten, Dataforce-Studie, Dataforce Verlagsgesellschaft für Business Informationen: Frankfurt a.M.

Eppstein, M. J., Grover, D. K., Marshall, J. S. and Rizzo, D. M. (2011). An agent based model to study market penetration of plug-in hybrid electric vehicles. Energy Policy, 39 (6): 3789–3802, June 2011.

Fraunhofer ISI. REM2030 Driving Profiles Database V2014-07. Technical report, Fraunhofer Institute of Systems and Innovation Research ISI, Karlsruhe, July 2014.

Geroski, P.A. (2000). "Models of technology diffusion". Research Policy 29 (4–5) (April): 603–625. doi:10.1016/S0048-7333(99)00092-X.

Globisch, J. and Dütschke, E. (2013): Anwendersicht auf Elektromobilität in gewerblichen Flotten. Ergebnisse aus den Projekten mit gewerblichen Nutzern von Elektrofahrzeugen im Rahmen des BMVBS-Vorhabens "Modellregionen für Elektromobilität 2009—2011". Fraunhofer ISI, Karlsruhe.

Gnann, T., Plötz, P., and Kley, F (2012). Vehicle charging infrastructure demand for the introduction of plug-in electric vehicles in Germany and the US. In *Electric Vehicle Symposium 26 (EVS 26)*, Los Angeles, May 2012.

Gnann, T.; Plötz, P.; Kühn, A.; Wietschel, M. (2014): Modelling Market Diffusion of Electric Vehicles with Real World Driving Data – German Market and Policy Options. Working Papers Sustainability and Innovation, No. S 12/2014. http://www.isi.fraunhofer.de/isi-wAssets/docs/e-x/working-papers-sustainability-and-innovation/WP12-2014_Modelling-Market-Diffusion-of-Electric-Vehicles_Gnann-et-al.pdf , Karlsruhe 2014.

Hacker, F., Harthan, R., Kasten, P., Loreck, C. Zimmer, W. (2011). Marktpotenziale und CO_2-Bilanz von Elektromobilität. Arbeitspakete 2 bis 5 des Forschungsvorhabens OPTUM: Optimierung der Umweltentlastungspotenziale von Elektrofahrzeugen. Anhang zum Schlussbericht im Rahmen der Förderung von Forschung und Entwicklung im Bereich der Elektromobilität des Bundesministeriums für Umwelt, Naturschutz und Reaktorsicherheit. Öko-Institut, Berlin.

Helms, H., Jöhrens, J., Hanusch, J. , Höpfner, U., Lambrecht, U. und Pehnt, M. (2011). "UMBReLA Umweltbilanzen Elektromobilität". Grundlagenbericht. Heidelberg: ifeu-Institut für Energie- und Umweltforschung Heidelberg GmbH.

Kalhammer, F. R., Kopf, B. M., Swan, D. H., Roan, V. P. and Walsh, M. P. Status and prospects for zero emissions vehicle technology, April 2007.

Kellner, C. (2008). Diffusion innovativer Technologien am Beispiel brennstoffzellengetriebener Pkws. Logos Berlin.

Kley, F. (2011). Ladeinfrastrukturen für Elektrofahrzeuge – Analyse und Bewertung einer Aufbaustrategie auf Basis des Fahrverhaltens. Karlsruhe: Fraunhofer Verlag.

Lund, P. (2006): Market penetration rates of new technologies, Energy Policy 34, S. 3317–3326, doi:10.1016/j.enpol.2005.07.002.

Massiani, J. (2010). "Modelling and Evaluation of the diffusion of electric vehicles: existing models, results and proposal for a new model for policy in European countries". Berlin: ESMT – European School of Management and Technology.

MOP (2010), Mobilitätspanel Deutschland 1994–2010. Tech. Rep., Projektbearbeitung durch das Institut für Verkehrswesen der Universität Karlsruhe (TH) www.mobilitaetspanel.de, accessed January 15, 2015.

NPE (2010). "Nationale Plattform Elektromobilität (NPE): Zwischenbericht der Nationalen Plattform Elektromobilität". Berlin: Gemeinsame Geschäftsstelle Elektromobilität der Bundes-regierung.

Öko-Institut e.V. (2011): Betrachtung der Umweltentlastungspotenziale durch den verstärkten Einsatz von kleinen, batterieelektrischen Fahrzeugen im Rahmen des Projekts "E-Mobility Berlin", Status-Seminar Elektromobilität Berlin-Brandenburg | Florian Hacker, Öko-Institut: Berlin.

Plötz, P., Gnann, T., Kühn, A. and Wietschel, M. (2013): Markthochlaufszenarien für Elektro-fahrzeuge – Langfassung. Studie im Auftrag der acatech und AG7 der Nationalen Plattform Elektromobilität. Fraunhofer ISI, Karlsruhe 2013.

