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End of the ICE Age:

The economics of the green transport transition

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FACULTÉ DES SCIENCES ÉCONOMIQUES

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Abstract

The significant negative externalities from vehicles' combustion of fossil fuels have the potential to be overcome through the increasing electrification of the transport sector. This transition faces, however, a wide range of externalities from car purchase and use, new technologies and developing infrastructure, and consumer travel behaviour. In this context, this thesis presents an analysis of travel choices, electric vehicle (EV) adoption barriers, and the importance of complementary network infrastructure.

Investments in a car or public transport pass could affect later travel modes. Chapter 1 presents a unique sequential choice experiment of 995 respondents that links car and public transport subscription choices to travel mode decisions. The choice analysis results show that EV adoption does not greatly affect mode choices beyond reactions to varied marginal travel costs. Sunk costs (upfront investment price) also have no influence. A mode commitment effect is largely rejected, however, respondents having chosen a mobility device show lower sensitivity to other modes' trip time. EV adoption, though, faces significant barriers; particularly as the market moves beyond early adopters towards mass adoption. Chapter 2 further presents an analysis of the car type preferences of 882 choice experiment respondents. It finds significant but inelastic EV demand regarding purchase prices, however insignificant sensitivity to driving range and driving costs. There is some heterogeneity, however, across respondents. It also shows stable car preferences among existing car owners and regular car users, while those without a car and public transport users are most likely to adopt an EV. A lack of charging network infrastructure is a further hindrance to the adoption of new technologies and suffers from a chicken-and-egg stand-off with charger providers. Chapter 3 analyses a panel of municipal-level data across Norway and demonstrates a significant impact of additional charging station installations on EV registrations. It especially shows the relatively large effect of early infrastructure provision and the long-lasting, path-determining impact of the very first stations.

Keywords: Transport; Electric Vehicles; Adoption; Behaviour; Externality; Charging Infrastructure; Environmental Policy.

JEL classification: D62, D90, L14, L91, O33, Q40, Q48, Q55, Q58, R40

Résumé

Les externalités négatives importantes de la combustion fossile par des véhicules ont le potentiel d'être surmonté par l'électrification croissante du secteur de transport. Cette transition fait face, cependant, à des externalités diverses dû à l'achat et à l'utilisation de la voiture, aux technologies nouvelles et l'infrastructure développant, et au comportement du consommateur. Dans ce contexte, cette thèse présente une analyse des choix de déplacement, des obstacles à l'adoption des voitures électriques (VE), et de l'importance de l'infrastructure complémentaire.

Les investissements dans une voiture ou dans un abonnement aux transports publics pourraient affecter les modes de déplacement. Chapitre 1 présente une expérience de choix séquentielle qui établit un lien entre les choix de voiture et d'abonnement aux transports publics, et les décisions de mode de déplacement. Les résultats des analyses montrent que l'adoption de VE n'affecte pas beaucoup les choix de mode de transport au-delà des réactions aux coûts marginaux de déplacement variés. Les coûts irrécupérables (prix de l'investissement initial) ont également aucune influence. Un effet d'engagement modal est largement rejeté, cependant, les répondants ayant choisi un dispositif de mobilité montrent une sensibilité plus faible à la durée des trajets d'autre modes. L'adoption des VE est néanmoins confrontée à des obstacles importants, en particulier pour atteindre une adoption de masse. Chapitre 2 présente également une analyse des choix de type de voiture des répondants de l'expérience ci-dessus. Elle constate que la demande de VE est significative mais inélastique en ce qui concerne le prix d'achat, mais que la sensibilité à l'autonomie et aux coûts de conduite est insignificative. Il existe toutefois une hétérogénéité entre les répondants. Il montre également des préférences technologiques stables parmi les propriétaires de voitures existantes et les utilisateurs réguliers de voitures. Le manque d'infrastructures de réseaux de recharge est un autre obstacle à l'adoption de nouvelles technologies et souffre d'une impasse de l'œuf et de la poule avec les fournisseurs de chargeurs. Chapitre 3 analyse un panel de données au niveau municipal à travers la Norvège, et démontre un impact significatif des installations de bornes de recharge supplémentaires sur les enregistrements de VE. Elle montre en particulier l'effet relativement important de la fourniture précoce d'infrastructures et l'impact durable des toutes premières stations.

Mots-clés: Transport ; Véhicules électriques ; Adoption ; Comportement ; Externalité ; Infrastructure de recharge ; Politique environnementale.

JEL classification: D62, D90, L14, L91, O33, Q40, Q48, Q55, Q58, R40

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Introduction

The global green energy transition – the transition to a carbon-neutral economy – requires significant changes to all energy systems and economic sectors (IPCC, 2022). The current transport sector is primarily technologically based on the internal combustion engine (ICE), which burns fossil fuels – mostly petrol/gasoline and diesel. The combustion of fossil fuels in ICEs creates a large negative externality through the emission of approximately 25 percent of global greenhouse gas (GHG) emissions (IEA, 2019a), as well as 57 percent of Nitrous Oxides, and 20 percent of particulate matter 2.5 (European Environmental Agency, 2018). These GHG emissions are a major contributor to global climate change, and emitted local pollutants contribute to respiratory health issues, decreased labour productivity, cognitive impairment and increased mortality (both infant and adult) (IPCC, 2022; Archsmith et al., 2018; Slezakova et al., 2013; Zivin and Neidell, 2012; Currie and Walker, 2011; Chay and Greenstone, 2003).[1] The electrification of the transport sector, and most easily and rapidly of private and public transport (as opposed to goods transport), is now commonly seen as a key part of eliminating its use of fossil fuels and related negative externalities (Sims et al., 2014). Already in the current electricity systems of many countries, electric vehicles (EVs) generate lower lifetime GHG emissions than comparable ICE vehicles (Knobloch et al., 2020; Ambrose et al., 2020; Xu et al., 2020), however, there is significant regional heterogeneity depending on the primary electricity energy sources (Holland et al., 2016). As the process of decarbonising electricity generation progresses worldwide, the benefits to the transport sector become increasingly large (Holland et al., 2020).

The green transport transition contains both technological and behavioural dimensions. Technologically, the (re-)development of the EV since the 1990s and 2000s has enabled

[1] Further negative externalities from private ICE car use include noise pollution and waterway pollution, while driving more generally contributes to congestion externalities, increased land use for roads, which in turn contributes to ecological damages and heat island effects, and accidents, which generate deaths, injuries and property damages (Bento et al., 2014; Anas and Lindsey, 2011; Edlin and Karaca-Mandic, 2006; Greene et al., 1997).

the mass adoption and use of the car engine system as a competitor to and replacement of the ICE. This development continues to particularly increase driving range without linearly increasing battery sizes and car weight (Standage, 2021). Despite the emissions and noise benefits, and lower operating costs, EVs also pose some barriers to adoption. They remain more expensive upfront than equivalent ICEs, and have a comparatively limited driving range before charging ('fuelling') is needed, which can also then take a long time depending on the car and charging technology (Egbue et al., 2017).

Their complete reliance on electric power means that battery electric vehicles (BEVs) are a totally different technology to conventional hybrid vehicles (CHs), for example. Plug-in hybrid vehicles (PHEVs) are one step between BEVs and CHs, possessing a chargeable battery and electric motor in addition to a traditional ICE. The adoption of electric power systems (BEVs, but also to some extent PHEVs) further requires the development, installation and use of complementary fuelling infrastructure – public or home-based EV charging stations (Clinton and Steinberg, 2019). While this thesis specifically focuses on battery-based electric vehicle technologies, BEVs and PHEVs, the barriers faced are similar for other developing technologies such as hydrogen fuel cell vehicles, and the lessons largely also apply.

These adoption barriers and technological changes feed directly into consumer adoption and use behaviours. Many car purchasers are reportedly apprehensive about the reliability of such an unfamiliar technology, are unwilling or unable to pay the high up-front costs despite future reduced expenses, and especially have "range anxiety", a fear that the battery range will not suffice and they will be unable to recharge where and when they want, and relatively quickly (Egbue and Long, 2012; Hidrue et al., 2011; Dimitropoulos et al., 2016; Rezvani et al., 2015; Franke and Krems, 2013; Chen et al., 2020; Hardman and Tal, 2016; Jenn et al., 2018; Sovacool and Hirsh, 2009).

The negative externalities stemming from ICE use cause a greater social cost of ICE use than the private cost alone. This situation results in a market failure whereby the purchase and use of ICEs is greater than the socially optimal equilibrium. The optimal correction to this market failure is a tax specifically on the negative externality-generating good or activity (a "Pigouvian Tax", in this case on fossil fuel consumption), or an emissions cap with tradeable pollutant emissions permits, however, this has proven politically and socially difficult to implement (Weitzman, 1974; Button, 1990; Sumner et al., 2011; Criqui et al., 2019).

Instead, to encourage a reduction in ICE purchases, many governments worldwide provide incentives for the purchase and use of so-called "zero-emissions vehicles", or specifically of EVs. Such incentives can reduce the upfront financial cost, reduce ongoing car use costs, increase the ease of use, or a combination of use ease and use cost. Subsidies to the upfront purchase price are a common mechanism used across Europe and North America, and can take the form of direct price subsidies, rebates, or tax exemptions (eg. Clinton and Steinberg, 2019). Ongoing financial incentives can include, for example, annual registration (or licence) fee exemptions or reductions (eg. Kester et al., 2018). Other ongoing financial benefits can reduce the use cost of an EV in certain circumstances. This includes, for example, the free use of toll roads, free parking, and reduced car-ferry tickets offered in Norway (eg. Bjerkan et al., 2016). Pure use benefits include the permitted use of high occupancy vehicle (HOV) lanes offered, for example, in California and Norway (eg. Jenn et al., 2018). Finally, given the need for new complementary charging infrastructure, many jurisdictions subsidise the installation of public or private EV charging stations (eg. Springel, 2021).

Car ownership and use occur in the context of the broader transport system. Therefore EV adoption behaviour must further be understood in its interactions with other transport options. EVs could replace ICEs one-to-one and be used in the same way, or there could be a rebound effect due to the lower use cost, which incentivises owners to drive more often (Dimitropoulos et al., 2018). This could take place in terms of greater transport demand overall, or EVs could replace public or soft transport use, for example. Some evidence indicates that EVs in the USA have, to this point on average, been driven smaller distances than ICEs – by owners who only drive short trips or for short trips by owners who have multiple cars, including an ICE that they use for longer distances (Davis, 2019). On the other hand, some have found that EV adopters start to drive more often and longer distances (Figenbaum, 2017), and even potentially replace past public transport use with driving (Halvorsen et al., 2009).

Given the large scale of the issue and the large cost of EV adoption incentive programs, analyses of their efficiency and effectiveness are important. Furthermore, consumer travel-related behaviours are complex and it is important to clarify and understand these in light of green market developments and government EV incentive policies. Several articles have attempted to determine the effect of subsidies on EV purchases. These range from $1000 to over $20,000 (USD-equivalent) and generate an increase in EV purchases by 2.5 to 8 percent per $1000 (Clinton and Steinberg, 2019; Jenn et al., 2018; DeShazo et al., 2017; Li et al., 2017; Bjerkan et al., 2016; Sierzchula et al., 2014). Another strand of literature argues that most straightforward financial subsidies are not as efficient or effective as is often suggested due to non-additionality. They find that many EVs that take advantage of subsidies would have been purchased regardless (up to 70 percent), or at least would have been a low-polluting alternative car in a subsidy-less counterfactual (thus overestimating GHG abatement by nearly 40 percent) (Xing et al., 2021; DeShazo et al., 2017).

Non-monetary incentives have been found to have mostly positive and relatively large impacts on EV adoption. Studies focus on HOV lane use by EVs and find this factor alone is responsible for up to 25 percent of EV purchases (eg. in California) (Fevang et al., 2021; Jenn et al., 2018; Sheldon and DeShazo, 2017; Bjerkan et al., 2016; Mersky et al., 2016; Figenbaum et al., 2014). Finally, public EV charging infrastructure has been found to have a significant effect on EV adoption. Both Li et al. (2017) and Springel (2021) find that subsidies for charging station installations have over double the impact on adoption than the same subsidy value on EV purchase prices. But they add that a combined approach is optimal. Other studies additionally find that consumers state or show that charger access is an important factor for adoption decisions (eg. Hardman and Tal, 2021; Sheldon and DeShazo, 2017; Mersky et al., 2016; Figenbaum et al., 2014).

This thesis provides three chapters that cohesively address different aspects of the green transport transition, including transport mode use decisions, barriers to EV adoption, and the role of public charging infrastructure. It takes a systemic approach to the transition, including investigations of the use of alternative transport modes, the influence of EVs on the transport system, as well as the replacement of combustion engines with EVs, and policies to support this. Chapter I tests the extent of behavioural effects of travel mode investments (cars or public transport passes) on travel mode choices in a greening car market. Chapter II determines the key EV adoption barriers and most hesitant consumer groups as the market develops past the early-adopter stage and as governments target broad adoption. Finally, Chapter III adds nuance to the discussion of public EV charging infrastructure, demonstrating non-linear effects in charger stock and the significant impact of the very first charger installations.

Chapter I identifies the impact of prior travel investments on travel mode choices – the effect of car or public transport pass ownership, and of EVs specifically. I test for behavioural deviations from 'rationally optimal mode usage'. Purchases of a car or public transport pass could be used ex-ante as a commitment device to that mode for overcoming self-control issues, or could affect mode choices ex-post through the regret of sunk costs. Further, EVs provide many use benefits that could induce increased driving beyond the influence of marginal driving costs, or, conversely, could be adopted as part of a multi-modal transport package and potentially be driven less than marginal costs would dictate. To investigate these questions the chapter presents a choice experiment conducted among 995 respondents from across Switzerland. The experiment creates a hierarchical design, linking 'long-' and 'medium-term' car and public transport subscription choices to a series of repeated trips with travel mode choice sets. The empirical framework then exploits this experiment design. I estimate a series of choice models that sequentially test the hypotheses of deviation from marginal trip cost and duration responsiveness in relation to prior investments.

The choice models demonstrate consistent responses to marginal trip costs and durations. I find no evidence to support the sunk cost hypothesis, but partial evidence in favour of commitment mechanisms. A prior investment decision decreases the respondent's responsiveness to variation of the other modes' travel time. However, such commitments do not seem to influence responses to changes in marginal travel cost. Furthermore, I find that EV adoption in the experiment does not result in a significant step-change in hypothetical usage patterns above rational marginal cost reactions. Our results thus reinforce the importance of financial incentives and marginal costs in policies aiming at a behavioural change in travel mode choices.

Chapter II then examines the barriers to EV adoption and further determines which consumer groups are most resistant. I analyse car-type choices – particularly EVs versus ICEs – to estimate the relative effects of purchase price, battery range and driving costs on BEV adoption probability. This chapter focuses on consumer heterogeneity to investigate how these barriers and drivers of EV adoption vary across consumer segments, and further, which consumer groups are the least likely to adopt an EV. I also particularly demonstrate the relationships between existing consumer transport habits and preferences, and EV adoption. As the EV market moves past the early-adoption stage and governments target mass EV adoption, adopter demographics and sensitivity to adoption barriers and drivers begin to change. Particularly, this study takes an experimental approach to estimate these across the broad population over the coming years. It uses the initial section of the choice experiment above (from Chapter I) to analyse the car type choices of 882 Swiss respondents. I estimate a series of choice models that investigate the relationship between respondent socio-demographics, past travel habits and environmental values, and car engine preferences. The chapter finally proposes alternative public policies to most efficiently and effectively encourage broad EV adoption.

The results demonstrate that the response to purchase price is inelastic, though the elasticity of the other adoption barrier, driving cost, and adoption driver, battery range, are insignificant. There is some variation across consumer groups, however – specifically, by level of urbanisation. Furthermore, existing car (mostly ICE) owners show particularly stable preferences for continued ICE selection. Over 20 percent of the respondents have no existing car, however adopt one in the experiment. These respondents and regular public transport users have a higher probability of choosing an EV. The overall low price elasticity indicates a relatively small potential impact of price subsidies across the broad population. A lack of significant findings for other EV attributes means that policies targeting these could also be relatively ineffective. The technological status quo preference among existing car owners further provides a hindrance to shifting car consumption towards EVs. As such, I suggest that significantly larger policies could be needed, compared to our analysis of marginal variations. These could be in terms of a large policy package tackling a variety of EV attributes and complementary infrastructure. However, in the end, stricter public policies such as technology mandates, or ICE sale or use bans may be the most effective way to facilitate broader adoption in the time frames many governments discuss.

Chapter III determines the impact of public charging station network infrastructure on EV adoption. It quantifies the effect of initial charger installations on new EV registrations and the non-linear relationship as the existing base grows. EV adoption could suffer from a chicken-and-egg problem with charging stations due to the indirect network effects between these two market sides. Private businesses have limited incentive to install charging stations so long as there is little demand – few EVs on the road. However, limited charging infrastructure also reduces adoption rates due to use limitations and range anxiety. So supporting the public charger network, particularly in the early market stages, could feasibly have a large and sustained impact on the EV adoption path. I create and exploit a novel dataset of quarterly EV registrations and charging station installations across 422 Norwegian municipalities from 2010 to 2017. I then take two complementary methodological approaches to examine this research question: instrumental variable control function regressions to determine the non-linear impact of chargers as the market and the installed charger stock grow; and synthetic control methods to focus on the effect of the very first local public charging stations. I further estimate control function models for both charging station numbers and individual charging points to determine the effect of station presence versus specific practical use value (there are usually multiple points per station).

The analyses show that there is an increasing but marginally diminishing elasticity of EV adoption regarding incremental charging station installations. In absolute terms the highest effect is at a low or non-existent charger stock. The effect of additional charging points is significantly smaller than for whole charging stations, consistent with the range anxiety bias and indicating a significant reassuring impact of the charger presence or visibility alone. Finally, the synthetic control approach further confirms that there is a significant impact on EV adoption from the very first public charging station installations. Moreover, the larger the initial installation wave (one versus multiple stations in a short time period), the greater the effect on EV registrations. This initial-charger effect is also long-lasting, setting the local municipality on a continued higher EV adoption path.

The experimental approach taken in chapters I and II overcomes a number of issues inherent in the existing revealed preference literature (eg. Simma and Axhausen (2001); Ho et al. (2018) for transport mode choices, or Xing et al. (2021); Li et al. (2017); Fridstrøm and Østli (2021) for EV adoption). Firstly, it allows the investigation of consumer preferences in new markets where the market share of new technologies is small. In this context, the share of EVs in the Swiss private car stock is 0.66 percent at the time of the survey, or 3.2 percent of new vehicle purchases (FSO, 2021). The specification of respondents' choice sets further allows the analysis of specific trade-offs of attributes that are difficult to determine in a revealed context. Finally, it overcomes the endogeneity problem of studying ex-post final decision outcomes. People make travel choices based to some extent on their self-determined choice set – i.e. based on if they have chosen to purchase a car or public transport pass, or proximity to transport infrastructure and services. Purchases of EVs have thus far been heavily concentrated in particular consumer segments (for example, higher income, young-middle aged, male: Archsmith et al., 2022). An experimental methodology with representative sample is able to analyse the preferences of the broader population and predict market changes going forward over the coming years.

On the other hand, chapter III exploits the more advanced market development of the Norwegian transport sector, from a base of essentially 0 percent EV market share in 2010 to 49 percent in 2017. It utilises more aggregate quarterly, municipality-level data of EV registrations and publicly accessible EV charging infrastructure to determine the influence of the latter on the former at the various market stages. This study takes a different approach to overcome potential endogeneity between local EV adoption and charger access. It first implements an instrumental variable (IV) with plausibly exogenous variation, constructed as a Bartik-style IV (Bartik, 1991) using municipal public parking spaces and the national EV adoption trend (similar to the approach of Li et al., 2017). It secondly employs a synthetic control method to construct a charger-free counterfactual municipality for each of those with new charging station installation shocks (eg. Abadie et al., 2010). These methodologies allow the estimation of local treatment effects of charging station installations on EV adoption at an aggregate, but still relatively fine scale.

Finally, the thesis conclusion brings together the findings of the three individual chapters in a cohesive manner. It summarises and further expounds on the policy implications of the results, and proposes ways forward for optimising EV policies. The conclusion ends with proposals for future research on the topic to fill remaining knowledge gaps.

Chapter I

Travel Mode Choices in a Greening Market: The Impact of Electric Vehicles and Prior Investments

This chapter is based on a paper co-authored by Mehdi Farsi and Sylvain Weber that has been published in *Transportation Research Record*.

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1 Introduction

Travel mode choices are the outcomes of multiple decisions that occur in different time horizons. While purchasing a vehicle or a travel pass is a relatively long-term decision, the mode choice at the time of travel occurs on a short-term basis. In a rational decision framework, these choices are assumed to be integral parts of a single decision about a "consumption bundle". In particular, a rational consumer should anticipate their travel choices when making a relatively long-term investment in a public transport pass, a private car, or even in a dwelling. However, the behavioural economics literature points to potential deviations from rationality. While these deviations are the subject of a large body of research, there is little empirical research testing such behavioural deviations in the travel choice context. We hypothesise that past long-term decisions (eg. car choice) could influence time-of-use choices. This is particularly important in the current context of a greening transport sector with increasing electric vehicle (EV) options available. Adoption of emerging technology requires relatively important initial investments facing future uncertainties, a favourable context for decisions based on behavioural heuristics and bounded rationality.

The rising proportion of global EV purchases benefits air pollution emissions from the transport sector, however could exacerbate other externalities through a rebound effect in car use (see, for example, Dimitropoulos et al., 2018). Given that the marginal cost of EV use is generally lower than for traditional internal combustion engine vehicles (ICEs), adoption of EVs could induce a higher usage. There is, however, little empirical research on whether EV adopters are likely to change their car use patterns beyond the direct effects of marginal costs.

We use the sequential decision structure to develop tests for potential deviations from rational decision-making in the context of personal travel. Our focus is on prior investments and their impact on the choice of travel mode at the time of use. We distinguish two competing hypotheses based on commitment mechanisms (Thaler and Shefrin, 1981) and sunk cost effects (Garland and Newport, 1991). We also include the market for green vehicles and test the impact of these on travel mode choices. Building on the preliminary work of Simma and Axhausen (2001, 2003), we provide the first tests of these theories in the context of travel mode choices through a choice experiment. Our experiment design aims to identify the possible impacts of EV adoption on usage patterns independently of marginal travel costs.

An experimental approach overcomes distinct issues inherent in revealed transport choice data (as in, for example: Simma and Axhausen, 2001; Ho et al., 2018). It allows us to investigate consumer behaviour in relation to new vehicle types when the market share of EVs is small. Specifically, in this new market context not enough drivers currently own EVs for a large sample (0.66 percent of Swiss cars in 2018 (FSO, 2021)). Furthermore, with revealed preference (RP) data, the specific choice sets, including alternatives faced by respondents are difficult to observe and many attributes are strongly correlated (eg. trip cost and duration). Stated preference (SP) choice experiments allow us to observe the whole choice set within which respondents make trade-offs. A well-designed experiment with repeated choice tasks for each individual additionally allows for variations in the choice attribute values, allowing for the identification of these effects. In this way, one can predict how consumer behaviour will change on aggregate as this market grows and develops. SP methods are hence widely used in behavioural economics and public policy (Louviere et al., 2000; Train and Wilson, 2008).

We surveyed a sample of 995 respondents across German- and French-speaking regions of Switzerland. Exploiting the sequential structure of transport decisions, we analyse trade-offs between each of three decision levels: long-term car purchase, medium-term public transport pass purchase, and time-of-travel transport mode choice. This setup allows us to analyse how respondents react differently to marginal travel costs, if they use commitment devices, if there is evidence of a sunk cost fallacy, and if EV adopters travel differently or use their cars more than marginal costs would dictate.

We provide the first experimental evidence that consumers do largely act rationally in their travel decisions. In particular, we do not find any evidence of sunk cost effects. Moreover, our results do not point to any commitment mechanisms that could distort the rational effect of marginal travel cost. However, we find evidence that prior investments distort the responsiveness to changes in trip duration, hence indicating a commitment effect to specific travel modes at this level. We finally find no travel mode choice differences for those having selected an EV compared to other car engine types. EV adopters do not inherently use their car more, and still react the same to marginal trip costs as those selecting ICEs. One exception here is a slight dampening of reactions to marginal car trip cost, and a slightly larger reaction to car trip durations, among those selecting a plug-in hybrid vehicle (PHEV).

Our findings demonstrate the importance of marginal travel costs in personal mobility decisions. It also indicates that the advent of new green car technologies does not automatically lead to a step-change in car use and transport mode decisions above changing marginal travel costs. Our findings have repercussions for government policy-making around transport, especially over the transition to more sustainable transport consumption patterns. We reinforce the fact that consumers can be incentivised to change mobility patterns through marginal cost adjustments such as fuel taxes, and fees for parking and road use.

The remainder of this chapter is structured as follows. *Background* provides an overview of the relevant literature and details the behaviours we test. *Methodology* outlines our approach, including the experimental design and econometric framework, and develops an empirical implementation of the specific hypotheses. *Data* then summarises our data, which is followed by our estimation *results*, and, finally, our *Conclusion*.

2 Background

Stated preference (SP) studies, and specifically choice experiments, have long been used to study consumer preferences and behaviour, and the topic of transport and travel has been a key part of its use and development (Louviere, 1979; Hensher, 1994). Many governments and businesses rely on these methods to predict consumer choices and preferences for various potential future policies or new products (Carson and Groves, 2007). This is especially true for new technologies pre-introduction or before a large enough market has developed that could provide a sufficient amount of RP data (Louviere et al., 2000; Becker and Axhausen, 2017). In the face of criticisms about hypothetical bias of SP responses and lack of external validity, a number of methodologies were developed to ensure incentive compatibility and the truthful elicitation of respondent preferences. Specifically, respondents must see their responses as having some chance of influencing public policy (or some agent's actions) (Carson and Groves, 2007; Vossler et al., 2012). Additionally, a level of familiarity with or understanding of the hypothetical scenario is required (Louviere et al., 2000). As further discussed in the *experimental design* section, our experiment fulfills these criteria. We inform respondents that their answers will be used to build Swiss energy and transport policy, and remind them of their household budget constraint. The context of car and travel mode choices is also very familiar, with respondents making these decisions regularly. The addition of new EV technologies primarily changes the relative fixed and marginal costs. EVs are commonly discussed in the media and in society, and their benefits and challenges seem to be widely known.

A range of behavioural literature in economics and psychology indicates that consumers may use commitment devices to lock themselves into particular future choices (eg. Thaler and Shefrin, 1981; Gul and Pesendorfer, 2004; DellaVigna and Malmendier, 2004; Laran, 2010; Kivetz and Simonson, 2002), or may take account of sunk costs (eg.

Friedman et al., 2007; Just and Wansink, 2011; Garland and Newport, 1991; Arkes and Blumer, 1985; Thaler, 1980; Staw, 1976). In the context of travel choices, the long- to medium-term ownership of a car or public transport pass may provide consumers with a commitment device to engage in specific mode choices at the time of travel. A car purchase could provide a pre-commitment (or an allowance) to car use at the time of travel even if such use is non-optimal from a marginal cost perspective, given the available alternatives (Steg, 2005). A public transport pass, on the other hand, could be purchased to commit oneself to using that mode in light of potential future temptation to indulge in driving a car (Kivetz and Simonson, 2002). The sunk cost effect would indicate that a consumer would overuse their car (compared to what relative marginal costs would dictate) due to regret about its purchase or self-justification (Aronson, 1968; Arkes and Blumer, 1985). Importantly, this effect would rise the greater the 'investment', i.e. the cost of the car (Garland and Newport, 1991).

Choice of travel mode, a seemingly simple decision at the time of travel, is in fact the result of a sequence of decisions at different time horizons. This sequence starts from relatively long-term investment decisions (occurring once every few years), such as purchasing a particular car. This is followed by intermediate-term decisions such as the purchase of a public transport pass/subscription (occurring once or a few times a year). The sequence ends with the choice of travel mode at the time of travel, occurring at a high frequency (eg. on a daily basis).

