Working Paper Sustainability and Innovation
No. S 12/2014

**Till Gnann**
**Patrick Plötz**
**André Kühn**
**Martin Wietschel**

# Modelling Market Diffusion of Electric Vehicles with Real World Driving Data

German Market and Policy Options

Fraunhofer
ISI

**Abstract**

Electric vehicles (EVs) have the potential to reduce green house gas emissions from the transport sector. However, the limited electric range of EVs could impede their market introduction. Still some potential users are willing to pay more for EVs. The combined effect of these and other influencing factors as well as the resulting future market evolution are unclear. Here, we study the market evolution of EVs in Germany until 2020. Our results reveal a great deal of uncertainty in the market evolution of EVs due to external conditions and the users' willingness to pay. We find the future share of EVs in German passenger car stock to range from 0.4% to almost 3% by 2020. 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. The high uncertainty of the market evolution implies that policies to foster market diffusion of EVs should be dynamically adaptable to react to changing framework conditions. We find a special depreciation allowance for commercial vehicles and a subsidy of 1,000 Euro as the most effective and efficient monetary policy options.

**Contents**

## 1. Introduction

The reduction of green house gases and the scarcity of conventional energy resources in combination with a drastic increase of mobility demand, especially in the BRICS countries, are the relevant challenges of the mobility sector in the 21st century [1]. Electric vehicles (EV) in combination with renewable energy carriers are one possible solution for these challenges. A standard approach to determine the market penetration of EVs are so-called total cost of ownership (TCO) models [2–4]. A common limitation of such models is the usage of average driving patterns [5]. This could yield misleading results, since individual driving profiles show great variations both between different users as well as from day-to-day for an individual user [6]. Another shortcoming is the limited integration of other decision factors than cost in the vehicle buying decision [7–9].

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 and user behavioural factors as consumer acceptance of this new technology or individual driving behaviour. The difficulty is to include this large variety if input factors into a model and be able to evaluate their contribution to results or suggest policy options consequently. To the best of our knowledge there is no model up to now which copes with all these factors explicitly and uses individual driving behaviour.

In a previous paper we introduced and evaluated a model that comprises the above mentioned factors [10]. In this part we put more emphasis on results and their implications by answering the following research questions: *How will the market for EVs in Germany evolve until 2020? Which factors influence the most and how could policy makers react?* In the following section 2 the model, the driving profiles and the main input data are presented. Section 3 comprises the results of the model application and an analysis of the main determining factors of the EV market penetration as well as of monetary policy options and a discussion of the results. In the final section 4 a summary and conclusions are given.

## 2. Methods and Data

The model ALADIN (**Al**ternative **A**utomobiles **D**iffusion and **In**frastructure) is a market diffusion model which allows to simulate the market diffusion of electric vehicles (EVs) based on a broad data set of user behaviour and has been comprehensively described in [10].

The core element of ALADIN is driving profiles of conventional vehicle users which are simulated as electric vehicles. Based on this simulation the vehicle with

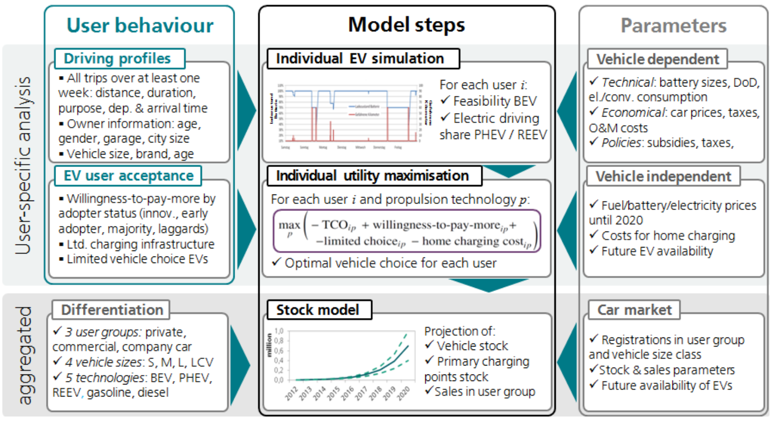


Figure 1: Model structure of ALADIN (**Al**ternative **A**utomobiles **D**iffusion and **In**frastructure). Data for user behaviour which is used in the model and differentiation options in first column, its three calculation steps in second and parameters differentiated by vehicle dependent and independent parameters as well as parameters for car market in third column.

the highest utility to each user is chosen by including the total cost of ownership, the willingness to pay more (in case of an EV), the cost for charging infrastructure and the limited availability of EVs. These steps are assembled individually for each user and aggregated in a simple stock model. 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.

We present the data for user behaviour in the next subsection, briefly describe the model steps in the following and finally introduce the parameters used in the calculations in the last subsection.

### *2.1. User behaviour*

Since driving varies noteworthy between drivers, we consider driving profiles to be appropriate for the representation of individual driving behaviour which has also been done in many other studies [5, 6, 11–13]. 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: small (cubic capacity $\leq$ 1400 ccm), medium (1400 ccm $<$ cubic capacity $\leq$ 2000 ccm), large (2000 ccm $<$ cubic capacity) and for fleet vehicles also light commercial vehicles

| Property | user group | | |
|---|---|---|---|
| | private | company | fleet |
| data source | MOP [14] | | REM2030 [16] |
| data collection | panel survey | | GPS-tracking |
| observation period | 7 | | 20 (on average) |
| no of vehicle profiles | 6,177 | 162 | 435 |
| no of vehicle trips | 168,329 | 4,649 | 60,203 |
| average daily driving | 41.7 km | 83.5 km | 69.7 km |

Table 1: Description of driving profiles used in the model

(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, [14]) 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 (see [6, 10, 15]). The same holds for fleet vehicles where our own collection of commercial driving profiles (REM 2030 driving profiles [16]) is, to the best of our knowledge, the only data set of commercial driving profiles of more than one day observation period for Germany [17].

As MOP is a household travel survey which focuses on people and their trips, we have to assign trips to vehicles if unambiguously possible (see [13, 15] for details). 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. For more details refer to Table 1.

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 [18, 19] and [10] for a detailed description and discussion of the WTPM). Users are grouped according to Roger's adoption groups [20] innovators, early adopter, early and late majority (as one group here) and laggards, while one data set is used for group sizes [21–24] and the other for the magnitude of the WTPM [25, 26]. 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 [27].

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. Formulas for the integration are given in the following section, the parameters used can be found in Table 4. The other explicitly modelled aspect against EVs is the limited choice of EVs available in the market. We use diffusion curves resulting from the EV market announcements for the next years and fit them with logistic curves. A more detailed explanation is given in [10].

### *2.2. Model steps*

The model consists of three steps: (1) the individual EV simulation, (2) the individual utility maximization and (3) the stock model which aggregates the users and estimates vehicle registrations.

In the EV simulation, we simulate the batteries of BEVs, PHEVs and REEVs to determine whether the driver could replace his vehicle by a BEV or which electric driving share would result for the hybrid options based on his driving profile. More specifically we calculate the battery state of charge (SCO) for every point in time as

$$\mathrm{SOC}(t+1) = \begin{cases} \mathrm{SOC}(t) - d_{\Delta t} \cdot c_e & \text{for} \quad d_{\Delta t} > 0 \\ \min\{\mathrm{SOC}(t) + \Delta t \cdot P_{loc_t}, C\} & \text{for} \quad d_{\Delta t} = 0. \end{cases} \tag{1}$$

where the initial value is given by SOC$(0) = C$. SOC$(t)$ denotes the state of charge at time $t$. The distance driven between $t$ and $t + \Delta t$ is given by $d_{\Delta t}$. $c_e$ is the consumption of electric power in kWh/km (depending on the car size), while $P_{loc_t}$ in kW describes the power for charging at the location where the car was parked at $t$ (If no charging infrastructure is available, $P_{loc_t} = 0$). $C$ denotes the net capacity of the battery analysed which is the capacity multiplied by its depth of discharge (DoD). If the car is driven ($d_{\Delta t} > 0$), the battery will be discharged by the energy needed for driving distance $d_{\Delta t}$. Otherwise ($d_{\Delta t} = 0$), it will be charged with the power $P_{loc_t}$ for the time $\Delta t$ if necessary and charging infrastructure is available ($P_{loc_t} > 0$).

