Who should buy electric vehicles? – The potential early adopter from an economical perspective

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Abstract
Electric vehicles have recently been introduced to market in Europe. Policy makers as well as car manufacturers have great interest to understand the first group of electric vehicle users, the so-called 'early adopters'. Due to the limited range of electric vehicles, they are commonly discussed as an option for drivers in metropolitan areas. However, not much is known characterising this important group of users. Here we characterise the potential first users of electric vehicles from an economic perspective: Taking into account the costs of owning and driving an electric vehicle which driving profiles make an electric vehicle cost-effective? As with many energy efficient technologies electric vehicles are typically more expensive in purchase but cheaper in usage, i.e., owners should drive many vehicle kilometres per year to reach sufficiently low payback times. We analyse a large database of German driving profiles and find the share of potential first users from different city sizes and statuses of employment. Our analysis is explicitly based on the individual driving behaviour and goes beyond simple averages. From this economical perspective we find the potential first users to be mostly full-time working and to live mainly in small to medium sized municipalities. In contrast to common belief, the share of users from major cities with more than 100,000 inhabitants is small. Full-time workers in small to medium sized cities also own most of the vehicles in Germany, yet we demonstrate that their expected share of electric vehicle ownership is significantly higher than their share of vehicle ownership in general. Our results can be applied in policy design and in discussions of potential financial incentives for electric vehicle purchase.

Introduction
Electric vehicles (EVs) are an innovative propulsion technology that can help to reduce green house gas emissions from the transport sector as well as local emissions (Chan 2007, Bradley and Frank 2009). In addition, electric propulsion is more efficient than propulsion via internal combustion engines and can support the shift from oil to other energy sources (Thomas 2012, Bradley and Frank 2009). Governments and institutions world-wide thus aim at fostering the market introduction and market diffusion of electric passenger cars. Financial support is available both for research and development as well as subsidies. An efficient and effective use of tax payer money requires a detailed understanding of the potential first buyers of commercially available EVs. Similarly, a new and large market opens for car manufacturers and their marketing strategies are more likely to be successful when they tailor-made for potential customers. Thus, reliable estimates of the characteristics of future costumers are therefore of great interest to policy makers and vehicle manufacturers alike. However, since the market is in a very early stage of its evolution, still little is known about these "early adopters" (Lieven et al. 2011, Anable et al. 2011).

The goal of the present paper is to give an additional piece of evidence in this task by characterising the potential early adopter from an economical perspective and to test the significance of different user groups' shares. Much of our methodology follows Biere et al. (2009) who performed a similar analysis and identified the full and part-time employees of small to medium sized cities as potential early adopters of electric vehicles based on user specific minimisation of total costs of ownership. We come to a similar conclusion but our focus is more specific here. The main point of our study is to determine whether the identified group of users could mainly be expected to own many EVs in the future simply because they own many vehicles or because their vehicle usage patterns differ significantly from average in order to make a significantly more attractive option. Put differently: if a potential group of users in our sample shows higher likelihood of buying an EV than could be expected from their share of car ownership, is this difference statistically significant or could it be a result of random fluctuations? Please note the difference: We first determine the potential share of future EV ownership in different user groups as was done by Biere et al. (2009) and in a second step we go beyond their work and check whether this share of EV ownership is significantly different from the user groups' share of car ownership in general.

The rest of the paper is organised as follows. We put out approach of identifying potential early adopters into context and discuss the methods and data being used in the paper in the following section. We continue with the results section where we highlight the heterogeneity of car usage in general and within the different user groups. We go on by identifying the share of potential EV owners from different user groups. The final part of the results section will be devoted to a comparison of expected and observed EV ownership in different user groups. We will close the paper with a summary and conclusions.

Data and Methods

METHODOLOGICAL FRAMEWORK

The first consumers of innovative technologies in general have received much interest in the literature, and the term "early adopter" is frequently used to refer to an early used group (Rogers 2003, Santini and Vyas 2005, and references therein). However, the term itself is used in different meanings. Rogers distinguishes several groups of adopters and coined the second group "early adopters", characterising them as "typically younger in age, have a higher social status, have more financial lucidity, advanced education, and are more socially forward than late adopters" (Rogers 2003). Here, we study one aspect of the potential early adopters. We focus on the total costs of ownership with different vehicle technologies and for users with different usage patterns. Based on a comparison of user data and their potential cost optimal choice, we determine who should buy electric vehicles in Germany based on economical considerations.

