Energy Policy 167 (2022) 113047

Contents lists available at ScienceDirect

Energy Policy

journal homepage: www.elsevier.com/locate/enpol

The effects of policies providing information and trialling on the knowledge about and the intention to adopt new energy technologies

Gracia Brückmann

Institute of Political Science and Oeschger Centre for Climate Change Research, University of Bern, Switzerland

ARTICLE INFO

Keywords:
Demand-side mitigation
RCT
Experience
Information
Battery electric vehicles
Knowledge
Intention to adopt

ABSTRACT

To increase adoption of new technologies many scholars suggested policies including information and trialling. This study reports on a randomised control trial (RCT) investigating whether information on and experience with Battery Electric Vehicles (BEVs) can alter knowledge and purchase intentions. A large (N = 4149) random sample of conventional car holders was randomly divided into three groups: one receiving comprehensive information on BEVs, another getting the same information plus an actual multi-day test drive with a BEV, and a control group without any intervention. For the first time, information and test-driving were assessed side-by-side in their effects on technology knowledge and adoption intention. This study shows that test-driving treatment largely (by 11%) and significantly increased BEV purchase intentions for a large group. Therefore, policymakers should facilitate direct experience to promote shifting individual motorised transport to electric vehicles in light of energy independence and climate considerations.

1. Introduction

To limit global warming, all industries must decarbonise their operations and processes (Intergovernmental Panel on Climate Change, 2018); passenger car transportation is no exception (Yang et al., 2018). Conventional cars are also characterised by high noise and particle emissions that harm people and the environment (OECD, 2014). However, limiting vehicle-related emissions is challenging due to political-economic car dependencies (Mattioli et al., 2020). The need for social distancing during the COVID-19 pandemic reinforces the challenge of reducing vehicle-related emissions (De Vos, 2020). One solution for lowering these emissions is replacing internal combustion engine cars with vehicles that do not rely on fossil fuels, such as battery electric vehicles (BEVs) in conjunction with energy from renewable sources (Ajanovic and Haas, 2016; Zhang and Fujimori, 2020; Alarfaj et al., 2020).

The technological availability of green technologies (e.g. BEVs) alone is not enough (Milovanoff et al., 2020) to reduce emissions as they cannot contribute to problem-solving if these technologies are not used (Carley et al., 2019; DellaValle and Zubaryeva, 2019). Many people currently associate BEVs with challenges or barriers, such as higher purchase prices, lower driving ranges, and long recharging times at sparse charging infrastructure (Graham-Rowe et al., 2012; Degirmenci and Breitner, 2017; Schuitema et al., 2013; Skippon and Garwood, 2011; Higueras-Castillo et al., 2020; Melliger et al., 2018; Wicki et al., 2022a, 2022b). This can also be partly attributed to information deficits as BEVs are not promoted as much as conventional cars at dealerships (Lynes, 2018).

Some governments tried to reduce consumers' reluctance to adopt electric vehicles[1] by implementing ambitious policies (Carley et al., 2019; Hardman et al., 2017; Hardman, 2019; Sierzchula et al., 2014; Axsen et al., 2020), such as (purchase price) subsidies or specific road space (e.g., bus lane) use privileges and policy mixes thereof. While primarily the *carrot* (instead of *stick*) policies have high public support and are therefore politically feasible (Axsen et al., 2020; Brückmann and Bernauer, 2020), these are mostly costly policies that will be eventually removed (Xu et al., 2020). Moreover, in contrast to subsidies, targeted programs to increase knowledge and experience might be ways to

Abbreviations: RCT, Randomised controlled trial; BEV, Battery-electric vehicle.

E-mail address: gracia.brueckmann@unibe.ch.

[1] The term "electric vehicles" (EVs) refers to all cars that run on electricity, sometimes in combination with another engine, as in the case of (plug-in) hybrid electric vehicles, which also have internal combustion engines. The term "EVs" also refers to fuel-cell electric vehicles and battery electric vehicles (BEVs). BEVs are the car type used in this study. It is powered 100% by energy that is charged with a plug from an energy outlet and stored in an on-board rechargeable battery pack (Egbue and Long, 2012; Jensen et al., 2013).

https://doi.org/10.1016/j.enpol.2022.113047
Received 4 January 2022; Received in revised form 6 May 2022; Accepted 8 May 2022
Available online 1 June 2022

achieve EV adoption-related goals more cost-effectively (Sierzchula et al., 2014). This study's research question follows previous papers' (e.g., Dumortier et al., 2015; Wicki et al., 2019; Huber and Wicki, 2021) suggestions about policies including information and experience and asks *"What is the effect of a policy that provides information and experience with a green technology on technology-specific knowledge and intention to adopt this new technology?"*

Offering potential consumers a BEV driving experience is expected to have substantial positive impacts on their adoption (Santos and Davies, 2020; Thøgersen and Ebsen, 2019; Carley et al., 2019; Kim et al., 2019) as it makes consumers aware of improvements in vehicle technology (Haustein et al., 2021). Besides trials, programs to increase customers' knowledge about green technologies can reduce energy consumption (Dumortier et al., 2015; Delmas et al., 2013; Carley et al., 2019). Both policy options, trials and information provisions are also expected to advance understanding of these technologies (Wang et al., 2018; Thøgersen and Ebsen, 2019; Liu et al., 2020). However, these two policy interventions (experience through trials and information provision) have so far not been analysed as to their (different) potential to change car purchase intentions in a randomised control trial (RCT). I address this research gap by reporting on an RCT field experiment among registered conventional vehicle holders and their altered (exclusively[2]) BEV knowledge and purchase intentions.

In this paper, I report on a field experiment conducted in Switzerland between two surveys, effectively establishing a panel for this experiment. After a baseline survey, I randomly divided a sizeable random sample (N = 4149) into three groups: one exposed to information on BEVs, another receiving the same information plus an actual multi-day test drive with a mass-market BEV, and a control group, which gets no treatment. After that, a follow-up survey assessed the same participants' knowledge and revealed that receiving information on and test driving a BEV increased the intention to purchase or lease a BEV as the next car by 11% among a significant subset, those answering environmental-related questions. In contrast to any previous study, this figure accounts that participants who take up the offer of a test drive (even without knowing it is in a BEV) might substantially differ from all motorists. These experimental findings support the causal claims of previous research, namely, that the perception of EVs undergoes a substantial change after the hands-on experience with an EV (e.g. Axsen et al., 2016; Graham-Rowe et al., 2012; Schneider et al., 2014). Test-driving was a stronger predictor of BEV purchase intention than any previously identified influence factor (Plötz et al., 2014; Javid and Nejat, 2017; Wang et al., 2020; Brückmann et al., 2021b; Wicki et al., 2022b). This is in line with previous findings on direct experiences with new technologies (Tomic et al., 2020; Krause et al., 2016). One-off information alone did not alter purchase intentions, consistent with prior research (Stern, 1999). This paper reports the importance of studying policy interventions in randomised control trials and documents the potential of trials as a policy option to increase consumers' purchase interest in green technologies.

This paper is structured as follows: The following section presents previous literature and the theoretical background for information and trialling based on energy policies. After that, I present the data set and methods. The following section reports the results of altering information and purchase intentions, which the discussion critically appraises. The last section offers conclusions and policy implications.

2. Previous literature

Some theories point to information and experience as important factors for the adoption of new technologies. Most notably, there is Rogers (2003)'s *Theory of Diffusion of Technology*. The trialability of a new technology directly influences the decision to adopt the new technology (Rogers, 2003; Carley et al., 2013). Same as information, it provides higher knowledge to (previously) less informed consumers. This section presents how this and other theories are used when studying the effect of policies to increase the adoption of battery electric vehicles, as one example of green technologies.

There is ample evidence that mainstream car consumers up to the present time lack knowledge about BEVs (e.g. Long et al., 2019; Wang et al., 2018; Krause et al., 2013), which partly explains their reluctance to adopt BEVs. Previous research mainly uses correlations between (self-assessed) knowledge about electric vehicles and adoption intentions. As a result, it has not been possible to test the causal relationships, although it has been proposed as suggestions for *further research* many times (Thøgersen and Ebsen, 2019; Wang et al., 2018; Liu et al., 2020).[3] Economically speaking, the information provided to participants reduces the costs of gathering this information. I expect this information to increase participants' knowledge about BEVs and their associated benefits and drawbacks. However, the information will only have a positive effect on purchase intentions (and potential, later actual purchases) if the information is relevant in the decision process for purchasing a BEV.

Based on these previous findings, I expect both treatments to positively influence the knowledge about, and purchase interests for, BEVs compared with the control group.

Hypothesis 1. Both treatments (information and experience) will lead to higher BEV-specific knowledge and higher BEV purchase intentions in comparison with the control group.

Following the same logic, trials reduce the lack of knowledge or uncertainty as well as potential misperceptions regarding new technologies and their ease of use, their associated benefits and drawbacks (Thøgersen and Ebsen, 2019). Assessing these advantages correctly is the reason why previous literature on innovations finds *trialability* to be strongly related to the speed of innovation spread (Gärling and Thøgersen, 2001; Petschnig et al., 2014; Rogers, 2003; Carley et al., 2019). Trialability means experiencing in use (with the intended context) (Schlüter and Weyer, 2019) and reduces perceived complexity (Tomic et al., 2020), making it crucial for the adoption of high-involvement purchases, such as cars (Molesworth and Suortti, 2002). A few existing studies (e.g. Larson et al., 2014) mention the possibility that direct experience with EVs might change consumers' preferences, e.g. through hearing the reduced noise and feeling the high acceleration. There is an overall consensus that experience matters for correct estimation of stated interest in EVs (e.g. Graham-Rowe et al., 2012; Schmalfuβ et al., 2017; Ziegler, 2012) as these cars are psychologically distant (Liberman et al., 2007) before trialling them. However, thus far, only a few studies have conducted experiments with participants test driving BEVs (e.g. Bühler et al., 2014; Burgess et al., 2013; Egbue and Long, 2012; Graham-Rowe et al., 2012; Jensen et al., 2013; Schneider et al., 2014; Franke and Krems, 2013; Hinnüber et al., 2019; Schmalfuβ et al., 2017). Roberson and Helveston (2020) add to this literature with a study where participants are chauffeured for a short

[2] This research purposefully omitted plug-in hybrid vehicles (PHEV) as they need less behavioural change as they can be driven just like conventional cars. While between the baseline and follow-up surveys, the descriptive stated interest in PHEVs did increase (see Supplementary InformationM.1), I do not provide experimental treatment effects for interest in purchasing PHEVs after information on BEVs and trialling a fully functional battery-electric vehicle, as the theoretical causal link is unclear.