Calculating all batteries states of charge for the driving profile, we are able to determine whether the driver is able to perform all his trips with a BEV (i. e. all SOC(t)>0) and which electric driving share a PHEV or REEV would have (i. e. the fraction of all trips with SOC(t)>0 and all trips of the profile).

Based on this first model step, we determine the most beneficial vehicle type from the five propulsion technologies $m$ (Gasoline, Diesel, PHEV, REEV and BEV) for every user $i$:

$$\max_m \Big( -\,\mathrm{TCO}_{im} + \mathrm{WTPM}_{im} - \text{limited choice}_{im} \Big) \tag{2}$$

Thus, we calculate the use for every propulsion technology $(m)$ as the sum of negative total cost of ownership ($\mathrm{TCO}_{im}$), the willingness to pay more ($\mathrm{WTPM}_{im}$) and the limited vehicle choice. Hence we combine monetary and non-monetary factors in a use function measured in EUR/yr. The WTPM and limited choice were explained in the previous section. The TCO are calculated as

$$\mathrm{TCO}_a = a^{\text{capex}} + a^{\text{opex}} \tag{3}$$

and consist of capital ($a^{\text{capex}}$) and operating expenditure ($a^{\text{opex}}$) for the vehicle and, in case of an electric car, for the primary charging point as well.

For the capital expenditure, we use the discounted cash-flow method and calculate the investment annuity for user $i$ as

$$a_i^{\text{capex}} \quad = \quad p\,\frac{\mathrm{LP}_i \cdot (1+p)^{T_1} - \mathrm{SP}_i}{(1+p)^{T_1} - 1} \quad + \quad I_{\mathrm{CI}_i} \quad \cdot \quad \frac{p\,(1+p)^{T_2}}{(1+p)^{T_2} - 1}. \tag{4}$$

In the first term $p$ stands for the interest rate, $\mathrm{LP}_i$ for the net list price for each vehicle and $\mathrm{SP}_i$ for the resale price, while $T_1$ is the vehicle investment horizon for the first vehicle purchase. The second term is for the infrastructure with different investment horizon ($T_2$) to discount the investment for infrastructure ($I_{\mathrm{CI}}$).

The operating expenditure ($a_i^{\text{opex}}$) for user $i$ is calculated as:

$$a_i^{\text{opex}} \;=\; \mathrm{VKT}_i \;\cdot\; \Big( s_i\, c_e k_e \;+\; (1 \;-\; s_i)\, c_c k_c \;+\; k_{\mathrm{OM}} \Big) \;+\; k_{\text{tax}} \;+\; k_{\mathrm{CI}_i}. \tag{5}$$

It consists of driving dependent and driving independent costs. The cost for electric driving consists of the electric driving share ($s_i$), deriving from the first model step, multiplied by the specific consumption for electric driving ($c_e$) in kWh/km and the specific cost for electricity ($k_e$) in EUR/kWh. The conventional driving cost is calculated by multiplying the fraction of conventional driving $(1 - s_i)$, the specific conventional consumption ($c_c$ in l/km), and the specific conventional driving cost for fuel ($k_c$ in EUR/l). By adding the cost for operations and maintenance ($k_{\mathrm{OM}}$) we obtain the specific cost per kilometre which are multiplied by the annual vehicle kilometres travelled ($\mathrm{VKT}_i$) for the driving dependent cost. Driving independent costs consist of annual vehicle tax ($k_{\mathrm{tax}}$) and the running costs for charging infrastructure ($k_{\mathrm{CI}}$).

Parameters vary between user groups and propulsion technologies, e. g. there is no VAT included for fleet vehicles and company cars or the operating expenditure is much simpler for conventional cars as there is no electric driving possible ($s_i = 0$) and charging infrastructure is not necessary ($k_{\mathrm{CI}} = 0$). For more details on this, see [10, 15, 28].

Finally we aggregate the individual analyses in the stock model. As we study three user groups and distinguish between four car sizes there are ten[1] vehicle groups ($l = 1, ..., 10$). Within these user groups we calculate the shares $p_l$ of vehicle types (Gasoline, Diesel, PHEV, REEV and BEV) and multiply them with the total number of vehicles in the group ($n_l$). Thus for every year the registrations are calculated as:

$$N_l(t) = p_l(t) \cdot n_l(t) \tag{6}$$

With the registrations and the surviving probability , we are able to calculate the vehicle stock for every year.

### *2.3. Parameters*

The market diffusion of electric vehicles is influenced by both the framework conditions in general and the parameters depending on the vehicles. 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 remains stable at 3.1 million cars per year until 2020 (i. e. the arithmetic mean of the values for 2007 until 2012, excluding 2009 because of the financial crisis' effects). The segment shares within the new registrations are assumed constant [29, 30]. Today approximately 30% of all new purchased cars are company cars [31, 32]. Combined with [33] the number of new purchased cars

[1] LCVs only considered for fleet vehicles.

per segment and user group (private, fleet and company cars) is obtained (see Table 4).

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 net purchase prices and their time evolution until 2020 (without battery) are taken from [32]. They are in line with the required efficiency gains in conventional vehicles to achieve the EU fleet targets. The combinations of drive trains and segments missing in [31, 32] are calculated based on the existing ratios of gasoline/diesel technology to alternative technology [32]. This leads for instance to slightly higher chassis prices (medium size) of BEVs with 18,000 EUR compared to 17,500 EUR of gasoline vehicles in 2020 (all values in Table 4).[2]

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 result from of a combination of already existing studies (cf. [6, 11, 19, 34]) and are assumed to be of 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).

Fuel costs are the second most important component of the TCO. All values for fuel consumptions are based on [35], 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 [36], these assumptions seem moderate. Note that the values represent real consumption and not driving cycle values. As our model calculates the TCO depending on individual driving behaviour with different shares of electric driving for PHEVs and REEVs, the illustrated conventional values in Table 4 represent a purely conventional operation after having fully depleted the battery, i. e. charge-depleting mode for PHEVs/REEVs.

Maintenance costs also differ among technologies. The simulation of failure probabilities for each drive train component, done in [37], leads to specific maintenance costs for medium sized vehicles while small deviations in battery size of BEV and REEV between our model and [37] lead to minor adaptations. Values for other size classes (gasoline and diesel) rely on [38, 39] and are transferred to the other segments based on [37].

Vehicle taxes are calculated based on the current German tax legislation which

[2]Note that only values for medium sized vehicles are given here. Values for small, large and light-commercial vehicles can be found in [15, p. 144-149].

| Parameter | unit | value 2011 | development | value 2020 | Reference |
|---|---|---|---|---|---|
| Pro-EV scenario | | | | | |
| battery price | EUR/kWh | 698 | exponential | 251 | [19] |
| gasoline price | EUR/l | 1.30 | linear | 1.50 | [40, 41] |
| diesel price | EUR/l | 1.19 | linear | 1.45 | [40, 41] |
| electricity price private car holder | EUR/kWh | 0.218 | linear | 0.244 | [42] |
| electricity price commercial car holder | EUR/kWh | 0.164 | linear | 0.181 | [42] |
| Medium scenario | | | | | |
| battery price | EUR/kWh | 798 | exponential | 281 | [19] |
| gasoline price | EUR/l | 1.30 | linear | 1.39 | [40, 41] |
| diesel price | EUR/l | 1.19 | linear | 1.33 | [40, 41] |
| electricity price private car holder | EUR/kWh | 0.218 | linear | 0.244 | [42] |
| electricity price commercial car holder | EUR/kWh | 0.164 | linear | 0.181 | [42] |
| Contra-EV scenario | | | | | |
| battery price | EUR/kWh | 898 | exponential | 311 | [19] |
| gasoline price | EUR/l | 1.30 | linear | 1.29 | [40, 41] |
| diesel price | EUR/l | 1.19 | linear | 1.20 | [40, 41] |
| electricity price private car holder | EUR/kWh | 0.218 | linear | 0.277 | [43] |
| electricity price commercial car holder | EUR/kWh | 0.164 | linear | 0.210 | [43] |

Table 2: Scenario-specific parameters used in the model ALADIN. All prices without VAT.

complete tax exemption for BEV owners. Variations of the tax legislation are considered within the framework of different policy measures (see chapter 3.3).