Much research has been conducted on car purchase decisions (Lave and Train, 1979; Hess et al., 2012; Brownstone et al., 2000; Bunch et al., 1993; Spissu et al., 2009; Bhat and Sen, 2006; Choo and Mokhtarian, 2004; Tompkins et al., 1998), and on travel mode choice separately (Vovsha, 1997; Schwanen and Mokhtarian, 2005; Shen, 2009; Richter and Keuchel, 2012; Hess et al., 2018; Waerden and Waerden, 2018; Azimi et al., 2020). We combine these into a joint framework of the inter-dependent mobility choice structure. To date, in the mobility domain, little attention has been devoted to the potential deviations from the standard assumptions of rational expected utility maximisation. The inter-temporal transport decision-making structure and the interdependencies between choices gives this sector prime opportunity for the appearance of such behavioural deviations.

The existence of commitment devices in other areas has long been demonstrated and fundamentally stems from the work on consumers' self-control by Schelling (1978, 1984) or Thaler and Shefrin (1981). They showed that individuals restrict their future self's choice set by pre-committing to a certain course of action, if they believe they will face a future lack of self-control, or be tempted into short-run gratification.

Only few authors (Simma and Axhausen, 2001, 2003; Loder and Axhausen, 2018) have discussed commitment devices within transport choices. Simma and Axhausen (2001, 2003) look into the difference in car and public transport use between those who own a car or a transport pass. Loder and Axhausen (2018) additionally include data on trips made by soft transport (cycling or walking). The authors conclude that they find evidence of commitments to transport modes as the consumers who own or have access to a particular mobility device (i.e. a car or public transport using a discount pass), use that mode relatively more. However, this fails to account for the impact of marginal trip costs, which are reduced for a given mode by purchase of the relevant transport device. Therefore the increased usage of a mode by device holders could be justified through rational decision theory. The authors state that this is indeed the case.

Our focus in this chapter is on a commitment effect beyond the rational response to lowered marginal costs. We argue that for evidence of a commitment effect, variations in marginal trip costs would engender a significantly smaller behavioural response among device owners than for non-device owning individuals. To our knowledge there is no empirical study that robustly tests such an impact and therefore credibly identifies the existence of commitment devices in the transport sector.

We contribute to the broader commitment effect literature, which has shown evidence for its existence in a wide range of sectors. Laran (2010) experimentally demonstrates it with healthy versus indulgent food consumption and money saving versus spending. DellaVigna and Malmendier (2004) explore the implications of the effect for contract design in gym memberships, credit cards and more. Kivetz and Simonson (2002) show that some consumers commit themselves to future indulgences if they are presently more prone towards saving.

The sunk cost effect, also known as the 'sunk cost fallacy', represents a behavioural tendency to consume more of a good, the larger the investments they have previously made in relation to the good, even though the investments are 'sunk' and should have no bearing on the consumption decision. In rational theory consumers should base their consumption decisions on marginal benefits and costs, regardless of the sunk cost. Deviations from this have been explained in that people feel a level of regret about their past investment and now continue to consume the good as self-justification for the previous expenditure (Aronson, 1968), or out of a desire to not appear wasteful (Arkes and Blumer, 1985). Some of the original studies of sunk costs include Staw (1976); Thaler (1980); Arkes and Blumer (1985). The last, for example, demonstrates that sunk costs have an impact on theatre attendance – the more paid for season tickets, the higher the rate of attendance across the season. Further studies reinforce that the greater the sum invested, the greater the impact it has on later decisions (Garland and Newport, 1991) in a range of areas, including food consumption (Just and Wansink, 2011), and business investments (van Putten et al., 2010). However, the evidence is not always positive. Friedman et al. (2007) show a mixture of findings across the broader literature, and their own computer-based lab experiment found a small and inconsistent sunk cost effect.

The transport sector is well-suited to the study of the impact of sunk costs given the large and variable investments in mobility devices and infrastructure, and the frequent, repeated transport decisions made. Ho et al. (2018) use data on car odometer readings across a number of years and changes in car registration costs in Singapore and Hong Kong, and show that the higher the amount invested in registering a car, the more it gets driven. However, this could be due to selection bias, as the higher registration costs leave only those with the greatest benefit from having a car (those who use it more). It could also be due to a non-psychological path – higher registration costs could induce more car sharing, at a minimum amongst family and friends, generating a reduction in the average number of cars per household but increasing the use of existing ones. Our experimental approach avoids such selection issues. Additionally, we again focus on marginal trip costs. Existence of a sunk cost fallacy would mean that larger sunk costs lead consumers to react less to variations in marginal costs.

3 Methodology

3.1 Experimental design

We design a sequential choice experiment embedded within the annual Swiss Household Energy Demand Survey (SHEDS) 2018 (for more details see Weber et al. (2017)). In total 5514 individual households took part in the 2018 survey wave, and 995 of these were randomly assigned to take our experiment. This assignment targets a representative sample along gender, age, region, and housing status.

The choice experiment is organised in a sequential structure to mimic the natural decision-making process. We first ask respondents to make a ‘long-term’ decision regarding a car they would like to purchase. This is followed by the ‘medium-term’ choice of a public transport pass, and finally, respondents are asked to make a series of time-of-travel mode decisions.

The choice tasks are designed with attribute levels of the car and transport mode tasks depending on the respondent's previous choices. This setup allows us to obtain accurate and reliable responses, and to accurately estimate the effect of past investments on consumers' transport mode choices. The questionnaire is provided in the *supplemental materials* for reference.

In more detail, the experiment proceeds as follows. We initially prime the respondents by providing a script to encourage accurate and truthful responses, in line with the literature on preference elicitation in stated preference studies (Vossler et al., 2012; Carson and Groves, 2007). We additionally include a reminder about the respondents' household budget constraints, and indicate that the decisions here would require trade-offs to be made (as per, for example, Johnston et al., 2017). See *Supplemental Materials: Questionnaire*, figure A1 for the script. Following this, we ask respondents to imagine that they have to make a choice about purchasing a primary household car "within the next year". This is a relatively common task for Swiss households as our data show an average car replacement period of about 5.5 years. This is also externally validated by a survey which finds Swiss households replace their car every 5 years (Comparis, 2013).

The first choice task, then, is to choose the car size, between 'micro', 'small', 'small-medium', 'mid-size', 'large' and 'SUV' (based on Touring Club Switzerland (TCS) standards (TCS, 2018)). We also give respondents the option of choosing no car. Those who choose some car size proceed on to the second choice task, which asks respondents to choose a specific car. This task is a labelled choice table with 6 options and 5 attributes, as illustrated in figure A3. The labels are each car engine type, with two options as 'electric' (i.e. BEV), two 'plug-in hybrid' (PHEV), one 'hybrid', and one 'internal combustion engine' (ICE). The attributes are 'price', 'driving cost per 100km', 'battery range', 'max. speed', and 'CO_2 emissions (g/km)'. Levels were set using data from the TCS on all cars currently available in Switzerland (TCS, 2018).

We do not explicitly include information related to EV charging in the experiment. In Switzerland, as in many countries, the topic of EVs is highly discussed and our experiment respondents therefore have at least some knowledge of the technicalities of using and charging an EV. We expect respondents to have a level of range anxiety, as seen in surveys domestically and globally, that would potentially discourage them from choosing an EV in the study relative to in the real-world market, where continued exposure to and experience with EVs and their charging may heighten adoption levels (Melliger et al., 2018; Franke and Krems, 2013).

Next, all respondents answer the medium-term question of whether to buy a public transport pass. Such passes are ordinarily renewable on a monthly or yearly basis and give unlimited access to public transport across the entire country or a specific region. The following pass options are provided: '1st class GA', '2nd class GA', a local 'regional pass', or 'none'. Both GA (*General Abonnement*) passes provide unlimited access to all public transport in the country, while regional passes offer the same within a defined region (usually a Swiss canton). The single attribute in this task is the pass price.

Finally, all respondents receive a series of choice tasks regarding the transport mode for specific trips. We repeat the transport mode task three times for each of three trip types (commute, local leisure, and weekend trip), giving nine choice situations per respondent in total. Respondents who do not ordinarily commute (do not work or work from home) are only given leisure and weekend trip choice situations. Choice tasks are composed of two attributes, trip cost and trip duration, and are labelled with the transport mode (see figure A5). Trip cost is defined with the following popup for respondents: "Trip cost corresponds only to the car's operating cost. It does not include other possible costs such as parking fees." There is a maximum of five mode alternatives available: public transport (PT), respondent's private car (CR), soft transport ('bike or foot' - ST), car sharing (CS), and 'car with a driver' eg. taxi (CD), with available alternatives and attribute levels depending on previous choices and responses. Irrelevant options are not displayed. In particular, respondents who choose no car in the first step do not receive the option to use one at this stage. For trip distances longer than 10km soft transport is less realistic and therefore not offered. The levels of the cost attribute are further tailored to the device decisions previously made by the respondents. For example, respondents who choose a GA public transport pass have a cost of 0 for using this mode. Those who choose a car receive different trip cost values depending on the efficiency of the car they select and the trip distance. In order to introduce some variability in the experimental design, the displayed attribute levels for each alternative additionally vary randomly between respondents and choice tasks, applying weights of 0.5, 1, or 1.5 to the calculated average values.

3.2 Econometric framework

Our primary objective is to analyse the impact of the first-stage transport decisions on the travel mode choice at the time of travel, while controlling for respondents' various socio-demographic and behavioural characteristics. To do this we propose a comprehensive choice model that considers the initial choice-level decisions as determining factors of the final outcomes.

Using a standard random utility model (RUM) framework as the basis of our estimations (McFadden, 1974), we estimate the choice of transport mode, between public transport (PT), private car (CR), and soft transport (ST). The two alternatives 'car with driver' and 'car sharing' are selected in less than 3 percent of choice tasks. Due to the low share, we exclude these two modes from the estimation. We test this restriction and see that it does not significantly alter the results.

Using the following utility function, respondent n's utility for mode i in choice task t is estimated by:

$$U_{nit} = \alpha A_{nit} + \beta_i + \gamma_i T_{it} + \delta_i X_n + \varepsilon_{nit} \tag{1}$$

where mode i is an element of P (public transport), C (car), and S (soft transport). The vector of coefficients of the choice task-mode-respondent specific attributes A_{nit} is given by α. Specifically this includes the cost (CHF) and duration (minutes) of the trip. The alternative specific constants (ASC) for each mode are represented by β_i. We estimate coefficients γ_i for each trip type T_{it} (commute, leisure, and weekend) and allow the trip type utility to vary by mode. We also include the respondent's individual characteristics and responses to the previous levels of transport choices through X_n. The impact of these choices and characteristics varies by transport mode, therefore the set of coefficients is given as δ_i. Finally, the error term ε_{nit} is a type I extreme value term, identically and independently distributed (IID) across respondents and alternatives.

Respondents select the transport mode i that maximises their level of utility – i.e. $U_{nit} > U_{njt}$ $(\forall j \neq i)$. We conduct this estimation using a standard multinomial logit (MNL) model, where the probability of a respondent selecting a particular transport mode is given by:

$$P_{nit} = \frac{e^{U_{nit}}}{\sum\limits_{j \in E} e^{U_{njt}}} \tag{2}$$

where E is the set of possible mode alternatives.

In our estimations we set PT as the base travel mode, that is:

$$\beta_i = \gamma_i = \delta_i = 0 \quad \text{for} \quad i = P \tag{3}$$

The variables in X_n include the respondent attributes: commute distance (natural log); residential location (city, agglomeration, rural); linguistic region (French/German-speaking); household size (1 person, 2 people, 3 or more people); biospheric values; and car and PT pass ownership in real life. We additionally include the responses to their previous transport choices: car yes/no; car size; car engine type; car price (natural log); and PT pass selection.

In A_{nit} we further add variables for the cost and duration of the trip by car (if available), and the duration of the same trip by PT. In this way we allow the impact of these trip costs/times on utility to vary from the average for those with specific mode alternatives available. Note we do not also use PT trip cost because of the lack of variation in this attribute within a respondent and trip type in the choice set construction, which allows the costs of other modes to then vary in relation to the PT trip cost. We additionally interact the above variables with a public transport pass dummy to detect whether pass holders react still differently. We finally also interact the car price with the above car trip costs.

The biospheric values measure the importance respondents attribute to environmental protection and pollution prevention. Respondents rated four values (respecting the earth, unity with nature, protecting the environment, and preserving nature) as "guiding principles in their lives" on a 5-point scale ranging from 1 "not important" to 5 "extremely important" (Steg et al., 2014). Aggregating the four answers gives the respondent's average biospheric value. We further create a binary variable with a value of 1 if respondents have an average biospheric value of 4 or more.

3.3 Empirical behavioural tests

To investigate the existence of mode-commitment device usage and a reaction to sunk costs among respondents, we focus on a few key variable interactions. We summarise these tests in table 1. We additionally test the effect of EV adoption on mode choice, compared to ICEs, both in absolute terms, and in terms of the user's reactivity to marginal trip costs. Overall, we naturally expect negative coefficients for *trip cost* and *trip time*. The tests we implement rely on interaction terms that capture divergence around the overall coefficients for some respondents.

If respondents were to display evidence of using a car as a commitment device, we would expect them to be less reactive to differences in the marginal travel costs than non-device-holding respondents. Specifically, those selecting a car should react less to variation in the costs of a trip by car as they are committed to using their car. Our primary car commitment tests are therefore if the coefficients of *CR trip cost*$_C$ and *CR trip time*$_C$ are positive. This would effectively indicate a reduced marginal disutility resulting from *trip cost* and *trip time* variables for car trips. Additionally, we would expect the respondents adopting a car to react less to changes in the costs of the al-

Table 1: Summary of behavioural tests

	Primary tests		**Secondary tests**	
	Variables	Expected direction	Variables	Expected direction
Car commitment	*CR trip cost*$_C$	>0	*PT trip time*$_C$	<0
	CR trip time$_C$	>0	$Car \times$ *PT trip time*$_S$	<0
Pass commitment	*PT pass* $\times$ *PT trip time*$_C$	<0	*PT pass* $\times$ *CR trip cost*$_C$	>0
	PT pass $\times$ *PT trip time*$_S$	<0	*PT pass* $\times$ *CR trip time*$_C$	>0
Sunk costs	*ln(car price)*$_C$	>0	*ln(car price)* $\times$ *CR trip cost*$_C$	>0
			ln(car price) $\times$ *CR trip time*$_C$	>0

Note: Based on equation 1. The subscripts C and S indicate to which mode alternative the utility coefficient applies, while the leading CR and PT indicate the fixed transport mode of the variable. For instance, "CR trip cost$_C$" is the cost of a given trip by car (CR) when the selected alternative is the car (C). "PT trip time$_S$" is the trip duration using public transport (PT) when the selected alternative is soft transport (S). *Car* and *PT pass* are respectively binary indicators for adoption of a car and public transport pass in the experiment.

ternative transport mode, *PT trip time*. As P is the base alternative with the reference utility (0), an increase in trip duration by public transport corresponds to a relative rise in the marginal utility of the other modes, namely car and soft transport. Therefore, our secondary test for a car commitment effect is for negative coefficients on the corresponding terms *PT trip time*$_C$ and $Car \times$ *PT trip time*$_S$, which would effectively reduce the magnitude of the car owner's reaction to PT travel times.

As for respondents opting for a PT pass, if it were to function as a commitment device their marginal disutility of the trip duration using public transport should be lower than those without a pass. Thus the interaction term *PT pass* $\times$ *PT trip time*$_P$ would be expected to be positive. However, as above, P is the base alternative, thus our primary PT pass commitment device test is the inverse of this, meaning we would expect negative coefficients for *PT pass* $\times$ *PT trip time*$_C$ and *PT pass* $\times$ *PT trip time*$_S$. Furthermore, among the respondents who opt for a car, those who additionally choose a PT pass should be less responsive to car trip attributes – namely, car trip cost and duration. Therefore, our secondary test is for an expected positive sign for the two interaction terms *PT pass* $\times$ *CR trip cost*$_C$ and *PT pass* $\times$ *CR trip time*$_C$.

The logic for evidence of consumer attention to sunk costs follows a similar pattern to the above, however, car use depends on the amount invested, i.e. the car price. If respondents were to display evidence of the sunk cost fallacy we would expect consumers to use their car more the greater the amount they paid for it. Therefore, the consumers' utility gained from using the private car mode should rise the greater the price of the car. Thus our primary test is *ln(car price)*$_C > 0$. We would also expect car owners' reaction to the trip costs from using the car alternative to be increasingly dampened the greater the car price. Thus we would secondarily expect *ln(car price)* $\times$ *CR trip cost*$_C$ to be positive. The same idea holds for trip duration, thus we should also see a positive impact of *ln(car price)* $\times$ *CR trip time*$_C$.

4 Data

4.1 Descriptive respondent statistics

The SHEDS sample is designed to be representative of the population at the national Swiss-level (excluding Ticino) (Weber et al., 2017). Our choice experiment respondents broadly match this requirement, and we summarise here the data for the 994 respondents used for analysis (see also Appendix B, table B1). Specifically, the age group targets are 18-34: 30%, 35-54: 40%, 55+: 30%. We slightly under-sample the youngest group and over-sample the older, with 24 and 35 percent, respectively. Further, we achieve sample proportions for renting versus owning that are close to the target of 63 percent tenants and 38 percent owners.

For our analysis, we also specifically targeted nine segments based on household size and region. We segment by single, 2-person and multi-person households, and city, agglomeration, and rural locations, as shown in table B1. Here the level of "urban character" is defined by the Swiss Federal Statistical Office and agglomerations are urban to semi-urban municipalities with high economic and commuting links to a neighbouring city centre (FSO, 2014). Over half of respondents live in the city, compared to 21 percent that are rural inhabitants and 28 in an agglomeration.

Respondents clearly vary in their real-life transport decisions, providing a good starting point for our experiment. About 26 percent of respondents do not own a car (table B1). This is slightly more than in the last Swiss Mobility and Transport Microcensus, which shows nearly 80 percent household car ownership in 2015 (FSO, 2017). Further, 45 percent of respondents own a public transport pass, slightly less than the 57 percent observed in the 2015 Microcensus, however the latter also includes some additional forms of passes (FSO, 2017). The majority of the public transport passes in our sample are GA travelcards of either 2nd or 1st class – 24 percent of all respondents.

4.2 Descriptive choice statistics

From the choice task responses, we gain an idea of the decision distribution and variation. Table B2 summarises the choices. Overall, 89 percent of respondents choose a car. This is slightly more than the historically stable Swiss car ownership rate of around 80 percent (FSO, 2017) and above the rate of 74 percent in our sample. Among the 882 respondents who select a car, the majority choose a small or small-medium sized car. Over a third (34 percent) of respondents select a pure-electric vehicle (BEV), and a similar proportion choose an ICE. In total 17 percent choose a PHEV and 15 percent a traditional hybrid.

Importantly for estimation of the impact of sunk costs, respondents who choose a car 'spend' 35 000 CHF at the median. The prices range from 24 000 to 53 000 CHF at the 25^{th} and 75^{th} percentiles, respectively. The car prices selected naturally vary between fuel types, and on average respondents choosing a BEV or PHEV are willing to spend more. The median BEV price is 40 000 CHF and PHEV price is 51 000 CHF. By comparison, the median ICE price is 24 000 CHF.

For the public transport pass choice, 53 percent choose not to buy one, while 25 percent choose a regional pass, and 23 percent a GA of either class. About 45 percent of respondents who choose to buy a car also choose a PT pass, allowing for analysis of the two potential commitment device behaviours together.

Pearson's chi-squared tests show that the choices made in the experiment about car size and fuel type, and PT passes are significantly related to the real life situation of respondents. That is, the stated car and PT pass preferences correspond with their revealed preferences. To some extent, this finding also illustrates consumer inertia. When faced with an important decision such as purchasing a car, consumers tend to favour a technology with which they are familiar. This has already been observed for example for heating system replacement (Lang et al., 2020), and broadly for repeated car ownership (Weis et al., 2010).

Following from the relatively high selection of transport devices (a car and/or PT pass), most respondents choose to use these two modes in the experiment. Overall, the private car is the most selected transport mode, around 49 percent, followed closely by public transport at 34 percent.

5 Results

We estimate four models based on equation 1: (1) including respondent characteristics and the car choice; (2) adding car-choice interactions to test the behavioural impact of green cars; (3) adding our primary behavioural tests; and (4) adding our secondary behavioural tests. The estimation results are shown in table 2, where the upper panel shows the utility coefficients for the trip attributes, namely the cost and duration of the trip, and the lower panel shows the estimated coefficients for the alternative specific variables.

The trip attribute coefficients are both significant and of the correct sign in all models. Specifically, higher travel costs in money and time both lead to decreases in utility. This means that increases in the costs of any particular transport mode alternative renders the selection of that mode less likely.

From the results of model (1), we focus on the impact of respondent characteristics on mode choices. We find that compared to city dwellers, those living in an agglomeration or the countryside gain more utility from using a car. Additionally, rural inhabitants are more likely to walk or cycle on average than those in other regions. Respondents from French-speaking Switzerland are shown to be more predisposed to using cars than those from the German-speaking region.

Commute distance naturally exerts a negative impact on the probability of taking soft transport, however does not influence car usage when controlling for other factors. Respondents who place a high importance on the environment obtain a disutility from car use and higher utility from soft transport. Finally, respondents who own a car in real life are significantly more likely to choose the private car mode, and those with a PT pass in real life are also much more predisposed to using that mode.

We consistently find that compared to those who choose a small-medium-sized car in the experiment, respondents who choose larger cars are significantly less likely to use public transport (We aggregate car sizes, combining 'Micro' and 'Small', and 'Mid-size' and 'Large'. This does not alter results significantly compared to a disaggregated estimation.). They gained greater utility from both car and soft transport use. In model (1) we find those who choose an electric car reduce their car use, however, this disappears once we further control for marginal car trip costs in models (2)-(4). Note that we also aggregate 'Hybrid' and 'ICE' car engine types together. This does not significantly alter any results compared to a disaggregated estimation. We additionally estimated the impact of car engine choice by trip type, all of which turns out to be insignificant.

Table 2: Estimation results

	(1)		(2)		(3)		(4)	
Trip attributes								
Trip cost (CHF)	-0.050^{***}		-0.054^{***}		-0.036^{***}		-0.039^{***}	
	(0.005)		(0.006)		(0.006)		(0.006)	
Trip time (minutes)	-0.020^{***}		-0.020^{***}		-0.020^{***}		-0.030^{***}	
	(0.001)		(0.001)		(0.002)		(0.002)	
Alternative specific variables	C	S	C	S	C	S	C	S
ASC	-1.052***	0.829***	-1.081***	0.792***	2.201	1.773	1.475	1.801
	(0.280)	(0.301)	(0.293)	(0.305)	(2.699)	(3.378)	(2.859)	(3.503)
Trip: Commute	*base*	*base*	*base*	*base*	*base*	*base*	*base*	*base*
Trip: Leisure	0.410*	-0.606**	0.310	-0.650***	0.374	-0.623**	0.507**	-0.588**
	(0.224)	(0.247)	(0.242)	(0.251)	(0.235)	(0.249)	(0.238)	(0.254)
Trip: Weekend	0.517**	–	0.157	–	0.417	–	0.750**	–
	(0.240)		(0.403)		(0.378)		(0.382)	
City	*base*	*base*	*base*	*base*	*base*	*base*	*base*	*base*
Agglomeration	0.384***	0.062	0.390***	0.066	0.345***	0.041	0.334***	0.034
	(0.110)	(0.137)	(0.110)	(0.137)	(0.111)	(0.138)	(0.110)	(0.143)
Countryside	0.336***	0.330**	0.335***	0.331**	0.328***	0.321**	0.315**	0.329**
	(0.124)	(0.155)	(0.125)	(0.155)	(0.124)	(0.155)	(0.122)	(0.159)
French-swiss region	0.347***	-0.173	0.341***	-0.175	0.351***	-0.156	0.341***	-0.165
	(0.113)	(0.141)	(0.113)	(0.141)	(0.115)	(0.142)	(0.114)	(0.146)
Single person household	0.202*	-0.046	0.210*	-0.038	0.237**	-0.023	0.225**	-0.025
	(0.114)	(0.133)	(0.114)	(0.133)	(0.115)	(0.134)	(0.113)	(0.138)
2 person household	*base*	*base*	*base*	*base*	*base*	*base*	*base*	*base*
3+ person household	-0.117	0.132	-0.120	0.130	-0.126	0.133	-0.130	0.143
	(0.113)	(0.132)	(0.114)	(0.132)	(0.114)	(0.132)	(0.113)	(0.136)
ln(commute distance)	0.026	-0.660***	-0.033	-0.687***	0.012	-0.667***	0.071	-0.660***
	(0.073)	(0.116)	(0.088)	(0.118)	(0.085)	(0.117)	(0.085)	(0.119)
Strong biospheric values	-0.237**	0.208*	-0.230**	0.211*	-0.217**	0.218*	-0.221**	0.225*
	(0.097)	(0.121)	(0.098)	(0.121)	(0.098)	(0.122)	(0.097)	(0.125)
Car in household	1.337***	0.065	1.331***	0.082	1.439***	0.110	1.413***	0.087
	(0.136)	(0.139)	(0.136)	(0.140)	(0.139)	(0.142)	(0.135)	(0.147)
PT pass in household	-1.068***	-0.962***	-1.052***	-0.951***	-0.504***	-0.789***	-0.517***	-0.809***
	(0.103)	(0.123)	(0.104)	(0.123)	(0.132)	(0.155)	(0.131)	(0.159)
Car: None	–	0.114	–	0.168	–	-0.695	–	-0.519
		(0.222)		(0.223)		(3.362)		(3.487)
Car: Micro–Small	-0.131	0.236	-0.122	0.237	-0.202	0.218	-0.208	0.241
	(0.122)	(0.149)	(0.122)	(0.149)	(0.148)	(0.179)	(0.146)	(0.184)
Car: Small-medium	*base*	*base*	*base*	*base*	*base*	*base*	*base*	*base*
Car: Mid–Large	0.417***	0.774***	0.405***	0.772***	0.505***	0.791***	0.508***	0.806***
	(0.134)	(0.168)	(0.135)	(0.168)	(0.173)	(0.220)	(0.171)	(0.227)
Car: SUV	0.667***	0.565***	0.622***	0.540***	0.847***	0.599*	0.826***	0.603*
	(0.151)	(0.195)	(0.153)	(0.195)	(0.248)	(0.313)	(0.243)	(0.320)
Car: BEV	-0.350***	0.076	-0.077	0.183	-0.11	0.148	-0.092	0.153
	(0.113)	(0.135)	(0.146)	(0.139)	(0.176)	(0.213)	(0.173)	(0.218)
Car: PHEV	-0.286**	-0.018	-0.157	0.023	-0.107	0.033	-0.090	0.021

Continued on next page

Table 2 – *Continued from previous page*

	C	S	C	S	C	S	C	S
	(0.127)	(0.161)	(0.180)	(0.166)	(0.165)	(0.208)	(0.162)	(0.213)
Car: ICE	*base*	*base*	*base*	*base*	*base*	*base*	*base*	*base*
Car-purchaser behaviour								
Car: BEV × CR trip cost			0.011	–				
			(0.040)					
Car: PHEV × CR trip cost			0.062*	–				
			(0.035)					
Car: ICE × CR trip cost			0.028	–				
			(0.020)					
Car: BEV × CR trip time			-0.003	–				
			(0.002)					
Car: PHEV × CR trip time			-0.006*	–				
			(0.003)					
Car: ICE × CR trip time			0.002	–				
			(0.002)					
PT pass					-0.995***	-0.394**	-1.306***	-0.461**
					(0.159)	(0.197)	(0.168)	(0.221)
Primary tests								
CR trip cost					0.027	–	-0.077	–
					(0.019)		(0.253)	
CR trip time					-0.002	–	0.042	–
					(0.002)		(0.030)	
PT pass × PT trip time					0.002	0.000	0.001	-0.002
					(0.002)	(0.006)	(0.003)	(0.007)
ln(car price)					-0.303	-0.079	-0.217	-0.030
					(0.263)	(0.329)	(0.278)	(0.341)
Secondary tests								
Car: yes × PT trip time							-0.016***	-0.016***
							(0.003)	(0.005)
PT pass × CR trip cost							0.000	–
							(0.023)	
PT pass × CR trip time							0.010***	–
							(0.003)	
ln(car price) × CR trip cost							0.011	–
							(0.024)	
ln(car price) × CR trip time							-0.004	–
							(0.003)	
N observations	7,657		7,657		7,657		7,657	
N respondent-trip types	2,604		2,604		2,604		2,604	

Notes: The dependent variable is U_{nit} – from equation 1. C and S denote the mode alternative to which the given alternative specific variable coefficient is relevant, respectively, car and soft transport. *Car: yes* and *PT pass* are respectively binary indicators for adoption of a car and public transport pass in the experiment. Standard errors clustered at the respondent-trip type level reported in parentheses. *, ** and *** respectively denote significance at 10%, 5% and 1% levels. PT: public transport; CR: car. We aggregate chosen car sizes, combining 'Micro' and 'Small', and 'Mid-size' and 'Large'. We also aggregate 'Hybrid' and 'ICE' car engine types together. This does not change any results compared to a disaggregated estimation. We additionally estimated the impact of car engine type by trip type, which was insignificant (not shown).

