SPATIAL AND INDIVIDUAL CHARACTERISTICS FOR BATTERY ELECTRIC VEHICLE ADOPTION

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Abstract

Individual motorized transport is a major source of greenhouse gas emissions and needs to be reduced in order to meet international agreements. Although alternatives to internal combustion engine vehicles are already on the market, without extensive political support, global adoption rates remain low. This paper presents the analysis of a novel revealed preference data set on battery electric vehicle (BEV) and conventional car holders from official sources. In combination with home location-based data, this allows for testing hypothesis on consumer and spatial characteristics of current BEV holders. A Logistic Generalized Linear Model estimating battery electric vehicle ownership shows that, for the first years of commercialization in Switzerland, ownership is predicted by environmental concern, ownership of multiple cars, male gender, living in one's own house, and by public charger availability. Altogether, the study at hand offers important insights to policy makers, energy grid and charging infrastructure operators, as well as the automotive industry, on the characteristics of early adopters of BEVs in a region free from strong EV policies.

1. Introduction

Decarbonization has become one of the major global challenges of our time (Rockström et al. 2017; Rogelj et al. 2015; Schellnhuber, Rahmstorf, and Winkelmann 2016). As of December 2015, 195 countries represented within the United Nations Framework Convention on Climate Change have agreed to limit anthropogenic global warming by 1.5-2 °C (UNFCCC 2015). Within the framework of the Paris agreement, Switzerland has set a goal to reduce greenhouse gas emissions by 50% until 2030 and by 75% to 80% until 2050 compared to 1990 levels (Burkhardt 2016). Transportation, a leading carbon contributors worldwide (Abergel et al. 2017), accounts for 32% of the overall carbon (CO_2) emissions in Switzerland alone (FOEN 2017). Thus, from a societal point of view, the adoption of electric vehicles (EVs) may present a suitable avenue to reduce carbon intensity, if a major share of electricity originate from renewables (Ajanovic and Haas 2016). Societal and environmental usefulness of EVs would be the case in Switzerland, as it already has a high share of renewable energies and is planning to substitute all non-renewable energy sources by 2050 (SFOE 2018). Moreover, while global EV adoption is currently highly dependent on strong EV policies (Lévay, Drossinos, and Thiel 2017; Sierzchula et al. 2014), Switzerland has no such policies. The federal government had set a policy target of 130g CO_2/km maximum emissions for the newly registered car fleet by 2015 and of 95g CO_2/km by 2021 (SFOE 2017). However, with average emissions of 134g CO_2/km in 2016 (SFOE 2017), the 2015 target could not be reached, and

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the target for 2021 seems out of reach. To attain the latter target, the electrification of the transportation sector (Pietzcker et al. 2014) has become a recognized political challenge (FEDRO 2016). Although EVs are already on the market, sales in Switzerland remain low, accounting only for 1.7 % of new registrations in 2018 (SFOE 2019), despite a high GDP/capita (IMF 2018) and an environmentally friendly population (Franzen and Vogl 2013). Therefore, the question as to why a low uptake of EVs persists is puzzling. As Switzerland's policy-makers and private sector unite their efforts to promote EVs (DETEC 2018), understanding current uptake patterns assists in the design of adequate policies. Additionally, as EV demand rises, it will be important to understand the spatial patterns of EV adoption to minimize the risks associated with spatial accumulation of EV owners and EV-related peak energy demand.

We focus exclusively on BEVs, as their energy efficiency is higher than that of other EVs (Helmers and Marx 2012) and because their battery capacity is greater, leading to potentially greater implications for electricity grids when recharged at peak hours and peak locations (Brenna et al. 2012; Hardman et al. 2018; Jakobsson et al. 2016; Moon et al. 2018; Schey, Scoffield, and Smart 2012; Wolbertus et al. 2018). Plainly speaking, this implies that if people return home from work at approximately the same time and their home locations are connected to the same grid, (fast) charging their BEVs could lead to problems in electricity distribution, including transmission congestion (Hu et al. 2017), and important voltage drops (Hoogsteen et al. 2015).

The current literature on EV adoption has mostly used stated-preference (SP) surveys to analyze characteristics of potential EV uptake. Only rarely, studies have used revealed preference (RP) approaches based on actual car ownership. While decisions in SP and RP studies are likely to be determined by similar factors, their effect on output probabilities will most likely differ substantially (Schuitema et al. 2013). RP studies are often favored, since SP studies are usually biased due to gaps between preference and actual behavior (Carlsson 2010).

As Bühler et al. (2014) note, the uptake of EVs depends on consumer perceptions, which explains our empirical assessment on private cars and their owners. This paper uses data that includes a mixed-mode survey of both, registered internal combustion engine vehicles (ICEV) and BEV owners. In doing so, our paper follows the call for "studies using representative samples and not only focusing on intention to adopt, but actual ('unforced') adoption" (Rezvani, Jansson, and Bodin 2015, 133), which is necessary to understand EV adoption. Analyzing official data in combination with the spatial characteristics of owners' area of residence in a logit choice model allows us to explore potential factors of EV adoption behavior, both at an individual and spatial scale. Therefore, this study allows also an assessment of the lessons learned from adopters of other EVs that can be transferred to BEVs. By identifying individual characteristics, as well as area characteristics that impact the spread of BEVs, our study is of interest to electricity providers, automotive manufacturers, as well as regional planning authorities and policy makers.