Plötz, P., Gnann, T., Wietschel, M. (2014): Modelling market diffusion of electric vehicles with real world driving data. part i: Model structure and validation. Ecological Economics (107), S. 411–421, doi: 10.1016/j.ecolecon.2014.09.021.

Rogers, E. M. (1962). Diffusion of innovations. Free Press of Glencoe.

Shafiei, E. , Thorkelsson, H., Asgeirsson, E. I., Davidsdottir, B., Raberto, M. and Stefansson, H. (2012). An agent-based modeling approach to predict the evolution of market share of electric vehicles: a case study from iceland. Technological Forecasting and Social Change, 79 (9): 1638–1653, 2012.

TAB (Büro für Technologiefolgen-Abschätzung beim Deutschen Bundestag) (2013): Konzepte der Elektromobilität und deren Bedeutung für Wirtschaft, Gesellschaft und Umwelt (Auto-Ren: Peters, A., Doll, C., Kley, F., Plötz, P., Sauer, A., Schade, W., Thielmann A., Wietschel, M., Zanker, C.). TAB-Arbeitsbericht Nr. 153, Berlin.

US Department of Energy (DOE) and Environmental Protection Agency (EPA) (2014) Fuel economy guide – model year 2014. http://www.fueleconomy.gov/feg/pdfs/guides/FEG2014.pdf.

Wietschel, M.; Plötz, P.; Gnann, T.; Kühn, A. (2013): Markthochlaufszenarien für Elektrofahr-zeuge – Kurzfassung. Studie im Auftrag der Acatech und der Nationalen Plattform Elektromobilität (AG7). Karlsruhe: Fraunhofer ISI.

Yabe, K., Shinoda, Y., Seki, T., Tanaka, H. and Akisawa, A. (2012). Market penetration speed and effects on CO_2 reduction of electric vehicles and plug-in hybrid electric vehicles in Japan. Energy Policy, 45 (0): 529–540, 2012.

Zhang, T., Gensler, S., and Garcia, R. (2011). A study of the diffusion of alternative fuel vehicles: An agent-based modeling approach. Journal of Product Innovation Management, 28: 152–168, 2011.

Annex A – Assumptions for vehicle attributes

Table 5. Technical and economical assumptions for vehicle attributes (all prices without VAT), taken from Plötz et al. (2014).

Parameter	unit	value 2011	development	value 2020
Vehicle market parameters				
vehicle registrations private small	-	486,599	linear	475,309
vehicle registrations private medium	-	710,766	linear	694,275
vehicle registrations private large	-	146,713	linear	143,309
vehicle registrations fleet small	-	238,780	linear	233,240
vehicle registrations fleet medium	-	465,806	linear	454,998
vehicle registrations fleet large	-	47,440	linear	46,339
vehicle registrations fleet LCV	-	204,000	linear	204,000
vehicle registrations company small	-	109,538	linear	106,996
vehicle registrations company medium	-	509,438	linear	497,681
vehicle registrations company large	-	250,372	linear	244,563
Vehicle parameters				
depth of discharge BEV (DoD)	-	0.9	none	0.9
depth of discharge REEV (DoD)	-	0.8	none	0.8
depth of discharge PHEV (DoD)	-	0.75	none	0.75
battery capacity BEV medium	kWh	24	none	24
battery capacity REEV medium	kWh	16	none	16
battery capacity PHEV medium	kWh	10	none	10
conventional consumption Gasoline medium	l/km	0.076	linear	0.065
conventional consumption Diesel medium	l/km	0.060	linear	0.053
conventional consumption PHEV medium	l/km	0.070	linear	0.061
conventional consumption REEV medium	l/km	0.082	linear	0.072
electric consumption BEV medium	kWh/km	0.233	linear	0.211
electric consumption REEV medium	kWh/km	0.233	linear	0.211
electric consumption PHEV medium	kWh/km	0.220	linear	0.198
operations and maintenance cost Gasoline medium	EUR/km	0.048	none	0.048
operations and maintenance cost Diesel medium	EUR/km	0.048	none	0.048
operations and maintenance cost PHEV medium	EUR/km	0.044	none	0.044
operations and maintenance cost REEV medium	EUR/km	0.033	none	0.033
operations and maintenance cost BEV medium	EUR/km	0.040	none	0.040
net list price Gasoline medium	EUR	17,165	linear	17,515
net list price Diesel medium	EUR	19,352	linear	19,702
net list price PHEV medium without battery	EUR	22,116	linear	22,116
net list price REEV medium without battery	EUR	20,983	linear	20,983
net list price BEV medium without battery	EUR	18,042	linear	18,042
vehicle tax Gasoline medium	EUR/yr	95 (2011), 130 (2014)	linear	101
vehicle tax Diesel medium	EUR/yr	191 (2011), 230 (2014)	linear	209
vehicle tax PHEV medium	EUR/yr	34	none	34
vehicle tax REEV medium	EUR/yr	20	none	20
vehicle tax BEV medium	EUR/yr	0	none	0