[3] A notable exemption from this lack of causal inference studies is Dumortier et al. (2015). Providing information about fuel-costs and total-cost-of-ownership in a survey experiment leads to higher interest in purchasing different kinds of EVs, at least for some consumer groups. Therefore, they call for further research on providing these kinds of information for emerging, energy-saving technologies, with high up-front costs and low running costs (Dumortier et al., 2015).

time, which already increases BEV purchase intentions.

A more noteworthy reduction in information costs should come from test-driving with information than from information alone. According to previous research (e.g., Barth et al., 2016) experience can have more positive effects than mere knowledge about EVs regarding the intention to use an EV. Therefore, the combined test-drive with information treatment is likely to have a more significant, positive effect than information alone on the intention to adopt a BEV.

Hypothesis 2. The test-drive with information treatment has a higher, positive effect on the intention to adopt a BEV.

While I argue that the test-drives with information are likely to treat participants with more information, I do not expect it to increase factual knowledge more than the information treatment. This follows two reasons: firstly, it could be that the sensory and experiential knowledge gathered through test-driving might add to the knowledge in a way that is not measurable against the survey items presented; secondly, it could be that the actual driving experience was more noteworthy for participants and they therefore forgot about the additional information from the treatment leaflet by the time they received the invitation to the next survey.

3. Data & methods

3.1. Study area

This study took place in four Swiss cantons (Aargau, Schwyz, Zug, and Zurich). These four Swiss cantons were chosen as they provide both rural and urban areas and slightly different vehicle-related (taxation) policies (Brückmann and Bernauer, 2020), while they still can be considered as lacking strong BEV policies (Brückmann et al., 2021b). They were also chosen due to their proximity to the test site (starting point for the test drives). In general, Switzerland has a quick adoption of new technologies (Herberz et al., 2020) and optimistic expectations about prospective BEV resale values (Brückmann et al., 2021a). Currently, 0.7% of all passenger cars are battery electric vehicles (Swiss Federal Office of Statistics, 2021). Still, sales are as high as 14.59% of new registrations in the third quarter of 2021 (Swiss Federal Office of Energy, 2021).

3.2. Sampling

This study is the first to investigate a random sample of conventional car holders, that had no BEV registered at the time of sampling, and their reactions to two possible policy interventions in an RCT. Random sampling from official sources, car registries, ensures a high-quality, unbiased sample, unlike previous studies that examine people from participant pools, car shows or online forums (Hinnüber et al., 2019; Skippon et al., 2016; Schmalfuβ et al., 2017). The random sample was provided by the car registries, which transferred the data to the researcher after ensuring they had a car, but no BEV, registered. Everyone in the random sample was then invited to participate in the study.

Therefore, 20′000 randomly selected conventional car holders in Switzerland (5′000 from each of the Swiss cantons of Aargau, Schwyz, Zug, and Zurich) were invited to take part in a mixed-mode survey (online and "pen-and-paper"), which served as a baseline survey. The study was approved in full by the institution's IRB, see Supplementary Information A. All study participants gave their informed consent at the beginning of the first and the following survey that they voluntarily participated and that their data was collected for research purposes, only.

3.3. Experimental design

4′149 owners of conventional cars who did not have a BEV registered took part in an unincentivised (baseline) survey of around 30 min to complete. This first survey was fielded from May 22, 2018, until October 2, 2018. The AAPOR response rate is 21% (The American Association for Public Opinion Research, 2016) after two postal reminders were used.[4] The baseline survey participation is depicted at the top of Fig. 1. In the baseline survey, all the main covariates, such as sociodemographic variables, car usage, and preferences, as well as attitudinal scales and (EV) policy preferences were assessed. Additional discussions of the baseline sample properties can be found in Supplementary InformationB.

The RCT started at the end of the baseline survey when participants were randomly assigned to one of three experimental treatment groups: (1) information on BEVs, relating to car attributes that buyers typically pay attention to; (2) the same information on BEVs, plus a multi-day test drive of such a car; (3) a control group with neither (1) nor (2). This is a modified two-by-two design (information yes/no, test drive yes/no) intentionally leaving out a group that would have gotten no information but a test drive. In Supplementary Information C I describe the information treatment in more detail, and in Supplementary Information D I provide the recruitment protocol for the test drive plus information treatment.

A follow-up survey took place around three weeks after the test drive treatment (November 2018–May 2019), if received, or in May 2019 for the information only treatment and control group. While endeavouring to achieve a high response rate (through invitation by postal mail and email as well as again two reminders) some attrition occurred, see Fig. 1. I used the follow-up survey to assess whether these interventions (treatments) affected respondents' knowledge of BEVs and intentions to adopt a BEV.

Everyone who was randomised into the test drive with information treatment group was asked for general "test drive sentiment" (in Fig. 1) at the end of survey wave 1. In order to reduce self-selection into treatment, it was not mentioned that test drives would be with a BEV, it was just stated it was a test drive in any car. Out of 1350 participants, the first survey asked, 462 did not want a test drive (see right part of Fig. 1). (See more details in Supplementary Information D.1 and Supplementary Information G for a model of the sentiment towards taking part in the test drive.) Additionally, 535 out of a total of 4149 baseline survey respondents did not consent to take part in another survey, the second wave. Only those positive (yes and maybe) about a test drive, who also agreed to engage in a follow-up survey, were entering the pool of people who were potentially invited to a test drive.

Only those in the respective treatment group and willing to take the test drive were offered multi-day test drives. However, additionally, 401 of 620 people who got offered the test drive declined (see "No test drive" in Fig. 1). Even while using eight cars, due to logistics, the maximum capacity was 217 multi-day test drives.

All people randomised into the treatment with test drives who did not take it up (at any stage) were randomised again, into either the other experimental treatment (information) or the control group (Fig. 1 omits this process of re-randomisation for visibility). Respondents who moved out of the study cantons ($n = 2$) or indicated they acquired a BEV ($n = 16$) before the second survey wave were excluded. This (conservative) procedure does not alter the main result (as shown by multiverse analysis in Supplementary InformationO).

This experimental design allows for within-subject and between-subject examination. In a within-subject investigation, researchers compare those who later receive treatment, to their (counterfactual) first wave "selves" without the treatment. Within-subject design is usually used in intervention studies, the most common form for BEV experience studies (Hinnüber et al., 2019; Degirmenci and Breitner, 2017). These studies measure an outcome before and after treatment as

[4] Except in the canton of Aargau. Due to legal reasons, only one reminder was sent there.

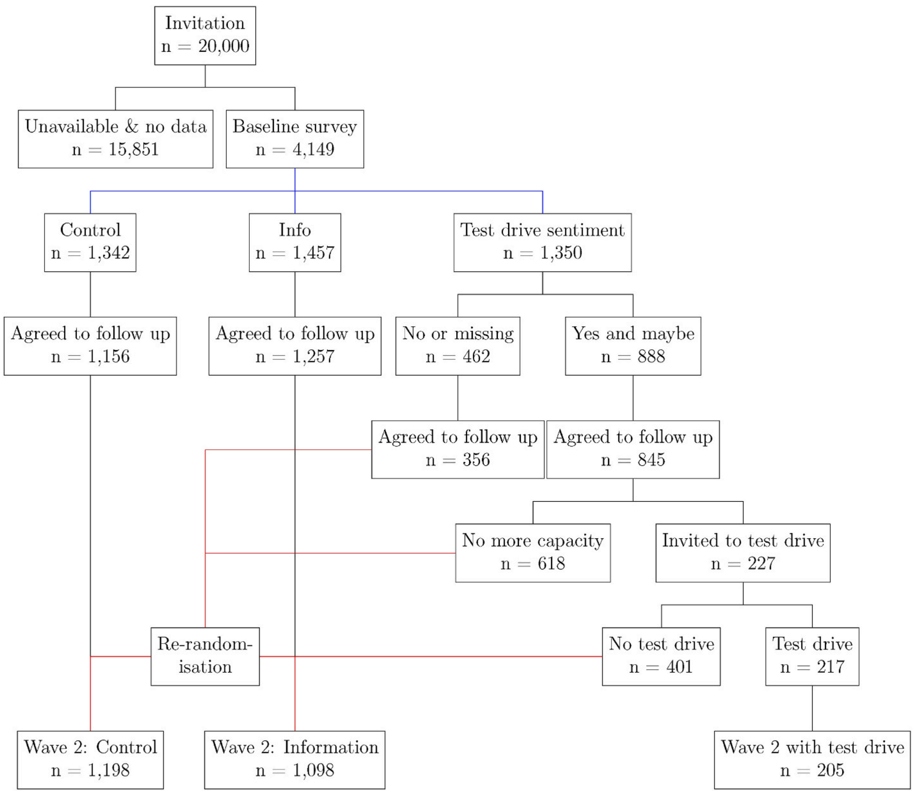

Fig. 1. Schematic flow of survey participants after initial random sampling, done by car registries, into baseline survey. From 20,000 car holders, the cantonal car registries randomly selected, 4149 participated in the baseline survey. They were randomly split (indicated in blue) into *Control* (n = 1342), *Information treatment* (n = 1457), and *Test drive with information treatment* (n = 1350). The blue lines, therefore, represent the intention-to-treatment randomisation. As the latter treatment (test drives) needed consent, everyone who was randomly assigned to this treatment was asked, if they were interested in participating in an (unspecified) test drive for research. Only those who (maybe) agreed to the test drive and agreed to be contacted for the next wave "*Agreed to follow up*" were invited to the test drive (n = 618) until the capacity limit was reached. Everyone who did indicate interest to participate in the second survey wave - but did not do the test drive - was randomly resorted into the control or the information treatment group. A red line indicates that those are randomly reassigned either to the control or to the information treatment group. In total, 217 test drives were administered and 205 of those took part in the second survey wave. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

they do not have a control group. In the between-subject design, I compare treatment groups (after treatment) with their untreated counterparts from the control group in an experimental design.