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 if it is parked at a private household or at the company site.

As we know from socio-demographics of [14] where private and company cars are usually parked overnight, we may 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 (see Table 4).

For battery prices, as well as electricity and fuel prices, we define three scenarios, which are summarised in Table 2. 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 [19](all values without VAT). Prices for diesel and gasoline are equal for all scenarios in 2011 based on [41]. The development until 2020 is based on the New Policy Scenario in [40] 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 [42] and a greater rise in the contra-EV scenario [43].

## 3. Market diffusion and analysis of determinants

After the description of model, data and parameters, we now turn to the results. In the following first subsection, we will take a look at the market diffusion followed by a deeper analysis of the determinants in the second. The third subsection holds analyses and implications for policy makers, while the fourth discusses the results.

### *3.1. Market diffusion*

The subsection for market diffusion is subdivided into an analysis of TCO gaps between electric and conventional vehicles and the results of market diffusion in the three scenarios.

#### *3.1.1. TCO gaps of electric and conventional vehicles*

The TCO of each propulsion technology for the individual user with his driving behaviour forms an important part of her or his buying decision. To demonstrate the wide range of TCOs for different users and the importance of the individual user behaviour, we analyse the TCO gaps between the different drive trains.

To start with, it should be noted that there are many individual TCO gaps (differences in the TCO between the drive systems) due to the large number of driving profiles, some of which have very different utilization patterns. With approximately 6,700 driving profiles, five drive trains and ten years of observation we obtain about 330,000 individual TCO. However, most important for the decision in favour of or against an EV is the TCO difference between the cheapest conventional and the cheapest electric vehicle type. In the following, TCO gap or TCO difference will denote the difference in TCO between the cheapest EV and the

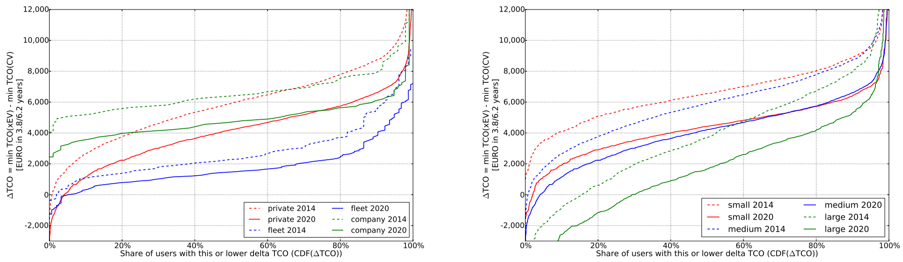


Figure 2: Difference between total cost of ownership between electric and conventional vehicle including the cost for vehicle and charging infrastructure. The difference is shown on the abscissa while the share of driving profiles if given on the ordinate. Graphs are shown as cumulative distribution functions. *Left panel:* Results for medium-sized cars. Private vehicles in red, fleet vehicles in blue and company cars green. Values for 2014 dashed and for 2020 in solid lines. *Right panel:* Results for private cars. Small vehicles in red, medium vehicles in blue and large vehicles green. Values for 2014 dashed and for 2020 in solid lines.

cheapest conventional vehicle, i.e. $\Delta\mathrm{TCO} \equiv \min_{p\in\mathrm{EV}} \mathrm{TCO}_p - \min_{p\in\mathrm{CV}} \mathrm{TCO}_p$ where $\mathrm{EV} = \{\text{BEV, PHEV, REEV}\}$ and $\mathrm{CV} = \{\text{gasoline}, \text{diesel}\}$. Since regular charging is required for EVs, we include the costs for the home charging option in the EV TCO for the following discussion and the results in Figure 2.

The individual TCO gaps are plotted against the share of vehicles with this or a smaller TCO gap (see Figure 2). The Figure shows these TCO gaps in ascending order on the y-axis with the share of users respectively driving profiles on the x-axis which have this or a smaller TCO gap. The graph corresponds statistically to a relative cumulative frequency distribution or empirical cumulative distribution function [44]. One advantage of this representation is statistical robustness.

Figure 2 demonstrates that electric vehicles are economically efficient for some users already today and display a rising tendency to be so in the future. The annual mileage is decisive here. At low mileages, gasoline cars continue to dominate because EVs are not able to compensate for their higher purchasing costs via their cheaper running costs per kilometre. At very high mileages, in contrast, diesel engines are the most cost-efficient option, because PHEV or REEV have to use their combustion engines too often and battery electric vehicles are unfavourable because of their limited range. Again, the electric driving share together with the annual mileage is decisive for the difference in TCO of each user. Sufficient annual mileage on its own is not enough.

For example, Figure 2 shows that the driving behaviour of 20% of the private users of small cars in 2014 (dotted red line) has an overall TCO gap of approximately 4,800 EUR or less (over the total ownership period which is 6.2 years for private drivers). This TCO gap decreases up to 2020 such that 20% of the users of private small cars in 2020 have a TCO gap of around 3,000 Euro or less. It can also be seen from Figure 2 that a proportion of the users in 2020 has a TCO gap less than or equal to zero. This means that an electric vehicle is more cost-effective in total for some users.

The large span of TCO differences is also visible in the two panels of Figure 2 and ranges from -3,000 EUR over 6.2 years to more than 10,000 EUR over 6.2 years. In addition, it is also apparent that large passenger cars have the highest economic attractiveness in all three user groups. The economic attractiveness is also higher among private owners than in the other two user groups as VAT plays a role alongside driving profiles. Because VAT has to be paid on fuels by private users, the consumption savings between EV and conventional engine systems per kilometre driven are higher for private than for commercial users.

When comparing the graphs of the three groups (left panel of Figure 2), it is noticeable that the curve of private users is the steepest and that of commercial fleets the flattest. There are several reasons for this: first, the effect of VAT, which has already been mentioned. Additionally, commercial users tend to have more uniform driving profiles and make long trips more rarely. As a result, the electric driving shares within this group tend to be similar compared to private users, and especially when compared to company car drivers. In addition, the depreciation options for commercial drivers have the effect that the gaps in the TCO shrink on account of the tax savings. A comparison of the TCO gaps in 2014 with those in 2020 reveals that only a very low potential for EVs exists under the assumptions made in 2014, but that it increases steadily over time.

Besides the purely economic substitutability, the analyses of the driving profiles and TCO gaps show that many drivers could achieve comparatively high electrical driving shares and have lower TCO for an EV than compared to their cheapest conventional vehicle. Many of these users can be expected to buy an EV. The next section shows the resulting market diffusion of EVs when the limited availability of models and the willingness to pay more of some users are additionally taken into account.