On very general grounds and without additional prior knowledge one may expect many EV users among those groups of a society that already own many vehicles. In our case this means the share of future EV users from a certain user group should be equal to each groups share of vehicle ownership in general. However, the characterisation of the potential EV users from an economical perspective, i.e. the calculation of the share of EV users from different user groups leads to a different share of users. Given the limited number of users in the survey under consideration (see below) we will check whether the difference between the expected and computed user shares are statistically significant (using a standard chi-squared test). To summarise, the calculation of and the difference between the expected user share and the calculated user share is at focus in the present paper.

DRIVING DATA

For answering the question who should buy electric vehicles, data from a public driving survey has been used. This large public data set of German driving behaviour (infas and DLR 2008) is used for the economic analysis and an identification of potential users of electric vehicles from an economical point of view has been performed by Biere et al. (2009). Here, we follow the methodology of Biere et al. (2009) and analyse the same data set with updated techno-economical parameters. In the public survey, about 25,000 households answered questions concerning their households, vehicle and driving behaviour. Overall, the survey respondents' answered included information on their driving distance on the day of the survey for 16,665 vehicles and could be used for the analysis of Biere et al. (2009) to be presented below.

For each vehicle the annual vehicle kilometres travelled were computed from the sum of the individual daily driving distances. In addition, the share of city driving has been estimated by calculating the share of trips with average velocity below 18 km/h based on the time and distance driven for the daily trips per household as given in the data set. The latter is important since fuel consumption – and thus operating costs – depend significantly on driving speed. Electric vehicles run most efficiently when many stops and low velocities characterise a driving profile, whereas internal combustion engine vehicles show relatively low fuel consumption in constant driving mode without stop-and-go.

TOTAL COST OF OWNERSHIP CALCULATION

Based on technical parameters (e.g. fuel consumption or battery size) and economical parameters (for example fuel costs, battery price, and vehicle prize) the costs for vehicle purchase and operation can be estimated for each vehicle taking into account the user's specific driving profile. Both purchase and operation costs enter the total cost of ownership (TCO) which is used to find the cost optimal vehicle typ. The annual TCO for user *i* are given by (see also Plötz, Gnann, Wietschel 2012)

$$\mathrm{TCO}_i = I \cdot a_n(p) + 365 \cdot L_i \cdot [s_i \cdot c^{ic} + (1 - s_i) \cdot c^{oc}]$$

Where I denotes the investment for the given vehicle option, $a_n(p)$ is the annuity for an interest rate of p over n years (we choose p = 5 % and n = 8a throughout), L_i denotes the daily driving distance of user i, s_i his or her share of inner city driving and c^{ac} (c^{oc}) are the fuel consumption costs in inner (resp. outer city) driving. We assume all vehicles to mid-size vehicles which is the largest group of cars (about 55 % of stock) in Germany (see Plötz, Gnann and Wietschel (2012) and references therein). This is done for each vehicle in the data base and allows to state to which group users with high shares of cost-effective electric vehicles belong. In particular the data base contains information of the working status of the user (full time employee, par time employee, pensioner or not working) and the size of the municipality in which the user is living. All technical

Table 1 Techno-economical parameters

Group	Parameter	Unit	Gasoline	Diesel	PHEV	BEV
Technical	Inner city fossil fuel consumption	l/100 km	8.5	6.3	7.0	-
	Inner city electric energy consumption	kWh/100 km	-	-	18.2	18.2
	Out of city fossil fuel consumption	l/100 km	5.7	4.5	6.2	-
	Out o city electric energy consumption	kWh/100 km	-	-	20.7	20.7
	Battery capacity	kWh	-	-	10.0	24.0
Economical	Investment for vehicle w/o battery	Euro	23,276	25,656	25,620	21,885
	Electric driving share	-	0	0	60%	100%
	Battery price incl. VAT	Euro/kWh	-	-	400	400
	Fossil fuel price	Euro/l	1.90	1.79	1.90	-
	Electricity price	Euro/kWh	-	-	0.24	0.24
	Pay back period	a	8	8	8	8
	Interest rate for investment	-	5%	5%	5%	5%

All parameters are based on (Fraunhofer ISI 2010; Helms et al. 2011; Bünger und Weindorf 2011, S. 87–100; Kley 2011) and are for a mid-sized vehicle.