3.3.1. Potential threats to perfect randomisation

While the randomly-assigned sub-samples do not look unbalanced between the control group and treatment groups (see Supplementary Information E), the experimental treatment with test drives could not be delivered to everyone initially assigned to this experimental group. Following Fig. 1, there are two reasons for this: Unwillingness to participate in the test drives (including survey dropout) and the test-drive capacity limit.

Subjects assigned to the test drive plus information treatment who did not take a test drive do not substantially differ from those who did (see Supplementary Information E, and Supplementary Information F), except that they were significantly less likely female (and insignificantly more technology interested and held prior BEV driving experience). Furthermore, the intention-to-treat analysis allowed me to measure the effect of the *assignment to treatment*, to deal appropriately with these imbalances in taking up the treatment. This will be discussed in the next section.

3.4. Statistical analysis

As intention to treatment and receiving treatment do not perfectly match, it is important to estimate intention to treat (ITT) and Local Average Treatment Effects (LATE) (Angrist et al., 1996). LATE uses baseline assigned treatment status as an instrumental variable (IV) to instrument received treatment status. ITT measures the effect of offering the intervention (either an offer for a test drive plus information or solely providing information on electric vehicles), taking into account those who decided not to comply with the treatment, i.e. not take a test drive. Therefore, ITT serves as an estimate of the lower bound of the treatment effect. The ITT is an ordinary least squares (OLS) regression of the treatment assignments on the dependent variable of interest.

$$Y_i = \delta^{ITT}\text{Treatment}_1 + \gamma^{ITT}\text{Treatment}_2 + \beta_i \boldsymbol{X} + \varepsilon_i, \quad (1)$$

where i denotes survey respondents. $\boldsymbol{X}$ refers to a vector of socio-demographic covariates, which is used to predict purchase intentions. The outcome Y is a binary indicator either for correct knowledge or BEV purchase intentions. Treatment_1 is a dummy (or binary indicator) that equates 1 for the information treatment, and 0 otherwise. Similarly, Treatment_2 is a dummy that is 1 for test drive plus information, and 0 otherwise. The control is the omitted category, where both Treatment_1 and Treatment_2 are 0. The multiple-dummies notation for treatment will be denoted with a that is either 1 or 2.

Measuring the effect of the treatment, for those who ended up receiving the test drive plus information or the information, is referred to as LATE. These are obtained using IV regressions, with baseline assignment to treatment (displayed in blue, in Fig. 1). This is a valid instrument as it alters which treatment a participant might get (causal effect on treatment received). The baseline assignment to treatment is completely random; it only affects the dependent variable through the received treatment. There is no confounding for the effect of baseline assignment to one of the actual treatments. This is to say, the baseline assignment to treatment causes variation in the treatments (received), and the baseline assignment to treatment has no direct effect on the outcome (BEV knowledge or car purchase intentions) that is not through the actual, received treatments. The first stages are as follows:

$$\text{realisedTreatment}_a = \psi\text{Treatment}_1 + \gamma\text{Treatment}_2 + \omega_i \boldsymbol{X} + \mu_i, \quad (2)$$

and the second stage

$$Y_i = \delta^{LATE}\widehat{\text{realisedTreatment}_a} + \beta_i \boldsymbol{X} + \varepsilon_i. \quad (3)$$

The dependent variable, Y, takes two forms. First, it is either whether facts about differently propelled cars were correctly identified, that is, whether respondents correctly recall facts. Second, the dependent variable is whether or not respondents intend to buy a BEV next. Respondents only viewed the question about their next car's drivetrain choice when they indicated they want to purchase or lease another car in the future. The drivetrain choice is assessed using a single-choice question about their most-likely choice for the next drivetrain. Only the choice for a BEV as the next car was coded with 1. (More details and alternative specifications, that do not substantially alter the results see Supplementary InformationM.)

To avoid the "forbidden regression problem" (Wooldridge, 2010, p.236), arising from "replacing a nonlinear function of an endogenous explanatory variable with the same nonlinear function of fitted values from a first-stage estimation" (which might lead to inconsistent estimates) only OLS regressions are performed in the IV regressions, even though the dependent variable Y is binary. For ease of comparison between the ITT and the IV estimate, I report OLS estimates for both. In all IV regressions, I perform the small-sample correction and in all regressions, I use robust standard errors. I employ Stata 15 for computation.

This study has a unique feature that allows the comparison of the magnitude (effect size) of test-driving with previously identified influence factors. These additional factors are likely to influence purchase intention. Therefore, covariates ($\boldsymbol{X}$) are included in the model for the purchase intention analysis. The choice of covariates was guided by the literature on the factors that influence the decision to adopt a BEV (Axsen et al., 2016; Carley et al., 2019; DellaValle and Zubaryeva, 2019; Thøgersen and Ebsen, 2019; Brückmann et al., 2021b; Wicki et al., 2022b). The list of covariates may include gender, age, education, the distance between the home address and test site, environmental concerns, interest in technology, annual kilometres driven by car, number of cars in household, on-street parking only, political attitudes on the left-right scale, membership in a car-sharing scheme, previous BEV experience, employment, monthly household income, housing type, political party preferences, and the survey mode (online or pen-and-paper). In Supplementary Information H, I provide evidence for the inclusion of the important covariates as well as explain their operationalisation in detail.

4. Results

4.1. Results on altering BEV purchase intentions

In this subsection, I present the main results for the dependent variable of BEV purchase intention. Please recall, BEV purchase intentions are 1 if the subject indicated they plan to buy or lease a BEV next, and it is 0 otherwise. In the main specification, respondents who indicated they are indifferent about their next car's drivetrain are omitted; however, this conservative omission does not alter the results (see Supplementary Information M).

4.2. Within-subject results on altering BEV purchase intentions

The within-subject design comparisons show that among those who later received the treatment with test-driving, the intention to buy a BEV stated in the first survey wave ($M = 0.1313$, $SD = 0.0240$) and the increased post-treatment purchase intention ($M = 0.1717$, $SD = 0.0269$) indicate that the treatment with test drives resulted in a higher purchase intention for BEVs, that is not statistically significant at the 5 %-level $t(197) = -1.7139$, $p = .0881$. The corresponding figure for the information-only treatment group is before treatment ($M = 0.0788$, $SD = 0.0084$) and after ($M = 0.1066$, $SD = 0.0096$), which is a significant increase, $t(1040) = -2.8958$, $p = .0039$. Lastly, for the control group the difference between baseline survey ($M = 0.0821$, $SD = 0.0082$) and follow-up survey ($M = 0.0962$, $SD = 0.0088$) purchase intentions for BEVs is not significantly different, $t(1130) = -1.6174$, $p = .1061$. Therefore, this study's within-subject comparisons mirrors the ambiguous findings from previous research using the pre-post-intervention method.

4.3. Between-subject results in altering BEV purchase intentions

Table 1 shows the results of the between-subject design. Column (1) contains the OLS results that represent the intention to treatment (ITT), while column (2) displays the IV result, the Local Average Treatment Effect (LATE). The first two columns show findings without using any control variables, using samples restricted to only respondents who answered questions regarding all control variables. (Table Supplementary Information N.1 gives first stage results, and Table Supplementary Information N.2 shows the whole sample.) The results with control variables are in columns (3)–(6) and are graphically represented in Fig. 2. The estimated model includes all covariates, but only selected covariates are displayed in Fig. 2.

Overall, Table 1 shows positive ITT values for the test drive with information treatment and slightly negative values for the information only treatment group, compared with the control group, see column (1). This positive effect for the test-driving offer remains, even after including relevant control variables, see column (3). Similarly, this translates to the LATE estimates in column (2) going in the same direction as the OLS estimate for both treatments. Unlike Hypothesis 1 stated, we cannot fully support the latter part of Hypothesis 1. However, and as expected, the combined treatment has a much higher positive effect than the information (only) treatment. The chances of choosing a BEV, controlling for other relevant covariates, increase by 31% (and not 95% statistically different from zero) compared with the control group for the information treatment. The comparable effect for the test drive plus information treatment is 10%, see column (6), which is also not statistically significant on the 95% level—utilising a Wald test to test whether the effects of both treatments are not the same yields a p-value of .1327. Therefore, at the 95% level of significance, the null hypothesis that the effect of information alone is the same as from the combined experience and information treatment cannot be rejected. This shows that both treatments increase intention to adopt a BEV (following Hypothesis 1) but, contrasting Hypothesis 2 that the effect is more pronounced for the test-driving with information treatment.

4.3.1. Other influences on participants' purchase intentions

In contrast to previous studies (e.g., Hinnüber et al., 2019; Skippon et al., 2016; Schmalfuβ et al., 2017), this study allows comparing the effect of test-driving with other factors that might influence the decision to buy a BEV. Here, I report on this comparison between covariates and the experimental treatments and refer to column (6) of Table 1.

This table features additional covariates such as standard socio-demographic variables (gender, year of birth, distance to test site from household's address), mobility-related covariates (number of cars in the household, taking part in car sharing, as well as dependence on on-street parking). All of these are not significantly influencing BEV purchase intentions.

I find that the significant effect of higher education (nearly a 5% increase) is larger in magnitude than the effect of the information treatment in the LATE specification. Similarly, it is well-known that the interest in new technologies (Brückmann et al., 2021b; Egbue and Long, 2012) is positively related to the dependent variable, which is mirrored in these results. The significant effect is also around 5%. While this is higher than tertiary education or the information treatment alone, it is lower than the combined effect from the test drive plus information treatment.

The number of annual kilometres driven has a negative impact on the intention to adopt a BEV. While the effect is significant, it seems small. However, the effect for the sample mean (12,914.03 km p.a.) is around −4.8%, which increases to −8.1% with one standard deviation ($SD = 8617.873$ km p.a.) increase.