#### *3.1.2. Market diffusion scenarios*

For market diffusion we defined three different scenarios in section 2.3. The results for EV market diffusion can be found in Figure 3. It shows the total number of electric vehicles on the ordinate over the years from 2011 until 2020 on the abscissa. Results are shown for the contra-EV scenario in red, the medium scenario in blue and the pro-EV scenario in green with 10% to 90%-confidence bands due to limited sample size (cf. [10] for details). Within the 10%-confidence band we find 100,000 to 300,000 for the contra-EV scenario ($\approx$0.4% of the German passenger car stock), 500,000 to 800,000 for the medium scenario ($\approx$1.5%) and 1.1

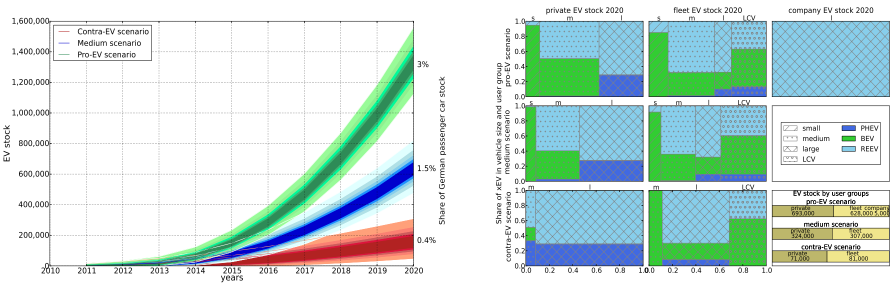


Figure 3: Results for the three market diffusion scenarios for Germany. *Left panel:* Shown are the years on the ordinate and the total electric vehicle stock on the abscissa. Results are shown with 10%, 30%, 50%, 70% and 90% confidence bands (cf. [10]), contra-EV scenario in red, medium scenario in blue and pro-EV scenario in green. EV share of the German passenger car stock on the right. *Right panel:* Distribution of vehicle share in stock. Shown are private vehicles in the first column of graphs, fleet vehicles in the second and company cars in the first line of the third column, while the pro-EV scenario is shown in the first row, medium scenario in the second and contra-EV in the third row. Each subgraph shows the distribution of EVs in stock according to vehicle size on ordinate (small with dashes, medium with dots, large with crosses and LCV with circles) and the share of the different electric vehicles on the ascissa (PHEV in dark blue, BEV in green, REEV in light blue). The lower right subplot gives an overview of the EV stock distribution to user groups (private in dark khaki, fleet in light khaki, company in blue).

to 1.5 million EVs for the pro-EV scenario (≈3.0%). These broad ranges arise from limited data samples that are considered as well as their error propagation over the years. The large differences between the three scenarios also show the influence of the input parameters as even small changes within the main drivers may change results significantly. We may also observe that market diffusion starts with high penetration rates (more than 5% of total market shares) from 2016/2017 on in the medium and pro-EV scenario, which derives from the limited availability of electric vehicles as well as the decreasing prices.

As mentioned in the previous section there is a large share of vehicles that have lower total costs of ownership for electric vehicles (especially large vehicles). We may observe this in the right panel of Figure 3 where the distribution of EVs to user groups, vehicle sizes and EV types in the three scenarios is shown. The first column of subplots shows private vehicles, the second fleet and in the first row of the third column company cars are shown. The rows stand for the scenarios: the first row is the pro-EV scenario, the second the medium scenario and the third row is the contra-EV scenario. These subplots show the distribution of the EV stock to vehicle sizes on the ordinate and the allocation to EV types within this group on the abscissa. We may read this as follows: There are about 55% of large private electric vehicles in the medium scenario of which some 25% are PHEVs and 75%

are REEVs. Thus in the medium scenario $55\% \cdot 75\% \approx 41\%$ of the private electric vehicle stock are large REEVs. This means the size of the area within this user group and scenario can directly be compared. Since there are no company EVs in the medium and contra-EV scenario, we use the bottom right subplot to show the share of EV user groups within the three scenarios in vehicle stock. As they are almost equally distributed between private and fleet vehicles, with a very small share of company cars in the pro-EV scenario, we may also compare the areas of private and fleet vehicles within one scenario.

As aforementioned, there are high shares of large electric vehicles for private users in all scenarios which tend to be even larger the worse market conditions are (contra-EV) which results from high possibilities to economise for large vehicles. These large private electric vehicles are distributed to about one quarter PHEVs and three quarters REEVs in all scenarios. The fastest growing private EV group from contra-EV to pro-EV scenario are medium sized vehicles. There is only 10% in the contra-EV scenario and almost 50% in the pro-EV scenario including a shift from PHEVs to BEVs. Within private vehicles there is a little less than 10% of small BEVs in the medium and a little more than 10% in the pro-EV scenario (including some small REEVs). For fleet vehicles we see almost the same shares of small vehicles within EVs in all scenarios with slightly more REEVs. Besides the light commercial vehicles which are only within this user group, we also observe the same tendencies (growing numbers of smaller vehicles and increasing number of BEVs towards the more EV-favouring scenarios) with a little less large hybrids on behalf of large BEVs. The share of LCVs within commercial EVs and the distribution within this group tends to stay equal and almost scenario-independent. Within the pro-EV scenario there is a very small quantity of large REEVs which will be exempted from the further analysis (due to larger uncertainties).

Thus we may retain that (1) we find a large influence of the scenario parameters, which change results significantly when changed altogether; (2) there is a large number of private and fleet driving profiles for which electric vehicles are, according to the model, a utility maximising solution resulting in high EV market shares (4% in the medium scenario in 2020); (3) although the availability is especially limited for large electric vehicles, the highest market potential lies within this vehicle size as it has the highest possibility to economise. (4) And finally, we find high shares of REEVs and PHEVs compared to BEVs because of some exceptional long trips that users might not fulfil with pure BEVs.

Considering the first point in this summary, we take a closer look at the determining factors of the EV market diffusion in the following section.

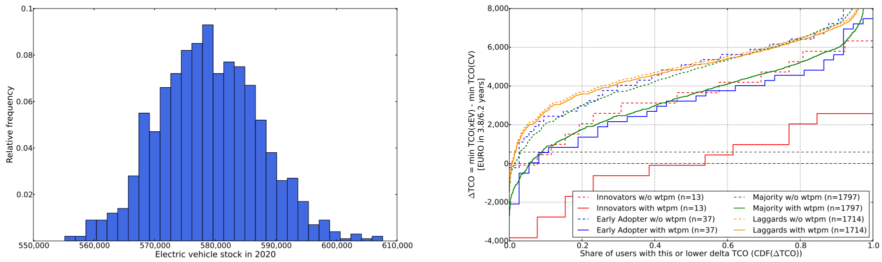


Figure 4: Influence of willingness to pay more (WTPM). *Left Panel:* Histogram of 1,000 simulations with a random allocation of the WTPM to the driving profiles. *Right Panel:* Difference between total cost of ownership between electric and conventional vehicle including the cost for vehicle and charging infrastructure. The difference is shown on the abscissa while the share of driving profiles if given on the ordinate. Graphs are shown as cumulative distribution functions and differentiate between adopter groups and if WTPM is considered (solid) or not (dashed). Innovators in red, early adopters in blue, majority in green and laggards in yellow.

### *3.2. Analysis of determinants*

The influence of individual factors is important for policy recommendations but obscured in scenarios in which several parameters change simultaneously. We thus study the influence of non-monetary factors (described in section 2.2) and monetary parameter variations individually. In these sections, we refer to the medium scenario.

#### *3.2.1. Influence of non-monetary factors*

In this subsection we compare the results to those without any favouring or obstructing non-monetary factors, i. e. the pure TCO-based results. For market diffusion including all non-monetary factors, we obtain about 630,000 EVs in the medium scenario compared to 250,000 EVs in the pure-TCO results. Remembering that we include the TCO for the primary charging point as well as brand loyalty and limited availability as obstructing factors, the willingness to pay more (WTPM) is the only favouring factor here. Thus the obstructing factors which reduce the pure TCO-results by about a third are overcompensated by the favouring factors in the model.

We discussed the sense of a WTPM as well as the allocation of the private WTPM data to the driving profiles in [10] and concluded that the allocation is slightly better than a random allocation. Nonetheless we want to understand the implication of a random allocation to market diffusion. Thus we randomly assign the WTPM to all private users in the driving profiles and run the simulation 1,000 times. The results are shown in the histogram in the left panel of Figure 4.

It shows the frequency (abscissa) of the total electric vehicle stock (ordinate) in 2020. We find an arithmetic average value of 579,000 EVs while the median is about the same (578,800 EVs). Also the first and third quartile (573,100 and 584,800 EVs) show a very narrow interquartile distance (11,700 EVs) and thus imply a robust result. The question on hand is, why there is a difference of about 60,000 EVs between these results and the structured allocation of WTPM to driving profiles which leads us to the right panel of Figure 4.