In the following sections, we review the literature on EV uptake studies to formulate hypotheses. Then, we briefly introduce the methods used and describe the results obtained before discussing our findings.

2. Literature review and hypotheses

Most previous studies on EV adoption are based on hypothetical vehicle choices to assess consumers' attitudes towards buying an EV (e.g. Bailey, Miele, and Axsen 2015; Bennett and Vijaygopal 2018; Junquera, Moreno, and Álvarez 2016; Priessner, Sposato, and Hampl 2018). In contrast, only very few studies (e.g. Axsen, Goldberg, and Bailey 2016;

Javid and Nejat 2017) investigate the characteristics of actual EV owners in comparison to the characteristics of owners of ICEVs. Many previous studies analyze characteristics of owners of different kinds of EVs (i.e. BEVs, (plug-in) hybrid electric vehicles) jointly without differentiating between them. A common focus is PEVs (plug-in electric vehicles), a category that includes BEVs and plug-in hybrid electric vehicles. However, as stated in current literature (Almeida Neves, Cardoso Marques, and Alberto Fuinhas 2018; Lane et al. 2018), we have to distinguish between different types of electric cars since their technologies differ. For instance, in contrast to BEVs, range-anxiety (of BEVs) is absent in plug-in hybrids (Lane et al. 2018).

Previous studies suggest that EV adoption can be linked to technologies, consumer characteristics, and context (Sierzchula et al. 2014). We add to the second and third strand of research. An overview of previous studies in these strands can be found in Javid and Nejat (2017) and W. Li et al. (2017). Besides consumer characteristics, the context consists of population density, charging infrastructure, policies, energy mix, and electricity/gas prices (Almeida Neves, Cardoso Marques, and Alberto Fuinhas 2018; Axsen, Goldberg, and Bailey 2016; X. Li, Chen, and Wang 2017; Priessner, Sposato, and Hampl 2018; Sierzchula et al. 2014).

We focus our literature review on scholarly debates in the areas of consumer characteristics and contextual criteria that vary within our regional scope (i.e. energy mix or gas price does not vary within Switzerland).

Consumer characteristics:

Many RP studies on PEVs (Axsen, Goldberg, and Bailey 2016; Axsen and Kurani 2013; Javid and Nejat 2017; Nazari, Mohammadian, and Stephens 2018; Tal et al. 2014), SP studies on BEVs (Hidrue et al. 2011), and Plötz et al. 2014, (an SP study on BEVs with some RP data), as well as most notable RP studies on BEVs (Almeida Neves, Cardoso Marques, and Alberto Fuinhas 2018), have found higher income and higher education to increase the likelihood of EV adoption. However, in two RP PEV-studies at the national level, educational achievements and income were found to be insignificant (X. Li, Chen, and Wang 2017; Sierzchula et al. 2014). This is likely attributed to the studies more coarse scope. Bernards, Morren, and Slootweg (2018), found a strong effect that levels off as income increases. Moreover, some SP studies have found income to be insignificant or less important for BEVs (Hidrue et al. 2011) and PEVs (Bailey, Miele, and Axsen 2015; Carley et al. 2013), which is understandable, as no (expensive) purchases were made. Altogether, given the higher predictive power of RP studies compared to SP ones, and our focus on BEVs, we formulate the following hypothesis:

H1: Unforced early adoption of BEVs is associated with both, higher educational attainment and income.

Manski and Sherman (1980) claim that household size matters for vehicle selection (through number of seats and trunk size). This was also found for PEVs (Bernards, Morren, and Slootweg 2018; Javid and Nejat 2017; Priessner, Sposato, and Hampl 2018). Since there are still fewer combinations of seat-numbers and trunk sizes available on the market for BEVs, compared to conventional vehicles, household size may affect the choice for purchasing BEVs (Almeida Neves, Cardoso Marques, and Alberto Fuinhas 2018; Plötz et al. 2014).

More cars in the household make EVs more acceptable (Jakobsson et al. 2016; Karlsson 2017; Tamor and Milačic´ 2015) as an ICEV can overcome range anxiety and long recharging times. In RP studies (on PEVs) findings are mixed:

while it matters in Canada (Axsen, Goldberg, and Bailey 2016), this is not the case in the US (Javid and Nejat 2017; Nazari, Mohammadian, and Stephens 2018). Similarly, owning a complete public transport (local trains, trams, ferries and busses as well as long-distance trains) subscription is linked to more openness towards new mobility tools (Guidon et al. 2018; Meyer de Freitas et al. 2019) and may play an analogous role in BEV ownership decisions.

One more variable associated with socio-economic status is home ownership, especially of single-family detached houses. This is found positive in all studies (e.g. Axsen, Goldberg, and Bailey 2016; Bailey, Miele, and Axsen 2015; Nazari, Mohammadian, and Stephens 2018) reviewed, except for one recent PEV RP study in California (Javid and Nejat 2017). In the Swiss context, the high proportion of tenants (Wehrmüller n.d.) may also influence BEV readiness through increased transaction costs for installing recharging facilities in rented dwellings.

H2: Owner-occupied houses are the most likely homes of BEV owners.