Previous BEV experience before the possible test drive treatment is highly significant and has just under a 7% effect on BEV purchase intentions. In contrast to the experimental treatment, it includes being driven, not only test-driving oneself. While the survey utilised the

Table 1

Between-subject results for altering BEV purchase intentions through experimental treatments. Dependent variable is a binary indicator that the next car is a BEV (linear probability models) with and without controls. Only complete cases are used for analysis (i.e. item non-responses omitted) in column (1) and (2), unlike Table Supplementary InformationN.2, which shows the full sample without covariates.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	ITT (OLS)	2nd stage (LATE (IV))	ITT (OLS)	1st stage Test with Info	1st stage Info	2nd stage (LATE (IV))
Assigned treatment = 1, Test with Info	0.0284		0.0327	0.288***	0.245***	
	(0.0210)		(0.0201)	(0.0207)	(0.0196)	
Assigned treatment = 2, Info	−0.00594		0.0110	0.00420	0.988***	
	(0.0185)		(0.0177)	(0.00325)	(0.00497)	
Female [0,1]			−0.0309*	−0.0314**	0.00403	−0.0276
			(0.0172)	(0.0138)	(0.0142)	(0.0173)
Year of birth			−0.000320	0.000281	0.000253	−0.000352
			(0.000801)	(0.000690)	(0.000655)	(0.000802)
Tertiary education [0,1]			0.0495***	0.0168	−0.000308	0.0477***
			(0.0182)	(0.0149)	(0.0145)	(0.0183)
Distance to test site [km]			0.000184	−0.000648	−0.000349	0.000255
			(0.000583)	(0.000435)	(0.000464)	(0.000587)
Tech scale [0–5]			0.0504***	0.00799	−0.000766	0.0495***
			(0.00865)	(0.00641)	(0.00610)	(0.00867)
Annual car km			−3.61e-06***	1.62e-06*	−7.62e-07	−3.78e-06***
			(8.69e-07)	(8.58e-07)	(7.04e-07)	(8.92e-07)
Nr. of cars in household			−0.000419	0.00754	0.00461	−0.00125
			(0.0124)	(0.0102)	(0.00853)	(0.0124)
On-street parking only [0,1]			0.0190	−0.00960	0.0190	0.0198
			(0.0671)	(0.0465)	(0.0500)	(0.0678)
Political att. [Left (0) - Right (10)]			−0.00418	−0.00596	−0.00375	−0.00352
			(0.00510)	(0.00390)	(0.00370)	(0.00507)
Carsharing [0,1]			−0.0521	−0.00583	0.0378	−0.0519
			(0.0421)	(0.0339)	(0.0313)	(0.0422)
Previous BEV experience [0,1]			0.0719***	0.0199	−0.00192	0.0698***
			(0.0195)	(0.0145)	(0.0134)	(0.0196)
Employed [0,1]			0.0153	−0.0127	0.00352	0.0165
			(0.0235)	(0.0195)	(0.0191)	(0.0235)
Mothly net household income = 1, Below CHF 4000			0.00554	−0.00116	0.0358	0.00528
			(0.0378)	(0.0327)	(0.0370)	(0.0386)
Mothly net household income = 2, CHF 4000-8000			−0.0321*	−0.0310*	0.0305*	−0.0292
			(0.0187)	(0.0159)	(0.0158)	(0.0184)
Mothly net household income = 4, CHF 12000-16000			0.0318	−0.0337*	−0.00139	0.0354
			(0.0255)	(0.0192)	(0.0159)	(0.0256)
Mothly net household income = 5, More than CHF 16000			0.0278	−0.0391*	0.0223	0.0317
			(0.0298)	(0.0226)	(0.0200)	(0.0298)
Housing category = 1, Own house			0.0197	0.0152	−0.00990	0.0182
			(0.0195)	(0.0154)	(0.0146)	(0.0194)
Housing category = 2, Owner-occupied flat			−0.00656	0.0183	0.00127	−0.00848
			(0.0216)	(0.0179)	(0.0171)	(0.0219)
Party preference = 1, BDP			0.0490	−0.0356	0.153***	0.0511
			(0.0532)	(0.0369)	(0.0520)	(0.0546)
Party preference = 2, CVP			0.0566	0.0304	−0.00235	0.0534
			(0.0352)	(0.0277)	(0.0244)	(0.0350)
Party preference = 3, EDU			−0.0231	−0.0148	0.209*	−0.0237
			(0.0277)	(0.0534)	(0.121)	(0.0264)
Party preference = 4, EVP			−0.00324	−0.00931	0.0236	−0.00252
			(0.0523)	(0.0416)	(0.0446)	(0.0528)
Party preference = 5, FDP			−0.00695	0.0183	0.0292	−0.00917
			(0.0252)	(0.0199)	(0.0208)	(0.0253)
Party preference = 6, GLP			0.112***	0.0322	0.0248	0.109***
			(0.0413)	(0.0279)	(0.0270)	(0.0414)
Party preference = 7, GPS			0.0447	−0.0160	0.0822**	0.0455
			(0.0569)	(0.0358)	(0.0396)	(0.0567)
Party preference = 9, SP			0.0198	0.0122	0.0236	0.0183
			(0.0371)	(0.0303)	(0.0312)	(0.0371)
Party preference = 11, None			−0.00622	0.0252	0.0346	−0.00922
			(0.0255)	(0.0208)	(0.0221)	(0.0257)
Party preference = 12, Other			−0.0685	−0.000802	0.0324	−0.0688
			(0.0535)	(0.0487)	(0.0530)	(0.0546)
Survey mode: pen and paper [0,1]			−0.0101	−0.0590***	0.0919***	−0.00496
			(0.0212)	(0.0147)	(0.0276)	(0.0210)
Realised treatment = 1, Test with Info		0.104				0.104
		(0.0668)				(0.0642)
Realised treatment = 2, Info		−0.00599				0.0107
		(0.0187)				(0.0179)
Constant	0.113***	0.113***	0.602	−0.544	−0.509	0.664
	(0.0134)	(0.0134)	(1.555)	(1.341)	(1.269)	(1.557)

(*continued on next page*)

Table 1 (*continued*)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	ITT (OLS)	2nd stage (LATE (IV))	ITT (OLS)	1st stage Test with Info	1st stage Info	2nd stage (LATE (IV))
Observations	1614	1614	1614	1614	1614	1614
R-squared	0.002	0.008	0.105			0.107

Robust standard errors in parentheses.
***p<0.01, **p<0.05, *p<0.1.

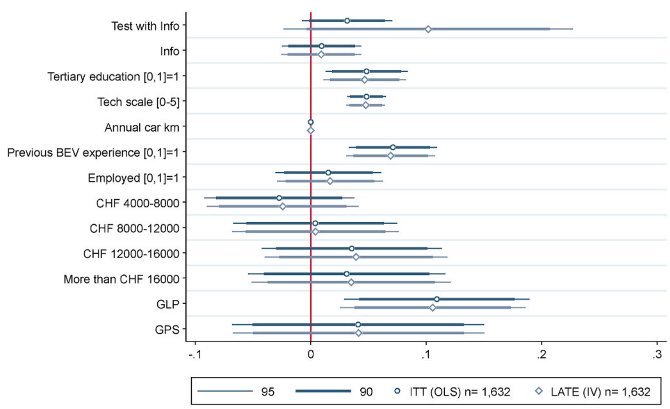

Fig. 2. Comparing effects of both experimental treatments on BEV purchase intentions, showing only selected covariates. Values represent results from ordinary least squares (OLS) regressions (darker lines with circles), that can be interpreted as the effect of the intention to treat (ITT) the respondents, e.g. the offer of a test drive. Lighter lines with diamonds refer to the instrumental variable (IV) estimates representing the treatment effect on the treated, the Local Average Treatment Effects (LATE) estimates. The vertical (red) line at zero represents the control group. Stronger lines indicate 90 %-confidence intervals and thinner lines 95 %-CIs. Note that GLP (Green Liberal Party) and GPS (Green Party of Switzerland) are the two green parties in Switzerland. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

wording "*Battery-electric vehicle, a car entirely powered by energy from the grid stored in a battery*" when assessing previous experience (and at all other instances, such as purchase intentions) confusion with other electric vehicles, especially plug-in hybrid electric vehicles, cannot entirely be ruled out. A better measure and a larger sample could, in future research, allow for an interaction term between previous experience and experimental experience.

While the findings for higher net-monthly household income categories are not significant, they show respondents with higher incomes are more interested in BEVs. Employment is also slightly positively related to BEV adoption intentions. Regarding political attitudes, I include self-placement on a ten-point left-right scale and party preferences. Regarding political party preferences, the only significant positive effect (on the 1 %-level) stems from party preferences is for the Green Liberal Party (GLP), compared with the baseline party preferences (SVP, the right-wing party with the highest vote share in the 2019 National Swiss elections). In contrast, the effect of the Green Party of Switzerland (GPS) is much more minor and insignificant. The effect size for GLP preferences is as much as nearly 11% higher compared with the reference category (SVP). Therefore, it is the highest single significant factor in BEV adoption intention after the experimental test drive plus information treatment.

House ownership was previously also found to be essential to study in the context of BEV adoption. More often than not, single-family detached houses tend to be the most likely homes of BEV owners (Axsen et al., 2016; Thøgersen and Ebsen, 2019; Brückmann et al., 2021b). In this study, neither living in an owner-occupied house has a significant (positive) effect nor living in an owner-occupied flat has a significant (negative) effect compared with living in a rented place. While not significant, the positive effect of the own house is quite substantial, even larger than the GLP party preference effect.

The last control variable that is compared in magnitude and significance to the main experimental treatments is whether the respondent answered on print-and-paper, compared to filling the online survey. While this variable has a slightly negative effect on the outcome of interest, it is not significant. It is to assume that people answering on paper are reluctant to use new technologies and are, therefore, more hesitant to adopt a BEV. Overall, as with all the other covariates, none of their effects exceeds the effect of the test drive with information treatment.

4.3.2. *Heterogeneous treatment effects*

In an experimental model, covariates serve to make estimates more precise. Another approach I use here is heterogeneous treatment effects. Like a lot of previous research (e.g., Carley et al., 2019; Plötz et al., 2014; Wicki et al., 2022b) points to the importance of environmental concern for the adoption of electric vehicles, the questionnaire had a 9-item environmental concern scale, following Diekmann and Meyer (2009). However, only 1718 respondents took the time to fill out all the statements, while 695 did not. I, therefore, create a binary indicator that is 1 if the respondent indicated their environmental concern (independent of its level/magnitude) and 0 otherwise.

Analysing heterogeneous treatment effects concerning the disclosure of environmental concerns shows an exciting pattern. For those, who shared the environmental information, the treatment effects of both treatments are highly significant. Including the environmental scale (that is, the respondents' answers) shows that it becomes significantly more positive. Contrary, for those who did not fill out the environmental questions in the first survey, the treatment effects remain insignificant (and slightly negative); see Fig. 3 (and the table in Supplementary Information Supplementary InformationI.1). This difference in answers is based on self-selection, and therefore, cannot be seen as a causal change as it is not induced by experimentation.