In model (2), we additionally interact the chosen car engine type with the marginal trip cost and trip time for the given trip with the car alternative. These show a slightly significant increase (decrease) in utility for using a PHEV the more costly (the longer) the trip. This indicates a slightly dampened reaction of PHEV adopters to trip cost, and a slightly heightened reaction to trip duration. These consumers thus display a higher valuation of travel time, which is supported by the observation that the PHEVs chosen have a relatively higher price and these respondents' incomes are also higher. However, this is only at the 10 percent significance level.

We find no other evidence, however, of BEV-selecting respondents being more or less reactive to marginal trip costs compared to those having chosen a traditional ICE car. Overall, we observe no real step-change in car-use patterns in the experiment due to green vehicle adoption beyond varied marginal trip costs.

Model (3) shows that respondents who select a public transport pass (GA or regional pass) are significantly more likely to use public transport than a car or soft transport – seen through the significant negative alternative specific variable coefficients on the *PT pass* dummy of both these modes. This matches the findings of Simma and Axhausen (2001, 2003). However, our primary behavioural tests from table 1 do not support the hypothesis of commitment device use.

Specifically, the primary car commitment device test variables, $CR\ trip\ cost_C$ and $CR\ trip\ time_C$ are insignificant. We thus reject the primary tests for car commitment device usage (summarised in table 3). The primary tests for PT pass commitment are also insignificant – *PT pass* $\times$ *PT trip time* for both car and soft transport modes. We therefore also reject the primary PT pass commitment device tests. The final primary behavioural test, is also rejected. We find the sunk cost (car price) has no impact on mode utility and car use.

As table 3 further summarises, the secondary tests in model (4) nuance the behavioural test findings. We find that selecting a car (as opposed to no car) does decrease the respondents' reactivity to variation in the trip duration for public transport. We further find that, while respondents selecting a car and a PT pass do not react differently to the cost of the trip by car, they exhibit a diminished reaction to variations in the trip time by car, as hypothesised. Finally, the secondary tests for sunk costs are rejected. We find no evidence that sunk costs have any effect on mode choices.

We expect that our results are not subject to a hypothetical situation bias and that the respondents are making realistic, informed choices. In fact, restricting all estimates for choices and behavioural tests to those who also owned the particular transport device (car or PT pass) in real life, did not change our results of hypothesis tests.

Table 3: Summary of test results

	Primary tests			Secondary tests		
	Variables	Hypothesis	Decision	Variables	Hypothesis	Decision
Car commitment	*CR trip cost*$_C$	>0	Reject	*PT trip time*$_C$	<0	Accept
	CR trip time$_C$	>0	Reject	*Car* × *PT trip time*$_S$	<0	Accept
Pass commitment	*PT pass* × *PT trip time*$_C$	<0	Reject	*PT pass* × *CR trip cost*$_C$	>0	Reject
	PT pass × *PT trip time*$_S$	<0	Reject	*PT pass* × *CR trip time*$_C$	>0	Accept
Sunk costs	*ln(car price)*$_C$	>0	Reject	*ln(car price)* × *CR trip cost*$_C$	>0	Reject
				ln(car price) × *CR trip time*$_C$	>0	Reject

Note: From model (4) above, we do one-sided T-tests of the listed variables and interaction terms. "Reject" ("Accept") means that we fail to find (do find) evidence to support the hypothesised sign. For variable definitions see table 1 notes.

6 Conclusion

In this study we conduct a sequential choice experiment and analyse transport consumers' decision-making process. We investigate the existence of travel mode commitment devices, the impact of sunk costs, and the differing choices of 'green' car consumers. By reducing the selection biases inherent in revealed transport data, our experimental approach allows a better estimation of future travel tendencies in a growing EV market. We find that what mostly drives consumer travel mode decisions is marginal trip costs and respondent characteristics, and build a nuanced response to our behavioural tests. Despite level differences in car and public transport use by the car size and PT pass chosen, we observed few changes to consumer responses to marginal costs.

We confirm experimentally that the selection of a larger car or a public transport pass does lead consumers to use relatively more of that mode, as similarly shown by Simma and Axhausen (2001, 2003). However, we provide the first tests of stronger commitment device usage based on response to marginal trip costs, and specifically show that there is only partial evidence for this. Those who choose these long- and medium-term transport investments still respond largely rationally to variation in marginal costs. Respondents who opt for a car do not react any less strongly to variation in the cost and duration of trips by car. However, they do display a lower reactivity to changes in the trip duration of the key alternative, public transport. Essentially we estimate no deviation in own-mode trip cost elasticity from average, and a smaller cross-mode trip time elasticity. Similarly for PT passes, our primary tests reveal no commitment effect. However, we do again see an altered cross-mode trip time elasticity. PT pass selection is associated with a slight reduction in car-owner response to marginal car trip duration.

We additionally provide the first robust tests in the literature for the sunk cost fallacy in private transport and contribute to the mixed results found across past studies of other sectors (Friedman et al., 2007). We experimentally isolate the effect of car price on transport mode choices and find that the magnitude of the sunk cost does not influence travel mode decisions. We further find no change in consumer reactivity to marginal trip costs linked to sunk costs.

While adoption of new technologies could lead to a different usage pattern associated with a rebound effect, our analysis provides little evidence of statistically significant difference in car usage behaviour between EV adopters and non-adopters. Those who choose an EV are no more or less reactive to marginal trip costs. One exception to this, however, is a slightly smaller reaction to car trip costs, and a slightly larger one to car trip duration, among those who selected a PHEV. Overall, we find that increasing uptake of EVs in the market does not lead to any step-change in transport patterns, which will remain largely dependent on marginal costs and demographics.

As we find supportive evidence that prior investments could have a partial mode committing effect in relation to travel duration, the effects of reducing this (eg. by more frequent public transport) can be moderated by prior decisions (eg. car ownership). This highlights the policy relevance of relatively long-term investment decisions and their effects on travel behaviour. An indirect policy implication is that influencing a consumer's investment decision (for instance not owning a car, or buying a public transport travel pass) can be achieved through long-term changes in trip time and other comfort attributes. However, this chapter's main result hinges on the largely rational choices observed in our experiment, suggesting that behavioural deviations if any, are not greatly important in policy design of financial instruments. There is little evidence of any distortion of responses to marginal costs based on prior decisions.

Our findings of broadly rational decision-making could also indicate that respondents do not make strictly sequential decisions, but rather they anticipate their short-term travel choices and make their investments accordingly. The rational decision theory suggests that the consumers make choices as a bundle, accounting for their personal characteristics such as residential location and commute distance, they know which travel mode they will mostly wish to take and purchase a car and/or PT pass to match their transport mode predictions.

While the hypothetical nature of the experiment and its sequential design provide the benefits described, the results and inferences drawn could be subject to limitations. Particularly, they can fall short in predictive power when estimating future market shares. However, this limitation is much less relevant and problematic for the estimation of trade-offs that individuals make. Otherwise, the series of transport decisions made here over some minutes would normally be taken across many years, over which preferences and behaviours can change. We also do not explicitly include some car-use costs such as parking fees and registration. This would not, however, affect our behavioural tests and would rather increase the car trip cost and therefore substitution away from this mode.

In conclusion, this chapter demonstrates the overwhelming importance of marginal costs in travel decisions. We find that transport consumers largely do not deviate from the traditional rational decision framework, as shown in other sectors. We do indicate, however, a partial commitment device effect via travel time. These findings are highly relevant for public policy makers. They highlight the importance of marginal travel costs in policy measures, such as fuel taxes, and road usage and parking fees.

Chapter II

Who is afraid of electric vehicles? An analysis of stated EV preferences in Switzerland

This chapter is based on a paper co-authored by Mehdi Farsi, that has been published in the working paper series of the Institute of Economic Research (IRENE), University of Neuchâtel (No. 22-04). An earlier version was presented by Jeremy van Dijk at the University of Melbourne Department of Economics PhD seminar series in June 2021.

van Dijk, J. and Farsi, M. (2022), "Who is afraid of electric vehicles? An analysis of stated preference EV preferences in Switzerland", *IRENE Working Paper Series*, WP 22-04, IRENE Institute of Economic Research, University of Neuchâtel.

1 Introduction

The global transition to a carbon-neutral economy requires large changes to existing transport systems, notably, electrification (Sims et al., 2014; Pietzcker et al., 2014).[1] While the development and adoption of electric vehicles (EVs) is an important factor for the decarbonisation of transport, and though the market share of EVs has increased over the past decade, in many countries it remains a minor fraction of new car sales (IPCC, 2022; IEA, 2021). A number of policy measures have been implemented by jurisdictions worldwide to encourage EV purchases. While pointing to relative effectiveness of such measures, a number of studies suggest that fostering adoption requires targeted policies informed by a better understanding of key barriers and their heterogeneity across various population groups (Archsmith et al., 2022; Jenn et al., 2020; DeShazo et al., 2017).

This chapter's objective is twofold. Firstly, we identify the key barriers to EV adoption and analyse their heterogeneity across consumers. Secondly, we identify the consumer groups that are relatively resistant to adoption. We specifically investigate the importance of different consumer travel habit-types, in addition to more traditional socio-demographic characteristics. This allows us to finally propose potential policies to address adoption barriers and encourage broader EV adoption.

To undertake this analysis, we conduct a choice experiment and exploit stated preferences of the broad consumer base, rather than the early adopters from previous revealed preference data. We analyse consumer preferences specifically across Switzerland. We particularly focus on the interactions between a number of consumer characteristics and EV choice preferences. We provide novel evidence for variation in the upfront car price barrier across consumer segments, as well evidence against a driving range barrier and driving cost motivator. We elucidate the moderating and augmenting influences of transport mode habits and car ownership experiences, including car preference stability. We further demonstrate the importance of environmental values for car preferences.

We run a choice experiment with a representative sample across Switzerland that provides insights into new and emerging car preferences. We set the available car attributes to match the newest market standards, and include a range of battery electric vehicles (BEV) and plug-in hybrid electric vehicles (PHEV), in addition to conventional hybrids

[1] This electrification must necessarily proceed hand-in-hand with a reduction in carbon intensity of electricity production. That process is underway and as it continues generates increasingly larger benefits to the electrification of other sectors (Holland et al., 2020).

(CH) and internal combustion engine vehicles (ICE). We ask respondents to purchase a particular car size, or no car, followed by a choice of car from the above fuel-alternatives. This somewhat simulates car market developments as consumers decide to replace existing vehicles or buy new ones (van Dijk et al., 2021). We employ a mixed logit model to analyse responses, which allows us to account for heterogeneity in respondent sensitivity to car attributes and correlations between alternatives. We are then able estimate probabilities of choice of each car type and the elasticities of choice probability with respect to the car attributes. We focus on 882 respondents who choose to adopt a car in the experiment. Through a series of model specifications, we estimate the relative importance of car attributes, demographics and socio-economic factors for car choices. We focus on three attributes, namely, upfront cost, operating costs and battery range. While relatively high purchase price and limited battery range can be considered barriers to EV adoption, the lower operating costs could be the opposite.

Our experimental approach allows us to avoid the small-sample problem faced in revealed-preference data. The EV market in most countries is still relatively new and small. In this setting, most EV purchases are not across a broad section of the population, but concentrated in distinct segments of early adopters – for example, high-income households, highly educated, young-middle aged (eg. Archsmith et al., 2022). We are, conversely, able to analyse the future preferences of a broad spectrum of the population. Moreover, lack of control for individual-specific choice sets could cause endogeneity bias typical in revealed data analysis. A choice experiment avoids such biases through a random design of choice attributes. Thus, the stated-preference (SP) approach allows analysis of the trade-offs consumers make, as we observe their full choice set.

Our results show that all specified attributes represent relatively small or insignificant effects, in that a relative change in an attribute brings a small or negligible change in adoption probability. In other words, the demand response is inelastic to all relevant attributes. In particular, our estimations suggest that the average elasticity of adoption probability of a BEV with respect to purchase price is -0.21. The driving cost and battery range elasticities are insignificantly different from 0. These results suggest that high upfront costs could be a relatively important barrier compared to battery range and charging concerns. Nonetheless, our aggregate price elasticity estimate is lower (in absolute value) than most of the findings in previous studies based on revealed data. In particular, previous studies tend to point to an elastic response. Though, previous studies encounter endogeneity of car prices and other attributes, and, although use methods such as instrumental variables to overcome it, cannot replicate the full choice sets consumers face.

We find some heterogeneity in relative adoption barriers across various consumer groups. Specifically, we estimate different car attribute elasticities by residential location, income and existing car ownership, and find significant variation in price elasticity across residential areas.

Analysing the marginal choice probability differences (marginal effects) between consumer groups, focus on transport behaviours, including car ownership and transport mode use, in addition to the standard socio-demographics used in previous studies (Rezvani et al., 2015; Fevang et al., 2021). We find these behaviours to be significantly larger determinants of car type choices. We identify the most EV-resistant groups as those who already own a car, those who use their car for all regular commuting and leisure trips, and those with low environmental values. These groups show the highest probabilities of choosing an ICE over all other options and greatest marginal effects relative to their base groups.

Finally, our mixed logit regression results indicate some smaller effects across socio-economic variables. We find some evidence for high income earners opting more for EVs generally, as well as rural and agglomeration residents being less likely than those from a city to choose a BEV or CH. Greater age, being female and tenants are also associated with lower utility from BEVs or PHEVs.

Our findings highlight some challenges for EV policies. Firstly, the inelastic responses to the key EV attributes, namely price, driving range and driving cost, indicate that it is difficult and relatively ineffective for any policy focusing on one of these to significantly increase adoption rates. Our analysis focusses on marginal variation in car attributes, however, so a very large subsidy, for example, could still have a greater relative impact. A substantial policy package targetting a range of aspects of EV purchase and use could also still have a significant effect. Ultimately, however, we conclude that more radical policies such as technology mandates or bans could be required to generate significant shifts in EV adoption in a short to medium time frame.[2]

The remainder of this chapter is structured as follows. Section 2 further contextualises the chapter in the existing EV market and government policies. Section 3 outlines our methodology, including the experimental design and econometric framework. Section 4 then summarises our data and section 5 presents our results. Finally, section 6 concludes.

[2] Such as, for example, those planned in France, UK, Canada, some US states, some Chinese cities (IEA, 2021).

2 Market and policy context

Electric vehicles, especially battery electric vehicles (BEVs), are largely sold on their environmental credentials – namely, a reduction in negative pollution externalities – compared to traditional internal combustion engine vehicles (ICEs). BEVs emit no tailpipe emissions and therefore have the potential for large transport sector emissions reductions.[3] From the consumer's perspective, the relatively low cost per kilometre driven could be considered a key adoption driver. The low operating cost compared to ICEs stems from the often lower price of electricity than petroleum fuels, the greater efficiency of electric motors, and lower BEV maintenance costs (Rapson and Muehlegger, 2021). Lower use costs are offset, however, by often a significantly higher upfront purchase price than equivalent ICEs (Archsmith et al., 2022). Recent estimates find that the payback time could be between 5 and 8 years on average, however, for some scenarios (eg. low use and low gasoline prices) could be up to 10 (Weldon et al., 2018; IEA, 2020). Moreover, some estimates indicate that highly intensive drivers (eg. taxis, ride sharing or other driving services) could currently recoup the purchase price difference as early as 2 years (Baik et al., 2019), and recent gasoline prices of well over 90 USD/barrel could reduce the payback period to 4-5 years for average drivers (extrapolated from IEA, 2020). As technology continues to improve and battery costs continue to fall, purchase prices could further decrease.[4]

Switzerland presents a fitting case study to investigate our research questions, as although it possesses a number of characteristics for high EV adoption, the market share remained low at the time of the experiment. The country has a high average per capita income (5th in the world according to the World Bank (2021)), low average daily travelling distance (under 37km) (FSO, 2017), and some of the strongest average environ-

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3 However, energy generation for recharging BEV batteries is shifted upstream, meaning that the true emissions produced through BEV use and whole lifecycle emissions depend on the marginal electricity generation at point-of-use, plus location of production and end-of-life. Overall, BEVs tend to currently produce fewer global and local air pollutants than their ICE counterparts, and the emissions continue to decline as electricity generation becomes cleaner (Rapson and Muehlegger, 2021; Ambrose et al., 2020; Holland et al., 2020; Ellingsen et al., 2016). However, it must be noted that in some places, currently, BEVs can produce higher air pollutant emissions.

4 These payback period estimates are dependent on many assumptions. IEA (2020) does not seem to discount future costs and seems to assume no battery replacement within the payback periods, but explicitly states: engine power 90-150kW, battery 50-70KWh, annual mileage 10000-17000km, petrol prices US$0.8-1.5/L. Weldon et al. (2018) explicitly does not discount, citing a lack of consensus over an appropriate rate, and uses a base petrol price of EUR 1.37/L, and electricity of EUR 0.168/KWh. Their different scenarios estimate either constant prices, or 5% or 10% annual increases. Battery replacement is assumed only for the 'high-mileage user' scenarios and with 3 different price levels of EUR 100/KWh, EUR 200/KWh or EUR 300/KWh.

mental preferences (Franzen and Vogl, 2013). At a national level, BEVs are exempt from the 4 percent car tax (value added tax-equivalent) (BAZG, 2021), and 20 out of 26 cantons give partial reductions or complete exemptions from registration fees (Electrosuisse, 2022). Despite all this, the market share of BEVs in 2018 was only 1.8 percent (BFE, 2021). EV market share as a whole (including plug-in hybrid vehicles – PHEVs) was 3.2 percent, compared to 49 percent in Norway, 4.5 in China, 2.2 in Western Europe, and 2.0 in the USA (IEA, 2021).[5] Furthermore, approximately 22 percent of Swiss households do not own a car (FSO, 2017), enabling the analysis of a variety of individual transport habit typologies.[6] Car ownership per person, however, rose slightly over the 21st century – by 9.1 percent from 2001 to a peak in 2016, before falling by 0.5 percent to 2021 (FSO, 2022).

The policy space for promoting EV diffusion is large. Most commonly, governments provide financial incentives for EVs in order to reduce the larger upfront costs in comparison to conventional ICEs (Hardman et al., 2017). Monetary incentives such as rebates and exemptions from registration tax and VAT have been shown to be effective in increasing EV purchases in a variety of regions, including the USA and Europe (Jenn et al., 2020; Clinton and Steinberg, 2019; Münzel et al., 2019; Figenbaum, 2017; Bjerkan et al., 2016; Tal and Nicholas, 2016; Helveston et al., 2015; Jenn et al., 2013). This is largely a continuation of early fuel efficiency policies, such as the financial incentives for CH adoption (Chandra et al., 2010; Gallagher and Muehlegger, 2011).

Additionally, many jurisdictions have implemented other EV incentives, such as use of bus lanes, or high-occupancy vehicle (HOV) lanes, free parking, and free toll road use (Jenn et al., 2018; Tal and Nicholas, 2016; Fevang et al., 2021). Charging options are an important consideration for potential EV adopters, and home charging opportunity especially is a facilitator of EV ownership (Hardman et al., 2018). The existence and extent of a local public charging network is a further consideration, which is especially relevant for those who cannot charge at home, and has been shown to be an important driver of EV adoption (Li et al., 2017; van Dijk et al., 2022). Some governments do also support public charging station infrastructure through subsidies (Springel, 2021).

Consumer heterogeneity, however, leads to variation in responses to incentives and therefore in adoption rates. This has not yet directly had much policy attention. One

5 Since 2018 EV market shares have risen in most of the world. The 2020 shares for the same countries are: Switzerland, 14.3 percent; Norway, 75; China, 5.7; Western Europe, 10; and the USA remains at 2 (IEA, 2021).

6 This figure has been fairly stable since the 1990s.

aspect of heterogeneity that relates to financial incentives is household incomes. Much evidence has shown that this is an important factor determining EV purchases and particularly, early adopters have relatively high incomes (Archsmith et al., 2022; Chen et al., 2020; Hardman and Tal, 2016; Lane et al., 2014; Tal and Nicholas, 2016). Xing et al. (2021) describe how EV rebates and subsidies are therefore greatly mistargeted and lead to inefficiencies in financial support policies. They show that EV adoption in North America is concentrated among high-income earners, and particularly those who would have bought a low-polluting car or EV anyway, even without a subsidy. Therefore, broader EV adoption among middle and lower income households requires different or larger, targeted incentives.

Lifestyle and behavioural factors, habits, education and environmental preferences are all further determinants of transport choices and EV adoption. Choo and Mokhtarian (2004), for example, show that travel attitudes, mobility behaviours, and lifestyle factors strongly determine the type of car one buys. They find that consumers in urban centres are more likely to prefer small and luxury cars, which matches well with early EV models. They also find that people with stronger pro-environmental attitudes are relatively more likely to own small cars used for shorter trips, and that frequent car users are more likely to have large cars. Others have since demonstrated that many various environmental preferences are significant predictors of purchasing a green car, such as CH vehicles (Kahn and Vaughn, 2009; Kahn, 2007) and EVs (Chen et al., 2020; Egbue and Long, 2012).

Individuals' regular driving distances and related range anxiety have been found to be key hindrances to EV adoption (Rezvani et al., 2015; Dimitropoulos et al., 2016). A dense charger network (especially fast chargers) enables adoption even with relatively low battery ranges. The existing distribution of charging stations shows, however, an opposite pattern – urban centres often have a higher charger density but lower driving distances (Li et al., 2017). Davis (2019) shows that EVs are driven significantly less on average in the USA compared to ICEs and CHs. Rather than being solely related to the limited battery range of early models, EVs have on average been bought by consumers who drive less – particularly, more highly urban residents and those with greener lifestyles – and those with additional, ICE vehicles. However, longer regular driving distances do not necessarily always end in reduced EV adoption likelihood. Mukherjee and Ryan (2020), for example, find that BEV adoption in Ireland has been greater among those with the longest daily commutes.

Chen et al. (2020) and Jensen et al. (2013) demonstrate that experience with owning or using an EV significantly increases preferences for adopting or continuing to own future EVs. This personal experience is a potentially important factor for adoption, indicating that once the initial hurdles and potential anxieties are overcome, consumers preferences can shift.

Our aggregate findings vary somewhat from the existing literature above. Studies based on real EV purchases tend to estimate elastic demand with regards to purchase EV prices (eg. -1.3 to -2.8: Springel, 2021; Xing et al., 2021; Li et al., 2017). In order to overcome the problem of endogeneity these analyses use instrumental variable methods. However, they still only have a limited pool of relatively early adopters as EV purchasers and do not fully observe each individual's full choice set and the trade-offs they make. Driving costs, somewhat more similarly to our study, are found to have a smaller effect on car demand. One study of Norwegian vehicle purchases finds highly inelastic BEV demand with regards to electricity (i.e. fuel) price of -0.18 (Fridstrøm and Østli, 2021); and an earlier Danish stated preference study estimates an 'EV fuel cost' elasticity of demand of -0.36 (Jensen et al., 2013). However, the former article does not correct for price endogeneity at all, and the latter covers a small sample of very early potential EV adopters who met specific living-circumstance criteria. As a comparison, a previous study of conventional hybrid car demand in the USA estimates an elasticity of 0.52 with regards to gasoline prices (Beresteanu and Li, 2011). Finally, in contrast to our average result, Jensen et al. (2013) also estimate a mean elasticity of BEV demand with regard to battery range of about 0.55, a larger effect than that for driving cost, above, however subject to the same limitations.

3 Methodology

3.1 Experimental design

We embed a choice experiment as part of the annual Swiss Household Energy Demand Survey (SHEDS).[7] The experiment simulates a realistic decision about purchasing a car. We start with a hypothetical scenario in which the respondent has to make a choice about purchasing a primary car "within the next year". The respondent is then asked to choose a car size among 6 categories plus a "no car" option. This is followed by a vehicle selection from among 6 alternative cars.[8]

7 For more details on SHEDS see Weber et al. (2017).

8 For a detailed description of our experimental design, see van Dijk et al. (2021). From 5515 total respondents, 995 are randomly assigned to take our experiment. This assignment targets a repre-

We follow standard discrete choice experiment (DCE) practice for accurate preference elicitation. Namely, we provide a priming script to encourage truthful responses, asking for their own personal preferences and explaining potential impacts on Swiss public policy (in line with Carson and Groves, 2007; Vossler et al., 2012). We further remind respondents about their household budget constraints and the trade-offs involved in purchasing and travel decisions (as per, for example, Johnston et al., 2017).

The range of cars available and their attribute values (eg. price) are set to match the current market, with a weighting towards providing green alternatives, and are based on data from the TCS (2018). The values further depend on the car size initially chosen. If a respondent chooses to buy some car, we offer them the choice between 6 car alternatives (2 BEVs, 2 PHEVs, 1 CH, and 1 ICE). We specifically provide details for 5 car attributes in addition to the engine type. These are the car purchase price, the driving cost, the range of the battery (for EVs), the maximum speed, and the CO_2 emissions[9] from using each car alternative. Descriptions of each attribute are available as pop-ups when respondents hover over the attribute title.

3.2 Econometric framework

We estimate the impact of car attributes on car selection, and of respondent characteristics and behaviours on the choice of car engine type. We also examine preference heterogeneity across a range of social segments and socio-demographic characteristics. To do this we propose a choice model that allows for potential correlations between car alternatives and heterogeneity in the sensitivity of individuals to alternative attributes. We then estimate the probabilities of car-type choice, and marginal effects (including elasticities).

Based in the standard random utility model (RUM) framework (McFadden, 1974), we estimate respondents' utility for each car alternative based on the levels of the car attributes and their choices. We assume respondents choose the alternative that provides them with the greatest level of utility.

To allow for flexible correlations between alternatives, particularly within fuel types,

sentative sample along gender, age, region, and housing status.

[9] We use so-called 'tailpipe emissions', from use of the vehicle, as provided by the TCS (2018), and do not account for manufacturing or electricity generation. BEVs are commonly marketed and classified as "zero-emissions". Actual emissions from marginal electricity generation and relatively higher ones from EV manufacturing (particularly of batteries) remain important issues.

we relax the independence from irrelevant alternatives (IIA) condition. We thus employ a mixed logit (ML) model and estimate a utility function with random coefficients (McFadden and Train, 2000; Brownstone et al., 2000):

$$V_{ni} = \alpha A_{ni} + \beta_n X_{ni} + \gamma_i Z_{ni}, \tag{1}$$

where V_{ni} is the observed component of the utility function, of respondent n for car alternative i.[10] We use unlabelled choice sets, meaning that we do not estimate alternative specific constants (ASCs) and instead focus on the outcome of primary interest, the choice of car type, between BEV, PHEV, CH, and ICE. A_{ni} is a vector of car attributes that are assigned a fixed coefficient, elements of the vector α. Z_{ni} is a vector of respondent characteristics, interacted with the car engine type in order to generate by-alternative variation. Finally, X_{ni} is the vector of car attributes allowed a random coefficient. Thus the coefficients β_n vary across respondents according to the density function $f(\beta)$. In our case we specify the density to be normal: $\beta_n \sim N(\mu, \Sigma)$. Where μ is the mean vector and Σ a diagonal variance-covariance matrix.