Most studies have shown environmental attitudes to matter for BEV support in SP studies (Noppers et al. 2015; Plötz et al. 2014) as well as for actual PEV adoption (Axsen, Goldberg, and Bailey 2016) and intent (Carley et al. 2013; Priessner, Sposato, and Hampl 2018; Schuitema et al. 2013). Still, further research on consumers' environmental consciousness continues to be encouraged (Almeida Neves, Cardoso Marques, and Alberto Fuinhas 2018). Apart from this, we also consider party preferences. We go beyond Kahn (2007) to study registered Green Party voters and hybrid electric vehicle owners expecting that representation through Switzerland's Green or Green Liberal party is likely to be positively associated with BEV uptake.

H3: Environmentalism and green party preferences are positively linked to BEV uptake probabilities.

Spatial characteristics:

(Electric) vehicle travel patterns and the link towards the built environment are on the research agenda of many scholars (Higgins et al. 2012; X. Li, Chen, and Wang 2017). Although the European Commission (2014) understands BEVs as a phenomenon of high density areas, the empirical evidence is mixed. Rather small effects of density were found on PEV adoption in California (Javid and Nejat 2017) and insignificant effects on intentions for PEV uptake in Austria (Priessner, Sposato, and Hampl 2018). In addition, while Plötz et al. (2014) showed that BEVs are most likely to be found in smaller settlements, i.e. in rural areas or suburbs, studies on a country level (International Energy Agency 2017; X. Li, Chen, and Wang 2017) found support for the statement of the European Commission. Therefore, univocal clarification on this topic is imperative (Bernards, Morren, and Slootweg 2018).

H4: Population density is related to BEV adoption.

As early as (1986) Sperling and Kitamura (1986) acknowledged the need for refueling infrastructure for the deployment of new transportation possibilities, which is shown to be especially important in the purchase decision of vehicles running on alternative fuels (Dagsvik et al. 2002). Nowadays, public (fast) chargers are an important part in making BEVs more attractive for future users (Neaimeha et al. 2017). Multiple cross-country RP studies (e.g. X. Li, Chen, and Wang 2017), RP studies on PEVs (Javid and Nejat 2017; Nazari, Mohammadian, and Stephens 2018), as well as in SP studies (Bailey, Miele, and Axsen 2015; Carley et al. 2013; Egbue and Long 2012) find that public charging stations are the drivers of electric mobility. In contrast, Bailey, Miele, and Axsen (2015) conclude that the relationship between the availability of out-of-home charging facilities and the uptake of EVs is not yet fully understood, which ,for now, remains true for actual adoption (RP) of BEVs and small-scale spatial resolutions. To close this gap, we formulate the fifth hypothesis:

H5: Public charging infrastructure availability is positively related to BEV adoption.

3. Data and Methods

This paper uses unique RP data on the private adoption of BEVs. The sample consists of BEV owners as well as owners of conventional cars with internal combustion engines which might be partially electrified, such as PHEV and HEV. We use administrative data on registered cars and invite car owners to a survey while incorporating administrative and census data on their home location communities. A Generalized Linear Model (GLM) is applied for a regression analysis of BEV ownership. In the next sections, we describe the data collection, followed by the empirical (logit model) approach.

Survey

The survey population is a random sample of Swiss car holders with registrations in the German-speaking Swiss Cantons Aargau, Schwyz, Zug, and Zurich. Per canton, 5000 car holders, that have no BEV registered yet, were randomly selected in each canton. Further, we invited all (2'627) current BEV owners. In total, this yields 22'627 survey invitations sent to the postal addresses provided by the official sources (car registration).

We selected these cantons for the study even though policies to foster the use of energy efficient cars that are currently in place (if any) can differ between cantons, as differences are mitigated by the fact that these cantons have nearly no such policies in place[1]. Moreover, we chose this regional scope due to its comprehensiveness. The cantons include Switzerland's largest city, the canton with the largest population (Zurich), as well as sub-urban and rural areas encompassing various different topologies, allowing for a survey in German only. The mixed mode survey could be completed online or on print (PAPI). The data-collection was started May 22, 2018 and ended October 2, 2018. Given that we obtained 5325 responses, we reach a minimum (AAPOR 2016) response rate of 23.5 %.

The survey was approved by ETH Zurich's ethics commission[2] and began after informed consent questions on (household) demographics, work status, mobility usage, environmental and technological attitudes, as well as car preferences. Thereafter the survey questions turned to political questions, dealing with the individuals' support for mobility policies. Lastly, all survey participants were asked about general political beliefs and positions as well as income.

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[1] Vehicle taxes (and their bases) always can vary between Swiss cantons. In the canton of Aargau, they depend on power, in Schwyz on car weight, in Zug on power and are always halved for BEVs, and in Zurich on energy efficiency and BEVs are completely exempted. For example, we requested the cantonal taxes for the EV registered most in Switzerland in 2018 (Renault Zoe). These are 180 CHF in Aargau, 158 CHF in Schwyz, 234 in Zug, and 0 CHF in Zurich. However, the cantons hardly differ in the outcomes of these slightly different taxations on EV: In 2018, the share of newly registered BEVs (the share of BEVs from the total fleet of all registered cars) was in Aargau: 1.8 % (0.40%), Schwyz: 2.1 % (0.51%), Zug: 2 % (0.80%), Zurich: 2.8% (0.68%); for comparison, in Switzerland it was 1.7 % (0.46%). (1 CHF ≅ 1 USD).