4.4. *Results on altering knowledge*

Whether respondents received the treatments can be measured in terms of altered knowledge, assessed in the follow-up survey. Therefore, I evaluate the knowledge about facts from the information sheet that members in both treatment groups received. Among other information, the sheet stated that BEVs are usually associated with higher purchase prices, lower life-cycle emissions, and higher energy efficiency than conventional cars. Therefore, respondents were asked to correctly identify whether internal combustion engine vehicles or BEVs have a higher purchase price, higher emissions, and higher energy efficiency. Fig. 4 shows in the three left figure parts that participants in the information treatment were at least as good in knowing facts about the BEVs as were the test drive plus information treatment group, compared with the control group. The right part of Fig. 4 shows the estimated share of respondents (in each group) stating that they do not know the answer to these knowledge questions. The figure shows that participants in both

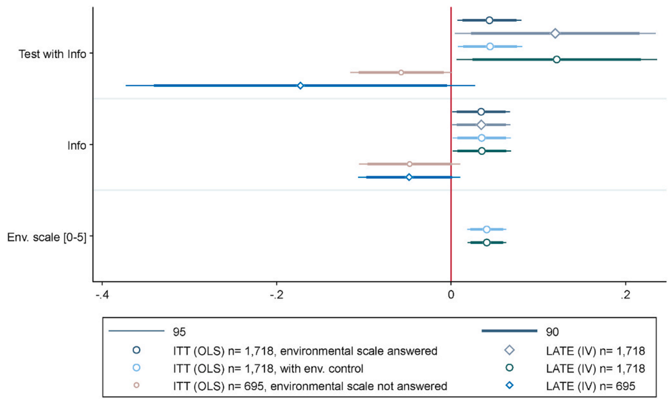

Fig. 3. Heterogeneous treatment effects depending on answers to environmental concern questions. Values represent results from ordinary least squares (OLS) regressions (upper lines with circles), that can be interpreted as the effect of the intention to treat (ITT) the respondents, e.g. the offer of a test drive. Lighter lines with diamonds refer to the instrumental variable (IV) estimates representing the treatment effect on the treated, the Local Average Treatment Effects (LATE) estimates. The first set of lines refers to respondents who indicated their environmental concern; the following two lines also refer to this group but additionally include the environmental concern as a control variable. The last two lines (with smaller symbols) refer to the sample who did not state their environmental concern. The vertical (red) line at zero represents the control group. Stronger lines indicate 90 %-confidence intervals and thinner lines 95 %-CIs. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

treatment groups read and processed the information. The differences between treatment and control groups indicate that the general population, proxied through the control group, cannot recall these facts as easily as the treatment groups.

Figs. 5 and 6 depict how information sticks with those who got it with their treatments and provide further evidence of increased knowledge in the treatment groups. Prior imbalances in the pre-treatment knowledge are depicted in Supplementary InformationJ but can hardly be found.

In Fig. 5 there are stated values for distances from home to the closest known public EV charger. While in the baseline survey (right part, outlined bars), only about half of the respondents were able to answer this question, there was no difference between the control group and the information treatment group. Among the test drive plus information treatment group, there was a slightly higher share of respondents assuming they answered correctly. Also, before any of the treatments, the stated distances in some cases were enormously large and therefore unreasonable (1% of respondents entered values greater than 100 km). After the treatment (left part, filled bars), knowledge is higher for both treatment groups compared with the control group (lower part of Fig. 5). The values for distances reported shrink: the test driving plus information group has a post-treatment median of 2 km (down from 3.5 in the first wave); the information-only treatment group has a median of 3 km (down from 4 km), and the control group has a median of 3 km (no change). The information (only) treatment is most-effective in reducing perceived distances to charging points. This is hardly due to prior imbalances, as Figure Supplementary InformationJ.1 shows by analysing this knowledge on BEV chargers in terms of assigned treatment status.

Similar to the distance to charging stations, Fig. 6 shows respondents' answers to the question of whether they can "estimate the range of a mid-sized (e.g., BMW i3, Nissan Leaf, Renault Zoe, VW e-Golf) BEV." Answers were given in kilometres, or respondents indicated that they did not know. While in the test drive plus information treatment group, the knowledge was highest (92.1%) before treatment. There was no substantial difference between the information treatment and control groups before treatment (both slightly over 80%). The median ranges given are 300 km in all three groups before treatment. After the treatment (left part with filled bars), the share of "don't know" reduces in both treatment groups (up to 10% for the information only treatment group) and slightly for the control group (lower part of Fig. 6). The median ranges for the treatment group with test drives went down to 250 km but remained at 300 km for the other two groups. Perhaps through the use of (mainly) mid-range BEVs (in the winter) in the experimental test drive treatment, the median range expectation decreased. An alternative specification that depicts differences in assigned treatment status and sentiment towards the test drives can be found in Figure Supplementary InformationJ.2.

Overall, the findings suggest that both treatment groups read and processed the information. The information (only) treatment group did not differ in prior knowledge from the control group. Moreover, the knowledge was also likely to be new to many members of the treatment groups. Another comparison between treatment groups' evaluation of facts from the information sheet can be found in Supplementary InformationK. This knowledge transfers to the evaluation of certain car features by treatment status, as shown in Supplementary InformationL. Taken together, I find support for the first part of Hypothesis 1, that both treatments increase participants' knowledge about BEVs.

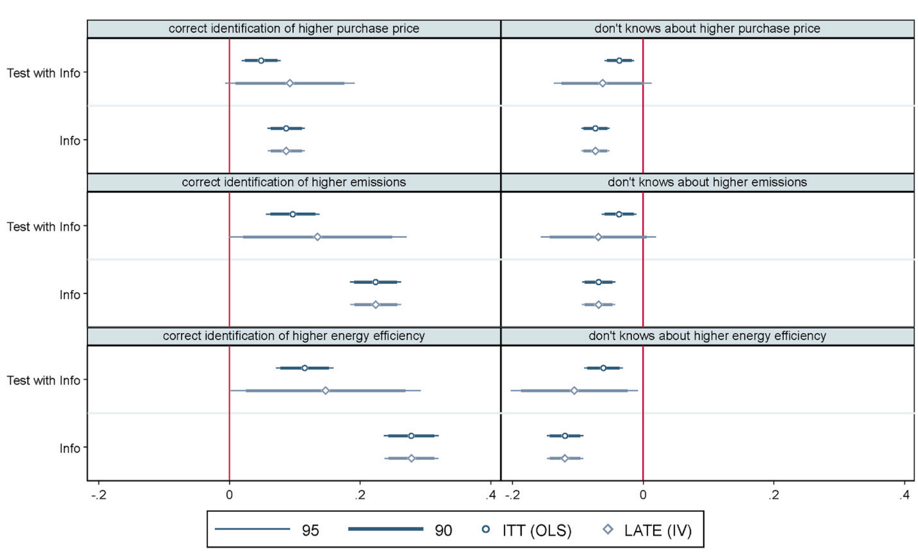

Fig. 4. Comparing estimated knowledge regarding comparisons of BEV with conventional cars attributes by treatment status. Stronger lines for 90 %-confidence intervals (CI) and thinner lines for 95%-CIs. Values represent results from ordinary least squares (OLS) regressions (darker lines with circles), which can be interpreted as the effect of a test drive offer. Formally, it is the intention to treat (ITT) the respondents. Lighter lines with diamonds refer to the instrumental variable (IV) estimates, representing the treatment effect on the treated, the Local Average Treatment Effects (LATE). The vertical (red) line at zero represents the control group. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

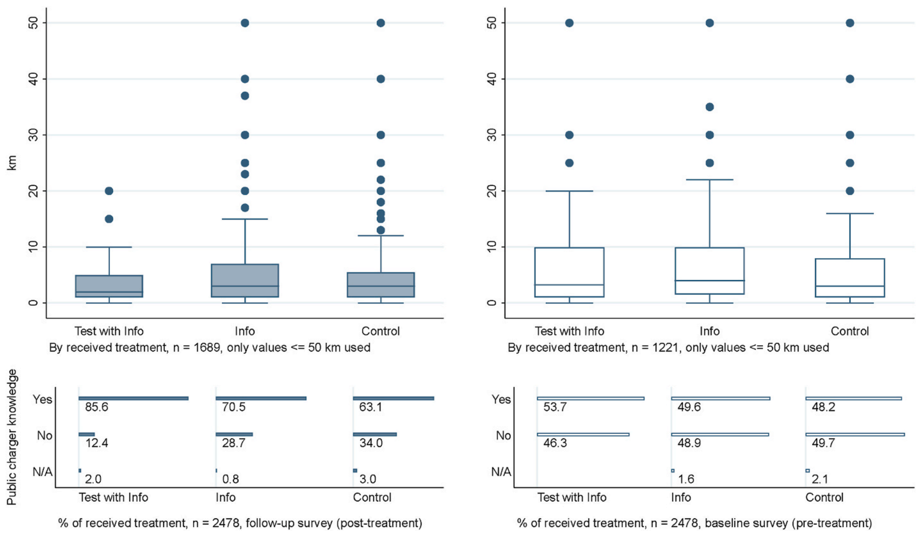

Fig. 5. Comparing knowledge about distances to closest public charging infrastructure by received treatment. The left part is after treatment (follow-up survey), and the right part is before (baseline survey). The answers are displayed in box-whisker plots. The box ranges from 25% percentile to 75% percentile over the mean (all shown with horizontal lines), and lines (whiskers) include all data points within the 1.5 interquartile range of the respective nearer quartile. The lower part shows how many respondents could answer the knowledge question in the upper part by receiving treatment. In the bottom part, "yes" includes those who only know chargers at work. The distance to the workplace (chargers) is unknown for privacy considerations. Values over 50 km are coded as "no" in the lower part (as they are above 99% of all values), and "N/A" indicates respondents who stated they do not know the answer.