The choice probability is then the integral of the base logit probabilities over all possible values of β_n weighted by the density $f(\beta)$:

$$P_{ni} = \int \left(\frac{\text{exp}(V_{ni})}{\sum\limits_{j \in E} \text{exp}(V_{nj})} \right) f(\beta)\; d\beta\;, \tag{2}$$

where E is the set of possible car alternatives. We simulate the probability estimates using $R = 500$ Halton draws, and estimate simulated maximum likelihood (Train, 2009; Bhat, 2001). The averaged simulated probabilities are used to calculate the simulated log likelihood function:

$$SLL = \sum_{n=1}^{N} \sum_{j=1}^{J} d_{nj}\; ln \left[\frac{1}{R} \sum_{r=1}^{R} \left(\frac{\text{exp}(V_{ni}(\beta^r))}{\sum_{j=1}^{J} \text{exp}(V_{nj}(\beta^r))} \right) \right]\;, \tag{3}$$

where $d_{nj} = 1$ if respondent n chooses alternative j and 0 otherwise, and (β^r) refers to the r-th draw from the distribution.

We exploit this ML framework to estimate a set of models that focus on different aspects of respondent choice determinants. We include each car's fuel type, price, maximum

[10] The utility function is: $U_{ni} = V_{ni} + \varepsilon_{ni}$, where ε_{ni} is the unobserved stochastic component.

speed, and driving cost in A_{ni}[11], and assign random coefficients to battery range (for BEVs) and CO_2 emissions (for non-EVs) through X_{ni}.[12] Then in Z_{ni} we include respondent characteristics. Specifically, these are household income (above or below median), residential location (city, agglomeration, rural), age category (younger or older than 55), reported gender, whether the respondent lives in a house or apartment (multi-family building), if they are tenants or owners of the dwelling, and if they own a car. We additionally include an indicator variable of the respondent's level of environmental preferences. All continuous variables are centred by subtracting the mean.

The environmental values variable measures the importance respondents attribute to environmental protection and pollution prevention, and is constructed as follows. Respondents rated four values (respecting the earth, unity with nature, protecting the environment, and preserving nature) as "guiding principles in their lives" on a 5-point scale ranging from 1 "not important" to 5 "extremely important" (as per Steg et al., 2014). Aggregating the four answers gives the respondent's average biospheric value. We create a binary variable, *environment-important*, with a value of 1 if respondents have an average biospheric value of 4 or more.

We further include respondents' travel behaviours through Z_{ni}, including whether they commute to work and a set of constructed travel mode typologies. We indicate if a respondent states in real life they always travel by public transport (PT), by soft transport (ST) (meaning walking, cycling or scootering), a mixture of PT and ST, or always uses their private car. The base category for comparison is using a mixture of car and other transport modes. These indicators are based upon responses to earlier survey questions about respondents' normal travel mode for work commutes, for local leisure or shopping trips, and relatively long-distance weekend trips. We also add the intensity of respondents' regular car use, specifically defined as low use if they drive their car less than 10,000 kilometres per year (km/yr), medium use from 10,000 to 20,000 km/yr, and high use of 20,000 km/yr or more.

We finally predict the choice probabilities for each car engine type at the median of observed variable values, and calculate the elasticities and marginal effects for each independent variable. Elasticities are calculated as the percentage change in choice probability for a one percent change in a continuous variable (car attributes). The

[11] Driving cost is given a quadratic form as this significantly improves the model fit.

[12] Note that the choice of which variables to give random coefficients was achieved through testing various models. Inclusion of other choice set attributes as random variables, such as price, driving cost and fuel type, leads to models failing to converge.

marginal effects are the difference in probability of choosing a particular car type between variable category levels. For example, the probability difference for a car owner versus a non-car owner. To calculate the elasticity and marginal effect standard errors we bootstrapped the model and predicted probabilities with 200 repetitions.

4 Descriptive statistics

Our data stem entirely from our choice experiment, as described in Section 3.1. The SHEDS sampling ensures representativeness at the Swiss-level (excluding Ticino) (Weber et al., 2017), and our choice experiment largely matches this (for further details see van Dijk et al., 2021). For this study we analyse respondents who choose to 'purchase' a car in the experiment, giving 882 respondents. We conduct a comparison of this group with those choosing not to buy any car in the experiment in Appendix C.

Respondent characteristics that we use in our analysis are summarised in Table 1, including our constructed travel behaviour typologies as described in Section 3.2. We implement a binary variable for whether a household's income is above the median, based on the original 6 SHEDS income categories. Here *above the median* means having a monthly income of 9000 CHF or more, and contains 37 percent of respondents. The distribution across residential regions is almost half living in cities, 30 percent in agglomerations, and 22 percent in rural areas. For age, we again use a constructed indicator of those 55 years old or more (34 percent). Slightly over half are male. Typically for Switzerland, over two thirds (68 percent) of respondents live in apartments, and we have nearly 60 percent tenants, matching the national 61 percent figure (FSO, 2019). Based on an aggregation of the four ecological value questions, as described in Section 3.2, over 62 percent of respondents place a high importance on the environment. Such a high fraction fits with the national-level findings of Franzen and Vogl (2013).

About 20 percent of respondents do not have a car in real life, close to the national 22 percent proportion (FSO, 2017). ICEs are almost ubiquitous amongst these. As for travel behaviours, nearly 78 percent of respondents commute to work (at the time of the survey). About 13 percent usually only use PT as their transport mode for all trip types. A further 11 percent usually only used ST for commuting and local leisure trips, while 11 percent used PT and ST exclusively for all trip types. On the other hand 30 percent of respondents usually always used their personal car for all trip types.

Table 2 provides a summary of the range of car attribute values offered to respondents.

Table 1: Descriptive statistics – respondent characteristics and travel behaviours

Characteristics	Frequency	Percent	Car and travel	Frequency	Percent
Income level[1]			*Car ownership*		
Below or at median	559	63.4	None	177	20.1
Above median	323	36.6	At least one	705	79.9
Location			*Commuter*	684	77.6
City	428	48.5			
Agglomeration	261	29.6	*Always use Public Transport*[4]	111	12.6
Countryside	193	21.9			
			Always use Soft Transport[4]	96	10.9
Age group					
< 55	584	66.2	*Use Public and Soft Transport*[4]	100	11.3
≥ 55	298	33.8			
			Always use car[4]	264	29.9
Gender					
Male	459	52.0			
Female	423	48.0			
Dwelling type					
Flat[2]	602	68.3			
House	280	31.7			
Dwelling ownership					
Owner	357	40.5			
Tenant	525	59.5			
Environmental values[3]					
Unimportant	333	37.8			
Important	549	62.2			

Note: Based on the total of 882 respondents. Percentages may not sum to 100 due to rounding. CH: Conventional Hybrid. EV: Electric Vehicle. ICE: Internal Combustion Engine vehicle. (1) Median category is 6000-8999 CHF/month. (2) A dwelling in a multi-family building. (3) Based on the environmental values questions described in section 3.2. (4) Respondents' usual travel mode, as described in section 3.2.

Prices vary considerably across the range of car sizes and engine types. There is significant overlap across these categories, though a trend for comparable BEVs being more expensive than hybrids (though not always) and ICEs. ICEs are always the cheapest alternative. For example, the cheapest car at 13,000 CHF is a small ICE, while the most expensive at 95,000 CHF is a large BEV. Driving cost is also related to engine type, with BEVs the cheapest to run and ICEs most inefficient – up to 11 CHF/100km. BEV battery range spans the range available in the market at the time of the experiment, up to 450 km, with a mean around 271 km. PHEVs have significantly smaller batteries than BEVs. Maximum car speeds are correlated with size and have an overall mean of 182 km/hr. The CO_2 emissions of BEVs are 0, and PHEVs small, while those from CHs and ICEs have an average of around 110 g/km.

Table 2: Descriptive statistics – offered car attribute values

	Mean	Median	Min.	Max.
Price (CHF)	45,091	42,000	13,000	95,000
BEV	49,902	47,000	21,000	95,000
ICE	30,222	24,000	13,000	61,000
Driving cost (CHF/100km)	4.9	4.3	2.0	11.0
BEV	2.7	2.6	2.0	4.1
ICE	8.5	8.3	6.2	11.0
BEV battery range (km)	271	220	90	450
PHEV battery range (km)	42	45	20	55
Max. speed (km/hr)	182	175	130	250
Non-EV CO_2 emissions (g/km)	110	110	65	165

Note: BEV: Battery Electric Vehicle. PHEV: Plug-in Hybrid Electric Vehicle. EV: Electric Vehicle. ICE: Internal Combustion Engine vehicle.

5 Results

We initially present choice statistics in section 5.1, summarising respondent decisions at a high level. We subsequently present the results from our mixed logit regressions in section 5.2, which provide estimates of our utility function. We briefly discuss the estimates, as they create the basis for our primary focus, the estimated probabilities and marginal effects. We present the probabilities of car choice, attribute elasticities and marginal effects of the variables included in the ML models in section 5.3.

5.1 Respondent choice statistics

In total 882 respondents choose to ‘buy’ a car in the experiment, of whom over a third (34 percent) choose a BEV and a similar proportion choose an ICE (Table 3: Panel A). In total 17 percent choose a PHEV and 15 percent a CH. There is a correlation of car choice with the ownership of a car in real life. Those who actually own a car tend to opt more for an ICE and relatively less for a BEV. Respondents who do not own a car mostly choose a BEV.

For our analysis we aggregate the raw car sizes selected by respondents into 3 categories: small, medium, large. Table 3: Panel B shows that the largest proportion of respondents chooses a medium-sized car, followed by small cars and large cars. There is also a correlation between the size of car a respondent owns in real life and their selection of car size in the experiment. Of those who own a small car, 60 percent choose

Table 3: Choice statistics – experimental car choices by actual car types

Panel A				
Car engine type	Frequency	Percent	Percent if own no car	Percent if own a car
BEV	303	34.4	57.1	28.7
PHEV	149	16.9	19.2	16.3
CH	133	15.1	13.0	15.6
ICE	297	33.7	10.7	39.4

Panel B						
Car size	Frequency	Percent	Percent if own no car	Percent if own small car	Percent if own medium car	Percent if own large car
Small	307	34.8	54.0	60.0	18.7	17.5
Medium	386	43.8	38.5	27.7	63.1	42.0
Large	189	21.4	7.5	12.4	18.2	40.5

Note: Based on the total of 882 respondents. Percentages may not sum to 100 due to rounding. BEV: Battery Electric Vehicle. PHEV: Plug-in Hybrid Electric Vehicle. CH: Conventional Hybrid. ICE: Internal Combustion Engine Vehicle. Choices vary within car engine categories – BEV 1: 17%; BEV 2: 17.4%; PHEV 1: 13.8%; PHEV 2: 3.1%.

the same size, with 28 percent moving one size larger, and a minority choosing a large car. We see a similar pattern for medium car owners. Over 63 percent of them select the same car size, while the remainder almost equally opted for one size smaller or larger. Finally, only around 41 percent of large car owners kept the same size in the experiment. A slightly larger proportion preferred a medium-size car, and a minority a small. At the margin, however, there could be an effect on large versus medium car choices or small versus medium due to differences in respondent perception of their car size and the official classification we use from the TCS (TCS, 2018).

5.2 Regression estimates

The results of model (1) in Table 4 show that most car attributes are significant and therefore important in differing ways to respondents' car purchase decisions. Higher car prices reduce respondent utility and likelihood of selection. A higher driving cost decreases respondent utility, however the marginal (negative) effect of driving cost decreases, fitting a quadratic functional form. As stated previously, this quadratic form provides an improved fit, with linear and other forms found insignificant.

Maximum car speed was not valued by respondents, however the exact effect varied. At lower maximum speeds, below 160 kilometres per hour (km/hr), respondents are

Table 4: Regression results

	Base	Characteristics	Behaviours	Car usage
BEV	-0.301	1.359	-1.547	0.479
	(0.652)	(1.198)	(1.063)	(1.173)
PHEV	–	1.998*	-0.325	1.608
		(1.112)	(1.022)	(1.079)
CH	–	1.596**	0.177	1.082*
		(0.710)	(0.512)	(0.649)
ICE	–	*base*	*base*	*base*
Car price (10,000 CHF)	-0.592***	-0.577***	-0.552***	-0.574***
	(0.098)	(0.130)	(0.134)	(0.135)
Driving cost (CHF)	-0.512**	-0.697***	-0.587**	-0.577**
	(0.234)	(0.223)	(0.238)	(0.238)
Driving cost^2	0.036***	0.051***	0.044***	0.041***
	(0.013)	(0.014)	(0.015)	(0.015)
Max speed 160 - 200km/hr	-1.045*	-0.277	-0.441	-0.457
	(0.556)	(0.249)	(0.328)	(0.342)
Max speed $\geq$ 200km/hr	-1.295**	-0.447	-0.658*	-0.670*
	(0.579)	(0.307)	(0.391)	(0.400)
BEV $\times$ Range (100km)	-2.342***	-0.522	-1.047*	-1.132*
	(0.853)	(0.402)	(0.584)	(0.609)
sd(BEV $\times$ Range)	3.930***	1.353**	2.112**	2.251***
	(1.324)	(0.546)	(0.828)	(0.866)
Non-BEV $\times$ CO_2 emissions (g/km)	0.022**	0.029**	0.023*	0.022*
	(0.010)	(0.012)	(0.012)	(0.012)
sd(Non-BEV $\times$ CO_2 emissions)	0.012***	0.022**	0.023**	0.021**
	(0.004)	(0.009)	(0.009)	(0.009)
Income > median $\times$ BEV	–	0.671**	–	–
		(0.329)		
Income > median $\times$ PHEV	–	0.801**	–	–
		(0.363)		
Income > median $\times$ CH	–	0.413	–	–
		(0.270)		
Agglomeration $\times$ BEV	–	-0.658*	–	–
		(0.369)		
Rural $\times$ BEV	–	-0.697*	–	–
		(0.402)		
Agglomeration $\times$ PHEV	–	-0.512	–	–
		(0.389)		
Rural $\times$ PHEV	–	-0.398	–	–
		(0.419)		
Agglomeration $\times$ CH	–	-0.520*	–	–
		(0.295)		
Rural $\times$ CH	–	-0.558*	–	–
		(0.323)		
Age $\geq$ 55 $\times$ BEV	–	-0.608*	–	–
		(0.313)		
Age $\geq$ 55 $\times$ PHEV	–	-0.601*	–	–
		(0.344)		
Age $\geq$ 55 $\times$ CH	–	-0.304	–	–
		(0.259)		
Female $\times$ BEV	–	-0.420	–	–
		(0.301)		
Female $\times$ PHEV	–	-0.796**	–	–
		(0.339)		
Female $\times$ CH	–	0.315	–	–
		(0.250)		
Environment-important $\times$ BEV	–	1.551***	–	–
		(0.371)		
Environment-important $\times$ PHEV	–	0.924**	–	–
		(0.376)		
Environment-important $\times$ CH	–	0.334	–	–

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Table 4 – *Continued from previous page*

	Base	Characteristics	Behaviours	Own car use
		(0.256)		
House × BEV	–	0.595	–	–
		(0.418)		
House × PHEV	–	0.216	–	–
		(0.437)		
House × CH	–	0.335	–	–
		(0.327)		
Tenant × BEV	–	-0.658*	–	–
		(0.398)		
Tenant × PHEV	–	-0.260	–	–
		(0.420)		
Tenant × CH	–	-0.437	–	–
		(0.319)		
Car in household × BEV	–	-2.809***	–	–
		(0.546)		
Car in household × PHEV	–	-2.229***	–	–
		(0.595)		
Car in household × CH	–	-1.366***	–	–
		(0.421)		
Commuter × BEV	–	–	0.361	–
			(0.379)	
Commuter × PHEV	–	–	0.042	–
			(0.386)	
Commuter × CH	–	–	0.041	–
			(0.296)	
Always PT × BEV	–	–	2.804***	1.802***
			(0.561)	(0.572)
Always PT × PHEV	–	–	0.768	-0.351
			(0.603)	(0.601)
Always PT × CH	–	–	0.830*	0.377
			(0.450)	(0.476)
Always ST × BEV	–	–	1.446***	1.284**
			(0.541)	(0.521)
Always ST × PHEV	–	–	0.275	0.173
			(0.579)	(0.539)
Always ST × CH	–	–	0.048	0.066
			(0.462)	(0.444)
Mixed PT-ST × BEV	–	–	1.686***	0.710
			(0.539)	(0.567)
Mixed PT-ST × PHEV	–	–	1.081*	-0.047
			(0.581)	(0.587)
Mixed PT-ST × CH	–	–	0.697	0.208
			(0.454)	(0.487)
Always Car × BEV	–	–	-0.014	0.029
			(0.391)	(0.390)
Always Car × PHEV	–	–	-0.609	-0.429
			(0.378)	(0.360)
Always Car × CH	–	–	-0.288	-0.329
			(0.274)	(0.271)
Low car-use (<10,000km/yr) × BEV	–	–	–	-2.066***
				(0.571)
Medium car-use (<20,000km/yr) × BEV	–	–	–	-1.635***
				(0.612)
High car-use (≥ 20,000km/yr) × BEV	–	–	–	-1.901**
				(0.769)
Low car-use (<10,000km/yr) × PHEV	–	–	–	-2.203***
				(0.645)
Medium car-use (<20,000km/yr) × PHEV	–	–	–	-1.942***
				(0.662)
High car-use (≥ 20,000km/yr) × PHEV	–	–	–	-2.358***
				(0.817)
Low car-use (<10,000km/yr) × CH	–	–	–	-1.203***
				(0.466)
Medium car-use (<20,000km/yr) × CH	–	–	–	-0.885*

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Table 4 – *Continued from previous page*

	Base	Characteristics	Behaviours	Own car use
				(0.487)
High car-use ($\geq$ 20,000km/yr) $\times$ CH	–	–	–	-0.531
				(0.546)
N respondents	882	882	882	882
N observations	5,292	5,292	5,292	5,292
Log simulated-likelihood	−1422.82	−1357.78	−1388.26	−1374.58
AIC	2865.64	2793.56	2830.52	2815.17
BIC	2931.38	3049.94	3008.02	3032.11

Notes: *, ** and *** respectively denote significance at 10%, 5% and 1% levels. BEV: Battery Electric Vehicle. PHEV: Plug-in Hybrid Electric Vehicle. CH: Conventional Hybrid. ICE: Internal Combustion Engine Vehicle. EV: Electric Vehicle.

largely indifferent to variation in speed. Above that, up to 200 and then even more beyond 200 km/hr maximum, respondents preferred reduced maximum speeds. We postulate this stems from the lack of practical usefulness of high maximum car speeds. In Switzerland, like many other countries, the legal maximum speed is 120 km/hr, thus the benefit of having a car capable of much more is small or zero, *ceteris paribus*.

Controlling for the absolute positive utility gained from choosing a BEV, we then find, however, significantly heterogeneous responses to battery range. Respondents are more likely to prefer vehicles with a lower battery range on average, however, the distribution of this coefficient was very large. This finding is somewhat contrary to expectations, however, perhaps ultimately comes down to trade-offs, with respondents significantly preferring to always minimise costs, for example.

Finally, from model (1), the CO_2 emissions from the non-EV alternatives also entailed significant response heterogeneity, however the utility distribution remains relatively close to zero. On average, respondents prefer cars with combustion engines that are more polluting. However, the size of the coefficient indicates this was a very minor concern relative to other attributes. We hypothesise that those who are more concerned about emissions would be more likely to opt for a technology change, to BEV, rather than minimise emissions from the more polluting car category.

In model (2), accounting for all car fuel types and a large range of respondent characteristics does not change the coefficients from the base model by much. The one notable change is the random variable BEV battery range, whose mean becomes insignificant (0), and whose distribution spread also reduces.

In terms of respondent characteristics, we find that high-income households have significantly greater preferences for both types of EVs, which matches the existing literature from Archsmith et al. (2022) and others. Both agglomeration and rural households gain negative utility from BEVs and conventional hybrid vehicles relative to ICEs, though regionality has little impact on the utility from PHEVs.

Older respondents have a preference against EVs, and seem relatively indifferent between CHs and ICEs, *ceteris paribus*. Female respondents also gain a significant disutility from PHEVs, however, we find no significant gender difference in relative BEV or CH utilities. Our measure of respondents' overall environmental preferences and interest, *environment-important*, shows a large and significant effect on EV preferences. Those who have greater stated eco-preferences are significantly more likely to choose an EV of either type, with highest utility gained from BEVs. We further find in this model that living in a house, compared to an apartment does not have any significant effect on car choice estimates, when also controlling for other characteristics. Being a tenant rather than home owner, however, does engender a slightly significant disutility from BEVs, which matches our assumptions about restrictions on home charging options for tenants.

Finally, model (2) also accounts for households' real car ownership. Controlling for all the household characteristics above, the simple fact of owning a car means a respondent is much more likely to choose to buy an ICE than any other car. This group gains significantly less utility from BEVs, followed by a smaller coefficient for PHEVs and smaller again for CHs. This indicates a possible stability in technological preferences, given the vast majority of cars owned are ICEs. It also demonstrates significantly greener preferences among non-car owners.

Delving into the impact of existing travel behaviours and habits, model (3) further indicates a significantly greater willingness among non-car users to purchase greener cars, especially EVs. We find that respondents who usually always take PT, ST, or both, for all commuting and leisure trips are much more likely to purchase a BEV than an ICE, and to some extent also gain positive utility from other green vehicles. Compared to the base category of mixed mode usage, respondents who say they always use their own car show little difference in car type selection. These travel mode choices accounted for, being a commuter or not engenders no difference in car utilities.

Model (4) adds to the previous mode use categorisation more nuanced variation in the extent of own car use, based on annual kilometres driven. The previous behavioural findings largely hold, and we find slight variation in utility by car use. All car users gain significant disutility from EVs, being most likely to select an ICE. Though the differences in coefficients are relatively small, the findings indicate among car users, medium users would have the least disutility from EVs. Low and medium car users are less likely to choose a CH over an ICE, however high car users gain no significant disutility, perhaps being the most likely group to want to benefit from fuel savings despite remaining technologically relatively static.

5.3 Choice probabilities and marginal effects

We further explore here the barriers to adoption addressed through the experiment, and the most- and least-resistant consumer groups. We present our estimates of the probability of car choice by engine type and marginal effects of the estimated variables on these probabilities. We sequentially focus on the barriers of car price, BEV battery range and driving cost, followed by the characteristics of car ownership, travel behaviours, and then basic respondent characteristics.

Adoption barrier elasticities

As previously discussed, one of the great barriers to EV adoption is the upfront purchase price. In our experiment, the median BEV price offered is 96 percent more than the median ICE price. On average, we find a price elasticity of -0.21 (Table 5: Panel A), meaning a 20 percent lower probability of choosing a BEV, at the median, on this basis alone. Comparing this to battery range shows price to be a significantly larger adoption barrier on average. However, both battery range elasticity and driving cost elasticity, as a motivator of adoption, are insignificantly different from 0. EV demand sensitivity in regard to purchase price is highly inelastic. This indicates that any marginal variations in EV prices through subsidies or other government policy will not have a significantly large effect on actual car type choices in itself, on average across the broad population. Furthermore, the cross-elasticities on ICE choice probability show that there isn't a direct substitute between ICEs and BEVs. Some proportion of respondents would switch to/from PHEVs or CHs, which has implications for estimates of pollution emissions changes, for example (as per Xing et al., 2021).

There are some differences in relative adoption barriers between consumer segments found. Table 5: Panel B presents attribute elasticity estimates across residential location, income group and car ownership. These estimates are based on the supplementary regressions found in Table D1 which expand model (2) to separately and sequentially interact car price, BEV range, and driving cost with the above consumer groups.

We specifically find that respondents from rural areas and cities are significantly more price sensitive than their agglomeration counterparts. Within those two, rural residents

Table 5: Car attribute elasticities

Panel A

Attribute	Car type: BEV-own	Car type: ICE-cross
Price	-0.21**	0.07
	(0.09)	(0.04)
Range	0.00	-0.05
	(0.21)	(0.09)
Driving cost	-0.96	0.36
	(0.75)	(0.30)

Panel B

Attribute	Group	Car type: BEV-own	Car type: ICE-cross
	City	-0.26**	0.09*
		(0.11)	(0.06)
	Agglomeration	-0.12	0.05
		(0.13)	(0.06)
	Rural	-0.32**	0.14
		(0.14)	(0.10)
Price	Income ≤ median	-0.12	0.05
		(0.13)	(0.05)
	Income > median	-0.04	0.03
		(0.14)	(0.08)
	No car	-0.07	0.12
		(0.15)	(0.26)
	Own car	-0.12	0.05
		(0.13)	(0.05)
	City	0.13	-0.06
		(0.18)	(0.09)
	Agglomeration	0.24	-0.18
		(0.19)	(0.15)
	Rural	-0.01	0.00
		(0.36)	(0.12)
Range	Income ≤ median	0.24	-0.18
		(0.19)	(0.15)
	Income > median	0.35	-0.30*
		(0.26)	(0.17)
	No car	0.07	-0.09
		(0.11)	(0.13)
	Own car	0.24	-0.18
		(0.19)	(0.15)
	City	-0.13	0.04
		(0.70)	(0.29)
	Agglomeration	-0.14	0.07
		(1.16)	(0.38)
	Rural	-0.07	0.02
		(0.88)	(0.30)
Driving cost	Income ≤ median	-0.14	0.07
		(1.16)	(0.38)
	Income > median	-0.34	0.16
		(0.85)	(0.37)
	No car	-1.16	1.23
		(1.01)	(1.14)
	Own car	-0.14	0.07
		(1.16)	(0.38)

Note: BEV own-elasticities of choice probability, and ICE cross-elasticities. Panel A calculated from model (2), and Panel B from supplementary estimations (Table D1). Standard errors in parentheses, from 200 bootstrap model repetitions. * and ** respectively denote 10% and 5% significance levels. BEV: Battery Electric Vehicle; ICE: Internal Combustion Engine Vehicle.

have a slightly greater elasticity point estimate. Across all other consumer groups and car characteristics, however, we find almost no significant elasticities. One exception is the cross-elasticity of demand for ICEs with regards to BEV battery range, which is significantly greater for high income earners. Otherwise, despite widely varying point elasticities, they are only imprecisely estimated at the average.[13]

We conduct an additional test by estimating the mixed logit models and attribute elasticities for the subsample of respondents who own a car in real life. The resulting coefficients and elasticities are not significantly different from those of the main models above, indicating that the non-car owners are not significantly driving the elasticities.

Marginal effects of characteristics

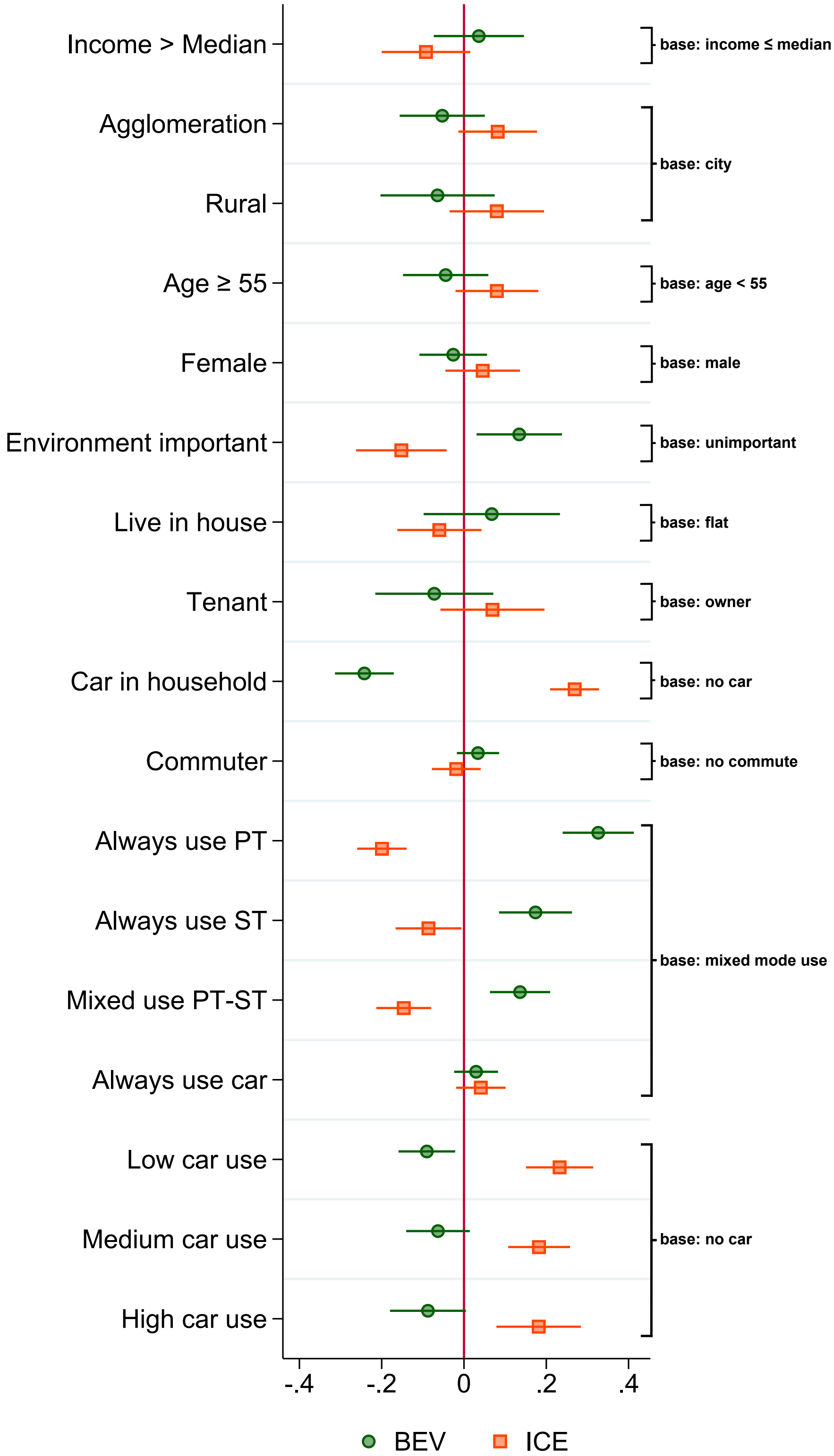
We next discuss the influence of respondent characteristics and behaviours on car choice probabilities, and identify key resistant consumer segments. Figure 1 presents the estimated marginal effects of these variables, meaning the differences in BEV and ICE choice probabilities between the base and categorical variable levels.