[2] Decision EK 2017-N-85

We received statistics from the cantonal car registries on gender and age, for the time of data provision, see Table 1. This data was provided exclusively for our research since statistics on car holders are usually undisclosed to the public. The main purpose of this data is to compare our survey respondents to the general population of car holders in the respective cantons. We acknowledge small differences when regarding our findings.

Table 1: Comparison between survey data and registered car holders ('-' represents data we did not receive)

		BEV survey	BEV registered	ICEV survey	ICEV registered
Aargau	Share female	20%	27%	47%	40%
	Mean age	56	59	61	52
Schwyz	Share female	21%	20%	37%	39%
	Mean age	54	-	53	51
Zug	Share female	9%	15%	33%	-
	Mean age	53	53	56	-
Zurich	Share female	16%	18%	38%	39%
	Mean age	55	53	57	52

Spatial Data

The survey data was complemented with spatial characteristics of respondents' residential zip codes. In contrast to municipality data, zip (postal) code areas are finer-grained in urban areas and coarser in rural areas. Information on the area level was merged to the individual survey data by the respondents' zip code. Spatial information, especially population density, was collected from the cantonal statistical offices, as well as from a private firm (lemnet.org) providing information on recharging infrastructure.

Generalized Linear Model

In our study, we predict the binary outcome of BEV-ownership or no BEV-ownership from a set of explanatory variables. To do so we make use of Generalized Linear Models. GLM's describe the relation of a dependent variable $y_i (i = 1, \dots, n)$ on a vector of regressors x_i. A GLM consists of a linear predictor η_i:

$$\eta_i = \beta_0 + \beta_1 x_{1i} + \dots + \beta_n x_{pn} , \quad (1)$$

a link function that describes how the mean $E(Y_i) = \mu_i$ depends on the linear predictor, and a variance function $var(Y_i)$ that describes how the variance function depends on the mean. For modelling data with binary outcomes, we use the logit link function, hence yielding probabilities. The variance function $var(Y_i)$ is:

$$V(\mu_i) = \mu_i (1 - \mu_i) , \quad (2)$$

and the link function is defined as:

$$g(\mu_i) = log\left(\frac{\mu_i}{1-\mu_i}\right) \tag{3}$$

A detailed model description can be found in Dunn and Smyth (2018), McCullagh and Nelder (1989), and Myers et al. (2010). The model estimation via maximum likelihood and all further analyses were done with the statistical software R[3].

Variable selection

We started with a broad set of spatial scale variables, namely population density, share of built up area per municipality, share of single-family houses per municipality, job accessibility (based on Hansen (1959), the municipality type (based on FSO (2017)) and availability of charging stations. We then checked for multicollinearity in the data through the application of variance inflation factors (Fox and Monette, 1992). As multicollinearity was found for most of the spatial characteristics, we dropped all variables except for population density and availability of charging stations. To choose which variables to drop we used different sets of variables for our regression and estimated model fit using likelihood ratio tests (Korner-Nievergelt et al. 2015) as well as AIC (Sakamoto et al., 1986). After checking for multicollinearity, we chose the set of variables for our model that provided the lowest AIC. We also tried interactions between the variables as well as non-linear terms (squared) but this did not improve our model fit.

Once literature was reviewed and multi-collinearity addressed (see above), to test our hypothesis, we selected 17 variables that are expected to influence BEV ownership, our dependent variable.

The respondents' education is reflected in `Higheduc`, a dummy reflecting attained tertiary education (1 = yes). `Hhinc` is the household's gross monthly income (see Table 2 for the full description). The variable `House` reflects the three possibilities that the household members own the house they live in, live in an owner-occupied flat, or live in a rented home. `Envsc` is a factor summarizing the respondent's environmental concern (Diekmann and Meyer 2009), which is then classified in three groups. `Party` refers to the (Swiss) political party the respondent best feels represented by. The base category is the Swiss People's Party[4]. All variables mentioned so far stem from the survey itself. `Popdens` refers to the population density in the respondent's zip code, as indicated by the address we received from the car registries, coded in accordance with Eurostat's (2019) Degree of Urbanization. `Charging` refers to the number of EV recharging facilities per 1000 inhabitants within their zip code area. The respondent's `gender`, as indicated by the survey respondent, was coded as a Boolean (dummy) variable (1 = female, 0 = men and people who opted for a gender other than male or female). `Age` was sorted into three groups and variable `employed` reflects whether a respondent is working. `Hhpers` refers to the sum of all people including the respondent and under-aged persons living in the household. `Hhcars` is the number of vehicles permanently available to the household including cars, minivans, SUVs, and business cars. `GA` is a dummy for owning a complete public transport subscription[5] (1 = yes)

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3 We used the packages stats (R CoreTeam 2017), pscl (Jackman 2017), lrtest (Zeileis and Hothorn 2002), pROC (Robin et al. 2011) and margins (Leeper, Arnold, and Arel-Bundock 2018).

4 We coded rare party mentions (below 50) together with the option "other". They were Evangelical People's Party (EVP), Federal Democratic Union (EDU), Party of Labour (PdA). We checked it, and this did not affect substantially any of the results shown here.

5 The Swiss public transport network offers subscriptions for both local public transport and all national railways and busses. This is commonly referred to as "*Generalabonement* (GA)".