The right panel of Figure 4 uses the same illustration as Figure 2: we find the TCO gap between the cheapest electric and conventional vehicle on the abscissa and the share of users with this or a lower TCO gap on the ordinate, i. e. a cumulative distribution function for 2020. Instead of two years (as in Figure 2) we show the TCO-results for medium-sized private vehicles with (solid) and without the WTPM (dashed) for the four adopter groups (innovators (red), early adopter (blue), majority (green) and laggards (yellow)). We also indicated the average WTPM over all user groups in 2020 of 626 EUR. Note that for users who are more willing to adopt (i. e. earlier users according to the adopter classification) the TCO-gap-curve is further right and thus their EV market share is higher independent of the inclusion or exclusion of the WTPM. This means that not only their higher WTPM is favourable for EV adoption, but also their driving behaviour.

We can now compare the market shares between a random and a non-random allocation. For the innovators' group, we would receive a market share of 55% in 2020 for the non-random (intersection of solid red function and zero) and 8% for the random allocation (intersection of dashed red curve and $\Delta$TCO=626). The difference of 47% multiplied by the profile share (13 out of 3,561 profiles $\approx$ 0.37%) results in a market share difference of 0.17% in 2020 or 1,200 EVs. By performing similar steps for the other adopter groups and summing up all differences for the medium-sized vehicles this leads to a change of 1.71% or 11,900 vehicles. Thus, the difference in EV sales in 2020 according to the model between a random and a non-random allocation is about 11,900 EVs. For all sizes of EVs in 2020 this means a change of 17,500 vehicles (or 1.33% on weighted average) and by summing up all differences over the years, we receive the 60,000 vehicle-delta.

To conclude, we observe a noteworthy impact of the allocation of the WTPM on driving profiles. The users that have the smallest $\Delta$TCO also have the largest WTPM for electric vehicles.

### *3.2.2. Sensitivities to parameter variation*

We now turn to the influence of the monetary input parameters which are examined in a sensitivity analysis for single parameters and a monte-carlo-simulation for the robustness of results. In the left panel of Figure 3 the influence of single parameter changes is shown in relation to the total electric vehicle stock in 2020.

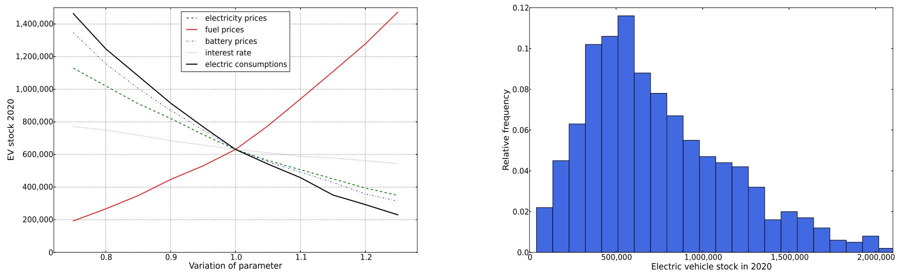


Figure 5: Sensitivities to parameter variation. *Left panel:* Shown is the influence of a variation of one single parameter on the total EV stock. The variation of parameters is shown as percentage for every single parameter on the ordinate and the total EV stock on the abscissa. Electricity prices in blue, fuel prices in red, battery prices in yellow, interest rates in green and electric consumptions in black. *Right panel:* Shown is the electric vehicle stock on the ordinate and its absolute frequency on the abscissa resulting from a random variation of fuel, electricity and battery prices.

On the ordinate a parameter change from 75% of the original value up to 125% is shown, while the abscissa shows the resulting total electric vehicle stock in 2020. We changed electricity prices (dashed green), fuel prices (solid red), battery prices (dash-dotted blue), interest rates (dotted light blue) and electric consumptions (solid black). Within the parameters we only changed the values for 2020 and adjusted the slopes from the 2011 values. We also changed the price of electricity for private households and commercial users in the electricity price sensitivity, the diesel and gasoline price in the fuel price sensitivity, the interest rates for private and commercial users in the interest rate sensitivity and finally all electric consumptions in the last sensitivity.

There are some clear and expected results: We find higher numbers of electric vehicles with increasing fuel prices and lower EV numbers when fuel prices decrease. For all other parameters changed, lower values lead to higher market shares, e. g. there are more electric vehicles in stock in 2020 when batteries are cheaper or the electricity price is lower. As investments for EVs are higher than for conventional vehicles, a decreasing interest rate is naturally favourable. More interesting is the magnitude of changes caused by parameter variation: We find the highest influences in fuel prices and electric consumption (+800,000 EVs) which seem almost mirrored in the upper part of the Figure, while very low fuel prices decrease the EV stock 2020 even further than very high electric consumptions (-400,000 EVs). The third most important input factors are the battery price and electricity prices (+700,000 for low battery, +500,000 for low electricity prices and -300,000 for rising prices). The lowest influence is found for changes in the interest rates (± 125,000 EVs with a parameter change of ± 25%).

Results of the monte-carlo-simulation can be found in the histogram in the right panel of Figure 5. On the ordinate the total EV stock in 2020 is shown, on the abscissa we find the number of simulation runs with this result, when we randomly change the fuel, electricity and battery prices 1,000 times. We use a normal distribution $\mathcal{N}(\mu, \sigma^2)$ for the parameter variation with the value of the medium scenario as $\mu$ and the maximum of the differences between the pro-EV and medium or contra-EV and medium scenario as $\sigma$ for the random variation of parameters.

We can observe that model results range from 50,000 to 2.2 million EVs in 2020, while the average is about 750,000 and the median 643,500 electric vehicles. The first quartile is at 443,000 EVs, the third at 995,000, resulting in an interquartile range of 552,000 electric vehicles. Thus the medium range of most results is not as wide as suggested by the scenarios. Also the medium scenario is very close to the median.

From the results in this subsection, we can retain that (1) the market evolution of EVs is susceptible to changes in fuel prices and electricity consumption, followed by battery and electricity prices. (2) Sensitivity analysis shows that an increase or decrease of the main influence factors by 25% can result in doubling the EV stock in 2020 or cutting it by about 60%. (3) From the monte-carlo-simulation, we can see that good conditions favour the EV market evolution more than bad conditions hamper it.

### *3.3. Policy options and implications*

The high uncertainty of the EV market solution necessitates policy options which can dynamically be adapted depending on framework conditions. We thus discuss different policy measures which are already effective in some countries. All of those potential measures were discussed during different workshops with stakeholders from policy and industry to decide on their configuration. The following economic policy measures were selected and their influence on the market diffusion is calculated:

1. Purchase price reduction. Target group: all users; a flat-rate, one-off subsidy of the investment; two variants: (a) 1,000 EUR in 2013 with a linear decline to 300 EUR until 2020 and (b) 2,000 EUR in 2013 decreasing to 600 EUR.
2. Lowering the interest rate for private car buyers. Target group: private users; special loans (lowering the interest rates on the investment from 5% to 4%).
3. Taxation of company cars. Target group: company cars; measure of the German Finance Act of 2013; reduction of the gross list price depending on the battery size; linear temporal development from 500 EUR/kWh(2013) to 150 EUR/kWh(2020).

| Policy option | EV stock 2020 | | subsidy | | | windfall gains |
|---|---|---|---|---|---|---|
| | total | increase | total | per EV user | per add. EV user | |
| *Units* | *EVs 2020* | - | *mln. EUR* | *EUR/EV-user* | *EUR/EV-user* | *mln. EUR* |
| Medium scenario | 631,000 | 0 | 0 | 0 | 0 | 0 |
| (1a) Flat-rate subsidy of EUR 1,000, decreasing | 1,118,000 | +77% | 744 | 666 | 1,529 | 381 |
| (1b) Flat-rate subsidy of EUR 2,000, decreasing | 2,128,000 | +237% | 3,224 | 1,515 | 2,153 | 762 |
| (2) Lowering private interest rate on investment | 1,143,000 | +81% | 2,493 | 2,182 | 4,873 | 644 |
| (3) Changing the taxation of company cars | 631,000 | 0% | 0 | 0 | 0 | 0 |
| (4) Special depreciation for commercial vehicles | 1,006,000 | +59% | 831 | 826 | 2,216 | 414 |
| (5) Special depreciation & company car taxation | 1,035,000 | +64% | 871 | 842 | 2,158 | 414 |
| (6) Tax exemption for PHEV, REEV | 685,000 | +9% | 68 | 99 | 1,248 | 34 |

Table 3: Financial policy options modelled: Shown are the EVs in 2020 resulting from the policy option and changes compared to medium scenario as well as necessary investments and windfall gains.