Existing car ownership has one of the largest marginal effects, where car owners are 30 percentage points more likely to choose an ICE than a non-car owner, on average. This group is significantly less likely to choose a BEV, by 25 percentage points. This indicates a significant stability of preferences of existing car owners to keep using their familiar technology. In absolute terms, car owners have a 44 percent probability of choosing an ICE, followed by 29 percent for BEV, 16 for PHEV and 11 for CH. On the other hand, respondents who are car free have the greatest probability of choosing a BEV, 55 percent. PHEVs have a 23 percent probability for this group, and ICEs and CHs are 14 and 9 percent, respectively.

Intensiveness of car use is a further factor for car choice, as seen in Figure 1. In absolute terms, the more a respondent uses their car in a given year, the less they are likely to select an ICE. However, the differences in marginal effects between use-levels are insignificant. Compared to those without a car, car drivers of all extents are statistically equally more likely to choose an ICE and less likely to choose a BEV. Overall, in point terms, respondents who drive over 10,000 km per year have about a 38 percent probability of choosing an ICE, compared to 44 percent for low users. BEVs are only 24-26 percent likely to be selected.

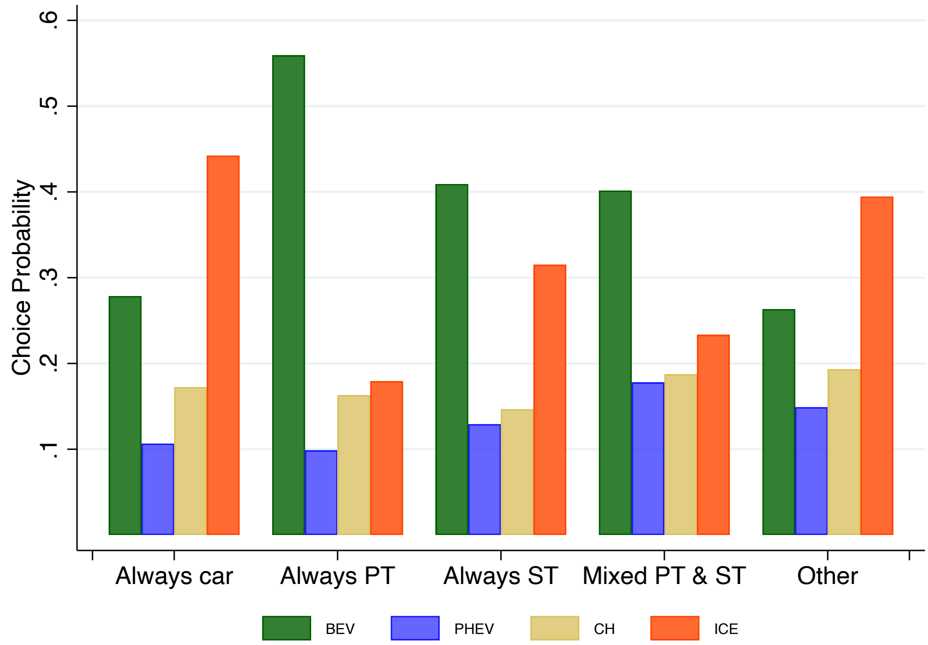
13 Note that we estimate a range of incremental bootstrap repetitions from 50 to 500 and find no significant difference in the results, nor any convergence towards particular standard error values.

Figure 1: Marginal effects on BEV and ICE choice probability at sample median



Notes: Central points show mean marginal effect and lines show 95 percent confidence intervals. Standard errors calculated through 200 bootstrap repetitions. Estimates stem from models (2) to (4).

Figure 2: Probabilities of car-type choice by respondent travel behaviour



Notes: Calculated from model (4).

In addition to respondents' existing car ownership, transport habits greatly influence stated car choices. Figure 1 also shows that compared to the base of mixed-mode-using respondents, those who use only their car for commuting and leisure trips are insignificantly different. However, those who always use PT or ST, or both, all have a significantly greater likelihood of choosing an EV if they buy a car, and a correspondingly lower probability of choosing an ICE. Exclusive PT users are about 33 percentage points more likely to select a BEV than mixed-mode users. Along with car ownership, this is one of the largest differences in the study. The marginal effect on BEVs for ST-only and mixed PT-ST travellers is around 15 percentage points. Figure 2 shows the absolute probabilities for these travel type groups, additionally including PHEVs and CHs, where the trends are more mixed. Again, as previously with car owners versus non-owners, we find that those with the experience and habit of owning and using a car are more likely to stick with buying ICEs, while those who have historically been car free or do not use a car regularly are more inclined to adopt the new car technology.

We further estimate the choice probabilities and average marginal effects of respondent characteristics from model (2). Overall, these characteristics have a much smaller effect on car choice than the above car ownership and travel behaviours. As seen in Figure 1, high income earners and residents of agglomerations are significantly (at the 10% level) respectively less and more likely to choose an ICE, each by about 9 percentage points. Though not large, these effects do match with our theories and the literature. The overall preference trend towards ICEs agglomerations is consistent with lower public charging availability than in cities and differing transport needs (eg. larger distances). The absolute choice probabilities for all characteristics and fuel types are shown in Figure D1.

Finally, the environmental and ecological attitude and preferences a respondent has a great influence their car choice. Those with strong environmental preferences are 15 percentage points less likely to choose an ICE than those with weaker preferences on average. They concurrently have a 14 percentage point greater probability of opting for a BEV. Preferences for hybrids, shown in Figure D1, vary insignificantly. The BEV and ICE differences fit with our behavioural findings above. We see that those who hold strong environmental values and who enact these day-to-day through transport habits are on average much more likely to adopt a BEV and less likely to opt for an ICE compared to less eco-friendly groups.

6 Conclusion

In this chapter we exploit a stated preference study of a hypothetical car market with multiple green vehicle and EV options. We provide evidence for the relative barriers to and drivers of EV adoption as the potential market broadens past early adopters over the coming decade. We further determine the key consumer groups who are most hesitant to adopt EVs. Building beyond the previous literature, we explore the variation in key barriers by consumer segments, and analyse the effect of current travel behaviours, car ownership and car use patterns on EV adoption. Our choice-experimental approach allows us to analyse the potential for changes in car-purchasing preferences over the medium term as increasing numbers of consumers decide to buy (or replace) a car and EV adoption starts to expand.

We find that the greatest barrier to EV adoption from among the car attributes is the purchase price. Although this is highly inelastic, all other tested attributes are insignificant. Our inelastic BEV price estimate is significantly lower than the elastic findings of the previous literature based on real car purchases (Xing et al., 2021; Li et al., 2017). Our experimental study is more representative of future market changes, rather than relatively early EV adopters, and is conditional on the selection of some car.

Regardless, there exists significant heterogeneity in price elasticity across consumer groups. Contrary to our hypothesis, price sensitivity varies across residential locations. Rural residents, followed by city dwellers, have the greatest BEV price elasticities, with this an insignificant barrier for those from agglomerations.

The strongest absolute consumer group preferences that we find in our study are based on travel habits, car ownership, and environmental values. We find that those who are most resistant to choosing an EV are car owners and those who use their car regularly for all trips, as well as consumers with relatively low environmental and ecological values. These groups are significantly more likely to choose an ICE than those without a car. This indicates a strong stability of car preferences and provides a large hurdle in getting existing car owners to shift demand to EVs.

On the other hand, we find that respondents holding strong environmental values are much less likely to opt for an ICE and shift towards BEVs, on average. People who regularly enact greener travel behaviours then show an even stronger preference difference. Respondents who choose to exclusively travel to work and for leisure purposes by PT or ST, rather than ever take a car, have a significantly greater probability of choosing a BEV than an ICE and a large marginal effect compared to the base mixed-mode category.

A large constraint to effective policy is the result of inelastic demand with regard to EV adoption barriers and drivers – particularly the upfront purchase price. This means that policies targetting this, such as subsidies or rebates, will be inefficient and ineffective in driving adoption over the longer term.

Given the strongly stable ICE preference among existing car owners, we suggest there is opportunity for alternative policies such as providing BEV information and experiences to nudge this group. Targeted information campaigns and providing the experience of using a BEV could decrease the unknown factors of EV ownership and use, and reduce the learning curve associated with the technological switch. For example, learning about local EV charging options and experiencing that EVs meet drivers' day-to-day needs could significantly reduce adoption hesitancy (as also somewhat indicated by Jensen et al. (2013)). This could potentially be implemented through car dealerships, charging station operators, and car-hire or -share companies.

Overall, however, our findings indicate that governments wishing to significantly increase a shift from ICEs to BEVs may have to opt for more radical policies. Technology mandates, or ICE sale and use restrictions or complete bans would be more effective at increasing BEV adoption in a shorter time frame. Such policies are already being discussed at various governmental levels across the globe. While some cities such as Oslo are introducing ICE driving bans, other state and national governments are planning bans on the sale of ICEs at future time points (commonly 2030 to 2040) (IEA, 2021).

Chapter III

Technology adoption and early network infrastructure provision in the market for electric vehicles

This chapter is based on a paper co-authored by Nathan Delacrétaz and Bruno Lanz, and published in ***Environmental and Resource Economics***.

van Dijk, J., Delacrétaz, N., and Lanz, B. (2022). "Technology adoption and early network infrastructure provision in the market for electric vehicles", *Environmental and Resource Economics*.

1 Introduction

The demand for personal mobility is associated with significant local and global externalities, and many countries consider electrification as the future of on-road transportation.[1] Even in the presence of externality-correcting taxes, however, indirect network effects hamper decisions to purchase an electric vehicle (EV) at the individual level (Greaker and Midttømme, 2016). In particular, the benefit of EV adoption depends on the size of charging infrastructure, whereas providers of charging stations will not invest in infrastructure provision when the base of EVs in circulation is small. In the presence of unpriced benefits to consumers (e.g. lower search costs), the private deployment of network infrastructure is likely suboptimal (Farrell and Saloner, 1986; Katz and Shapiro, 1986; Cabral, 2011). In turn, policies supporting the early provision of public charging infrastructure can alleviate a chicken and egg dilemma between EV consumers and charging station providers.

In this setting, the objective of this chapter is to provide novel evidence about how increments to charging infrastructure affect EV adoption decisions, and study how consumers respond to charger installations at early and developed market stages. We employ data for all 422 Norwegian municipalities from 2010 (the first year of comprehensive charger data availability) to 2017, with quarterly information on EV registrations (both battery-only electric vehicles - BEV - and plug-in hybrid vehicles - PHEV) by make and model, and the number of available charging stations, together with the number of charging points within these. Figure 1a illustrates how registrations of new EVs increased from around 90 in Q2 2010 to around 23,000 in Q4 2017, the latter representing 49 percent of all new car registrations (OFV, 2018), the world's highest rate of EV use (IEA, 2019b). Over the same period, the number of charging stations increased from around 640 in Q2 2010 to 2194 by the end of 2017 (Figure 1b). Charging points follow a similar trend, rising from around 2,600 to 10,240 over the period. Note that EVs can sometimes be recharged at home, however potential adopters still derive utility from the availability of *public* charging infrastructure. Particularly, Norwegian geographical specificities make a public charging network important (eg. large distances, cold weather, mountainous terrain – see Springel (2021) for a discussion). This issue is es-

[1] The transport sector is responsible for about 25% of GHG emissions globally (IEA, 2019a), 57% of Nitrous Oxides, and 20% of particulate matter 2.5 (European Environmental Agency, 2018). See IEA (2019b) for projected trends in EV adoption. Importantly, Holland et al. (2016) emphasize regional heterogeneity in the benefits associated with the electrification of transports in relation to the use of alternative electricity generation technologies. Norway produces around 98% of its electricity from hydro and wind sources (SSB, 2018).

pecially important for battery-only EVs (BEVs), but plug-in hybrids (PHEVs) can also benefit from public charging stations once they run out of electricity.

Norway has implemented a range of incentive schemes to promote EVs, including subsidies for charging infrastructure, financial incentives such as exemptions from registration tax and VAT, the free use of toll roads, public parking spaces and bus lanes, and discounted ferry tickets. The Bjerkan et al. (2016) survey, for example, showed that these incentives have varying importance to consumers and differing impacts on uptake, but financial incentives are by far the most critical for purchasing decisions.[2] For a small subset of the population, however, non-financial incentives, particularly free toll road and bus lane use, were 'critically important' for their EV purchase decision. We emphasize that these policies were mostly implemented nationally before 2010 (Norwegian EV Association, 2021; Fevang et al., 2021), have limited within-municipality temporal variation, and are controlled for in our estimation strategy. Our objective is to isolate exogenous variation in charging infrastructure and quantify its impact on EV purchase.

We use two complementary strategies to identify the impact of charging infrastructure on EV adoption from the emergence of the market in 2010 to a more mature market in 2017. First, we regress the log of new EV registrations on the log of charging stations available in a given municipality-quarter, and thereby estimate the elasticity of EV purchases with respect to incremental charging infrastructure. The primary issue with this analysis, however, is endogeneity in the municipality-level availability of charging infrastructure (Li et al., 2017). In particular, demand for EVs and the availability of charging infrastructure are potentially jointly affected by unobserved factors such as environmental preferences and associated government policies (e.g. subsidies for local charging infrastructure). Moreover, indirect network effects imply a reverse causality problem whereby greater EV registrations lead to more charger installations, for example through higher expected financial returns.

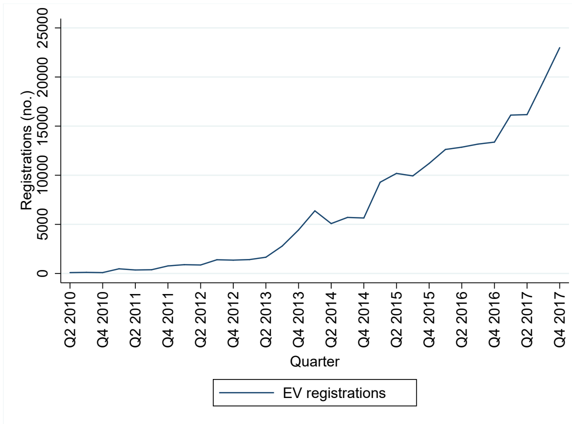
To isolate the impact of incremental charging infrastructure on EV adoption, we follow Li et al. (2017) and construct a Bartik (1991) instrument based on the stock of public parking spaces available in each municipality and the nation-wide trend of charger installations.[3] In this context, identification rests on two assumptions: (i) more abundant parking space isolates plausibly exogenous variation in the opportunity to supply charg-

[2] Note Bjerkan et al. (2016) did not address charging stations.

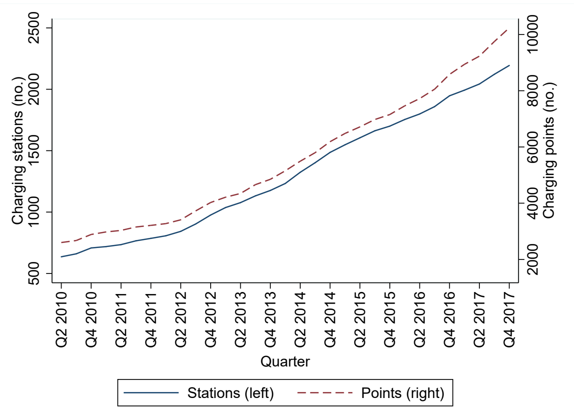
[3] In this we include all registered public parking spaces (SSB, 2018) such as government-controlled on- and off-street parking, schools, churches, sports facilities, and other parking lots.

Figure 1: Electric vehicle registrations and charging stations/points in Norway, 2010 - 2017

(a) New registrations of electric vehicles (source: OFV, 2018)



(b) Cumulative charging stations/points (source: NOBIL, 2018)



ing infrastructure, and (ii) municipalities with more parking space are more likely to respond to a nation-wide trend in charger installation.[4] Importantly, these assumptions are conditional on a set of control variables capturing differential changes in prices and income, among other things, as well as quarter fixed effects (capturing national technology trends and policy incentives for EVs), and municipality-model fixed effects (controlling for time invariant EV attributes and within-municipality preferences, as well as municipality characteristics, such as proximity to workplaces and urban centres, commuting routes, and toll road, bus lane and ferry prevalence). This instrumental variable (IV) approach limits any potential omitted variable bias.

Based on this, the first contribution of this chapter is to exploit the development of the EV market in Norway to investigate how the pre-existing stock of installed charging stations affects the charger-elasticity of EV demand. We use a set of control function (CF) regressions (Wooldridge, 2015) in which residuals from the first stage are included in the second stage, allowing us to estimate flexible polynomial specifications in the size of the charging infrastructure.[5] Our results show that charger-elasticity estimates increase

[4] Not all charging stations must be on public parking places, especially fast chargers, however, we exploit the correlation between the two, given the existing use of public spaces. Li et al. (2017), for example, show the use of private (grocery store) parking spaces, however in Norway these data are lacking.

[5] This approach is based on Hausman (1978) and Heckman and Robb (1985), as described by Wooldridge (2015). It is similar to Terza et al. (2008)'s otherwise named two-stage residual inclusion procedure.

with the stock of charging stations, which suggests that incremental charger installations are subject to increasing returns from network externalities. We further show that the largest impact of incremental charging infrastructure occurs when there is little to no pre-existing charger network. As discussed in Meunier and Ponssard (2020), this is consistent with declining marginal benefits associated with charging infrastructure as the size of the network grows (e.g. through declining disutility associated with locating and reaching a charging point). From a policy perspective, this suggests that subsidizing early infrastructure provision in small EV markets can mitigate the associated inefficiencies and therefore complement other instruments tackling transport externalities (e.g. a carbon tax).

Quantitatively, we estimate that a 10 percent increase in charging stations causes a rise in EV registrations by around 2.2 percent at the mean of our sample.[6] We further provide suggestive evidence that consumers respond differently to the provision of charging *points*, with a corresponding estimate of 1.2 percent. A higher elasticity for the provision of stations vs. points is consistent with existing empirical evidence documenting a behavioural bias called "range anxiety", whereby drivers tend to systematically over-estimate their required driving range.[7] See for example DeShazo et al. (2017) and Dimitropoulos et al. (2016). This behavioural effect magnifies the network externality problem, and suggests that expanding the network of infrastructure with charging stations with a single or few charging point(s) delivers the greatest benefits to consumers.

The second empirical strategy is geared towards the role of initial infrastructure provision. We focus on a subset of 64 Norwegian municipalities with a base of zero charging stations in 2010 and for which we observe either just one station being installed (one-station group) or multiple stations installed within a window of 4 consecutive quarters (multi-station group). To quantify the impact of this one-off infrastructure provision on EV registrations, we employ the synthetic control method (SCM – Abadie and Gardeazabal, 2003; Abadie et al., 2010).[8] In this approach, a synthetic municipality is constructed by giving weights to all those in a set of potential control units (the donor pool), which we take to be all municipalities that never installed any charging stations

[6] We note, however, that our results do not account for second-order feedback effects from EV purchases to charging station installation. These elasticities can therefore be interpreted as lower bound estimates.

[7] The average daily distance travelled in Norway is around 47 kilometers (Hjorthol et al., 2014).

[8] The SCM is a quantitative tool for case study analysis which can be applied in situations where there is no clear, observed counterfactual for comparison. See for example Moser (2005), Mideksa (2013), Barone and Mocetti (2014), Andersson (2019) and Clinton and Steinberg (2019).

over the entire observation period. The weights attributed to each municipality in the donor pool are selected so as to minimize pre-treatment differences in cumulative EV sales between a given treated unit and the synthetic municipality. For this purpose, we implement the ridge-augmented SCM (Ben-Michael et al., 2021), which adds a bias-correction term to the original SCM weights and allows for the use of negative weights in the construction of the synthetic control unit (see also Abadie and Imbens, 2011).

Building on an absence of difference in EV registrations for pairs of treated and synthetic municipalities during the pre-treatment period, the trajectory for the synthetic municipality can be interpreted as a counterfactual trajectory for EV adoption in the absence of treatment. Consequently, a comparison of the treated municipalities and their respective synthetic municipalities quantifies the impact of initial infrastructure provision on cumulative EV purchases. Overall, our results suggest a positive impact of the first charging stations. One year after the installation the cumulative EV sales in treated municipalities increases on average by 5.4 percent for one-station group and 8.0 percent for multi-station group relative to control. The average treatment effect increases with time, and two years post-treatment we estimate 21.7 and 46.2 percent increases in the one-station and multi-station groups respectively. These results confirm large (unpriced) consumer benefits associated with early infrastructure provision, so that policy intervention in nascent markets can significantly contribute to initiate adoption dynamics.

These results contribute to a broad literature on indirect network effects and two-sided markets in relation to early technology adoption (see Caillaud and Jullien, 2003; Armstrong, 2006; Rochet and Tirole, 2006). For example, Gandal et al. (2000) studies the adoption of CDs and how this depends on and affects the diffusion of CD player hardware, so that both sides of the market await developments in the other before making a commitment. Rysman (2004) demonstrates a positive network effect in the two-sided Yellow Pages market, and Rochet and Tirole (2002) analyze the interaction between payment card users (consumers) and merchants' acceptance of such cards. Lee (2013) investigates the feedback between consumer demand for video game hardware and software, and software demand for various hardware platforms, demonstrating the negative impact of incompatibility. In our context, these network effects hinder the effect of policies targeting externalities associated with mobility, and therefore call for a policy intervention.

Our work also contributes to a growing literature focusing on the adoption of EVs.[9] In

[9] A related literature studies the adoption of alternative-fuel vehicles and the provision of fueling

particular, our work is closely related to Li et al. (2017), who study the early development of the U.S. market for EVs based on 2011 to 2013 data for 353 metropolitical statistical areas (MSA) with significant EV sales. They employ a Bartik-style instrument based on the number of local supermarkets to generate exogenous variation in the provision of charging stations, which also uses an assumption that more abundant parking areas facilitate the installation of EV chargers without affecting the trade-off between EVs and standard vehicles. They report an elasticity of around 0.8, which is significantly larger than our central estimate (0.22). Our results suggest, however, that part of this difference can be attributed to the size of the stock of charging infrastructure in MSAs considered in their analysis: 22.13 in Li et al. (2017), and only 3.09 in our data. Using our polynomial specification, we find that the elasticity corresponding to a stock of stations of 22 in our data is 0.54, which illustrates the importance of studying early infrastructure provision in the design of policies supporting EV adoption.

Related evidence focuses on the role of policy incentives for the adoption of EVs. For example, Clinton and Steinberg (2019) uses 2011 to 2015 data for the U.S. to quantify the impact of direct financial incentives in Texas and Massachusetts on EV adoption.[10] Using both panel data and SCM, they show that subsidies increase adoption, although they suggest that the net welfare effect of direct EV subsidies is negative. Similarly, Springel (2021) uses 2010 to 2015 data for 19 Norwegian counties to study subsidies for EVs and charging stations.[11] She estimates a structural demand model for EVs, showing that subsidizing charging stations is more efficient than directly subsidizing EVs. Relative to these two studies, we provide a first set of empirical results suggesting that indirect network effects are large when the stock of charging stations is small, which provides novel insights for optimal policy targeting charging infrastructure provision in nascent EV markets (Meunier and Ponssard, 2020).

Finally, our research is related to the non-monetary and psychological barriers to adoption of new energy technologies demonstrated by Fowlie et al. (2015). Jaffe and Stavins

infrastructure. For example, Corts (2010) and Shriver (2015) provide empirical evidence that fueling stations supplying ethanol increase the adoption of ethanol-compatible vehicles in the U.S., and discuss the provision of subsidies to fuel retailers.

10 On the impact of direct financial incentives on EV and hybrid purchases, see also DeShazo et al. (2017), Sallee (2011), Beresteanu and Li (2011), Chandra et al. (2010), Gallagher and Muehlegger (2011), and Diamond (2009).

11 While the purpose of our work is different, our data is closely related to Springel (2021), with a few differences. First, we work at a more disaggregated municipality-level, with 422 cross-sectional units instead of 19 counties. Second, our analysis includes 2016 and 2017, and during these years EV sales increased by more than 80 percent, charging stations rose by a quarter, and charging points grew by around 40 percent (see Figure 1). Lastly, our data covers both charging stations and charging points.

(1994) argue that a lack of uptake of energy efficient technologies is due to factors such as incomplete information and unobserved costs, while Heutel and Muehlegger (2015) shows that consumer learning about the practical use and attributes of new technologies increases adoption. Other papers demonstrate the effect of community and personal environmental preferences on the adoption of traditional hybrid vehicles (Kahn, 2007; Kahn and Vaughn, 2009), for which we account in our analysis.

One question we do not directly address is different charger speeds (fast vs. slow) and their relative benefits in varied use-cases. In theory, slow chargers may be better suited to urban areas and locals charging as a supplement to or replacement of home-charging. Fast chargers could be more beneficial on long-distance driving routes, leisure destinations, and therefore, potentially, rural areas. As Greaker (2021) discusses, fast charger availability has been given as an important factor for EV adoption, particularly as an enabler of long-distance and leisure trips. Their theoretical model finds that fast charger standardisation and infrastructure roll-out would increase EV purchases and consumer welfare. This chapter somewhat abstracts from these differences, using overall charger numbers. However, on average, 85 percent of charging stations in our data are slow chargers. This, along with our analysis of within-municipality network and EV purchase variations, gives us confidence that we are analysing the local effects of nearby charger installations on EV adoption.

This chapter proceeds as follows. Section 2 outlines our empirical strategy, first by providing our data and laying out summary statistics, and second by detailing our panel data and SCM approaches. Section 3 then reports our empirical results. Finally, Section 4 provides concluding comments.

2 Empirical strategy

In this section we first give a summary of our data, and then present our two complementary empirical approaches to identify the impact of charging infrastructure on EV demand.

2.1 Data overview

Our dataset covers all of Norway's 422 municipalities for each quarter from Q3 2010 to Q4 2017 (T=30). The data includes the quantity of newly registered EVs by car model, month and municipality, and the prices for each car (OFV, 2018). Car models here refer to the broadest classification thereof (e.g. Tesla Model S or Nissan Leaf). We obtain data on every publicly accessible EV charging station across Norway from the Norwegian Charging Station Database (NOBIL, 2018), including its location, opening date and number of charging points.[12] [13] Other variables capturing municipality-level characteristics originate from Statistics Norway (SSB, 2018).

Table 1 summarizes our data. The average quantity of each EV model sold per quarter in each municipality is 0.56, and the total number of EVs sold of all models per municipality per quarter is over 16 on average. Note that, since EV models enter and exit the Norwegian car market over the period considered, we have an unbalanced panel. In 2010 there are only 4 models available, and this rose progressively to reach 50 in 2017.