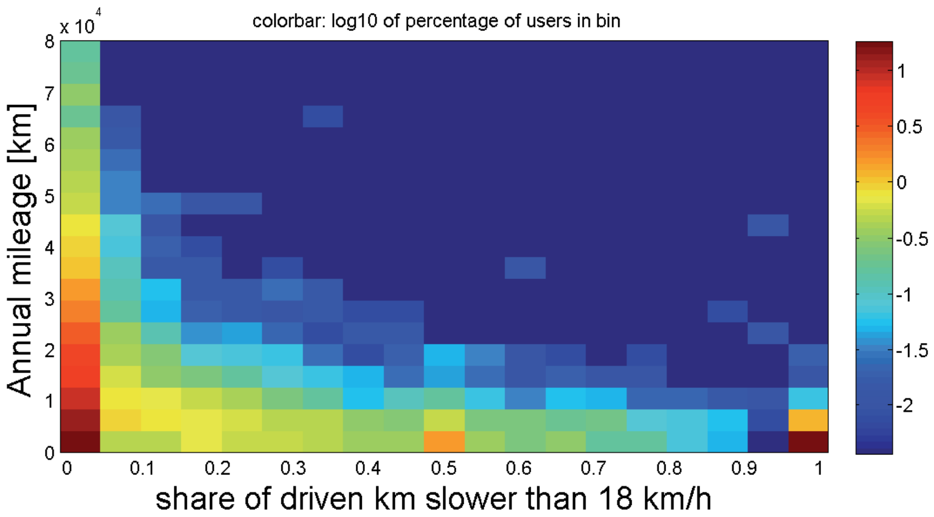

Figure 1. Density plot of distribution of VKT and inner city driving of all users. Please note the logarithmic colour coding: The colours correspond to the decimal logarithm of the share of users in a given class of annual mileage and inner-city driving (small boxes in the figure).

and economical parameters used in our calculations are summarised in the following Table 1.

Results

HETEROGENEITY OF DRIVING BEHAVIOUR

As discussed above, the annul VKT and share of inner city driving has been determined for all vehicles in the sample. We thus obtained two coordinates to characterise the driving of each user. The corresponding probability distribution of finding a user with VKT and inner city driving share is thus a two-dimensional (note the difference to a two-parameter distribution such as in (Plötz et al. 2012)) and not straight forward to visualise. Figure 1 shows the distribution of users in this two-dimensional space in a density plot. Since large shares of users fall into a small number of classes, we chose a logarithmic (with base 10) colour coding for the density plot. To be more precise, a class of a colour corresponding 1 indicates that 10^1 % = 10 % of the users fall into that class (and likewise: 0 indicates 10^0 % = 1 % fall into that class).

We observe from Figure 1 that large shares of all users drive less than 10,000 km per year either mainly outside of cities or inside (approximately 15–20 % for each group). Furthermore, between these two extremes a wide range of VKT and inner city driving is found among users. That is, except for the two dominating classes no particularly dominating usage pattern seems to be identifiable from Figure 1. Such behaviour could be expected at least for the VKT from the heavy-tailed distribution of VKTs known to be present in VKT data (Plötz et al. 2012). However, the dominance of the two extremes (and also the small peak at 50 % inner city driving) could partially be due to lack of data: Many drivers in the sample have only one or a few trips per in the sample and thus only simple fractions such as 0, ½, or 1 can be obtained for these users. In this respect the large share of users with differing VKTs in between the two extremes and their heterogeneity in driving we want to emphasise here might even be underestimated from Figure 1.

Let us continue with the driving behaviour of different user groups. The data base contains information of the employment status of the different users and the size of the municipality they