Table 2: summary of explanatory variables

Variable	Description	Levels	All	ICEV	BEV
Higher Education	Degree in higher education [yes/no]	no	1414	1179	235
		yes	998	667	331
Mean monthly household income	Mean monthly gross income [CHF]	< 4000	87	84	3
		4001-8000	688	606	82
		8001-12000	731	563	168
		12001-16000	462	323	139
		> 16000	444	270	174
Property ownership	House owner or rental of house or apartment	Rented house/flat	832	720	112
		Own house	1075	732	343
		Owner-occupied flat	505	394	111
Environmental concern	Scale	low	760	626	134
		medium	1194	927	267
		high	458	293	165
Party preference	Political party that best represents one's opinion	Green Liberal Party (GLP)	318	181	137
		Green Party (GPS)	96	48	48
		Swiss People's Party (SVP)	315	263	52
		Conservative Democratic Party (BDP)	74	64	10
		Christian Democratic People's Party (CVP)	202	178	24
		The Liberals (FDP)	519	411	108
		Social Democratic Party (SP)	269	215	54
		Other	85	56	29
		None	534	430	104
Population density	Population density of residents' ZIP-code area [inhabitants/km^2]	rural	339	256	83
		agglo	1378	1050	328
		urban	695	540	155
Charging availability	Number of charging stations of residents' ZIP-code area [count/km^2]	continuous	Mean: 0.23 Standard deviation: 0.35 Min: 0 Max: 5.99		
Gender	Female or male (or other)	male	1710	1232	478
		female	702	614	88
Age	[years]	continuous	Mean: 56 Standard deviation: 14.7 Min: 22 Max: 96		
Employed	State of Employment [yes/no]	no	770	641	129
		yes	1642	1205	437
Cars per household		1	1119	941	178
		2	1069	747	322

	Number of cars available per household [count]	> 2	224	158	66
Persons per household	Number of persons permanently living in household [count]	1	405	332	73
		2	1131	889	242
		> 2	876	625	251
Season ticket ownership	Owner of an annual season ticket (unlimited travel on Swiss trains) [yes/no]	no	2163	1669	494
		yes	249	177	72

4. Results

Regression results

The regression results are summarized in Table 3. For the regression, only complete cases were retained, which reduces the dataset to 2412 observations. There is a total of 566 BEV holders and 1846 ICEV holders.

Table 3: summary of logistic regression results

Groups	Coefficients	Estimate	Std. Error	z value	Pr(>|z|)	
Higher education	Yes	0.432	0.121	3.578	0.000	***
Mean monthly household income	> 16000	2.185	0.641	3.410	0.001	***
	12001-16000	1.798	0.638	2.818	0.005	**
	8001-12000	1.525	0.630	2.421	0.015	*
	4001-8000	1.096	0.628	1.746	0.081	.
Property ownership	Owner-occupied flat	0.921	0.177	5.196	0.000	***
	Own house	1.313	0.165	7.981	0.000	***
Environmental concern	medium	0.282	0.135	2.087	0.037	*
	high	0.854	0.167	5.111	0.000	***
Party preference	Green Liberal Party (GLP)	1.000	0.220	4.553	0.000	***
	Green Party (GPS)	1.534	0.303	5.062	0.000	***
	Conservative Democratic Party (BDP)	-0.540	0.398	-1.355	0.175	
	Christian Democratic People's Party (CVP)	-0.497	0.287	-1.732	0.083	.
	The Liberals (FDP)	-0.118	0.209	-0.563	0.573	
	Social Democratic Party (SP)	0.157	0.246	0.637	0.524	
	Other	1.238	0.312	3.967	0.000	***
	None	0.100	0.207	0.482	0.630	
Population Density	Agglo	0.130	0.166	0.784	0.433	
	Urban	0.066	0.200	0.327	0.744	
Charging availability	Charging	0.303	0.157	1.926	0.054	.
Gender	Female	-1.165	0.142	-8.197	0.000	***
Age	Age	-0.019	0.006	-3.179	0.001	**

Employed	Yes	0.093	0.179	0.520	0.603	
Cars per Household	2	0.909	0.134	6.780	0.000	***
	> 2	0.755	0.206	3.659	0.000	***
Persons per household	2	-0.666	0.180	-3.696	0.000	***
	> 2	-1.106	0.202	-5.472	0.000	***
Annual season ticket holder	Yes	0.058	0.172	0.338	0.735	
	(Intercept)	-3.115	0.740	-4.212	0.000	***
	Log Likelihood	-1,054.316				
	Akaike Inf. Crit.	2,166.633				
	McFadden Pseudo R2	0.198				

Signifiance codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1

In Figure 1, we present the predicted probabilities for our different groups of variables, using average marginal effects.