The number of charging stations available per municipality and quarter ranges between 0 and 376, with an average of 3.09. These values indicate large differences in charging infrastructure between municipalities and over time. Moreover, while the average number of charging points available is over 13, many charging stations only provide 1 or 2 points. Although the average municipal-level number of points per station goes up to 40 points.

We further use the number of parking places per municipality in 2017 as part of our instrument, which averages 570 and also has a large range. As additional control variables we use the car price, household income, the number of hybrid vehicles per municipality in 2008, population size, the proportion of households in a municipality that are detached houses or duplexes (as a proxy for level of urbanisation), and, separately, the categorical degree of urbanisation (urban/city, suburban/town, rural). The proportion of municipalities classified as urban is 2.8 percent, while 22.3 percent are sub-urban, and 74.9 percent rural. The number of traditional (ICE-) hybrid vehicles is used as an indicator of municipal green preferences before the mass-introduction of EVs, and willingness to buy new, green car technologies.

One remarkable feature of the data is that, despite the relatively large market share of EVs, there are still many Norwegian municipalities that have either no or very few charging station installations over our observation period. We exploit this feature of

[12] Note that we do not differentiate chargers by speed, connector type, owning company, or access and usage fees. This includes both so-called 'fast' (level 3) and 'slow' (level 2) chargers, the majority of which (85 percent on average) are the latter (see Li (2019) for a discussion of charger types and compatibility, and Greaker (2021) on fast charger standardisation).

[13] The NOBIL database is only available from 2010 and thus limits our panel's time range.

Table 1: Descriptive statistics for all 422 Norwegian municipalities

	Mean	Std. Dev.	Min	Max
New EVs per model	0.56	5.44	0	528
Total of new EVs	16.07	93.54	0	3 815
EV models available	28.93	14.64	4	50
Charging stations	3.09	14.36	0	376
Charging points	13.46	78.77	0	2 331
Points per station	3.63	2.48	1.00	40.33
Parking spaces	570.06	1 472.56	0	19 719
Car price	547 575.60	395 827.50	124 108.30	2 027 016.00
Mean household income	385 606.10	40 471.95	285 091.80	841 848.80
Hybrids 2008	10.11	46.09	0	736
Population	121 000.97	37 064.02	196	672 062
Detached houses	85.52	12.37	14.61	100

Notes: Data sources are OFV (2018), NOBIL (2018), and SSB (2018). Car price and mean municipal household income are measured in 2015 Norwegian kroner (NOK), with 1 USD approx. 8 NOK in 2015. Detached houses is measured as the percentage of all households that are detached or duplex.

the data with a SCM strategy. First, 110 municipalities had zero charging stations over the entire period (donor municipalities). Second, we observe 47 municipalities that installed a single charging station in 1 quarter between Q1 2011 and Q1 2017, with no installations before or after (one-station municipalities). Third, we additionally observe 17 municipalities that installed multiple stations over a period of up to 4 consecutive quarters, however that had zero stations prior to Q1 2011 and no more after their 4-quarter installation period (multi-station municipalities). In this group, between 2 and 13 stations were installed over the installation period, with an average of 2.94.

Table 2 shows the difference in the outcome and treatment variables (EV numbers and charging stations available, respectively) between these 3 municipality groups across the entire observation period.[14] Aside from differences in charging stations, cumulated EV registrations is higher in the two treatment groups than in the donor group. We further observe that the municipalities in these three groups are similar in terms of their population size, wealth, and urban density. In particular, while the mean donor population is lower than those of the treated groups, it is less than two-thirds of a standard deviation smaller. We observe that the support of observables for all three groups overlap.

[14] Appendix E lists the names of these 3 groups of municipalities, and provides the quarters of charger installation.

Table 2: Descriptive statistics for municipalities in the synthetic control analysis

	Mean	Median	Std. Dev.	Min	Max
One-station municipalities					
Cumulative EVs	23.51	2	62.98	0	654
Charging stations	0.38	0	0.49	0	1
Population	4 756.27	3 549	3 411.46	346	18 709
Household income	382 723.20	373 923.30	43 237.82	300 324.10	541 030.90
Detached houses	90.30	92.24	6.37	67.23	98.36
Multi-station municipalities					
Cumulative EVs	12.52	1	25.37	0	151
Charging stations	0.90	0	2.28	0	13
Population	4 781.40	4 060	3 222.24	1 003	11 723
Household income	374 043.80	373 378.30	28 878.90	303 889.10	461 981.80
Detached houses	87.03	90.04	10.14	58.06	97.25
Donor municipalities					
Cumulative EVs	10.51	1	35.84	0	395
Charging stations	0	0	0	0	0
Population	2 879.55	2 016	2 879.07	196	18 850
Household income	370 738.70	367 781.60	36 625.30	285 091.80	841 848.80
Detached houses	92.04	93.85	5.56	68.83	100

Notes: Data sources are OFV (2018), NOBIL (2018), and SSB (2018). Mean municipal household income is measured in 2015 NOK, with 1 USD approx. 8 NOK in 2015. Detached houses is measured as the percentage of all households that are detached or duplex.

2.2 Panel data approach

The objective of our panel data strategy is to estimate the non-linear impacts of EV charging infrastructure on the number of EVs purchased. Our main outcome variable is the quantity of new cars registered, at the car model-level m, and across municipalities i, and quarters t. Our treatment variable is the number of charging stations (or alternatively charging points) available in a given municipality i and at a given time t.

Formally, our baseline panel data specification is given by:

$$\textit{ln(EV)}_{mit} = \alpha + \beta\, \textit{ln(chargers)}_{it} + \gamma\, X_{mit} + \delta_{mi} + \theta_t + \varepsilon_{mit}\,, \tag{1}$$

where $\textit{ln(EV)}_{mit}$ is the log of new cars registered by model, municipality and quarter, $\textit{ln(chargers)}_{it}$ is the natural log of publicly accessible EV charging stations (or charging points).[15] X_{mit} is a set of control variables including the log of a municipality's mean

15 We deal with values of zero EVs, charging stations/points, and parking places by adding one before

household income and the gross list price of each car.[16] We also further include two trend variables. First, we interact household income with a time-trend to allow for the income effect to change over time as the EV market becomes more mature. Second, we interact the quantity of hybrid vehicles registered in 2008 (before our sample period) with a time-trend to proxy for environmental preferences in each municipality. Next, we include municipality-model fixed effects δ_{mi}, which capture model-specific preference heterogeneity across municipalities due to availability of certain brands, or practicality of certain car characteristics such as battery range or different car styles. This further controls for municipality characteristics that are time-invariant and could affect EV demand, such as degree of urbanisation, toll road or bus lane prevalence, commuting behaviours, average driving distances, technological hesitancy, etc. Quarter fixed effects θ_t capture country-wide trends, including technological improvements in EV models (e.g. increased battery range) and changing competition environment across the country. Lastly, ε_{mit} is a random error term.

One conceptual issue with equation (1) is the potential endogeneity of charging infrastructure. As discussed above, demand for EVs can be affected by various factors that vary across time and municipalities, and that also influence investments in chargers and therefore their quantity. Additionally, through reverse causality, a greater number of EVs in circulation could lead to more investments in EV charging stations.

In an attempt to address this problem, we exploit plausibly exogenous variation in the availability of public parking places in each municipality as part of an instrumental variable strategy. The first stage model is driven by the fact that public charging infrastructure generally requires space to park electric vehicles, so that available publicly regulated parking areas in a municipality increase the probability and level of treatment by providing locations for charger installations.

We further argue that the exclusion restriction, which requires that our instrument Z_{it} affects EV purchases in any given municipality-quarter only through the variable *ln(chargers)*$_{it}$, is plausible. First, municipality fixed effects control for any time-invariant individual municipality effects. Second, we use the number of parking places in a fixed year, 2017, and specify a Bartik-type instrument (Bartik, 1991) to generate exogenous

log-transforming the data. A comparison to conducting an inverse hyperbolic sine transformation (Bellemare and Wichman, 2020) generates no significant difference in estimated coefficients.

[16] Note that this specification is very similar to structural models for market shares (Berry, 1994), although for our purpose a linear specification makes the elasticity interpretation more transparent. See Li et al. (2017) for further discussion of this issue.

temporal variation:

$$Z_{it} = ln(\textit{car parks}_i) \times ln(\sum_{j,j \neq i} chargers_{j,t-1})\,, \tag{2}$$

where the first part of Z_{it} is the log of publicly regulated parking places in municipality i, and the second is the lagged log of charging stations (or points) installed in all other municipalities. This yields the following first stage equation:

$$\textit{ln(chargers)}_{it} = \tau + \sigma Z_{it} + \pi X_{mit} + \psi_{mi} + \xi_t + \mu_{mit}\,, \tag{3}$$

where the notation follows from above and μ_{mit} is a random error term.

This identification strategy is close to Li et al. (2017), who interact the log of the number of grocery stores with the lagged log of charging stations in other MSAs. Similarly, our instrument in equation 2 captures the exogenous national trend in charger installations, accounting for all national subsidies and incentives, as well as national-level shocks to costs, technologies, culture and policies, and interacts the municipal potential for installations. Intuitively, national-level trends affect municipalities differently based on their local characteristics, and municipalities with more abundant parking spaces are expected to be more likely to install charging infrastructure in response to national trends or shocks.

In order to document non-linearities presumably associated with network effects, we estimate a set of specifications using polynomial forms of the instrumented charger variable. For this purpose, we implement the CF approach discussed in Wooldridge (2015), whereby residuals from the first stage regression $\hat{\mu}_{mit}$ are included in the second stage to control for variability that is *not* associated with the instrumental variable:

$$\textit{ln(EV)}_{mit} = \alpha + f(chargers) + \gamma\, X_{mit} + \delta_{mi} + \theta_t + \rho\, \hat{\mu}_{mit} + e_{mit}\,, \tag{4}$$

where $f(\cdot)$ is a quadratic or cubic function.[17]

Finally, we also carry out the following robustness checks. First, we drop the car price from the estimation, so as to document concerns that endogeneity in this variable may affect our estimated elasticities.[18] Second, we use the number of parking spaces in 2015

17 Bootstrapped standard errors are estimated based on 500 replications.

18 As discussed in Berry (1994) and Berry et al. (1995), the price variable is likely endogenous because of unobserved quality attributes. In our setting, however, our focus is on identification of the coefficient associated with charging infrastructure, and our IV strategy implies that we do not necessarily

rather than 2017 to construct an alternative instrument and test it's robustness to an alternative measure in the number of parking places.[19] Third, we construct an alternative instrument that excludes neighboring municipalities, addressing potential concerns associated with regional effects. Fourth, we interact the treatment variable with a dummy for BEVs, and test for differences in the provision of charging infrastructure as compared to plug-in hybrids. Fifth, we add further control variables, namely municipal-level population, and level of urbanization. Sixth, we estimate a separate treatment elasticity for 'early' and 'late' periods of our sample, splitting between observations in 2010-2013 and 2014-2017.

Lastly, we separate treatment elasticity by the municipality's degree of urbanisation – urban/city, suburban/town or rural. The fixed effects above capture time-invariant municipality differences such as access to toll roads and bus lanes, commuting methods, and overall EV preferences. However, some factors could lead to varied EV adoption responses to charger installation. For example, if acceptance of the new technology is lower in rural areas and evolves over time at a slower rate to in cities, this would not be captured by fixed effects. Furthermore, denser urban environments lend themselves to greater peer and network effects through proximity and ease of observation. Finally, the base of installed charging infrastructure varies considerably across degree of urbanisation. Thus if the above non-linear elasticity estimates are significant, this would directly follow through to mean treatment elasticity values in municipalities with greatly differing charger numbers.

2.3 Synthetic control method

We now discuss the SCM approach, which allows us to estimate the impact of providing charging infrastructure in municipalities that previously had none. Specifically, we focus on 47 one-station municipalities that installed a single charging station, and on 17 multi-station municipalities that installed more than one station. For each treated unit, we construct a counterfactual "synthetic" unit by estimating a set of weights applied to the 110 municipalities with zero charging stations included in the donor pool. Intuitively, the weights are selected so as to minimize the distance between the pre-treatment outcome of the treated unit and that of the synthetic unit, and the latter is

need to control for car prices.

[19] Note that, ideally, we would want to consider parking space data before 2010, but 2015 is the first year for statistics on parking spaces were collected.

used as a counterfactual to quantify post-treatment differences with the treated unit.

Formally, in the SCM approach derived from Abadie and Gardeazabal (2003) and Abadie et al. (2010), for each treated municipality j (either in the one-station and multi-station groups) the outcome is the cumulative number of EV purchases EV_{jt}. We define a synthetic municipality as a weighted sum of the cumulative number of EV purchases EV_{it} in all municipalities i of the donor pool:

$$EV_{jt}^{SCM} = \sum_{i} \omega_{ji} EV_{it} \ , \tag{5}$$

where ω_{ji} is the weight attributed for municipality i in constructing a synthetic control for treated municipality j. The weights result from minimization of the squared-sum of pre-treatment differences in our outcome variable, cumulative EV sales, between each synthetic and treated municipality – the mean squared prediction error (MSPE):

$$\min_{\omega_{ji}} \ \sum_{t=0}^{T_0} (EV_{jt} - \sum_{i} \omega_{ji} EV_{it})^2 \tag{6}$$

$$s.t. \ \sum_{i} \omega_{ji} = 1 \ , \quad \omega_{ji} \geq 0 \, ,$$

where T_0 is last quarter before treatment. Note that the quarter of treatment differs for each municipality, and thus the number of periods before and after treatment also varies (see Appendix E). We therefore use a staggered design, where the analysis time-points are centred around each municipality's period of treatment $(T_0 + 1)$. We restrict our treated municipalities to those with at least 4 quarters pre-treatment and at least 4 post-treatment to allow for sufficient matching and comparison dimensions. The matching period is then the entire observed pre-treatment period available, ranging from 4 to 26 periods, with an average of 18.8. Having a relatively long matching period is desirable to minimise potential bias and the MSPE, while we simultaneously maintain maximum model sparsity through fitting only on the outcome variable (Abadie, 2021).

Before treatment, the difference between observed cumulative EVs, EV_{jt}, and the counterfactual synthetic outcome EV_{jt}^{SCM} should be as close as possible to 0. Post-treatment, the difference between EV_{jt} and EV_{jt}^{SCM}, denoted ϕ_t, measures the treatment effect. Formally we calculate:

$$EV_{jt} = \phi_t D_t + EV_{jt}^{SCM} \ , \tag{7}$$

where D_t is the post-treatment period indicator. We repeat the above for every treated municipality in the 2 treatment groups, and show the variation in impacts between these, as well as the overall trend and average treatment effects.

Abadie and Imbens (2011) show, however, that the SCM is subject to a version of the curse of dimensionality, whereby the probability that the weights assigned achieve a perfect match between the synthetic and treated unit decreases with the dimension of the matching. This can lead to a bias in the estimated treatment effect. To overcome this the ridge-augmented SCM approach adds a bias-correction term derived from a ridge regression of post-treatment outcomes for donor units on pre-treatment outcome values. The estimated ridge regression coefficients, $\hat{\eta}$, are then introduced into the model as the bias correction (see Ben-Michael et al., 2021).[20] Formally, the ridge-augmented SCM weights are derived from:

$$EV_{jt}^{RASCM} = \sum_{i} \omega_{ji}^{RASCM} EV_{it} + (Y_j - \sum_{i} \omega_{ji}^{RASCM} Y_i) \cdot \hat{\eta} \tag{8}$$

where Y is the vector of pre-treatment cumulative EVs, and $(Y_j - \sum_i \omega_{ji} Y_i)$ is an estimate of the SCM bias. Importantly, the ridge-augmented SCM weights ω_{ji}^{RASCM} are not constrained to be positive, which provides additional flexibility for fitting pre-treatment outcomes. Ben-Michael et al. (2021) show that the ridge-augmented SCM achieves smaller pre-treatment residuals, and in turn generates a more accurate estimate of the treatment effect. In our results, we focus primarily on the ridge-augmented SCM results and report the standard SCM results in Appendix G for comparison.

We further conduct extensive robustness analysis of our ridge-augmented SCM results. Consistent with the SCM literature, these take the form of placebo tests where certain aspects of treatment assignment are changed in order to rule out spurious effects (Abadie and Gardeazabal, 2003). First, we carry out a spatial placebo analysis, where observed treatment interventions are iteratively reassigned to every untreated municipality in the donor pool, generating placebo treatment corresponding to the treatment dates among treated municipalities. From this we are able to compute p-values for our original estimates (see also Abadie et al., 2015; Andersson, 2019). Specifically, the p-value is calculated as the proportion of placebo estimates that are at least as large as the average treatment effect estimated for treated municipalities.[21]

As a second robustness check, we conduct a set of temporal placebo tests (Abadie et al.,

[20] See also Abadie (2021) for a discussion of SCM extensions and bias-correction methods.

[21] Following Andersson (2019), we restrict the analysis of placebo results to municipalities in the donor pool for which a good synthetic unit can be found. In particular, we consider only those units with a MSPE smaller or equal to the worse fit achieved in our set of treated units. This focuses the comparison among units for which the fit of the SCM approach is similar.

2015), based on Heckman and Hotz (1989) and Bertrand et al. (2004). Specifically, for each treated municipality we shift the treatment period a year (4 quarters) earlier and estimate the ridge-augmented SCM weights. In other words, the pre-treatment matching period is reduced by four quarters in order to check that the estimated effect is not spurious. If we observe systematic, sizeable differences between treated and synthetic outcomes after the artificial treatment period, this would provide evidence against the ridge-augmented SCM estimates.

Finally, we conduct a version of the "leave-one-out" test (Abadie et al., 2015; Andersson, 2019) to assess the potential influence of urban-proximate municipalities in the donor pool. Specifically, we remove any donor group municipalities that have a weekday morning driving-time proximity to cities and urban municipalities, based on the SSB (2018) classification, and repeat the ridge-augmented SCM analysis to remove potential bias from EV adoption incentives in these untreated units due to commuting ties, toll road use, or similar. If we observe large differences in the estimated treatment effects, we would potentially be concerned about bias in our primary results by not explicitly accounting for such non-charger incentives. Such a bias, though, would theoretically reduce our treatment effect estimations, meaning we originally underestimate or find a lower-bound estimate.

3 Estimation results

This section reports our empirical results. First, we present the panel data analysis, documenting non-linear impacts of EV charging infrastructure on the number of EVs purchased. Second, we discuss results from the ridge-augmented SCM, and document the impact of initial charging infrastructure provision on cumulative EV sales.

3.1 Panel data results

We start by estimating a set of linear specifications (equation 1), which closely align with the work of Li et al. (2017). Next, we consider non-linear specifications based on polynomial function of charging stations (equation 4). Lastly, we report robustness results.

Linear specifications

Our estimation results from the linear models are reported in Table 3. In columns (1), we report OLS estimates for a regression of the log of EV registrations on the log of charging stations. In column (2) we report results for the same function estimated with 2-stage least squares (2SLS). Columns (3) and (4) repeat this sequence, with charging points as the treatment variable instead of charging stations. All models include quarter and municipality-model fixed effects, and standard errors are clustered at the municipality level and reported in parentheses. First-stage results for the 2SLS specifications are provided in Table F1.

OLS results in column (1) indicate no statistically significant effect of charging stations on EV purchases. Comparing this to the 2SLS specification in column (2), suggests a negative endogeneity bias. Our IV specification in column (2) shows a highly significant estimated elasticity of charging stations on EVs of 0.126. Furthermore, our instrument interacting parking spaces with trends in national charger availability has significant explanatory power over the quantity of charging stations available in a given municipality-quarter, with a first-stage F-statistic associated with the instrument of 19.01. A comparison of columns (3) and (4) confirms a downward bias associated with OLS estimation, with the 2SLS estimate for the elasticity of charging points on EVs of 0.074. The F-statistic associated with the instrument for charging points in the first-stage regression is 25.54.

Our results show that the elasticity with respect to charging points is almost half the magnitude of the elasticity for charging stations. This suggests that consumers respond more on average to the simple visual presence of stations than to the specific number of plugs available. That is, ceteris paribus, constructing more EV charging stations with fewer points each would tend to engender more EV purchases than installing fewer stations with more points each. This is consistent with a psychological reassurance effect that the charging station network provides to curbing drivers' range anxiety.

Non-linear specifications

Table 4 reports results from the polynomial forms using a CF approach (equation 4). Columns (1) to (3) respectively provide linear, quadratic, and cubic model estimates with charging stations as the treatment variable. Columns (4) to (6) repeat the same sequence of estimations but using charging points as the treatment variable. In all models we additionally include quarter and municipality-model fixed effects. Standard

Table 3: Baseline results from panel data estimation

	Charging stations		Charging points	
	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)
ln(charging stations)	-0.008	0.126**	–	–
	(0.006)	(0.054)		
ln(charging points)	–	–	-0.004	0.074***
			(0.003)	(0.026)
ln(car price)	0.108***	0.110***	0.108***	0.110***
	(0.008)	(0.008)	(0.008)	(0.008)
ln(income)	-0.007	-0.036	-0.007	-0.025
	(0.092)	(0.109)	(0.092)	(0.110)
ln(income) x Time	-0.0002	0.0001	-0.0003	-0.0001
	(0.005)	(0.005)	(0.005)	(0.005)
ln(hybrids) x Time	0.008***	0.008***	0.008***	0.008***
	(0.001)	(0.001)	(0.001)	(0.001)
Constant	-1.298	-1.370	-1.290	-1.348
	(1.090)	(1.314)	(1.089)	(1.334)
N	367,984	366,296	367,984	366,296
Within-R^2	0.0779	0.0675	0.0779	0.0646
1st-stage partial F-stat.	–	19.01	–	25.54

Notes: In all columns, the dependent variable is the log of new electric vehicle registrations ($ln(EV)_{mit}$). Columns (1) and (2) consider charging stations as the treatment variable, and columns (3) and (4) instead use charging points. All specifications include quarter and municipality-model fixed effects. The 1st stage partial F-statistic for the instrumental variable (columns (2) and (4)) are derived from first-stage regression reported in Appendix F, Table F1. Standard errors clustered at the municipality level reported in parentheses. *, ** and *** respectively denote significance at 10%, 5% and 1% levels.

errors are clustered at the municipality level, bootstrapped with 500 replications, and reported in parentheses.[22]

Based on the overall model fit, our preferred model for charging stations is the cubic form (column 3), and we illustrate the implied schedule for elasticity estimates in Figure 2a (panel a). At low values for the installed stock of charging stations, the elasticity of chargers on EV purchases is similar across specifications (e.g. at the sample mean of 3.09 charging stations the cubic specification gives an elasticity of 0.22). However, cubic polynomial results indicate a significant increase in the elasticity of charging stations on EV purchases as the stock of installed stations rises. At around 100 charging stations

22 Note that results in column (1) and (4) correspond to Table 3, column (2) and (4) respectively, illustrating that 2SLS and CF procedures generate the same coefficient estimates whereas bootstrapped standard errors differ slightly. First-stage results remain the same and are reported in Table F1.

Table 4: Results from control function estimation

	Charging stations			Charging points		
	Linear (1)	Quadratic (2)	Cubic (3)	Linear (4)	Quadratic (5)	Cubic (6)
ln(charging stations)	0.126***	0.043	0.131***	–	–	–
	(0.045)	(0.041)	(0.046)			
ln(charging stations)^2	–	0.046***	-0.036	–	–	–
		(0.008)	(0.029)			
ln(charging stations)^3	–	–	0.018**	–	–	–
			(0.009)			
ln(charging points)	–	–	–	0.074***	0.025	0.132***
				(0.021)	(0.020)	(0.021)
ln(charging points)^2	–	–	–	–	0.015***	-0.055***
					(0.003)	(0.094)
ln(charging points)^3	–	–	–	–	–	0.012***
						(0.002)
ln(car price)	0.110***	0.110***	0.110***	0.110***	0.110***	0.110***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
ln(income)	-0.036	-0.099	-0.130	-0.025	-0.057	-0.108
	(0.100)	(0.087)	(0.080)	(0.103)	(0.091)	(0.077)
ln(income) x Time	0.0006	0.002	0.003	-0.0001	0.001	0.002
	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.004)
ln(hybrids) x Time	0.008***	0.006***	0.006***	0.008***	0.007***	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.0005)
First stage residuals	-0.137***	-0.127***	-0.136***	-0.080***	-0.071***	-0.079***
	(0.046)	(0.039)	(0.038)	(0.021)	(0.019)	(0.018)
Constant	-1.370	-1.288	-1.062	-1.348	-1.389	-1.118
	(1.214)	(1.256)	(1.127)	(1.211)	(1.201)	(1.033)
N	366, 296	366, 296	366, 296	366, 296	366, 296	366, 296
Adjusted within-R^2	0.0778	0.0796	0.0817	0.0779	0.0790	0.0826
1st-stage partial F-stat.	19.01	19.01	19.01	25.54	25.54	25.54

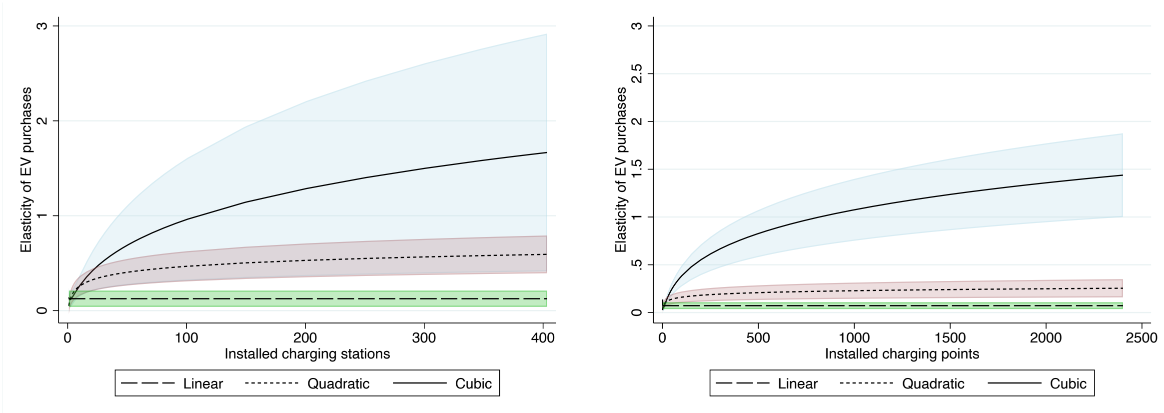
Notes: In all columns, the dependent variable is the log of new electric vehicle registrations ($ln(EV)_{mit}$). Columns (1) to (3) consider charging stations as the treatment variable, and columns (4) to (6) instead use charging points. All specifications include quarter and municipality-model fixed effects. The 1st stage partial F-statistic for the instrumental variable is derived from first-stage regression results reported in Appendix F, Table F1. Standard errors bootstrapped with 500 replications and clustered at the municipality level reported in parentheses. *, ** and *** respectively denote significance at 10%, 5% and 1% levels.

available, the elasticity is approximately unity, although the rise in elasticity for each additional installed station quickly diminishes.

Interestingly, our non-linear results also provide a rejoinder with the elasticity estimates of about 0.8 reported in Li et al. (2017), which refer to 353 MSAs with relatively significant EV sales over the period from 2011 to 2013. These MSAs also feature a stock of installed chargers of 22.13, which is significantly larger than what we have in our sample. Evaluating the polynomial function for a stock of installed chargers of 22, we obtain an elasticity of 0.54.

Figure 2: Elasticity of electric vehicle registrations as a function of the charging infrastructure

(a) Elasticity schedule for charging stations (b) Elasticity schedule for charging points



Notes: Based on the model estimates shown in Table 4. The graphed lines provide point elasticity estimates, and the shaded areas cover the 95% confidence intervals.