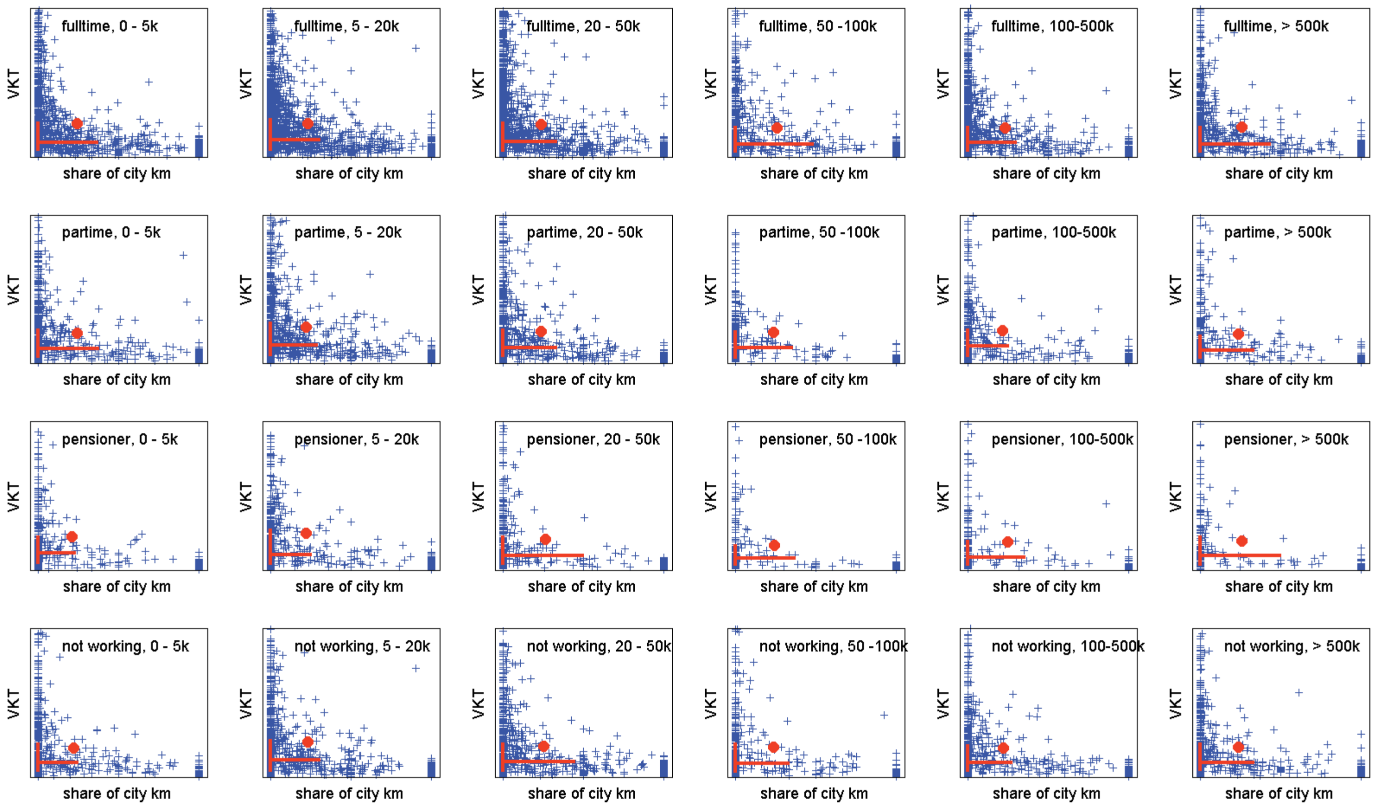

Figure 2. Calculated VKT and inner city driving share for all users within each user grouped. Shown are the estimated VKT and share of inner city driving for each user within his group. From top to bottom we vary the employment status (full time, part time, pensioner, not working) and the city size increasing from left to right. Please note that the axis ticks have been omitted for lack of space, but all axis are the same and range from 0 to 1 for the x-axis (share of inner city km, i.e., km driven with average speed < 18 km/h) and from 0 to 60,000 km for the y-axis (similar to Figure 3). The red dot marks the group average of both coordinates. The two red bars mark the inter-quartile range both in x- and y-direction and cross in the medians.

are living in. Following the data base we distinguish four major employment statuses (full time, part time, pensioner, not working) and 6 different city size (< 5,000; 5,000–20,000; 20,000–50,000; 50,000–100,000; 100,000–500,000; > 500,000 inhabitants). Combining these two distinctions, we obtain 24 different user groups. The driving behaviour in terms of estimated VKT and inner city share for all users is shown in Figure 2, split into the 24 user groups.