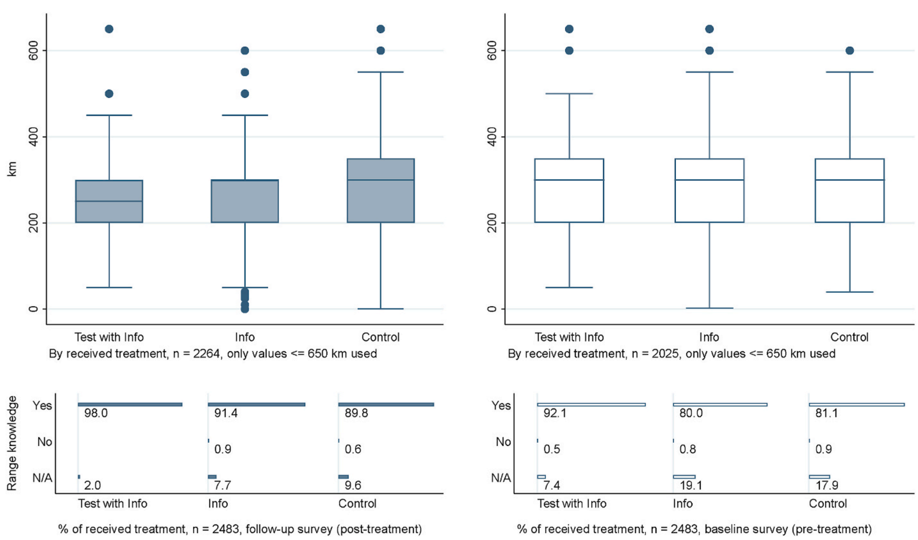

Fig. 6. Comparing knowledge about possible BEV ranges by received treatment. The left part is after treatment (follow-up survey), and the right part is before (baseline survey). The answers are displayed in box-whisker plots. The box ranges from 25% percentile to 75% percentile over the mean (all displayed with horizontal lines) and lines (whiskers) include all data points within the 1.5 interquartile range of the respective nearer quartile. The lower part shows how many respondents were able to answer the knowledge question in the upper part by received treatment. In the lower part, values over 650 km are coded as "no". "N/A" indicates respondents who stated they do not know the answer.

5. Discussion

The findings of this experimental study point towards strong effects of increased BEV knowledge and intention to adopt through both treatments. A positive intention to treat effect and high LATEs for the test drive with information treatment demonstrate increased intention to adopt BEVs after the test drive with information treatment. The treatment effect is substantial in the preferred specification, which jointly estimates treatment effects and other determinants of BEV purchase intentions. Taken together, a series of different estimations turn out similar.

In this study, I analyse the intention to adopt a BEV, not the actual purchase of a BEV. While behavioural intentions are an acceptable and widely used proxy for actual behaviour (Ajzen, 1991), a substantial gap remains between the two. Further research could examine actual adoption. Further research should also assess the effects of BEV information and trialling in other jurisdictions and with different times between intervention and utilising additional time spans between intervention and surveys on BEV adoption intention. A larger sample would also allow differentiating who is most perceptive for experience and information policies using preregistered interaction terms.

In this study, all findings are intentionally conservative to avoid overestimating any effects. One example is that the test drives were deliberately performed in winter. Colder temperatures lead to lower BEV performance, as additional energy for heating is needed. Consequentially, participants who received the test-driving treatment indicated lower maximal ranges of any BEV, see Fig. 6. Still, the results concerning the intention to adopt a BEV show that experiencing shorter ranges than anticipated remains enough to increase adoption intentions among this experimental group. This finding is in line with research showing that most (99% of) trips can be completed with a BEV (e.g. Melliger et al., 2018).

In line with previous research that performed test drives, I demonstrate highly positive (11%) (and significant on 95% confidence levels) treatment effects when only considering the majority of respondents. That is, those who also had filled in environmental concern data. People who fill out these questions are likely to be open about their ecological beliefs. They do not try to hide their low environmental concerns. They prioritise answering questions about the environment, energy, and mobility to a slight gain in their time and remain in the sample. In my interpretation, the group indicating their answers to this longer part (9 items) in the questionnaire is closest to those seeking out adverts in newspapers and online about experiments, including test drives. These studies (e.g., Franke and Krems, 2013; Schmalfuβ et al., 2017), and those done at car fairs (e.g., Roberson and Helveston, 2020), are usually consisting out of people who are interested in the topic, and also take the time, to fill out the relevant questionnaires completely. I argue that those who complied with the effort of data collection and are willing to share their level of environmental concern are closest to the people studied in non-random samples, such as through social networks and alike (e.g., Degirmenci and Breitner, 2017).

6. Conclusion and policy implications

Drawing additionally on the stated importance of experience for BEV adoption (Brückmann, 2022; Thøgersen and Ebsen, 2019; Ensslen et al., 2016; Kim et al., 2019), I examine the effectiveness of two new policy options (information campaigning and extensive test-driving opportunities) to promote BEV adoption and usage. In an RCT, I randomly assigned a high-quality sample of registered car holders without a BEV to two treatment groups and a control group (no intervention). Unlike any previous study, this study performs an appropriate measure to estimate correct, causal treatment effects, taking into account that only some of the study subjects test drove after being randomly offered this treatment. The main finding is that both treatments positively affect the knowledge about BEVs and, as expected, the intention to adopt a BEV. The effect of the test-driving with information treatment increases the intention to adopt a BEV by 11% compared to the control group, among the large majority who also answered longer survey questions. It is important to study if these two potential policy measures have the potential to overcome barriers to the adoption of energy-efficient technology, especially in the case of BEVs, as buying a car is an expensive and infrequent purchase associated with long-term environmental consequences (Anable et al., 2012; Nolan, 2010).

The results from this experiment on information provision and test-driving on stated preferences for BEV adoption are likely to be specific to the context and population at hand. One foremost critic of previous studies with plug-in vehicle user experience is the oversampling of multi-car households (Daramy-Williams et al., 2019), which is also seen to a small extent in this study. In Switzerland, 71% of households with cars own only one car (Swiss Federal Statistical Office (FSO), 2017) as of 2015. Only half of the respondents live in single-car households in the sample used here. This difference could arise through unknown regional differences between Switzerland as a whole and the studied area or through time. Furthermore, pure "unlucky" random sampling could have led to inviting more multi-car households to the survey. However, the differences could also arise through self-selection, as multi-car household members might be more interested in a study on mobility topics. Moreover, experimental effects, such as "Hawthrone" and "subject bias", could potentially impact the results. To nullify these concerns, in further research, the (post-treatment) follow-up survey results could have been compared to other conventional car holders who were not randomly sampled in this study.

This study cannot entirely deny the question posed by Hinnüber et al. (2019), of whether information sheets alone can alter behavioural intentions to the same extent as test-driving plus information. Only those who are also answering all questions on environmental concerns (see Fig. 3) show a noticeable difference between the two treatment effects. The lower engagement with the new technology and different mental processing reduces the treatment effect for only the information sheets. In the future, with an increase in the number of charging stations, long-range BEV models, and the availability of novel BEV product bundles, information provision alone might have a prominent effect. Those improvements may also reduce the negative effect of high annual car kilometres on the BEV adoption intention. Repeating this study in the future will provide insights into this claim. An exciting avenue for further research might be personalised information treatments that consider what each person perceives as barriers and possible ways to alleviate these.

This study is in line with suggestions that extended trial experiences are effective tools (Thøgersen and Ebsen, 2019) for increased BEV adoption. Most importantly, as not everyone may want to take a test drive, this study shows that the offer of a test drive (alone) helps to increase stated interest in BEVs. Therefore, this paper goes beyond examining the importance of experience for BEV adoption (Thøgersen and Ebsen, 2019; Ensslen et al., 2016; Kim et al., 2019). For the promotion of BEVs, extended test drive opportunities facilitated not only by dealerships are a new, low-intrusive policy proposal.

A short note on the ethics of such policy proposals seems necessary. While equality could be achieved by offering test drives to everyone, the equity question about public investments in a technology is still a concern since it is only economically feasible for a fraction of society (Lane, 2019). Lastly, individual electric mobility is no silver bullet for problems we already have with automobility, in general, such as hypermobility, unsustainable trends in land use, or the energy intensity of mobility (Milovanoff et al., 2020).

Many available green technologies to mitigate climate change suffer from low adoption rates, as potential customers lack experience with them. These are often said to be overcome by information policies that include trialling. I argue these findings for BEVs are transferable to other green technologies (e.g., low-flow showerheads (Tomic et al., 2020) or renewable energy generation (Krause et al., 2016) and, further, new applications). This method provides a valuable tool for evaluating green technologies with low consumer demand that need behavioural adoption. Direct experience, in addition to information provision, could be a promising and low-intrusive policy option.

Data availability

An anonymised data set containing a unique identifier for each participant and their assigned and realised treatment status and primary outcome variables concerning knowledge and BEV adoption intention has been deposited in a repository (link: https://osf.io/b5uzq/?view_only=dd40f70b653549439e836143d07f7452). To preserve the anonymity of subjects, it is impossible to share the full data set. The data set available permits replication of all figures and tables and the full computer code used to generate all results is also available at the repository. Similarly, the full computer code used to generate all results in tables and figures, including the Appendix, is also available at the repository (link: https://osf.io/b5uzq/?view_only=dd40f70b653549439e836143d07f7452) and will be made public for readers.

Funding statement

The research was funded by the Swiss Federal Office of Energy (SFOE) and ETH Zurich's ISTP Mobility Research Incubator Program.

CRediT authorship contribution statement

Gracia Brückmann: the sole author, is responsible for everything.

Declaration of competing interest

The author declares that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

I am extremely grateful to Thomas Bernauer, Lukas Fesenfeld, Isabelle Stadelmann-Steffen, Robert Huber, Dennis Kolcava, Vally Koubi, Franziska Quoss, Megan Seipp, Keith Smith, Michael Wicki, and participants at the 4th AIEE Energy Symposium and PSA ECN for very helpful comments on previous versions. Many thanks to Najmeh Karimian-Narnani and Moira Ettlin for English language spell checking. I extend my gratitude to Thomas Bernauer, Isabelle Stadelmann-Steffen, and Kay W. Axhausen for accepting this work as part of my PhD thesis.

Christer Jan Anders Viridén made the implementation of the test-drive treatment possible and I am very grateful for his support throughout carrying out the experimental part. I am also grateful to Basil Huber, Ursin Gstöhl, Alen Salihovic, and David Schärer for valuable research assistance and the team of ETH Transportation & Vehicles for their generous support, including the provision of one of the battery electric vehicles. Many thanks to the companies AMAG Import AG, BMW Switzerland, Hyundai Suisse, Kenny's Auto-Center AG, Kia Motors AG, MM Automobile Schweiz AG, and Renault Suisse SA for providing a battery electric vehicle each for this study.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.enpol.2022.113047.