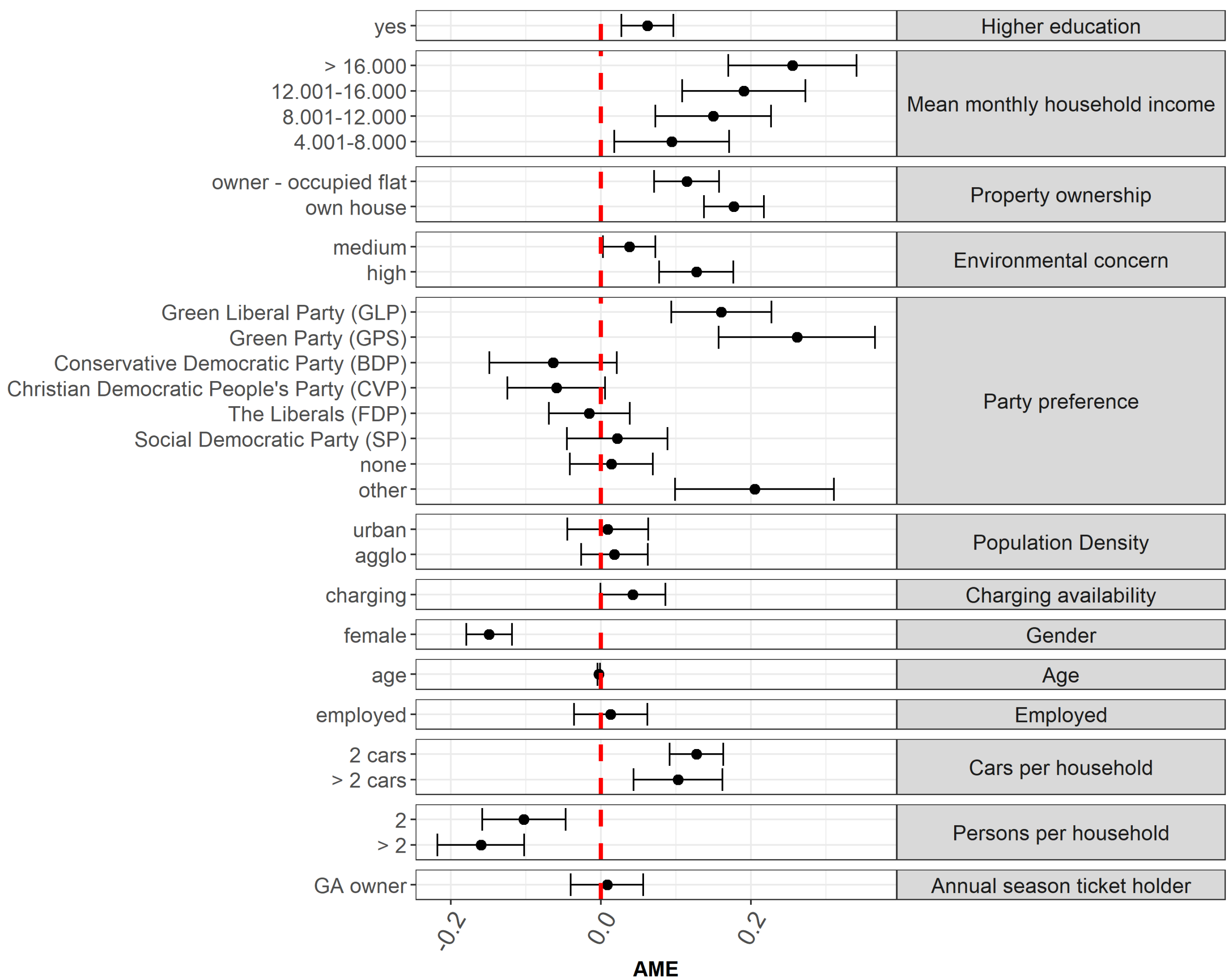

Figure 1: Average Marginal Effects (AME) plot on the probability of EV-ownership.

Consumer characteristics:

There is a significant positive effect of higher education on BEV ownership. Therefore, we cannot reject the first part of the null for H1 (i.e. that unforced early adoption of BEVs is not associated with higher educational attainment). The average marginal effect of higher education on BEV adoption is around 5%. The GLM logit model shows significant positive effects for the higher income groups. The average marginal effects plot for household income show that a higher income group is always associated with higher probabilities of BEV adoption. Overall, we acknowledge evidence in favor of our first hypothesis:

H1: Unforced early adoption of BEVs is associated with both, higher educational attainment, and income.

Living in an owner-occupied house, in comparison to a rented house or flat, or an owner-occupied flat, shows a positive relationship to BEV ownership (see Figure 1). These effects are highly significant, see Table 2. Moving from a rented house/flat to an owner occupied flat already increases BEV ownership probability by more than 10 % and to an owned house by more than 15%. We therefore find support for our second hypothesis:

H2: Owner-occupied houses are the most likely homes of BEV owners.

Compared to the base category (Swiss People's Party), the green parties, most notably the Green Party of Switzerland and the Green Liberal Party, are associated with significantly higher likelihood of BEV uptake. Moreover, preferences for Conservative Democratic Party, Christian Democratic People's Party, and the Liberals go in the opposite direction, compared to the baseline. Green party preference is one of the single strongest predictors for BEV adoption in our sample, as it yields average marginal effects above 20%. Given that environmental concern is also clearly and significantly positively linked to BEV adoption, this is in line with our third hypothesis. Therefore, we can reject the corresponding null hypothesis in favor of:

H3: Environmentalism and green party preferences are positively linked to BEV uptake probabilities.

Moreover, female respondents are less likely to own a BEV and younger age shows significant positive effects on adoption. Multi-car households appear to be more likely to have a BEV, but whether a household has two cars or more, does not affect BEV adoption. Our model results suggest that the lower the number of people living in a household, the less likely BEV adoption is. Aside from that, employment and complete public transport subscription ownership are not significantly related to BEV adoption.