Simple visual inspection of Figure 2 suggests that more users are full time working than not working or on pension (this is supported by Figure 4). Furthermore, the data is widely scattered over the plane indicating the heterogeneity of driving behaviour even within the different user groups. Also shown are the average values for VKT and inner city driving for each user group (red dots) and the inter-quartile range in both directions (red crosses, the inter-quartile ranges intercept in the median values). Both measures of the centre of the distribution appear to be misleading or not sufficiently indicating the wide range of user behaviour. Furthermore, the overall density distribution observed in Figure 1 seems to be present in all user groups: Many users very high or very low share of inner city driving and a high amount of users with comparably high VKT but no apparent differences between the user groups.

CHARACTERISATION OF POTENTIAL EARLY ADOPTERS

Let us now turn to the determination of the cost optimal vehicle technology option for each individual user. We perform a TCO calculation as outlined in the methods section using the parameters given in the ANNEX and determine the cheapest technology option for each user choosing from gasoline, diesel, PHEV or BEV. Since the purchase prices are fixed for the different technological option, the driving behaviour determines the usage costs and thus the optimal TCO. For example, electric vehicles are more expensive in purchase but cheaper in usage and can therefore only become cost-efficient when a minimal VKT is reached. Furthermore the specific minimal VKT also depends on the share of inner city driving since combustion engines are more efficient at constant high speeds and EVs are more efficient when braking and accelerating frequently. Regions within the VKT-inner-city-driving plane with cost-optimal domains of our calculations are show in Figure 3. The qualitative statements just made can be easily observed in Figure 3. There is an inner-city-driving dependent break even line between diesel and gasoline engine cars since diesel vehicles are more expensive to purchase but more efficient in driving. Additionally, the finite battery capacity of BEVs implies an effective upper boundary for the daily and thus annual VKT of BEVs (explaining the straight upper line

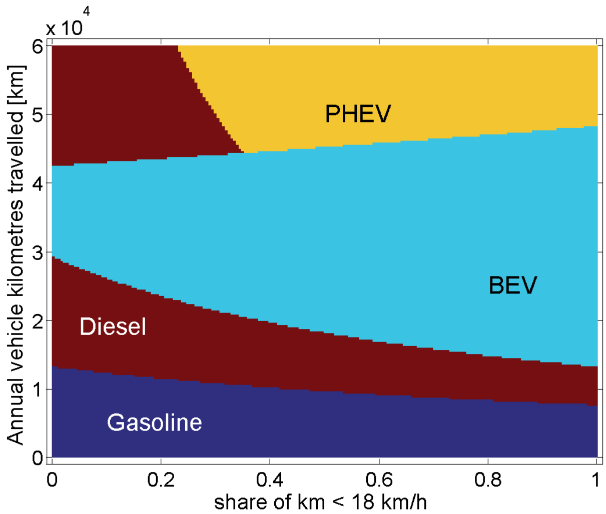

Figure 3. Regions of cost optimal vehicle technologies. Regions where different vehicle technology options are cost optimal have been obtained from TCO calculations as explained in the text. The cost optimal domains are highlighted as dark blue for gasoline, brown for diesel, light blue for BEV and yellow for PHEV.

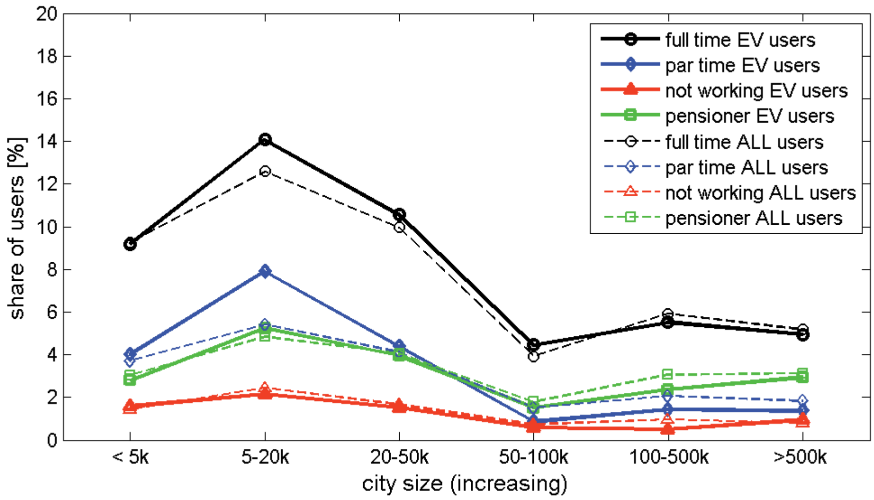

Figure 4. Share of EV users and all users. Shown are the user shares in overall car ownership (dashed lines) and in EV ownership (solid lines) for the user groups with different employment status and city size.