4. Special depreciation. Target group: company cars and fleets; 50% of the depreciation amount in the first year.
5. Taxation of company cars and special depreciation. Target group: company cars and fleets; combination of the two measures mentioned above.
6. Vehicle tax reduction (PHEV, REEV). Target group: all users; BEV already completely tax-exempt; elimination of the base amount based on engine size for REEV and PHEV.

Table 3 summarises the impacts of the individual measures on the stock of electric vehicles in 2020 and the increase compared to the medium scenario. Also the amount of subsidies needed in total, per EV user and per additional EV user is shown. Finally, there is the windfall gain effects, i. e. the amount of money that is paid to users that would also buy an EV without this policy measure.

The policy measures relate to both, private and commercial users. Despite similar subsidy concepts used for both user groups, the effects on private and commercial users are quite different. Taking a closer look at the effects on the total number of EVs in 2020, the flat-rate subsidy seems to be the most effective measure for private vehicles. As the absolute price reduction remains the same within all segments, the benefits of small vehicle buyers are higher. As the flat-rate subsidy is granted to private and commercial users both groups profit. Lowering the private interest rate on the investment (purchase price) for the electric vehicles means that larger segments will get higher absolute price reductions compared to the smaller segments. That explains a similar total effect on the fleet of both measures ((1) and (2)) combined with higher cost per vehicle for a lower private interest rate. The tax exemption for PHEV and REEV (6) with relatively low costs increases the EV stock only by 10% in 2020. A comparison of the policy measures stimulating the commercial EV stock development leads to the substantial insight that a special depreciation for commercial vehicles (4) seems to be the most effective measure.

Both, the relative increase of the EV stock and the subsidies per EV user are comparable to the flat-rate subsidy for private and commercial users (1). It is also remarkable that the windfall gain effects as well as the total amount of subsidies are nearly on the same level. Changes in company car taxation (3) do not retain any effect. The reason for this is the complexity of the decision process within this user group. On the one hand the company has to decide on which types of vehicles the company fleet should consist of. This decision is normally motivated by a mixture of economic reasons, marketing decisions and human resource management. On the other hand, users choose their vehicles from a company specific selection of cars. As our model combines the TCO of both, the company and the private user, changes in the company car taxation have no remarkable influence on the EV stock. The same holds for policy option (5) with a combination of special depreciation and changes in company car taxation. Those effects will always occur if buyers purchase an electric car even without subsidies and therefore profit from additional monetary advantages.

The results of all policy measures show that even small financial incentives in the commercial sector can be sufficient to significantly increase the number of EVs in the stock of vehicles which we already observed in the TCO gap analysis in section 3.1.1. Besides, the growth of the EV-fleet due to the special depreciation, the lower TCO-gaps of the commercial owners also lead to greater effects on the flat-rate subsidies (1,000 and 2,000 EUR) compared to private owners.

### *3.4. Discussion*

The results of our model are exposed to a number of uncertainties: (a) an inherit model design uncertainty, (b) an uncertainty caused by parameters and (c) an uncertainty due to the data used in the model. While we focussed on uncertainties based on model design in [10, sec. 4.1], we address the parameter uncertainty with scenarios (3.1.2) and a sensitivity analysis (3.2.2) as well as the data uncertainty by showing the influence of sample size with confidence bands (see also [10, sec. 4.3]) and the analysis of the WTPM (3.2.1). Thus we addressed all possible uncertainties within the both papers.

Although we use a very small variety between scenarios the influence of monetary parameters is noteworthy. This results from very small differences between propulsion technologies which is visible in the TCO gap analysis (3.1.1), especially for fleet vehicles, on which parameters have a large influence. Further research should thus focus on fleet vehicles and their buying decision since they are the group which influences results the most.

User acceptance has a large impact on market diffusion but is difficult to measure and predict. However, surveys clearly show that some user groups are willing to pay a premium for the new technologies in general and EVs in particular. Thus, the inclusion of a higher willingness to pay of some users is necessary to model future market diffusion of EVs. Future research should put emphasis on retrieving more quantifiable data for the WTPM, especially for its evolution over time. Besides, the connection between the WTPM and the driving profiles has large influence on the market evolution (3.2.1) although its allocation is only slightly statistically significant [10, sec. 4.5]. The connection between the two could also be interesting for further analysis.

We analysed several monetary policy options in section 3.3. Besides those, policy measures like emission based tolls (both, in inner cities and on motor-ways) and the reduction of parking fees for electric vehicles in inner cities are possible but difficult to integrate in a TCO-based model as the share of motorway and inner city trips is missing as well as information about parking behaviour. Incentives for longer charging periods and other subsidies concerning the public charging network are not considered as well. Policy measures changing the current tax legislation are not taken into account as such changes seem to be quite unlikely in the medium term (until 2020). The additional macroeconomic effects of all the measures (e.g. changes in employment, growth or decline of the gross value added) are beyond the scope of this paper.

Still, we may retain several robust results on EV market evolution and their influence factors as the monte-carlo-simulations prove (3.2.1 and 3.2.2) which are summed up in the following last section.

## 4. Summary and Conclusions

The present paper analysed the market evolution of electric vehicles in Germany until 2020. An analysis of the main monetary and non-monetary influence factors was followed by the effects of monetary policy options. The user-specific potential for electric vehicles was ascertained by considering several thousand real-life driving profiles of conventional cars, as well as technical, economic and user behavioural data for different scenarios. Factors which can hinder the diffusion of electric cars, their restricted driving range, for example, or the limited offer of models, were integrated as supporting factors in the form of the willingness to pay more for an innovative technology.

Our results demonstrate a great deal of uncertainty surrounding the market evolution of EVs because it depends heavily on external framework conditions such as price developments for batteries, crude oil and vehicle consumptions, which may double results with small changes ($\pm$25%) of relevant input parameters. Also non-monetary factors do have meaningful influence as e. g. the willingness to pay more for a new technology may cut the EV stock in 2020 to half when it is not reflected. This large influence of monetary and non-monetary factors necessitates policy measures which are easily adaptable.

Nevertheless, the target of the German government of one million electric cars by 2020 can be reached under favourable conditions for electric cars without monetary support for the purchase of EVs. Even under less favourable conditions, a significant number of electric cars should be able to enter the market by 2020 (about 0.4% of the total vehicle stock). Significant market growth can be achieved in commercial fleets with comparatively modest financial support. Special depreciation allowances or a purchase subsidy (of 1,000 EUR, decreasing) seem the most appropriate instrument here. Thus, research and policy support should focus more on commercial vehicles to gain relevant EV market shares.

Our results suggest a high share of plug-in hybrid and range-extended electric vehicles which might derive from the strict exclusion of BEVs, if they cannot perform all of their driving electrically. In further analyses we could loosen this restriction by adding the possibility to use rental or car-sharing vehicles for long-distance trips [45] or by including public charging facilities into the model, which could also help to increase the user acceptance.

**Acknowledgement**

The authors would like to thank Elisabeth Dütschke, Julia Michaelis and Simon Funke for stimulating discussions and support. The research was made possible as part of the REM 2030 project, which is funded by the Fraunhofer Society and the federal state of Baden-Württemberg as well as part of the project ”Market evolution scenarios for electric vehicles” commissioned by acatech - German National Academy of Science and Engineering and Working Group 7 (AG 7) of the German National Platform for Electric Mobility (NPE).

**References**

[1] S. Kahn Ribeiro, S. Kobayashi, M. Beuthe, J. Gasca, D. Greene, D. S. Lee, S. Muromachi, P. J. Newton, S. Plotkin, D. Sperling, R. Wit, and P. J. Zhou. Transport and its infrastructure. Technical report, Working Group III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change [B. Metz, O.R. Davidson, P.R. Bosch, R. Dave, L.A. Meyer (eds)], Cambridge, United Kingdom and New York, NY, USA, 2007.