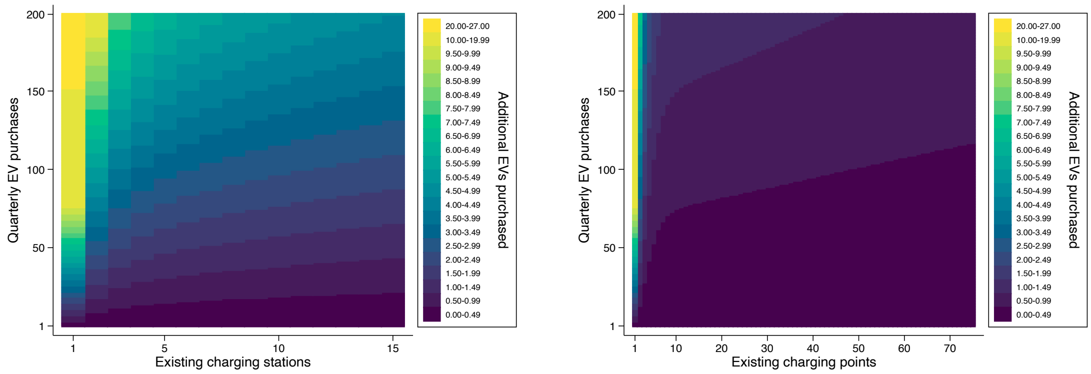
Results for charging points (Table 4 columns (4) to (6) and Figure 2b also support an increasing elasticity schedule as the number of available charging points rises, although at a declining rate. In our preferred cubic specification (column 6), the elasticity evaluated at the mean value of charging point availability (13.46) is 0.12. At 200 charging points, the elasticity is around 0.57, and surpasses unity for a stock of around 800. Overall, the consumer reaction to a marginal increase in charging points is smaller compared to an increase in charging stations, which further supports the behavioural bias discussed previously.

Implications of cubic specifications are further illustrated in Figure 3, which reports the impact of a 1-station increment (panel a) and a 1-point increment (panel b) on EV registrations across varying levels of existing infrastructure and EV purchasing. This shows that the largest impact from installing an additional charging station is at a low level of existing infrastructure, and that the impact increases with the number of EVs purchased in the quarter just before installation. As the existing stock of stations grows, the additional EVs generated by further incremental installations diminishes. The pattern for charging points is similar, although the consumer reaction declines more rapidly than for charging stations, which is in line with a behavioural difference between charging stations and points discussed above.

Figure 3: Electric vehicle registrations associated with incremental charging infrastructure

(a) Unit change in the stock of charging stations

(b) Unit change in the stock of charging points



Notes: Based on the cubic model estimates shown in Table 4. This shows the number of new EVs registered after the installation of a single charging station (panel a) or point (panel b), across varying levels of existing infrastructure and previous EV purchases. "Quarterly EV purchases" refers to the quantity in the period before the charger installation.

Robustness checks for panel data estimation

Next, we report robustness checks for charging stations (Table 5) and points (Table 6). In both tables, column (1) reports results excluding the car price variable; column (2) uses 2015 parking spaces to construct the instrument instead of 2017; in column (3) the instrument excludes each municipality's neighbors; column (4) adds the interaction between chargers and BEVs; column (5) adds extra control variables; column (6) allows the treatment elasticity to vary between early and late periods in our dataset; and column (7) estimates different treatment elasticities for urban, suburban or rural areas. For simplicity and ease of interpretation we focus on linear specifications, and provide estimates of our preferred cubic specifications in Table F2 and Table F3.[23] All models are estimated with a CF procedure and bootstrapped standard errors (500 replications) clustered at the municipality level are reported in parentheses. First stage results for all specifications are reported in Tables F4 and F5 for charging stations and points, respectively.

Starting with results for charging stations (Table 5), we find that the elasticity estimates remain close to our primary linear elasticity estimate of 0.126, and the partial F-statistics associated with the instrument are also very similar across specifications. This suggests

[23] It suffices to note here that robustness results for the cubic specifications do not substantially differ from the primary results in Table 4, and that explanations for linear robustness checks in Tables 5 and 6 apply to the cubic specifications, too.

Table 5: Alternative panel data specifications – charging stations

	No price (1)	2015 parking (2)	No neighbours (3)	Chargers x BEV (4)	Additional controls (5)	Chargers x time (6)	Chargers x urban (7)
ln(charging stations)	0.126***	0.139**	0.140***	0.121***	0.131***	–	–
	(0.046)	(0.055)	(0.048)	(0.046)	(0.045)		
ln(charging stations) x BEV	–	–	–	0.011**	–	–	–
				(0.005)			
ln(charging stations) x early	–	–	–	–	–	0.130***	–
						(0.046)	
ln(charging stations) x late	–	–	–	–	–	0.128***	–
						(0.045)	
ln(charging stations) x urban	–	–	–	–	–	–	0.289**
							(0.125)
ln(charging stations) x town	–	–	–	–	–	–	0.146***
							(0.047)
ln(charging stations) x rural	–	–	–	–	–	–	0.124***
							(0.042)
ln(car price)	–	0.110***	0.110***	0.108***	0.110***	0.110***	0.110***
		(0.008)	(0.008)	(0.007)	(0.008)	(0.008)	(0.009)
ln(income)	-0.036	-0.038	-0.039	-0.036	-0.065	-0.035	-0.003
	(0.096)	(0.095)	(0.089)	(0.095)	(0.098)	(0.095)	(0.099)
ln(income) x Time	0.001	0.001	0.001	0.001	0.002	0.001	-0.001
	(0.005)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
ln(hybrids) x Time	0.008***	0.008***	0.008***	0.008***	0.008***	0.008***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ln(population)	–	–	–	–	-0.034	–	–
					(0.122)		
Proportion of detached and duplex dwellings	–	–	–	–	0.003	–	–
					(0.003)		
First stage residual	-0.137***	-0.149***	-0.150***	-0.136***	-0.142***	-0.139***	-0.140***
	(0.046)	(0.055)	(0.048)	(0.046)	(0.045)	(0.045)	(0.042)
Constant	0.051	-1.382	-1.383	-1.346	-1.368	-1.139	-1.108
	(1.190)	(1.163)	(1.169)	(1.232)	(1.631)	(1.269)	(1.218)
N	366, 296	366, 296	366, 296	366, 296	366, 296	366, 296	366, 296
Adjusted within-R^2	0.0767	0.0778	0.0779	0.0779	0.0779	0.0778	0.0778
1st-stage partial F-stat.	18.32	11.29	16.80	19.01	19.51	19.01	19.01

Notes: In all columns, the dependent variable is the log of new electric vehicle registrations ($ln(EV)_{mit}$). Column (1) omits the car price variable. Column (2) uses the number of parking spaces in 2015 to construct the instrument. Column (3) excludes neighboring municipalities to construct the instrument. In column (4), we interact the treatment variable with a dummy for battery-only EVs. Column (5) includes further control variables. In column (6), we estimate separate elasticities for observations in 2010-2013 and 2014-2017. Column (7) estimates separate elasticities by municipal degree of urbanisation – urban/city, town/suburban, rural. All specifications are estimated with a control function approach and include quarter and municipality-model fixed effects. The 1st stage partial F-statistic for the instrumental variable is derived from first-stage regression results reported in Appendix F, Table F4. Standard errors bootstrapped with 500 replications and clustered at the municipality level reported in parentheses. *, ** and *** respectively denote significance at 10%, 5% and 1% levels.

that endogeneity in the car price variable does not influence our elasticity of interest (column 1). Using parking space data for 2015 (column 2) or removing neighboring municipalities from the instrument (column 3) have only minor effects on the elasticity estimates, which reinforces our confidence in the instrument. Similarly, changing the set of controls (column 5) also has very little impact on the elasticity estimates, and population and urbanization are not statistically significant at conventional levels. This suggests that our control strategy, which closely follows Li et al. (2017), already captures these potential drivers of EV purchases. Interacting the treatment variable with an indicator for BEVs (column 4) suggests that the elasticity for BEVs is slightly larger (p-value $<$0.05). Column (6) suggests no significant difference in the treatment effect for early and late time periods.

We finally find the treatment effect does vary significantly with urbanisation. Rural areas, accounting for three quarters of observations, have a similar elasticity estimate to the main specification, with intermediate regions (towns or suburbs) slightly more elastic. Cities and urban areas, under three percent of observations, display a significantly

Table 6: Alternative panel data specifications – charging points

	No price (1)	2015 parking (2)	No neighbours (3)	Chargers x BEV (4)	Additional controls (5)	Chargers x time (6)	Chargers x urban (7)
ln(charging points)	0.074^{***}	0.087^{***}	0.079^{***}	0.072^{***}	0.077^{***}	–	–
	(0.020)	(0.026)	(0.022)	(0.021)	(0.022)		
ln(charging points) x BEV	–	–	–	0.005^{*}	–	–	–
				(0.003)			
ln(charging points) x early	–	–	–	–	–	0.081^{***}	–
						(0.023)	
ln(charging points) x late	–	–	–	–	–	0.076^{***}	–
						(0.022)	
ln(charging points) x urban	–	–	–	–	–	–	0.134
							(0.146)
ln(charging points) x town	–	–	–	–	–	–	0.083^{***}
							(0.026)
ln(charging points) x rural	–	–	–	–	–	–	0.073^{***}
							(0.022)
ln(car price)	–	0.110^{***}	0.110^{***}	0.108^{***}	0.110^{***}	0.110^{***}	0.110^{***}
		(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.006)
ln(income)	-0.025	-0.029	-0.027	-0.025	-0.059	-0.025	-0.019
	(0.097)	(0.100)	(0.099)	(0.097)	(0.103)	(0.098)	(0.098)
ln(income) x Time	-0.0001	-0.0002	-0.0002	-0.0001	0.001	-0.0003	-0.000
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
ln(hybrids) x Time	0.008^{***}	0.008^{***}	0.008^{***}	0.008^{***}	0.008^{***}	0.008^{***}	0.008^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ln(population)	–	–	–	–	-0.049	–	–
					(0.124)		
Proportion of detached and duplex dwellings	–	–	–	–	0.003	–	–
					(0.002)		
First stage residual	-0.080^{***}	-0.093^{***}	-0.085^{***}	-0.080^{***}	-0.083^{***}	-0.083^{***}	-0.080^{***}
	(0.020)	(0.026)	(0.022)	(0.021)	(0.022)	(0.022)	(0.021)
Constant	0.074	-1.364	-1.355	-1.326	-1.259	-1.427	-1.329
	(1.234)	(1.170)	(1.186)	(1.166)	(1.577)	(1.220)	(1.180)
N	366, 296	366, 296	366, 296	366, 296	366, 296	366, 296	366, 296
Adjusted within-R^2	0.0768	0.0779	0.0780	0.0780	0.0780	0.0780	0.0780
1st-stage partial F-stat.	24.57	14.17	23.73	25.54	23.04	25.54	25.54

Notes: In all columns, the dependent variable is the log of new electric vehicle registrations ($ln(EV)_{mit}$). Column (1) omits the car price variable. Column (2) uses the number of parking spaces in 2015 to construct the instrument. Column (3) excludes neighboring municipalities to construct the instrument. In column (4), we interact the treatment variable with a dummy for battery-only EVs. Column (5) includes further control variables. In column (6), we estimate separate elasticities for observations in 2010-2013 and 2014-2017. Column (7) estimates separate elasticities by municipal degree of urbanisation – urban/city, town/suburban, rural. All specifications are estimated with a control function approach and include quarter and municipality-model fixed effects. The 1st stage partial F-statistic for the instrumental variable is derived from first-stage regression results reported in Appendix F, Table F5. Standard errors bootstrapped with 500 replications and clustered at the municipality level reported in parentheses. *, ** and *** respectively denote significance at 10%, 5% and 1% levels.

greater reaction to new charging stations, with a more than doubled treatment elasticity of 0.289. This is directly related to the level of charging infrastructure available in each municipality group, as demonstrated in our previous non-polynomial model. As discussed above, our charger elasticities increase the larger the base of installed stations. Urban municipalities have a mean of 41 charging stations in our sample, compared to 5 and 1 in intermediate and rural municipalities, respectively. This means that, as per our polynomial findings, the urban-rural elasticities will also vary along with their respective stages of charging infrastructure build-up. The varied responses to charger installations could further be indicative of behaviours and preferences that are not captured in the municipality fixed effects, such as an overall hesitancy towards the technology that dampens reactions to incentives such as charger installations, a lesser importance of public chargers due to more prevalent home charging ability, or a relatively greater impact of visibility, and peer and network effects in denser, urban environments.

Results for charging points (Table 6) follow the same logic, and elasticity estimates from alternative specifications do not part significantly from the primary linear model's 0.074. Column (1) suggests that results do not suffer from otherwise unaccounted endogeneity through the vehicle price, and columns (2) and (3) show that our instrument stands up to changes in both halves of the Bartik construction. We also observe insignificant changes when we add an interaction term for BEVs (column 4), control variables (column 5), and check for differences between early-period and late-period elasticities (column 6). Rural and sub-urban areas follow the same pattern as for stations, given greater mean charging point numbers the more urban the municipality classification (respectively 209, 20 and 4 points in urban, sub-urban and rural areas). However the treatment elasticity for charging points in urban areas, while also larger, cannot be precisely estimated (column 7). Overall, each of these alternative specifications supports our primary estimations and the strength of our instrument.

3.2 Synthetic control results

We now report results from the SCM approach, quantifying how cumulative EV purchases respond to the installations of the first charging station(s). We focus on results from the ridge-augmented SCM, which tends to generate smaller pre-treatment residuals, and report results for the traditional SCM approach in Appendix G. We then follow with a set of placebo tests to document robustness of the analysis.

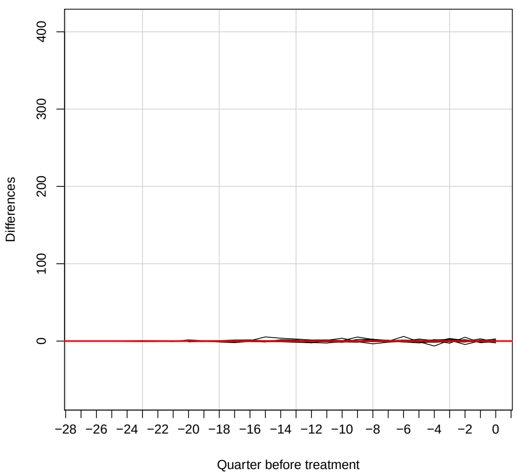
Pre-treatment matching and treatment effect estimates

Figure 4, panels 4a and 4b, present our ridge-augmented SCM estimation results for pre-treatment matching periods for the one-station treatment group and multi-station treatment group, respectively. These show that, for both treatment groups, the differences between the numbers of EVs registered in each treated municipality and its synthetic counterpart prior to the charger installation shock is close to zero across the pre-treatment periods. This suggests that synthetic control units precisely track EV registrations in the pre-treatment period, and gives confidence that synthetic municipalities can be used to derive credible counterfactual information for each treated municipality in the absence of charging infrastructure.[24]

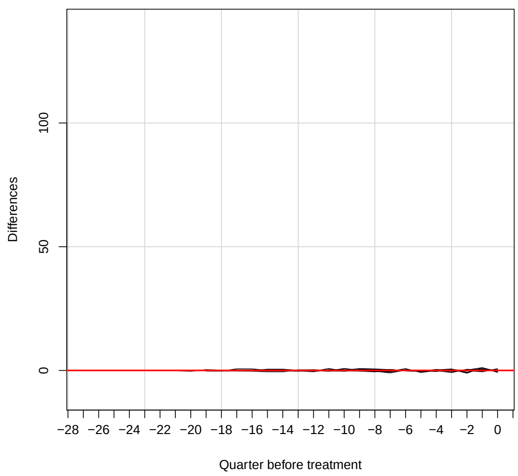
[24] As expected, the ridge augmented SCM provides a more precise matching relative to the traditional SCM, as shown in Figure G1, panels G1a and G1b. Treatment effects, discussed next, are however consistent across the two approaches.

Figure 4: Gap in cumulative EV stock between treated municipalities and synthetic controls

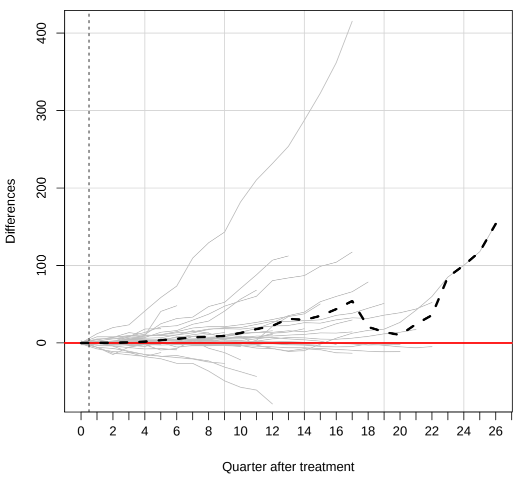
(a) One-station municipalities: matching periods



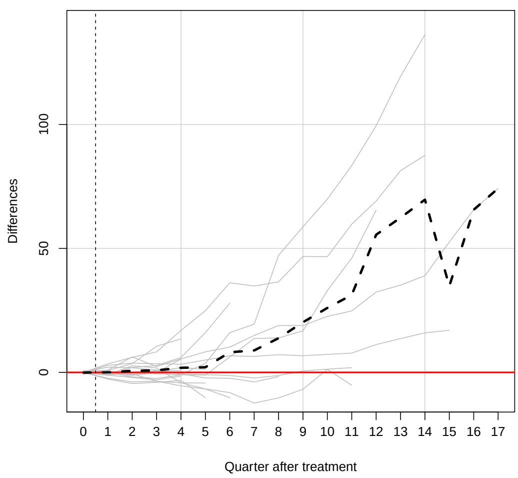
(b) Multi-station municipalities: matching periods



(c) One-station municipalities: treatment effect



(d) Multi-station municipalities: treatment effect



Notes: The solid gray lines represent the ridge-augmented SCM estimated differences between each treated municipality and its synthetic counterpart. The black dashed lines present the mean differences across treated units.

In panels 4c and 4d, we report post-treatment quarterly differences between numbers of EVs in a treated municipality and the corresponding number for the estimated synthetic municipality, for the one-station and multi-station treatment groups, respectively. We also plot the average treatment effect across treated municipalities as a dashed line, and

Table 7: Summary of post-treatment synthetic control results

Quarter post-treatment	One-station municipalities			Multi-station municipalities		
	Obs.	Mean	Median	Obs.	Mean	Median
1	47	0.20	-0.08	17	0.01	-0.05
2	47	0.18	0.04	17	0.64	-0.14
3	47	0.74	0.50	17	0.82	0.59
4	47	1.68	0.52	17	1.85	-0.58
5	46	3.50	0.66	13	2.07	-0.93
6	38	5.31	1.88	10	8.12	6.45
7	36	7.19	3.83	8	8.86	10.06
8	35	7.96	3.65	8	13.81	10.53
9	33	9.15	4.97	7	20.22	16.71
10	30	12.81	5.99	7	25.99	22.60
11	26	17.85	6.63	7	31.23	24.80
12	24	22.08	9.95	5	55.53	65.42
13	20	31.31	12.09	4	62.40	58.28
14	18	29.67	8.80	4	69.68	63.26
15	17	34.91	4.98	2	34.80	34.80
16	14	43.66	9.40	1	65.60	65.60
17	13	54.09	14.25	1	74.20	74.20
18	8	20.64	12.37			
19	7	14.25	11.76			
20	6	10.20	5.88			
21	4	24.31	29.82			
22	3	35.81	52.23			
23	1	85.06	85.06			
24	1	100.16	100.16			
25	1	117.87	117.87			
26	1	153.76	153.76			

Notes: This table summarizes results for the post-treatment gap in cumulative EV stock between treated municipalities and synthetic controls. Mean and median reported refer to the distribution of treatment effects estimated from the ridge-augmented SCM.

provide the mean and median differences between treated and synthetic municipalities for each post-treatment quarter in Table 7.[25]

Overall, results suggest that the provision of an initial charging station has a positive impact on EV registrations. Quantitatively, we estimate a one-station average treatment effect of 1.7 extra EVs registered four quarters post-installation. Eight quarters post-treatment, the estimated difference rises to 8.0 more EVs than would otherwise be

[25] Due to the differing dates of charging station installation across treated units, the number of post-treatment periods varies across municipalities. One implication, shown in Table 7, is that the number of treated-synthetic municipality pairs declines over time from the initial provision of charging infrastructure.

registered. This is equal to 5.4 and 21.7 percent more EVs than would otherwise have been bought after one and two years, respectively. Evidence further suggests that the impact increases with the size of the shock – the multi-station average treatment effect is larger. Four quarters after the first installation, this group had on average 1.9 additional EVs registered. We also observe an upward trend in the treatment effect, as the average difference between treated and synthetic units increases to 13.8 extra EVs two years post-treatment. The positive treatment effect associated with multi-station installations amounts to about 8.0 and 46.1 percent more EVs on average, respectively.

These results also match the panel data findings above in Section 3.1, where we see the immediate impact of the first charging infrastructure is low when there are few EVs previously registered. Applying the single-increment results from Section 3.1 and Figure 3 to the two SCM municipality groups, we find that the installation of the first charging station in the one-station group generated approximately 0.39 new EVs, on average, directly in the period of installation. For the multi-station group, an average of 3 charging stations were installed in the initial phase, and we therefore find that this lead to an average of around 0.78 additional EVs being purchased in the initial treatment period. Moreover, we find that when there is no existing charging infrastructure, the installation of the first charging point has a similar impact to that of the first station. Fundamentally, we see it takes time for the network dynamics to play out and the full benefits of early charger provision to be seen.

Robustness: Placebo tests for synthetic control results

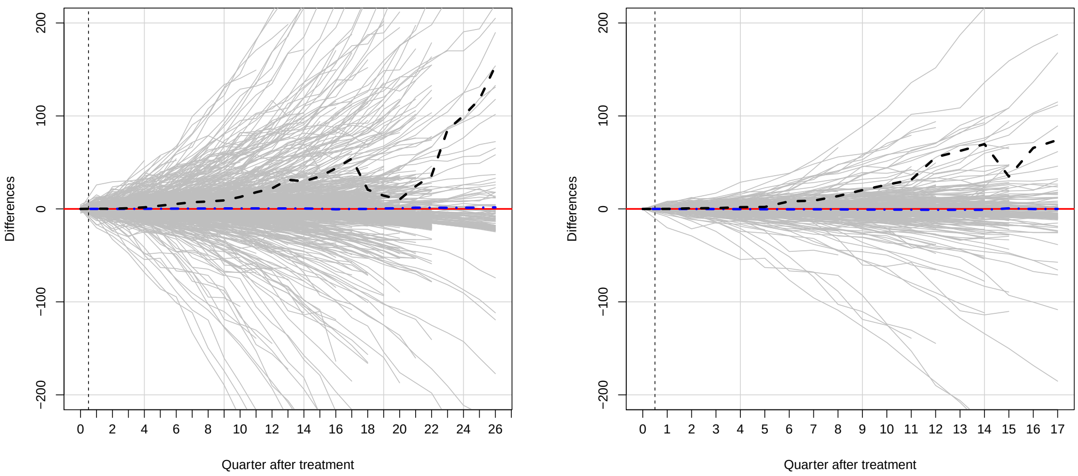
We now we present the results of placebo tests to document robustness of our SCM findings. As described above, we first conduct a set of spatial placebo tests, with results shown in Figure 5 for one-station municipalities (panel 5a) and multi-station municipalities (panel 5b). In both panels, individual placebo estimates of EV number differences are displayed in gray, while the dashed-dotted line shows the average placebo 'treatment effect' for comparison to the black dashed line with the average treatment effect of our treated municipalities.[26]

The estimated placebo differences in EV purchases exhibit significant heterogeneity, although the average placebo treatment effect for both one-station and multi-station is

[26] Placebo tests include only estimates for which pre-treatment MSPE is at least as good as the largest MPSE obtained for treated units. This leads us to exclude 7 municipalities from the one-station group (out of 2200) and 134 municipalities from the multi-station group (out of 990).

Figure 5: Synthetic control results for the spatial placebo tests

(a) One-station municipalities (b) Multi-station municipalities



Notes: This figure shows the results for the spatial placebo tests, comparing average gap in cumulative EV stock between treated municipalities and synthetic controls with placebo gaps for the control municipalities. The solid grey lines represent the placebo difference estimates for donor pool municipalities. The black dashed lines provide the mean difference estimates for the treated municipalities from Figure 4. The dashed-dotted lines give the means of the placebo estimates.

estimated to be consistently close to 0. This is also shown in Table 8, which provides per period average and median spatial placebo estimates for each group. We also report an estimate of the p-value associated with the average treatment effect reported in Table 7, each period, as measured by the share of placebo estimates that are larger than the average treatment effect estimated on treated municipalities.

Results generally indicate that the significance of our average treatment effect increases over time. For one-station municipalities, the treatment effect estimates for treated municipalities are marginally significant, and we find that it is below a 10 percent threshold between the 11th and the 18th quarters.[27] Results for multi-station municipalities provide further evidence for the greater impact of a larger treatment, as the p-value for the multi-station average treatment effect falls under 0.10 in the 6th quarter post-treatment, and below the 0.05 threshold after two years.

Results for the second placebo test are reported in Figure 6, which shows our temporal placebo results. The solid grey lines present the individual placebo estimates generated by giving each municipality an artificial treatment 4 quarters prior to the observed one.

27 The p-value for the average treatment effect estimate is also below 10 percent after the 23rd quarter, although it refers to only one municipality. See Table 7.

Table 8: Summary results for spatial placebo tests

Quarter post-treatment	One-station municipalities				Multi-station municipalities			
	Obs.	Mean	Median	p-value	Obs.	Mean	Median	p-value
1	2193	0.02	-0.08	0.244	856	-0.06	-0.11	0.293
2	2193	0.04	-0.15	0.311	856	-0.11	-0.30	0.263
3	2193	0.08	-0.23	0.255	856	-0.18	-0.40	0.251
4	2193	0.14	-0.28	0.204	856	-0.27	-0.43	0.189
5	2086	0.23	-0.34	0.150	773	-0.38	-0.34	0.189
6	1977	0.29	-0.47	0.123	688	-0.48	-0.48	0.063
7	1867	0.38	-0.66	0.111	598	-0.44	-0.74	0.074
8	1757	0.47	-0.65	0.118	598	-0.51	-0.87	0.050
9	1648	0.51	-0.94	0.126	509	-0.74	-1.17	0.037
10	1539	0.51	-1.21	0.110	509	-0.75	-1.54	0.033
11	1430	0.54	-1.81	0.092	509	-0.83	-1.64	0.033
12	1320	0.47	-2.16	0.084	411	-0.99	-2.03	0.024
13	1210	0.49	-2.83	0.069	312	-0.95	-1.92	0.029
14	1100	0.40	-2.86	0.080	312	-0.98	-2.27	0.029
15	990	0.23	-3.59	0.085	211	0.59	-3.07	0.076
16	880	-0.44	-4.82	0.076	107	-0.17	-5.15	0.056
17	770	-0.03	-5.69	0.075	107	-0.04	-5.57	0.056
18	660	-0.05	-6.57	0.155				
19	550	0.49	-7.40	0.187				
20	440	0.71	-8.13	0.209				
21	330	1.29	-8.98	0.148				
22	220	1.34	-9.36	0.118				
23	110	1.15	-9.38	0.082				
24	110	1.24	-10.91	0.055				
25	110	1.37	-10.65	0.064				
26	110	1.62	-12.02	0.055				

Notes: This table summarizes results for the post-treatment gap in cumulative EV stock for non-treated municipalities subject to placebo treatments corresponding to the treatment dates among treated municipalities, and synthetic controls. We report mean and median placebo treatment effects. The p-values represent the proportion of placebo difference estimates that are at least as large as the average treatment effect for treated municipalities.

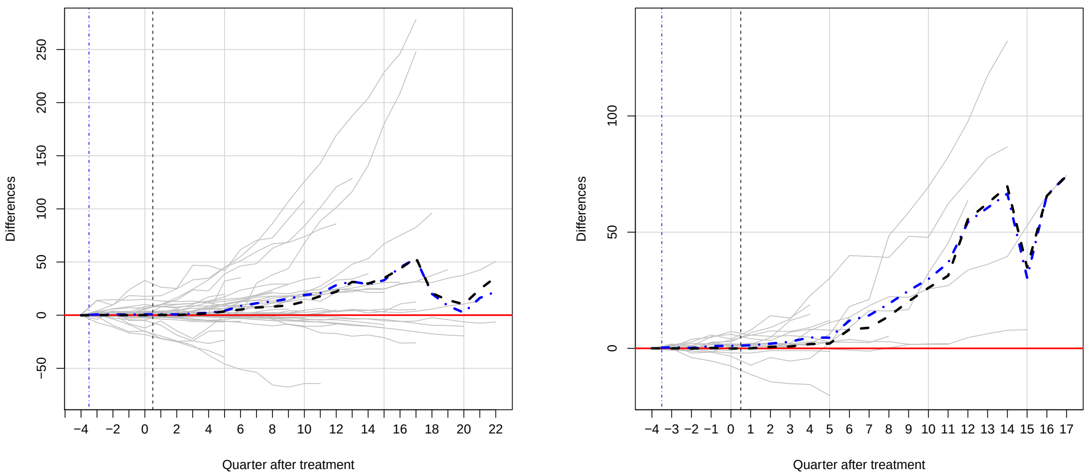
The dashed-dotted line shows the mean placebo differences, and the black dashed line the original SCM average treatment effect estimates. Table G2 in the appendix provides the means and medians of the temporal placebo estimates for the two treatment groups.