between regions of cost optimal BEVs and PHEVs/Diesel). Of course, daily driving fluctuates and users are not likely to cover the whole BEV range every day. Thus, the boundary between BEV and PHEV is probably not that strict for real purchase decisions of user and many users might prefer a PHEV over BEV since the former does not face the same fundamental range limits. For our analysis, we incorporate both BEVs and PHEVs separately and calculate potential first users for each vehicle typ. However, we will not distinguish between BEV and PHEV users when analysing the share of users from different employment statuses and city sizes but take both groups together as EV users.

As mentioned before, we perform such TCO calculation for each individual user with his estimated VKT and inner city driving share. In total, we find 1,320 driving profiles of the 26,090 to be cost-optimal as EVs. This share corresponds to 5 % of the sample and seems not to optimistic taking into account the large variability in user behaviour.

The determined potential EV users are not equally distributed among the 24 different user groups just as the car ownership (here: the size of the group since all users in the sample are car owners) is not equally distributed. Figure 4 shows the share of overall car users from the 24 different groups (dashed lines) together with share of EV users from each group among all EV users (solid lines).

In agreement with Biere et al. (2009) Figure 4 shows that based on TCO calculations most EV users in Germany can be expected to be full time or part time employees living in the small to medium sized (0–50,000 inhabitants) municipalities. Similarly these groups also own large shares of the cars in general.

If driving behaviour in terms of VKT and inner city driving was completely identical in all groups, the dashed and solid lines would match. That is, if no additional information on the probability of EV ownership was available one would simply expect the share of EV users to be similar. Instead we observe

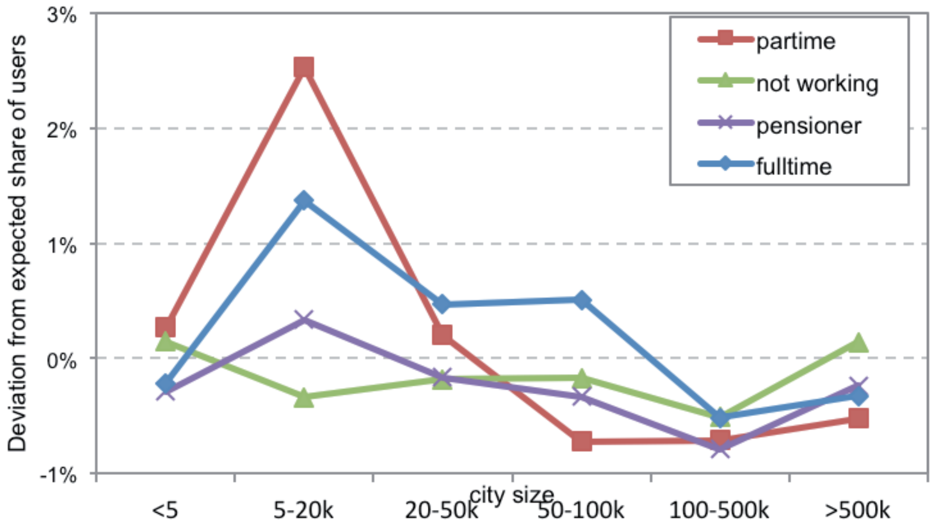

Figure 5. Deviation from expected share of EV users. Shown are the differences between shares of car ownership and share of potential EV ownership of the different user groups as a function of city size.

some deviations between the overall shares in car ownership and in EV ownership. The differences between shares of car ownership and share of potential EV ownership of the different user groups can be interpreted as deviations from the expected share of EV users and are shown in Figure 5.

We observe the largest positive difference between expected and calculated user share for the largest user groups: par time and full time employees living in small to medium sized cities. Furthermore, an overall negative trend with growing city size is present in Figure 5. This is often explained by the lower average VKT of car users living in larger cities (Wietschel et al. 2012). However, since the variability in the user groups is large and the sub samples are of finite size, these deviations and trends are not necessarily statistically significant. We will test their statistical significance in the following section.