Spatial characteristics:

EV adoption does not seem to be driven by the density of residential areas. Therefore, we find no support for our fourth hypothesis.

H4: Population density is related to BEV adoption.

The effect of charging infrastructure availability on BEV uptake is positive. Areas with higher availability of charging infrastructure show a significant positive link to BEV adoption. For each three additional public chargers in the respondents' zip code, BEV uptake increases by over 10% (see Figure 1). Taken together, we find support for our last hypothesis.

H5: Public charging infrastructure availability is positively related to BEV adoption.

Goodness of Fit

To estimate the overall fit of our model we used the ROC curve as a visual performance indicator as well as McFadden's pseudo R^2. First, we estimated the overall fit of our model using the Receiver operating characteristic (ROC) curve and area under the curve (AUC). A ROC curve visualizes (see Figure 2) the performance of a binary regression with discrete output and shows the specificity (the proportion of correctly classified negative observations) and sensitivity (the proportion of correctly classified positive observations) as the output threshold is moved over the range of all possible values. In simple terms, it plots the "false alarm" rate versus the "hit rate". ROC curves do not depend on class probabilities, which allows for interpretation and comparison across different data sets (see variable selection above). A higher AUC means a better classification (Robin et al. 2011, 1). For our model the AUC is 0.796, which means there is a 79% chance that the model will be able to distinguish between BEV and no BEV. These results indicate a reasonably good model fit. The pseudo R^2 developed by McFadden (1977) is the second performance indicator used in this study. In his contribution (McFadden 1977) states that a pseudo R^2 of 0.2-0.4 represents a good model fit. For our model, we obtain a McFadden Pseudo R^2 of 0.198.

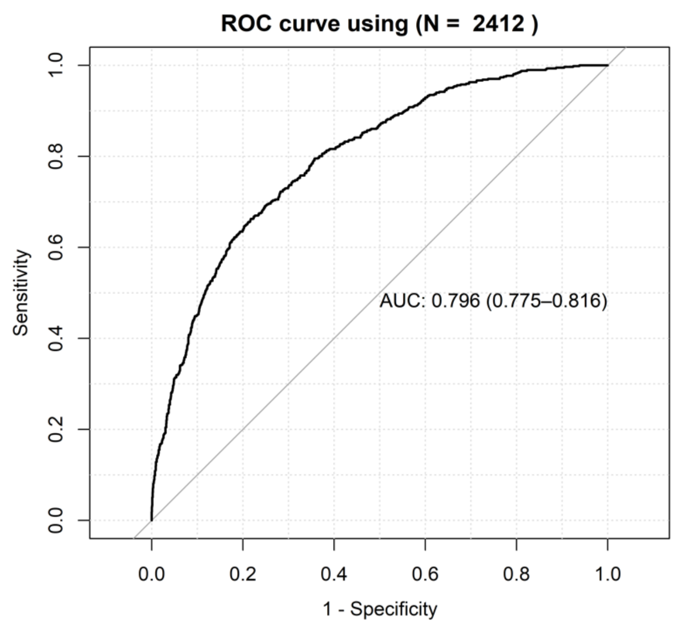

Figure 2: ROC curve of the fitted binomial (logit) GLM

5. Discussion and Conclusion

In this paper, we analyze the effect of individual and spatial characteristics on BEV adoption in four Swiss cantons. The analysis is based on a revealed preference survey with actual BEV and ICEV owners, sampled from cantonal car registry official database. We develop a logistic regression model of BEV ownership based on variables present in the literature on EV adoption and find clear support for most of our hypotheses.

As our findings show, actual BEV adoption strongly depends on personal characteristics, such as education and income. The importance of income, especially in Switzerland, where governmental support for EV adoption is low, is intuitive. This finding clearly differs from findings in previous literature using SP studies, both for BEVs (Hidrue et al. 2011) and PEVs (Bailey, Miele, and Axsen 2015; Carley et al. 2013). This could be a result of hypothetical bias (Schuitema et al. 2013). Cross-country studies on PEVs have not found income to be significant (X. Li, Chen, and Wang 2017; Sierzchula et al. 2014), potentially due to coarser data and/or insufficiently capturing the effects of governmental market interventions.

In contrast to owning a flat, we find that home-ownership of detached dwellings is positively linked to BEV adoption. Given that this is highly uncommon in Switzerland, where most people live in rented homes, this finding may serve as a possible explanation for slow overall uptake of BEVs. It is also important to note, that this finding remains true when controlling for income and other variables representing socioeconomic status, such as multiple cars and employment.