References

Ajanovic, A., Haas, R., 2016. Dissemination of electric vehicles in urban areas: major factors for success. Energy 115, 1451–1458. https://doi.org/10.1016/j.energy.2016.05.040.

Ajzen, I., 1991. The theory of planned behavior. Organ. Behav. Hum. Decis. Process. 50, 179–211, 10.1016/0749-5978(91) 90020-T.

Alarfaj, A.F., Griffin, W.M., Samaras, C., 2020. Decarbonizing US passenger vehicle transport under electrification and automation uncertainty has a travel budget. Environ. Res. Lett. 15, 0940c2 https://doi.org/10.1088/1748-9326/ab7c89.

Anable, J., Brand, C., Tran, M., Eyre, N., 2012. Modelling transport energy demand: a socio-technical approach. Energy Pol. 41, 125–138. https://doi.org/10.1016/j.enpol.2010.08.020.

Angrist, J.D., Imbens, G.W., Rubin, D.B., 1996. Identification of causal effects using instrumental variables. J. Am. Stat. Assoc. 91, 444–455. https://doi.org/10.1080/01621459.1996.10476902.

Axsen, J., Goldberg, S., Bailey, J., 2016. How might potential future plug-in electric vehicle buyers differ from current "Pioneer" owners? Transport. Res. Transport Environ. 47, 357–370. https://doi.org/10.1016/j.trd.2016.05.015.

Axsen, J., Plötz, P., Wolinetz, M., 2020. Crafting strong, integrated policy mixes for deep CO2 mitigation in road transport. Nat. Clim. Change 10, 809–818. https://doi.org/10.1038/s41558-020-0877-y.

Barth, M., Jugert, P., Fritsche, I., 2016. Still underdetected - social norms and collective efficacy predict the acceptance of electric vehicles in Germany. Transport. Res. F Traffic Psychol. Behav. 37, 64–77. https://doi.org/10.1016/j.trf.2015.11.011.

Brückmann, Gracia, 2022. Test-drives & information might not boost actual battery electric vehicle uptake? Transport. Res. Transport Environ. 160, 204–218. https://doi.org/10.1016/j.tra.2022.03.025.

Brückmann, G., Bernauer, T., 2020. What drives public support for policies to enhance electric vehicle adoption? Environ. Res. Lett. 15, 094002 https://doi.org/10.1088/1748-9326/ab90a5.

Brückmann, G., Wicki, M., Bernauer, T., 2021a. Is resale anxiety an obstacle to electric vehicle adoption? Results from a survey experiment in Switzerland. Environ. Res. Lett. 16, 124027. https://doi.org/10.1088/1748-9326/AC3531.

Brückmann, G., Willibald, F., Blanco, V., 2021b. Battery Electric Vehicle adoption in regions without strong policies. Transport. Res. Transport Environ. 90, 102615. https://doi.org/10.1016/J.TRD.2020.102615.

Bühler, F., Cocron, P., Neumann, I., Franke, T., Krems, J.F., 2014. Is EV experience related to EV acceptance? Results from a German field study. Transport. Res. Part F: Psychology and Behaviour 25, 34–49. https://doi.org/10.1016/j.trf.2014.05.002.

Burgess, M., King, N., Harris, M., Lewis, E., 2013. Electric vehicle drivers' reported interactions with the public: driving stereotype change? Transport. Res. Part F: Psychology and Behaviour 17, 33–44. https://doi.org/10.1016/j.trf.2012.09.003.

Carley, S.R., Krause, R.M., Lane, B.W., Graham, J.D., 2013. Intent to purchase a plug-in electric vehicle: a survey of early impressions in large US cites. Transport. Res. Transport Environ. 18, 39–45. https://doi.org/10.1016/j.trd.2012.09.007.

Carley, S.R., Siddiki, S., Nicholson-Crotty, S., 2019. Evolution of plug-in electric vehicle demand: assessing consumer perceptions and intent to purchase over time. Transport. Res. Transport Environ. 70, 94–111. https://doi.org/10.1016/j.trd.2019.04.002.

Daramy-Williams, E., Anable, J., Grant-Muller, S., 2019. A systematic review of the evidence on plug-in electric vehicle user experience. Transport. Res. Transport Environ. 71, 22–36. https://doi.org/10.1016/j.trd.2019.01.008.

De Vos, J., 2020. The effect of COVID-19 and subsequent social distancing on travel behavior. Transp. Res. Interdiscip. Perspect. 5, 100121. https://doi.org/10.1016/j.trip.2020.100121.

Degirmenci, K., Breitner, M.H., 2017. Consumer purchase intentions for electric vehicles: is green more important than price and range? Transport. Res. Transport Environ. 51, 250–260. https://doi.org/10.1016/j.trd.2017.01.001.

DellaValle, N., Zubaryeva, A., 2019. Can we hope for a collective shift in electric vehicle adoption? Testing salience and norm-based interventions in South Tyrol, Italy. Energy Res. Social Sci. 55, 46–61. https://doi.org/10.1016/j.erss.2019.05.005.

Delmas, M.A., Fischlein, M., Asensio, O.I., 2013. Information strategies and energy conservation behavior: a meta-analysis of experimental studies from 1975 to 2012. Energy Pol. 61, 729–739. https://doi.org/10.1016/j.enpol.2013.05.109.

Diekmann, A., Meyer, R., 2009. Schweizer Umweltsurvey 2007 Analysen und Ergebnisse. Technical Report.

Dumortier, J., Siddiki, S., Carley, S.R., Cisney, J., Krause, R.M., Lane, B.W., Rupp, J.A., Graham, J.D., 2015. Effects of providing total cost of ownership information on consumers' intent to purchase a hybrid or plug-in electric vehicle. Transport. Res. Pol. Pract. 72, 71–86. https://doi.org/10.1016/j.tra.2014.12.005.

Egbue, O., Long, S., 2012. Barriers to widespread adoption of electric vehicles: an analysis of consumer attitudes and perceptions. Energy Pol. 48, 717–729. https://doi.org/10.1016/j.enpol.2012.06.009.

Ensslen, A., Paetz, A.G., Babrowski, S., Jochem, P., Fichtner, W., 2016. On the Road to an Electric Mobility Mass Market—How Can Early Adopters Be Characterized? Springer, Cham, pp. 21–51. https://doi.org/10.1007/978-3-319-24229-3{_}3.

Franke, T., Krems, J.F., 2013. Understanding charging behaviour of electric vehicle users. Transport. Res. F Traffic Psychol. Behav. 21, 75–89. https://doi.org/10.1016/j.trf.2013.09.002.

Gärling, A., Thøgersen, J., 2001. Marketing of electric vehicles. Bus. Strat. Environ. 10, 53–65. https://doi.org/10.1002/1099-0836(200101/02)10:1{\textless}53::AID-BSE270{\textgreater}3.0.CO;2-E.

Graham-Rowe, E., Gardner, B., Abraham, C., Skippon, S., Dittmar, H., Hutchins, R., Stannard, J., 2012. Mainstream consumers driving plug-in battery-electric and plug-in hybrid electric cars: a qualitative analysis of responses and evaluations. Transport. Res. Pol. Pract. 46, 140–153. https://doi.org/10.1016/j.tra.2011.09.008.

Hardman, S.J., 2019. Understanding the impact of reoccurring and non-financial incentives on plug-in electric vehicle adoption – a review. Transport. Res. Pol. Pract. 119, 1–14. https://doi.org/10.1016/j.tra.2018.11.002.

Hardman, S.J., Chandan, A., Tal, G., Turrentine, T., 2017. The effectiveness of financial purchase incentives for battery electric vehicles – a review of the evidence. Renew. Sustain. Energy Rev. 80, 1100–1111. https://doi.org/10.1016/j.rser.2017.05.255.

Haustein, S., Jensen, A.F., Cherchi, E., 2021. Battery electric vehicle adoption in Denmark and Sweden: recent changes, related factors and policy implications. Energy Pol. 149, 112096. https://doi.org/10.1016/j.enpol.2020.112096.

Herberz, M., Hahnel, U.J., Brosch, T., 2020. The importance of consumer motives for green mobility: a multi-modal perspective. Transport. Res. Pol. Pract. 139, 102–118. https://doi.org/10.1016/j.tra.2020.06.021.

Higueras-Castillo, E., Guillén, A., Herrera, L.J., Liébana-Cabanillas, F., 2020. Adoption of electric vehicles: which factors are really important? Int. J. Sustain. Transport. 1–15. https://doi.org/10.1080/15568318.2020.1818330.

Hinnüber, F., Szopik-Depczynska, K., Szarucki, M., 2019. The effects of a first-time experience on the evaluation of battery electric vehicles by potential consumers. Sustainability 11. https://doi.org/10.3390/su11247034.

Huber, R.A., Wicki, M., 2021. What explains citizen support for transport policy? the roles of policy design, trust in government and proximity among Swiss citizens. Energy Res. Social Sci. 75, 101973. https://doi.org/10.1016/J.ERSS.2021.101973.

Intergovernmental Panel on Climate Change, I, 2018. Global warming of 1.5°C. An IPCC special report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways. In: The Context of Strengthening the Global Response to the Threat of Climate Change. Technical Report. Geneva. https://www.ipcc.ch/sr15/.

Javid, R.J., Nejat, A., 2017. A comprehensive model of regional electric vehicle adoption and penetration. Transport Pol. 54, 30–42. https://doi.org/10.1016/j.tranpol.2016.11.003.

Jensen, A.F., Cherchi, E., Mabit, S.L., 2013. On the stability of preferences and attitudes before and after experiencing an electric vehicle. Transport. Res. Transport Environ. 25, 24–32. https://doi.org/10.1016/j.trd.2013.07.006.

Kim, J.H., Lee, G., Park, J.Y.J., Hong, J., Park, J.Y.J., 2019. Consumer intentions to purchase battery electric vehicles in Korea. Energy Pol. 132, 736–743. https://doi.org/10.1016/j.enpol.2019.06.028.

Krause, R.M., Carley, S.R., Lane, B.W., Graham, J.D., 2013. Perception and reality: public knowledge of plug-in electric vehicles in 21 U.S. cities. Energy Pol. 63, 433–440. https://doi.org/10.1016/j.enpol.2013.09.018.