STATISTICAL SIGNIFICANCE

Observing the deviations in Figure 5, we want to know if these are statistically significant, i.e. if the correlation of distinct characteristics (city size, employment status) has real influence on an outcome or whether there is no statistically valid connection. To test this, we constructed contingency tables for different sub samples with the absolute number of EV users from different employment statuses and different city sizes. We divided the full sample into smaller groups according to their employment status in: full time employees, part-time employees, both together and all statuses. Of these groups we examined the share of users from different city sizes (or groups of city sizes) and compared the observed number of users with expected number. We computed the chi-square statistics and the corresponding p-values to compute the probability that the observed fluctuations are only due to random effects. In Table 2 the subsamples are given with their corresponding sub sample size, the calculated chi-square value as well as the p-value as measure for statistical significance.

We find some of the deviations observed in Figure 5 to be statistically significant with p-values below 1 %. In particular the shares of potential EV users that are part time employees from small to medium sized cities differ significantly from the shares that could be expected from the shares of car ownerships of these users. A similar claim for full time employees does not differ significantly from the expected user shares. However, joining part time and full time employees from different city sizes to one larger group of employees, the differences are again significant.

Conversely, Figure 5 indicated a share of EV users from larger cities (with more than 100,000 inhabitants) lower than their corresponding share of car ownership. On average, these users actually cover shorter VKT but still show large variability within their vehicle usage (c.f. Plötz et al. 2012). However, Table 1 indicates that the reduction of the EV shares of the part time and full time employees from larger cities observed in Figure 5 is not significant (at least not at the 1 % level) and the reduction could be a result of random fluctuations.

Discussion and Conclusion

The analysis performed in the present paper is naturally based on several assumptions that require further testing. Concerning the data, we estimated VKTs and average inner-city driving shares from one day's driving. This is certainly questionable but larger data sets including socio-economic information (such as employment status and city size which were vital for the present analysis) are rare. In addition, we discussed only the economical aspect of car ownership and based our analysis on a buying decision under optimisation of the total costs of ownership. It is well known that other non-monetary aspects influence the buying decision as well (de Haan et al. 2007, Peters et al. 2011) and a more comprehensive analysis should take non-financial aspects into account when identifying the potential early adopters (Schneider et al. 2013). Yet even within the limits of a purely rational economic decision many of the techno-economical parameters are difficult to determine and vary between different cars (e.g. fuel consumption) and users (acceptable pay back period). Future studies should test the robustness of (a) the identified potential early adopters and

Table 2. Significance of non-random deviation of EV users in different sub samples from average.

Sub sample definition		Statistical significance		
Employment status	City size	Sub sample size	Chi squared	p-value
Full time	5 – 20 k	196	2.24	13.4%
Full time	0 – 20 k	324	1.04	30.8%
Full time	0 – 50 k	471	1.64	20.1%
Part-time	5 – 20 k	110	16.4	$<10^{-4}$
Part-time	0 – 20 k	166	12.49	0.04%
Part-time	0 – 50 k	227	10.44	0.12%
Full time or part-time	5 – 20 k	698	13.66	0.02%
Full time or part-time	0 – 20 k	490	9.89	0.17%
Full time or part-time	0 – 50 k	698	12.04	0.05%
All statuses	5 – 20 k	409	10.78	0.10%
All statuses	0 – 20 k	654	8.22	0.41%
All statuses	0 – 50 k	938	10.89	0.10%
Part-time	> 500 k	19	1.96	16.5%
Part-time	100–500 k	20	3.18	7.47%
Part-time	> 100 k	39	5.17	2.30%
Full time or part-time	> 500 k	88	1.42	23.4%
Full time or part-time	100–500 k	97	2.63	10.5%
Full time or part-time	> 100 k	185	4.37	3.65%

(b) the significant deviations between obtained and expected EV user shares. For example, by relaxing some parameters in favour of EVs the number of potential EV users within the data set would increase and lead to a larger number of significances. However, we are confident that the overall 5 % of users from the data base for which EVs would be an economically attractive vehicle (which is also a result of our parameter choices) are realistic within the near future and that the significance of our results is not overestimated.

To summarise, the potential EV users are likely to be full or part time employees from small to medium sized cities. In detail more EV users are likely to come from these groups than expected from vehicle usage but it is not justified by our data and analysis to expect less (than based on their car ownership share) users from larger cities.