[2] C. Thiel, A. Perujo, and A. Mercier. Cost and {CO2} aspects of future vehicle options in europe under new energy policy scenarios. *Energy Policy*, 38(11):7142 – 7151, 2010. Energy Efficiency Policies and Strategies with regular papers.

[3] McKinsey & Company. A portfolio of power-trains for europe: a fact-based analysis - the role of battery electric vehicles, plug-in hybrids and fuel cell electric vehicles. Technical report, 2011.

[4] S. Pfahl, P. Jochem, and W. Fichtner. When will Electric Vehicles Capture the German Market? And Why? In *Proceedings of Electric Vehicle Symposium 27 (EVS 27)*, Barcelona, Spain, 11 2013.

[5] P. Mock, D. Hülsebusch, Ungethüm J., and S. A., Schmid. Electric vehicles - a model based assessment of future market prospects and environmental impacts. In *Proceedings of Electric Vehicle Symposium 24 (EVS 24)*, Stavanger, Norwegen, May 2009.

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

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

[8] M. G. Mueller and P. de Haan. How much do incentives affect car purchase? Agent-based microsimulation of consumer choice of new carsPart I: Model structure, simulation of bounded rationality, and model validation. *Energy Policy*, 37(3):1072–1082, 2009.

[9] P. de Haan, M. G. Mueller, and R. W. Scholz. How much do incentives affect car purchase? Agent-based microsimulation of consumer choice of new carsPart II: Forecasting effects of feebates based on energy-efficiency. *Energy Policy*, 37(3):1083–1094, 2009.

[10] P. Plötz, T. Gnann, and M. Wietschel. Modelling Market Diffusion of Electric Vehicles with Real World Driving Data – Part I: Model structure and validation. Submitted Paper, Preprint: `http://www.isi.fraunhofer.de/isi-media/docs/e-x/de/working-papers-sustainability-and-innovation/WP04-2014_Modelling-Market-Diffusion-of-EVs.pdf`.

[11] F. Hacker, R. Harthan, P. Kasten, C. Loreck, and W. Zimmer. Marktpotenziale und $CO_2$-Bilanz von Elektromobilität - Arbeitspakete 2 bis 5 des Forschungsvorhabens OPTUM: Optimierung der Umweltentlastungspotenziale von Elektrofahrzeugen. Annex to final report. Funded by the Federal

Ministry of Environment, Nature Conservation and Nuclear Safety, Öko-Institut, Freiburg, Berlin, October 2011.

[12] P. Plötz, T. Gnann, and M. Wietschel. Total ownership cost projection for the german electric vehicle market with implications for its future power and electricity demand. Dresden, April 2012.

[13] F. Kley. *Ladeinfrastrukturen für Elektrofahrzeuge - Analyse und Bewertung einer Aufbaustrategie auf Basis des Fahrverhaltens*. Fraunhofer Publishing, Karlsruhe, June 2011.

[14] MOP. Mobilitätspanel Deutschland 1994-2010. Technical report, Project cunducted by the Institute for Transport Studies at the Karlsruhe Institute of Technology (KIT). Available at: www.clearingstelle-verkehr.de, 2010.

[15] P. Plötz, T. Gnann, M. Wietschel, and A. Kühn. Markthochlaufszenarien für Elektrofahrzeuge Langfassung. Commissioned by acatech - German National Academy of Science and Engineering and Working Group 7 of the German National Platform for Electric Mobility (NPE), 2013.

[16] Fraunhofer ISI. REM2030 Driving Profiles Database V2013. Technical report, Fraunhofer Institute of Systems and Innovation Research ISI, Karlsruhe, 2014.

[17] T. Gnann, M. Haag, P. Plötz, and M. Wietschel. Market potential for electric vehicles in the German commercial passenger transport sector. In *Proceedings of Electric Vehicle Symposium 27 (EVS 27)*, Barcelona, Spain, 11 2013.

[18] P. Mock. *Entwicklung eines Szenariomodells zur Simulation der zukünftigen Marktanteile und $CO_2$-Emissionen von Kraftfahrzeugen (VECTOR21)*. PhD thesis, University of Stuttgart, Stuttgart, October 2010.

[19] S. Pfahl. 4. Alternative Antriebskonzepte: Stand der Technik und Perspektiven–Die Sicht der Automobilindustrie. In *Alternative Antriebskonzepte bei sich wandelnden Mobilitätsstilen: Tagungsbeiträge vom 08. und 09. März 2012 am KIT, Karlsruhe, KIT Scientific Publishing*, pages 81–108. Jochem, Patrick and Poganietz, Witold-Roger and Grunwald, Armin and Fichtner, Wolf, 2013.

[20] E. M. Rogers. *Diffusion of innovations*. Free Press of Glencoe, 1962.

[21] M. Wietschel, E. Dütschke, S. Funke, A. Peters, P. Plötz, U. Schneider, A. Roser, and J. Globisch. Kaufpotenzial für Elektrofahrzeuge bei sogenan-

nten "Early Adoptern". Final report, Fraunhofer ISI, IREES GmbH, Karlsruhe, 2012.

[22] A. Peters and J. Hoffmann. Nutzerakzeptanz von Elektromobilität: Eine empirische Studie zu attraktiven Nutzungsvarianten, Fahrzeugkonzepten und Geschäftsmodellen aus Sicht potenzieller Nutzer. Technical report, Fraunhofer ISI, Karlsruhe, 2011.

[23] A. Peters, A. Agosti, M. Popp, and B. Ryf. Electric mobility – a survey of different consumer groups in Germany with regard to adoption. Technical report, Belambra Presqu'Île de Giens, France, June 2011.

[24] E. Dütschke, U. Schneider, A. Peters, A.-G. Paetz, and P. Jochem. Moving towards more efficient car use – what can be learnt about consumer acceptance from analysing the cases of LPG and CNG? Technical report, Belambra Presqu'Île de Giens, France, June 2011.

[25] J. Wesche. Nutzerakzeptanz von Stromladetarifen im Bereich der Elektromobilität. Master's thesis, Kassel University and Fraunhofer ISI, 2013.

[26] E. Dütschke, A.-G. Paetz, and J. Wesche. Integration Erneuerbarer Energien durch Elektromobilität? Inwieweit sind Konsumenten bereit, einen Beitrag zu leisten? *uwf UmweltWirtschaftsForum*, 21:233–242, 2013.

[27] Dataforce Verlagsgesellschaft für Business Informationen. Elektrofahrzeuge in deutschen Fuhrparks  Zur künftigen Bedeutung von Elektrofahrzeugen in deutschen Flotten, 2011.

[28] M. Wietschel, P. Plötz, A. Kühn, and T. Gnann. Market evolution scenarios for electric vehicles - summary. Commissioned by acatech - German National Academy of Science and Engineering and Working Group 7 of the German National Platform for Electric Mobility (NPE), 2014.

[29] KBA. Federal Motor Transport Authority (KBA): Registrations of passenger cars 2001 - 2012 distinguished by segments and models (FZ11), 2012.

[30] KBA. Federal Motor Transport Authority (KBA): Registrations of trucks 2002 – 2011 distinguished by total weight allowed, 2012.

[31] NPE. Nationale Plattform Elektromobilität (NPE): "Zweiter Bericht der Nationalen Plattform Elektromobilität". Technical report, Federal Government's Joint Unit for Electric Mobility (GGEMO), Berlin, May 2011.

[32] NPE. Nationale Plattform Elektromobilität (NPE): Anhang des zweiten Berichts der Nationalen Plattform Elektromobilität. Technical report, Federal Government's Joint Unit for Electric Mobility (GGEMO), May 2011.

[33] NPE. Nationale Plattform Elektromobilität (NPE): Fortschrittsbericht der Nationalen Plattform Elektromobilität (Dritter Bericht). Technical report, Federal Government's Joint Unit for Electric Mobility (GGEMO), Berlin, May 2012.