Krause, R.M., Pierce, J.C., Steel, B.S., 2016. The impact of auditory and visual experience with wind turbines on support for wind production and proximity-based opposition. Soc. Nat. Resour. 29, 1452–1466. https://doi.org/10.1080/08941920.2016.1171936.

Lane, B.W., 2019. Revisiting 'An unpopular essay on transportation:' the outcomes of old myths and the implications of new technologies for the sustainability of transport. J. Transport Geogr. 81, 102535. https://doi.org/10.1016/J.JTRANGEO.2019.102535.

Larson, P.D., Viáfara, J., Parsons, R.V., Elias, A., 2014. Consumer attitudes about electric cars: pricing analysis and policy implications. Transport. Res. Pol. Pract. 69, 299–314. https://doi.org/10.1016/j.tra.2014.09.002.

Liberman, N., Trope, Y., Stephan, E., 2007. Psychological distance. In: Social Psychology: Handbook of Basic Principles, ume 29. Guilford Press, New York, pp. 353–381 (chapter 15).

Liu, R., Ding, Z., Jiang, X., Sun, J., Jiang, Y., Qiang, W., 2020. How does experience impact the adoption willingness of battery electric vehicles? The role of psychological factors. Environ. Sci. Pollut. Control Ser. https://doi.org/10.1007/s11356-020-08834-w.

Long, Z., Axsen, J., Kormos, C., 2019. Consumers continue to be confused about electric vehicles: comparing awareness among Canadian new car buyers in 2013 and 2017. Environ. Res. Lett. 14, 114036. https://doi.org/10.1088/1748-9326/ab4ca1.

Lynes, J., 2018. Dealerships are a tipping point. Nat. Energy 3, 457–458. https://doi.org/10.1038/s41560-018-0173-5.

Mattioli, G., Roberts, C., Steinberger, J.K., Brown, A., 2020. The political economy of car dependence: a systems of provision approach. Energy Res. Social Sci. 66, 101486. https://doi.org/10.1016/j.erss.2020.101486.

Melliger, M.A., van Vliet, O.P., Liimatainen, H., 2018. Anxiety vs reality – sufficiency of battery electric vehicle range in Switzerland and Finland. Transport. Res. Transport Environ. 65, 101–115. https://doi.org/10.1016/j.trd.2018.08.011.

Milovanoff, A., Posen, I.D., MacLean, H.L., 2020. Electrification of light-duty vehicle fleet alone will not meet mitigation targets. Nat. Clim. Change 1–6. https://doi.org/10.1038/s41558-020-00921-7.

Molesworth, M., Suortti, J.P., 2002. Buying cars online: the adoption of the web for high-involvement, high-cost purchases. J. Consum. Behav. 2, 155–168. https://doi.org/10.1002/cb.97.

Nolan, A., 2010. A dynamic analysis of household car ownership. Transport. Res. Pol. Pract. 44, 446–455. https://doi.org/10.1016/j.tra.2010.03.018.

OECD, 2014. The Cost of Air Pollution. OECD Publishing, Paris. https://doi.org/10.1787/9789264210448-en.

Petschnig, M., Heidenreich, S., Spieth, P., 2014. Innovative alternatives take action – investigating determinants of alternative fuel vehicle adoption. Transport. Res. Pol. Pract. 61, 68–83. https://doi.org/10.1016/j.tra.2014.01.001.

Plötz, P., Schneider, U., Globisch, J., Dütschke, E., 2014. Who will buy electric vehicles? Identifying early adopters in Germany. Transport. Res. Pol. Pract. 67, 96–109. https://doi.org/10.1016/j.tra.2014.06.006.

Roberson, L.A., Helveston, J.P., 2020. Electric vehicle adoption: can short experiences lead to big change? Environ. Res. Lett. 15, 0940c3 https://doi.org/10.1088/1748-9326/aba715.

Rogers, E.M., 2003. Diffusion of Innovations. Free Press.

Santos, G., Davies, H., 2020. Incentives for quick penetration of electric vehicles in five European countries: perceptions from experts and stakeholders. Transport. Res. Pol. Pract. 137, 326–342. https://doi.org/10.1016/j.tra.2018.10.034.

Schlüter, J., Weyer, J., 2019. Car sharing as a means to raise acceptance of electric vehicles: an empirical study on regime change in automobility. Transport. Res. F Traffic Psychol. Behav. 60, 185–201. https://doi.org/10.1016/j.trf.2018.09.005.

Schmalfuß, F., Mühl, K., Krems, J.F., 2017. Direct experience with battery electric vehicles (BEVs) matters when evaluating vehicle attributes, attitude and purchase intention. Transport. Res. F Traffic Psychol. Behav. 46, 47–69. https://doi.org/10.1016/J.TRF.2017.01.004.

Schneider, U., Dütschke, E., Peters, A., 2014. How does the actual usage of electric vehicles influence consumer acceptance? Evolutionary Paths Towards the Mobility Patterns of the Future 49–66.

Schuitema, G., Anable, J., Skippon, S.M., Kinnear, N., 2013. The role of instrumental, hedonic and symbolic attributes in the intention to adopt electric vehicles. Transport. Res. Pol. Pract. 48, 39–49. https://doi.org/10.1016/j.tra.2012.10.004.

Sierzchula, W., Bakker, S., Maat, K., van Wee, B., 2014. The influence of financial incentives and other socio-economic factors on electric vehicle adoption. Energy Pol. 68, 183–194. https://doi.org/10.1016/j.enpol.2014.01.043.

Skippon, S.M., Garwood, M., 2011. Responses to battery electric vehicles: UK consumer attitudes and attributions of symbolic meaning following direct experience to reduce psychological distance. Transport. Res. Transport Environ. 16, 525–531. https://doi.org/10.1016/j.trd.2011.05.005.

Skippon, S.M., Kinnear, N., Lloyd, L., Stannard, J., 2016. How experience of use influences mass-market drivers' willingness to consider a battery electric vehicle: a randomised controlled trial. Transport. Res. Pol. Pract. 92, 26–42. https://doi.org/10.1016/j.tra.2016.06.034.

Stern, P.C., 1999. Information, incentives, and proenvironmental consumer behavior. J. Consum. Pol. 22, 461–478, 10.1023/A: 1006211709570.

Swiss Federal Office of Energy, 2021. Kennzahlen alternative antriebe neuwagen. URL: https://www.bfe.admin.ch/bfe/de/home/versorgung/statistik-und-geodaten/kennzahlen-fahrzeuge/kennzahlen-alternative-antriebe-neuwagen.html.

Swiss Federal Office of Statistics, 2021. Fahrzeuge. URL: https://www.bfs.admin.ch/bfs/de/home/statistiken/mobilitaet-verkehr/verkehrsinfrastruktur-fahrzeuge/fahrzeuge.html.

Swiss Federal Statistical Office (FSO), 2017. Verkehrsverhalten der Bevölkerung Ergebnisse des Mikrozensus Mobilität und Verkehr 2015. Neuchâtel.

The American Association for Public Opinion Research, 2016. Standard Definitions Final Dispositions of Case Codes and Outcome Rates for Surveys, ninth ed.

Thøgersen, J., Ebsen, J.V., 2019. Perceptual and motivational reasons for the low adoption of electric cars in Denmark. Transport. Res. F Traffic Psychol. Behav. 65, 89–106. https://doi.org/10.1016/j.trf.2019.07.017.

Tomic, U., Moser, C., Blumer, Y., Stauffacher, M., Seidl, R., 2020. Exploring the role of positive direct experience in the adoption of energy efficient technologies: evidence from a Swiss field study on the promotion of low-flow showerheads. PLoS One 15, 1–18. https://doi.org/10.1371/journal.pone.0230255.

Wang, S., Wang, J., Li, J., Wang, J., Liang, L., 2018. Policy implications for promoting the adoption of electric vehicles: do consumer's knowledge, perceived risk and financial incentive policy matter? Transport. Res. Pol. Pract. 117, 58–69. https://doi.org/10.1016/j.tra.2018.08.014.

Wang, L., Fu, Z.L., Guo, W., Liang, R.Y., Shao, H.Y., 2020. What influences sales market of new energy vehicles in China? Empirical study based on survey of consumers' purchase reasons. Energy Pol. 142, 111484. https://doi.org/10.1016/j.enpol.2020.111484.

Wicki, M., Brückmann, G., Quoss, F., Bernauer, T., 2022b. What do we really know about the acceptance of battery electric vehicles? – turns out, not much. Transport Rev. 1 https://doi.org/10.1080/01441647.2021.2023693. –26doi.

Wicki, M., Fesenfeld, L., Bernauer, T., 2019. In search of politically feasible policy-packages for sustainable passenger transport: insights from choice experiments in China, Germany, and the USA. Environ. Res. Lett. 14, 084048 https://doi.org/10.1088/1748-9326/ab30a2.

Wicki, Michael, Brückmann, Gracia, Bernauer, Thomas, 2022a. How to accelerate the uptake of electric cars? Insights from a choice experiment. J. Clean. Prod. 355, 131774 https://doi.org/10.1016/j.jclepro.2022.131774.

Wooldridge, J.M., 2010. Econometric Analysis of Cross Section and Panel Data. The MIT Press, pp. 1–752.

Xu, G., Wang, S., Li, J., Zhao, D., 2020. Moving towards sustainable purchase behavior: examining the determinants of consumers' intentions to adopt electric vehicles. Environ. Sci. Pollut. Control Ser. 27, 22535–22546. https://doi.org/10.1007/s11356-020-08835-9.

Yang, Z., Mock, P., German, J., Bandivadekar, A., Lah, O., 2018. On a pathway to de-carbonization – a comparison of new passenger car CO2 emission standards and taxation measures in the G20 countries. Transport. Res. Transport Environ. 64, 53–69. https://doi.org/10.1016/j.trd.2017.06.022.

Zhang, R., Fujimori, S., 2020. The role of transport electrification in global climate change mitigation scenarios. Environ. Res. Lett. 15, 034019 https://doi.org/10.1088/1748-9326/ab6658.

Ziegler, A., 2012. Individual characteristics and stated preferences for alternative energy sources and propulsion technologies in vehicles: a discrete choice analysis for Germany. Transport. Res. Pol. Pract. 46, 1372–1385. https://doi.org/10.1016/j.tra.2012.05.016.