Effects for environmentalism and (green) political party preferences also confirm our hypotheses and much of previous research (Axsen, Goldberg, and Bailey 2016; Carley et al. 2013; Kahn 2007; Noppers et al. 2015; Plötz et al. 2014; Priessner, Sposato, and Hampl 2018). We contribute to the literature by taking a broader view on policy preferences, compared to e.g. Kahn (2007) focusing on registered Green Party voters in California, by analyzing respondents' party preferences. Apart from the green parties' positive effect, in comparison to the right wing (Swiss People's Party; reference category) on BEV adoption, more central parties like the Christian Democrats, the Liberals, and the Conservative Democratic Party are likely to be reluctant to BEV adoption. This could be due to lower climate change awareness (at same levels of environmental concern) in these parties. Most surprisingly, results for the Social Democratic Party (that usually also is in favor of 'green' policies) do also not have a significant positive effect compared to the baseline. These findings might be explained by the sampling strategy that only includes car owners and might thus be rather representative for the traditional workers and union wing who are predominantly voting for the Social Democrats due to social rather than green policy issues. Also, even the baseline category is chosen as it is the largest party in the Swiss parliament at the time, it is a right-wing party appealing to both low and (very) high income individuals, that tend to have a low climate change awareness, and the former Motorists' or Automobile Party (Stadelmann-Steffen 2011) has been integrated in this party. In sum, it seems that green party sympathizers also act up on their political beliefs in very costly consumption decisions and buy electric cars. This adds interesting insights to the scientific literature on politicized consumption in this revealed preference case.

Following the contextual factors (Sierzchula et al. 2014), one of our spatial hypotheses is not supported by the results, as the likelihood of BEV adoption in middle to high densely populated areas does not significantly differ from the rural reference category. The built environment affects BEVs considerations and plug-in vehicles as a single EV category (Javid and Nejat 2017; Priessner, Sposato, and Hampl 2018). Altogether, our findings do not corroborate the literature on density, despite a focus on BEVs.

Increased EV charger availability is also related to higher BEV adoption probabilities, following out last hypothesis. However, at this point, we acknowledge the possibility this could be co-determined by other factors such as high-income locations (likely spots for public charging infrastructure) or that public chargers' placement responds to actual demand. Therefore, we conclude that the temporal component of PEV (plug-in hybrids and BEV) registration in communities and charger built-up should be explored in further research.

For the scientific community studying EV adoption, our findings show that actual BEV adoption differs from stated-preference studies and from studies using PEVs. The difference to SP studies becomes clear, when focusing exemplarily at household income effects. Given that SP studies have not observed effects from household income, we interpret this as a hint towards hypothetical bias (see Schuitema et al. (2013)). Likewise, the main difference between our study, using RP data on actual BEV adoption, and those using PEVs, lies in density effects. The effects of population density for PEVs do not differ for BEVs, but they do in revealed (Javid and Nejat 2017) and stated-preference studies (Priessner, Sposato, and Hampl 2018). Our assessment of transferability of knowledge generated from other EVs to BEVs then reveals that different types of EVs should be investigated separately, in line with suggestions from other studies (Almeida Neves, Cardoso Marques, and Alberto Fuinhas 2018; Lane et al. 2018).

All things considered, our findings have profound implications for policymaking, as understanding the individual and spatial factors that lead to BEV ownership can assist in the design of electric mobility policies. A focus should be recharging infrastructure. Furthermore, information on the spatial and household characteristics for which adoption is more likely can be particularly valuable, is highly beneficial for electricity grid operators. Information on which type of settlement structure can expect a greater BEV uptake (i.e. not same density, rather neighborhoods with certain shared household characteristics) is imperative, so electricity grid operators can assess whether existing infrastructure can handle the increasing loads during peak EV charging times. This can be of particular importance if other decentralized energy-consuming (e.g. other types of EVs, heat pumps) and energy-generating technologies (e.g. solar PV) follow similar spatial adoption patterns (Bernards, Morren, and Slootweg 2018) and since "neighborhood effects" (Axsen, Mountain, and Jaccard 2009; Kahn 2007; Mau et al. 2008; Pettifor et al. 2017) could lead to growing spatial clusters of EVs, resulting in a spatial concentration of electricity demand. Lastly, the visibility of EVs is of utmost importance to the adoption of this new technology. Subsequently, the more their adoption grows, the more attractive EVs will become for car buyers (Axsen, Goldberg, and Bailey 2016; Mau et al. 2008). Therefore, in areas of high spatial concentration of electricity demand, grids may need to be strengthened and dynamic pricing policies must be implemented. Meanwhile, policy options to promote BEVs in "lagging" regions, such as local information events and test-driving opportunities (Bühler et al. 2014; Jensen, Cherchi, and Mabit 2013; Schmalfuß, Mühl, and Krems 2017; Skippon and Garwood 2011) can help to smoothen the BEV uptake. Consequently, given that EVs still are mostly adopted by wealthy customers and home-owners, policy should target charging station deployment as well as possibly reducing the EV costs.

A possible extension of this paper would aim at better understanding people who do not currently own a BEV but state interest in a BEV as their next car. Axsen, Goldberg, and Bailey (2016) call them "Potential Early Mainstream" in contrast to those who do not wish to buy a BEV next, whom they call "Potential Late Mainstream". Their classification could then potentially be combined with another idea from previous research that demonstrated technological enthusiasm is correlated with intentions of PEV adoption (Plötz et al. 2014; Smith et al. 2017) as well as actual BEV adoption (Lane et al. 2018). All in all, the study at hand could further be enhanced by examining the technological interest of different (potential new) consumer groups besides further spatial and/ or neighborhood effects.

Altogether, our findings on BEV adoption by rich, highly educated individuals, with environmental concern, living in their own houses in agglomerations fit well with previous scholarly work. These findings represent fundamental patterns of individuals in the adoption of new mobility and energy technologies, especially when far-reaching policies are wanting. Our research allows us to derive general recommendations for policy making (electricity pricing as well as promotion policies) that can facilitate the transition to electric mobility.

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