[34] J. Linssen, S. Bickert, W. Hennings, et al. *Netzintegration von Fahrzeugen mit elektrifizierten Antriebssystemen in bestehende und zukünftige Energieversorgungsstrukturen-Advances in Systems Analyses 1*, volume 1. Forschungszentrum Jülich, 2012.

[35] H. Helms, J. Jöhrens, J. Hanusch, U. Höpfner, U. Lambrecht, and M. Pehnt. UMBReLA Umweltbilanzen Elektromobilität. Technical report, ifeu – Institute for Energy and Environmental Research, Heidelberg, October 2011.

[36] P. Mock, J. German, I. Riemersma, N. Ligterink, and U. Lambrecht. From laboratory to road – A comparison of official and real-world fuel consumption and $CO_2$ values for cars in Europe and the United States. ICCT. Technical report, Beijing, Berlin, Brussels, San Francisco, Washington, 2013.

[37] B. Propfe, M. Redelbach, D. J. Santini, and H. Friedrich. Cost analysis of Plug-in Hybrid Electric Vehicles including Maintenance & Repair Costs and Resale Values. In *Proceedings of Electric Vehicle Symposium 26 (EVS 26)*, Los Angeles, USA, May 2012.

[38] K. Frühauf. Was kostet Autofahren im Vergleich zu 1980 wirklich?, Progenium GmbH & Co.KG, Berlin., 2012.

[39] ADAC. ADAC Autokosten-Rechner, 2013.

[40] International Energy Agency (IEA). World Energy Outlook 2012, 2012.

[41] Mineralölwirtschaftsverband (MWV). Statistiken-Preise, Association of the German Petrol Industry, 2013.

[42] McKinsey & Company. Die Energiewende in Deutschland - Anspruch, Wirklichkeit und Perspektiven, 2012.

[43] Boston Consulting Group. Trendstudie 2030+ Kompetenzinitiative Energie des BDI. Study of the Boston Consulting Group in behalf of the Federation of German Industry (BDI), 2013.

[44] L. Fahrmeir, R. Künstler, I. Pegeot, and G. Tutz. *Statistik – Der Weg zur Datenanalyse*. Springer, 2011.

[45] P. Plötz. *How to estimate the probability of rare long-distance trips*. Fraunhofer ISI, 2014. Working papers on sustainability and innovation No. S1/2014, `http://www.isi.fraunhofer.de/isi-de/x/publikationen/workingpapers_sustainability_innovation.php`.

[46] Federal Ministry of Finance (BMF). Übersicht zur Kraftfahrzeugsteuer für Personenwagen., 2014.

| Parameter | unit | value 2011 | development | value 2020 | Reference |
|---|---|---|---|---|---|
| Vehicle market parameters | | | | | |
| vehicle registrations private small | - | 486,599 | linear | 475,309 | [29] |
| vehicle registrations private medium | - | 710,766 | linear | 694,275 | [29] |
| vehicle registrations private large | - | 146,713 | linear | 143,309 | [29] |
| vehicle registrations fleet small | - | 238,780 | linear | 233,240 | [29] |
| vehicle registrations fleet medium | - | 465,806 | linear | 454,998 | [29] |
| vehicle registrations fleet large | - | 47,440 | linear | 46,339 | [29] |
| vehicle registrations fleet LCV | - | 204,000 | linear | 204,000 | [30] |
| vehicle registrations company small | - | 109,538 | linear | 106,996 | [29] |
| vehicle registrations company medium | - | 509,438 | linear | 497,681 | [29] |
| vehicle registrations company large | - | 250,372 | linear | 244,563 | [29] |
| Vehicle parameters | | | | | |
| depth of discharge BEV (DoD) | - | 0.9 | none | 0.9 | [6, 11, 19, 34] |
| depth of discharge REEV (DoD) | - | 0.8 | none | 0.8 | [6, 11, 19, 34] |
| depth of discharge PHEV (DoD) | - | 0.75 | none | 0.75 | [6, 11, 19, 34] |
| battery capacity BEV medium | kWh | 24 | none | 24 | [6, 11, 19, 34] |
| battery capacity REEV medium | kWh | 16 | none | 16 | [6, 11, 19, 34] |
| battery capacity PHEV medium | kWh | 10 | none | 10 | [6, 11, 19, 34] |
| conventional consumption Gasoline medium | l/km | 0.076 | linear | 0.065 | [35] |
| conventional consumption Diesel medium | l/km | 0.060 | linear | 0.053 | [35] |
| conventional consumption PHEV medium | l/km | 0.070 | linear | 0.061 | [35] |
| conventional consumption REEV medium | l/km | 0.082 | linear | 0.072 | [35] |
| electric consumption BEV medium | kWh/km | 0.233 | linear | 0.211 | [35] |
| electric consumption REEV medium | kWh/km | 0.233 | linear | 0.211 | [35] |
| electric consumption PHEV medium | kWh/km | 0.220 | linear | 0.198 | [35] |
| operations and maintenance cost Gasoline medium | EUR/km | 0.048 | none | 0.048 | [37] |
| operations and maintenance cost Diesel medium | EUR/km | 0.048 | none | 0.048 | [37] |
| operations and maintenance cost PHEV medium | EUR/km | 0.044 | none | 0.044 | [37] |
| operations and maintenance cost REEV medium | EUR/km | 0.033 | none | 0.033 | [37] |
| operations and maintenance cost BEV medium | EUR/km | 0.040 | none | 0.040 | [37] |
| net list price Gasoline medium | EUR | 17,165 | linear | 17,515 | [19] |
| net list price Diesel medium | EUR | 19,352 | linear | 19,702 | [19] |
| net list price PHEV medium without battery | EUR | 22,116 | linear | 22,116 | [19] |
| net list price REEV medium without battery | EUR | 20,983 | linear | 20,983 | [19] |
| net list price BEV medium without battery | EUR | 18,042 | linear | 18,042 | [19] |
| vehicle tax Gasoline medium | EUR/yr | 95 (2011), 130 (2014) | linear | 101 | [46] |
| vehicle tax Diesel medium | EUR/yr | 191 (2011), 230 (2014) | linear | 209 | [46] |
| vehicle tax PHEV medium | EUR/yr | 34 | none | 34 | [46] |
| vehicle tax REEV medium | EUR/yr | 20 | none | 20 | [46] |
| vehicle tax BEV medium | EUR/yr | 0 | none | 0 | [46] |
| Charging infrastructure parameters | | | | | |
| investment wallbox private car holder with garage | EUR | 420 | linear | 370 | [13, 15] |
| investm. charging point private car holder w/o garage | EUR | 714 | linear | 537 | [13, 15] |
| investment wallbox commercial car holder | EUR | 420 | linear | 370 | [13, 15] |
| variable cost wallbox private car holder with garage | EUR/yr | 0 | linear | 0 | [13, 15] |
| var. cost charging point private car holder w/o garage | EUR/yr | 305 | linear | 246 | [13, 15] |
| variable cost wallbox commercial car holder | EUR/yr | 0 | none | 0 | [13, 15] |
| General TCO parameters | | | | | |
| interest rate private | - | 0.05 | none | 0.05 | [19] |
| interest rate commercial | - | 0.05 | none | 0.05 | [19] |
| investment horizon private vehicles | years | 6.2 | none | 6.2 | [19] |
| investment horizon commercial vehicles | years | 3.8 | none | 3.8 | [19] |
| investment horizon charging infrastructure | years | 15 | none | 15 | [19] |

Table 4: Parameters used in the model ALADIN. All prices without VAT.

Authors' affiliations

Till Gnann
Patrick Plötz
André Kühn
Martin Wietschel
Fraunhofer Institute for Systems and Innovation Research, Karlsruhe, Germany

Contact: Brigitte Kallfaß

Fraunhofer Institute for Systems
and Innovation Research (Fraunhofer ISI)
Breslauer Strasse 48
76139 Karlsruhe
Germany
Phone: +49 / 721 / 6809-150
Fax: +49 / 721 / 6809-272
E-Mail: brigitte.kallfass@isi.fraunhofer.de
www.isi.fraunhofer.de

Karlsruhe 2014