References

Bradley, T.H. and Frank, A.A. (2009): Design, demonstrations and sustainability impact assessments for plug-in hybrid electric vehicles. In: Renewable and Sustainable Energy Reviews 13, 115.

Chan, C.C. (2007): The state of the art of electric, hybrid, and fuel cell vehicles. In: Proceedings of the IEEE, 95, 704.

Schneider, U., Globisch, J., Dütschke, E. Plötz, P. 2013. Who will buy electric vehicles? – Identifying the German early adopter, in preparation.

Peters, A., Gutscher H., & Scholz, R.W. (2011). Psychological determinants of fuel consumption of purchased new cars. Transportation Research Part F: Psychology and Behaviour, 14, 229–239.

de Haan, P., Mueller, M.G., Peters, A. (2007). Anreizsysteme beim Neuwagenkauf: Wirkungsarten, Wirksamkeit und Wirkungseffizienz. Bericht zum Schweizer Autokaufverhalten Nr. 14. ETH Zürich, IED-NSSI, report EMDM1561.

Rogers, E.M (2003): Diffusion of Innovations. Fifth Edition. New York: Free Press.

Biere, D.; Dallinger, D.; Wietschel, M. (2009): Ökonomische Analyse der Erstnutzer von Elektrofahrzeugen. Zeitschrift für Energiewirtschaft 33 (2009), Nr.2, pp. 173–181.

Plötz, P. Gnann T. and Wietschel, M. *Total Ownership Cost Projection for the German Electric Vehicle Market with Implications for Future Market Shares and Electricity Demand*. Enerday Dresden 2012.

Follmer, R., Gruschwitz, D., Jesske, B., Quandt, S., Lenz, B., Nobis, C., Köhler, K., Mehlin, M. (2010): Mobilität in Deutschland 2008 – Ergebnisbericht. Techn. Ber., infas – Institut für angewandte Sozialwissenschaft, Institut für Verkehrsforschung des Deutschen Zentrums für Luft- und Raumfahrt e. V., Berlin

Helms, H., Jöhrens, J., Lambrecht, U. (2011): Umweltbilanzen Elektromobilität. Wissenschaftlicher Grundlagenbericht. Institut für Energie- und Umweltforschung (IFEU) Heidelberg.

Thomas, C.E.S. 2012. "How green are electric vehicles?", International Journal of Hydrogen Energy, Volume 37, Issue 7, April 2012, Pages 6053–6062.

Anable, Jillian; Schuitema, Geertje; Skippon, Stephen; Kinnear, Neale (2011): Who will adopt electric vehicles? A segmentation approach of UK consumers. In: eceee Summer Study Energy Efficiency First: The Foundation Of A Low-Carbon Society, S. 1015–1026.

Lieven, Theo; Mühlmeier, Silke; Henkel, Sven; Waller, Johann F. (2011): Who will buy electric cars? An empirical study in Germany. In: Transportation Research Part D: Transport and Environment 16 (3), S. 236–243.

European Council 1970: COUNCIL DIRECTIVE of 20 March 1970 on the approximation of the laws of the Member States on measures to be taken against air pollution by emissions from motor vehicles (70/220/EEC). online:

http://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=CONSLEG:1970L0220:20070101:EN:HTML.

Helms, Hinrich, Julius Jöhrens, Jan Hanusch, Ulrich Höpfner, Udo Lambrecht, und Martin Pehnt. 2011. *UMBReLA Umweltbilanzen Elektromobilität*. Ergebnisbericht. Heidelberg: ifeu – Institut für Energie- und Umweltforschung Heidelberg GmbH. http://www.emobil-umwelt.de/images/ergebnisbericht/ifeu_%282011%29_-_UMBReLA_ergebnisbericht.pdf.

infas and DLR. 2008. *Mobilität in Deutschland (MiD) 2008*. Bonn, Berlin: infas Institut für angewandte Sozialwissenschaft GmbH, Deutsches Zentrum für Luft- und Raumfahrt e. V. (DLR).

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

Santini, D.J.; Vyas, A.D. (2005): Suggestions for a New Vehicle Choice Model Simulating Advanced Vehicles Introduction Decisions (AVID): Structure and Coefficients. Report, Argonne National Laboratory. available online: http://www.transportation.anl.gov/pdfs/TA/350.pdf.

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