Results suggest that the mean placebo differences remain close 0 in the initial 4 placebo treatment periods. After the true treatment period, the temporal placebo average closely follows our average treatment effect estimates. The small differences from the original estimates can be explained by the use of a shorter matching period, which implies slightly different weights attributed to donor municipalities. This provides further confidence that our estimated difference in EV purchases can be attributed to the early installation of charging infrastructure at observed dates.

The results of the final robustness check, the "leave-one-out" tests that omit certain

Figure 6: Synthetic control results for the temporal placebo tests

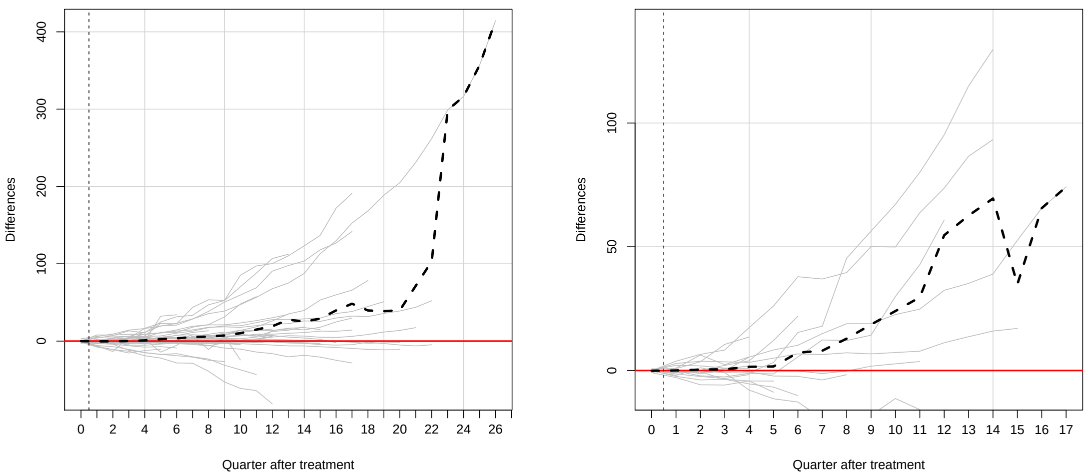
(a) One-station municipalities (b) Multi-station municipalities



Notes: This figure shows the results for the temporal placebo tests, comparing average gap in cumulative EV stock between treated municipalities and synthetic controls with those derived with an artificial 4-quarter earlier treatment. The solid grey lines represent the estimated differences between each treated municipality and its synthetic counterpart, with a placebo installation of charging stations 4 quarters prior to the actual installation. The black dashed lines provide the mean difference estimates for the treated municipalities from Figure 4. The dashed-dotted lines present the means of the placebo estimates. See Appendix G, Table G2, for the underlying data.

Figure 7: Synthetic control results for "leave-one-out" tests

(a) One-station municipalities (b) Multi-station municipalities



Notes: This figure shows the results for the "leave-one-out" test. This is a repeat of Figures 4c and 4d, excluding six city-proximate donor group municipalities (Table G3). The solid gray lines represent the ridge-augmented SCM estimated differences between each treated municipality and its synthetic counterpart. The black dashed lines present the mean differences across treated units.

urban-proximate municipalities, are shown in Figure 7. This provides little evidence that our main results are sensitive to the presence of urban-proximate municipalities in the donor pool. We find six donor group municipalities that are less than a one hour drive to a city or urban municipality (see Table G3).[28] The exclusion of these units from the donor pool does not greatly impact the estimations except for the one-station estimated differences between periods 18 and 22, where the treatment estimate is larger, and then from period 23, where only one treated municipality remains, with a much larger estimated difference. Specifically, at the mean, we estimate here 0.9 and 5.7 more EVs purchased by periods quarters 4 and 8, respectively, in the one-station group. This is slightly lower than the original estimates, though the medians remain almost identical. For the multi-station treatment group, we estimate an effect of 1.5 and 12.9 EVs by quarters 4 and 8, respectively. This is very close to the original estimates. Again, the medians remain similar. We provide the full “leave-one-out” estimates in Table G4.

4 Discussion and conclusions

In this study, we have provided novel empirical evidence on the impact of EV charging infrastructure on the adoption of EVs, focusing on how the size of the infrastructure network affects the response of consumers. Our work is based on fine-scale temporal and geographical data for Norway, from the emergence of the market and the early movers of 2010 to the mature market with large market share by 2017.

Our results provide a first account of consumer response to infrastructure in locations that previously had none. We show that the very first charging station installations initially induce a small response by consumers, although a one-off shock has a lasting, increasing impact over time after installation. We have also shown that the size of the initial installation shock matters, as providing multiple charging stations leads to a larger response by consumers. Beyond initial charging infrastructure, we have identified a non-linear relationship between the adoption of emerging EV technology and the size of the associated charging infrastructure network. Our results imply that the greatest effect of incremental infrastructure on EV purchases is when little to no pre-existing infrastructure exists, and when EV sales are already substantial. This is consistent with

[28] Specifically, we calculate the driving time on a representative weekday morning between the population-weighted geographical centre-points of each donor and urban municipality using the *georoute* Stata package (Weber and Péclat, 2017).

indirect network effects, and suggests an initial hurdle to the adoption of EVs. Moreover, the response by consumers gradually declines as the pre-existing network infrastructure expands.

Taken together, a low consumer response when existing EV purchases are small and a decreasing marginal installation impact trend can lead to a stand-off between initial EV purchases and charger investments. Once some EVs have been purchased, however, further charger installations do imply indirect network effects, fostering growth in both sides of the market. As the charging network grows, incremental charging infrastructure have a declining impact on EV sales, suggesting declining marginal benefits to consumers. This indicates that unpriced benefits to consumers are largest at the initial stage of the market, suggesting that early government interventions such as subsidies for charging infrastructure deployment have the largest impact on market inefficiencies and EV adoption rate.

Our results further support the view that a behavioural bias magnifies indirect network effects on the market for EVs, as the impact of charging points on EV registrations is consistently lower than that of stations. The fact that consumers respond more to additional installations of charging stations than they do to the addition of more charging points, ceteris paribus, supports the view that consumers' behavioural response is in part driven by range anxiety. This makes the number of charging points potentially less relevant than the physical presence of a charging station. Furthermore, the evidence that charging stations have a significantly greater effect on EV purchases in urban regions relative to rural or less-urban could indicate potential greater visibility and proximity effects, or hesitancy in rural areas that dampens reactions to new infrastructure. That said, this result further supports our non-linear approach, demonstrating a higher treatment elasticity in municipalities with a larger installed base of chargers (eg. urban, compared to rural).

While this chapter contributes to an active research agenda on electric vehicles, we close by emphasizing that much remains to be done. Our analysis does not account for feedback effects from EV purchases to charging station installation, so that our estimate can be seen as a lower bound of the impact of charging infrastructure on EV adoption. Future research may consider how such feedback loops are affected by the pre-existing stock of charging infrastructure.

Conclusion

This thesis empirically investigates consumer EV adoption behaviour, its drivers and barriers, and its context of the overall, greening transport sector. In particular, I demonstrate that car investments mostly do not influence travel mode choices beyond responses to marginal travel costs (Chapter I), and the relative importance of key barriers to EV adoption, as well as how to overcome them (Chapters II and III). The EV adoption analyses focus on car attributes, and consumer travel habits and socio-demographics in a broadening EV market scenario (Chapter II), and the role of complementary network infrastructure provision, especially at early market stages (Chapter III).

The main findings of this work provide important insights for climate policies relating to the transport sector. A variety of targeted policies promises the largest impacts on furthering the green transport transition more quickly and efficiently. In sum, policies to encourage the use of sustainable travel modes can effectively do so through the manipulation of relative marginal travel costs. Furthermore, while a rising EV market share reduces driving costs for those users, it does not generate a further sunk cost effect or significant commitment effect. Beyond early adopters, however, as EVs expand into the broader market they face low price elasticity of demand and a relative resistance to new technological adoption. This indicates that existing policies such as EV price subsidies will have a low effectiveness in furthering EV adoption at this stage. Early provision of public charging network infrastructure, moreover, is an effective policy with a significant and lasting impact on the local EV adoption path. Overall, low elasticities of demand and relatively consistent future car preferences indicate that a large and rapid green transport transition may require greater, non-marginal policies. This could include larger subsidies or significant, broader policy packages including multiple attributes of trips and vehicles. Alternatively, strict policies such as technology mandates or bans.

In the first chapter, I study travel mode choice rationality and the impact of prior travel mode investments. I test the existence of mode commitment devices, sunk cost effects and the relative effect of EV adoption. The stated preference analysis stems from a choice experiment with a novel sequential question set moving from long-term (car investment) to short-term (trip mode) decisions, with personalised alternatives and attribute levels. The results show that consumers overwhelmingly make travel decisions based on marginal costs and are little swayed beyond this by prior investments. There is no sunk cost effect, and no BEV effect beyond marginal trip costs. I also find no direct commitment device usage, however some evidence for an indirect commitment effect, reducing sensitivity to the trip duration of the primary mode alternative (PT/car). These findings suggest that policy makers should largely focus on relative marginal travel costs as a means to encourage sustainable transport choices, and that largely, in the growing green (EV) transport market, there is unlikely to be a significant step-change in travel behaviours, but rather reactions to varying travel costs.

Chapter II shows that the key barrier to EV adoption, purchase price, is highly inelastic across the broad population. The other potential EV attribute barriers to and drivers of adoption are, on the other hand, insignificant. Furthermore, there is some heterogeneity across consumers. Existing car owners are particularly resistant to changing to EV technology. These findings are somewhat in contrast to the revealed preference literature on previous adopters. As it is based on a choice experiment with a representative sample, it provides insight into EV market developments as it broadens and evolves past early adopters. Investigating consumer heterogeneity, adoption barrier elasticity point estimates vary considerably residential location, income and car ownership, however most are found to be insignificant. Nonetheless, price sensitivity is significantly greater in rural areas and cities than in agglomerations. Overall, however, existing car owners and regular car users exhibit persistent technology preferences and are both the least likely groups to adopt an EV. On the other hand, regular public or soft transport users and those with high environmental values are the most likely.

This suggests that public policies to foster EV adoption should move beyond marginal changes to attributes such as price in order to increase effectiveness. The low sensitivities to marginal variation in EV attributes and stability of car type preferences demonstrates a need for more substantial policies. Larger subsidies or a package targetting multiple aspects such as price, driving costs, charging availability, and potentially other ease-of-use factors could together have a larger impact on adoption. Although these are beyond the scope of Chapter II's analysis. However, ultimately a more effective approach (especially in a short target time frame) would be stricter policies such as technology mandates or sales bans.

The third chapter further expands on analysing the barriers and drivers of EV adoption.

It specifically provides nuance to the early literature on the impacts of public EV charging station networks on EV adoption and overcoming the chicken-and-egg stand-off between infrastructure providers and EV adopters. It shows that the largest effect from new charging station installations is at the early market stages when little such infrastructure exists. Particularly, the initial public charger installations have a significant and long-lasting impact on the local EV adoption path. This finding indicates that a particularly important way in which governments can encourage EV adoption is through the support for or provision of early charging network infrastructure development. Compared with ongoing EV price subsidies and similar policies, this has the benefit that it can be more easily time and expenditure restricted while providing ongoing adoption encouragement through continued network effects. Furthermore, responses to charger point installations are significantly smaller, indicating that the presence of a broader network of smaller charging stations is more effective in furthering EV adoption than a smaller number of large stations. These findings are based on a detailed dataset of revealed EV purchases and charger installations across Norway from early to relatively late market stages.

The results of this thesis lead to further avenues for future research. Chapter I uses a choice experimental approach to account for self selection and endogeneity of travel device investments and mode choices. However, random assignment of car or public transport pass prices, would be the ideal method for testing the impact of sunk costs on transport mode use. Therefore, a sunk cost effect could be further tested through a field or natural experiment. Such a field experiment could easily become cost-prohibitive, but on the other hand, a natural experiment, if found, could provide the beneficial random assignment of car prices to a random population sample. The question of sunk costs in a greening transport sector is not insignificant, given the relatively large upfront prices of EVs.

Furthermore, some of the specific policy proposals from Chapter II would benefit from greater investigation. The inelasticity of EV demand regarding EV attributes across a broader population indicates that the transition to an electrified transport sector in a timely manner could require technology mandates or ICE sales bans. The social welfare effects of such a policy, however, are unclear and have not been well researched. One article, Holland et al. (2021), creates a theoretical dynamic car market model with a representative EV and ICE, and shows ICE bans can be deadweight loss minimising under certain circumstances. Conversely, if there is low cross-price elasticity between ICEs and EVs this would be significant. Substitutability of EVs for ICEs is thus important, and depends both on further technological development and consumer travel behaviour.

This leads to further questions about impacts on the used car market of a ban on new ICE sales, or of the transition to EVs more generally. The used car market has particular distributional implications given lower-income households are more likely to buy used than new cars. Boosting new EV sales should cause older EVs to trickle down into the second-hand car market and allow for gradual increases in adoption there. However, low-income households in many places are subject to higher rates of local air pollution and could therefore benefit more greatly from a regional reduction in ICE use (Currie and Walker, 2011; Chay and Greenstone, 2003). They would also benefit more highly from reduced car operating costs. On the other hand, premature scrappage of existing ICEs could potentially increase overall GHG emissions, particularly as EVs have higher embedded manufacturing emissions. Furthermore, the higher upfront costs of EVs could plausibly lead to lower-income households holding onto existing, more polluting, ICEs for longer than they otherwise would before updating their car. Therefore, policies to optimally foster used EV adoption or adoption by low-income households require specific and differentiated research attention.

Moreover, given the car technology preference inertia among existing ICE owners shown in Chapter II, alternative policies warrant exploration to specifically encourage EV adoption among this most-resistant segment. Chapter II proposes a targeted information campaign to clarify EV benefits and ease-of-use, or facilitating and encouraging EV driving experiences through car loans, hires or shares that can further allow drivers to learn first-hand about the practicalities of using an EV without an upfront commitment. Jensen et al. (2013) demonstrate that EV driving experiences can shift preferences for EVs overall and for specific attributes. A broader and less-intensive policy encouraging the theoretical and practical learning about EV use to decrease the required learning-curve from such a technological shift post-purchase, however, remains unexplored and could potentially provide a cost-efficient method for nudging EV preferences.

Finally, Chapter III and the pre-existing literature on charging infrastructure focus on chargers at a relatively aggregate level. The results of this chapter, however, show variation in responsiveness to charging stations by residential level of urbanisation (city, agglomeration, rural). Chapter III finds that cities have a significantly greater charger elasticity of EV demand (about double) than suburbs and rural areas. The optimal infrastructure policies to allow and foster EV adoption in different urban zones thus requires further investigation. For example, it could be that specific types of chargers (speeds or access locations) or network density are more important in agglomerations and towns compared to cities. Fast chargers or home chargers could theoretically be especially relevant in rural areas with greater driving distances. Alternatively, ICE-EV substitutability could be the most significant issue in rural areas (for example, utility vehicles rather than hatchbacks, sedans or SUVs).

Ultimately, this thesis finds that marginal costs are important for consumers' travel mode choices, however this is not necessarily the case for car (and EV) purchasing decisions. Across the broad public there seems to be a lower sensitivity to car attributes such as price, driving range and driving cost for adoption of EVs. This could indicate an importance of external factors that haven't been accounted for, such as socio-cultural trends, general usability or complementary infrastructure. In fact, the final chapter shows that public charging networks do foster greater EV adoption. Though the chapters use data from different countries, they remain generalisable across contexts. For example, in Switzerland, where there remains a relatively small public charging network, this could be a target for governments to set the environment for greater EV uptake. The same applies to other countries and to the other lessons, including the ability of varying marginal travel costs to encourage shifts towards sustainable travel mode use.

Appendix

A Choice experiment questionnaire (Chapters I-II)

Figure A1: Priming script

In this part of the survey, we focus on **your transport choices** for different trip types. We will collect information on your current transport choices and ask you to choose amongst hypothetical future options.

The information that we collect will be used to **inform Swiss energy and transport policy**, and it is therefore important that **your answers reflect your specific situation and your personal tastes**. In particular, some of the following questions will involve costs to your own household; please give careful consideration to how these costs would affect your financial budget.

Figure A2: Choice 1 car size

For the next set of questions, please imagine that you decide to purchase a car or replace your car within the next year.

Which of the following options best describes your most preferred choice of primary car?

None	Micro	Small	Small-medium	Mid-size	Large	SUV
○	○	○	○	○	○	○

Figure A3: Choice 2 car type choice set (example)

Which of the following car options would you purchase?

Additional information is provided if you place the mouse over the column or row headers.

	1	2	3	4	5	6
	Electric	**Electric**	**Plug-in hybrid**	**Plug-in hybrid**	**Hybrid**	**ICE**
Price (CHF)	79,000	95,000	75,000	92,000	84,000	53,000
Driving cost (CHF/100km)	3.30	2.80	5.30	6.00	9.50	10.5
Range of battery (km)	400	450	30	35	-	-
Max speed (km/h)	230	180	250	250	250	250
CO_2 emissions (g/km)	0	0	50	45	165	150

	1 Electric	**2 Electric**	**3 Plug-in hybrid**	**4 Plug-in hybrid**	**5 Hybrid**	**6 ICE**
Your choice:	○	○	○	○	○	○

Figure A4: Choice 3 public transport pass (example)

You have stated that you have the following public transport pass: General abonnement 2nd class.

Given your purchase of the chosen car above, which of the following passes would you choose to buy?

GA 1st class CHF 6,300	GA 2nd class CHF 3,860	Regional Pass CHF 1,000	None CHF 0
○	○	○	○

Figure A5: Choice 4 transport mode choice set (example)

Among the following options, which transport method would you choose to **commute to your workplace**?

Additional information is provided if you place the mouse over the column or row headers.

	Public transport	Car sharing	Car with driver	Your car	Bike or foot
Trip cost (CHF)	0	5	11.25	0.38	0
Trip time (minutes)	20	29	10	21	60

	Public transport	Car sharing	Car with driver	Your car	Bike or foot
Your choice:	O	O	O	O	O

B Descriptive supplements (Chapter I)

Table B1: Descriptive statistics - respondent characteristics

	Frequency	Percent	SHEDS target (%)
Age group			
18-34	239	24.0	30
35-54	405	40.7	40
55+	350	35.2	30
Gender			
Female	483	48.6	51
Male	511	51.4	49
Housing			
Rent	605	60.9	63
Own	389	39.1	38
Location			
City	505	50.8	
Agglomeration	282	28.4	
Rural	207	20.8	
Linguistic region			
French-swiss	229	23.0	
German-swiss	765	77.0	
Household size			
1	277	27.9	
2	426	42.9	
3+	291	29.3	
Public transport passes			
General abonnement	236	23.8	
Regional pass	211	21.2	
None	547	55.0	
Car ownership			
Car owner	732	73.6	
No car	262	26.4	

Note: Percentages may not sum to 100 due to rounding. Includes the 994 respondents used for analysis.

Table B2: Descriptive statistics - choices

	Frequency	Percent
Car size		
None	112	11.3
Micro	20	2.0
Small	287	28.9
Small-medium	225	22.6
Mid-size	161	16.2
Large	39	3.9
SUV	150	15.1
Car engine		
Electric	303	34.4
Plug-in hybrid	149	16.9
Hybrid	133	15.1
ICE	297	33.7
Public transport pass		
General abonnement	225	22.6
Regional pass	243	24.5
None	526	52.9
Travel mode choice		
Public transport	2612	34.1
Car	3744	48.9
Soft transport	1301	17.0

Note: Percentages may not sum to 100 due to rounding.

C Comparison of non-respondent statistics (Chapter II)

Table C1: Summary statistics by respondent group – means and t-test for differences

	Group		
	Analysis	No car chosen	p-value
Income $>$ median	0.37	0.24	0.004
Residential location	1.73	1.43	0.000
Aged $\geq$ 55	0.34	0.46	0.015
Female	0.48	0.53	0.307
Dwell in house	0.32	0.17	0.000
Tenant	0.60	0.72	0.009
Environmental values important	0.62	0.80	0.000
Car owner	0.80	0.24	0.000
Always uses PT	0.09	0.24	0.000
Always uses ST	0.06	0.11	0.095
Always uses car	0.30	0.04	0.000

Note: The 'analysis' group includes the 882 respondents used for analysis in the article. The 'no car chosen' group is the 113 respondents who chose "no car" and are excluded from the analysis. p-values from t-test of the two groups' means.

Of the total 995 respondents taking part in the choice experiment, 882 chose to purchase a car in the experiment and continued through all car choice sets. The remaining 113 respondents chose the "no car" option at the first experiment question. This group was therefore not offered any car choice set and is excluded from this analysis.

Table C1 provides a brief comparison of the key variables analysed between the two groups, similar to the descriptive statistics of Table 1. The respondents who chose not to purchase any car differ in many ways from those who did. We particularly see that those opting out of car ownership have somewhat lower incomes on average, tend to be more urban (city-resident), slightly older on average, and more likely to live in a unit and be renting. They also have higher environmental values and differ in terms of transport habits. The opt-out group are significantly less likely to own and use a car in real life, and more likely to use public transport (PT).

These differences seem to indicate that this study's analysis is not necessarily conducted across the entire (representative) population, but maybe rather the potential car-buying population. One potential limitation could stem from the way that the 'no car' choice was offered and the way in which the original question was framed. The question setup gets respondents to "please imagine that you decide to purchase a car or replace your current car within the next year". This is followed by the choice of car size, and includes the option for "no car". Overall, this could potentially induce some respondents who would not normally have selected any car to do so. Nonetheless, 13 percent of respondents still opted out and the group comparisons indicate substantial differences that backup the realistic and consistent choices made, all giving us confidence in the analysis.

D Supplementary Tables and Figures (Chapter II)

Table D1: Supplementary estimation results – attribute interactions

	Price	Range	Driving cost
BEV	3.439** (1.649)	2.575** (1.154)	0.294 (2.783)
PHEV	2.210* (1.285)	2.279** (1.035)	-0.979 (2.194)
CH	1.773** (0.772)	1.434** (0.655)	1.104 (1.154)
ICE	*base*	*base*	*base*
Car price (10,000 CHF)	–	-0.601*** (0.123)	-0.581*** (0.154)
Driving cost (CHF/100km)	-1.237*** (0.326)	-1.439*** (0.248)	–
Driving cost^2	0.056*** (0.016)	0.052*** (0.012)	–
Max speed 160 - 200km/hr	-0.575* (0.295)	-0.267 (0.192)	-0.960** (0.390)
Max speed $\geq$ 200km/hr	-0.725** (0.342)	-0.386* (0.215)	-1.032** (0.433)
BEV $\times$ Range (100km)	-0.707 (0.449)	–	-1.429** (0.717)
sd(BEV $\times$ Range)	1.579*** (0.596)	–	2.833** (1.135)
Non-EV $\times$ CO_2 emissions (g/km)	0.024* (0.013)	0.040*** (0.010)	0.006 (0.020)
sd(Non-EV $\times$ CO_2 emissions)	0.024*** (0.009)	0.013** (0.006)	0.043** (0.019)
City $\times$ Car price (10,000 CHF)	-0.564*** (0.205)	–	–
Agglom. $\times$ Car price (10,000 CHF)	-0.114 (0.212)	–	–
Rural $\times$ Car price (10,000 CHF)	-0.844*** (0.246)	–	–
Income $\leq$ median $\times$ Car price (10,000 CHF)	-0.250 (0.186)	–	–
No car $\times$ Car price (10,000 CHF)	0.180 (0.248)	–	–
City $\times$ BEV $\times$ Range (100km)	–	0.277* (0.161)	–
Agglom. $\times$ BEV $\times$ Range (100km)	–	0.449** (0.180)	–
Rural $\times$ BEV $\times$ Range (100km)	–	0.115 (0.190)	–
Income $\leq$ median $\times$ BEV $\times$ Range (100km)	–	-0.146 (0.141)	–
No car $\times$ BEV $\times$ Range (100km)	–	-0.120 (0.163)	–
City $\times$ Driving cost (CHF/100km)	–	–	-1.229* (0.628)
City $\times$ Driving cost^2	–	–	0.111** (0.045)
Agglomeration $\times$ Driving cost (CHF/100km)	–	–	-0.873 (0.844)
Agglomeration $\times$ Driving cost^2	–	–	0.042 (0.045)
Rural $\times$ Driving cost (CHF/100km)	–	–	-0.928 (0.723)
Rural $\times$ Driving cost^2	–	–	0.072* (0.043)

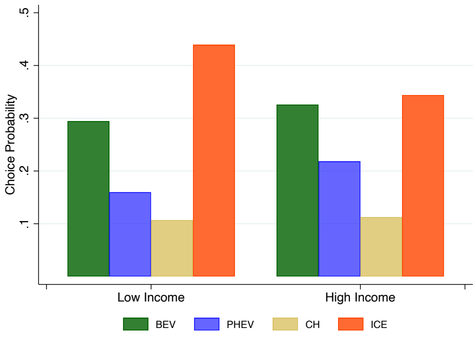
Continued on next page

Table D1 – *Continued from previous page*

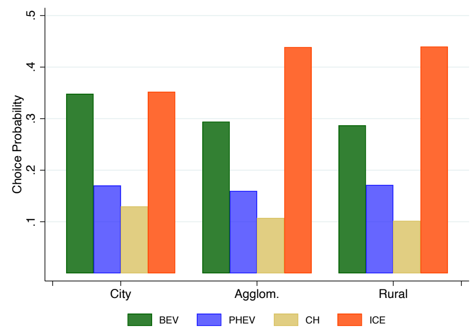
	Price	Range	Driving cost
Income $\leq$ median $\times$ Driving cost (CHF/100km)	–	–	0.942
			(0.620)
Income $\leq$ median $\times$ Driving cost^2	–	–	-0.072
			(0.044)
No car $\times$ Driving cost (CHF/100km)	–	–	-2.032**
			(0.955)
No car $\times$ Driving cost^2	–	–	0.060
			(0.063)
Characteristics	Yes	Yes	Yes
N respondents	882	882	882
N observations	5,292	5,292	5,292
Log simulated-likelihood	-1350.98	-1359.81	-1348.09

Note: *, ** and *** respectively denote significance at 10%, 5% and 1% levels. BEV: Battery Electric Vehicle. PHEV: Plug-in Hybrid Electric Vehicle. CH: Conventional Hybrid. ICE: Internal Combustion Engine Vehicle. EV: Electric Vehicle.

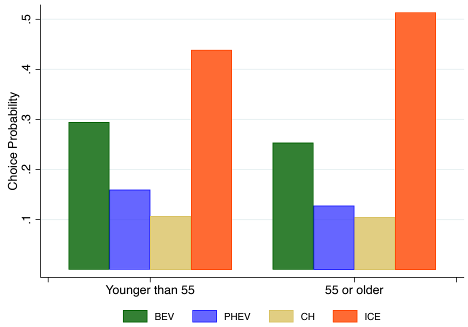
Figure D1: Probabilities of car-type choice by respondent characteristics



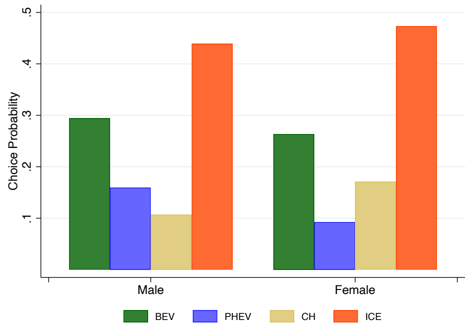
(a) Income group (≤ or > median)



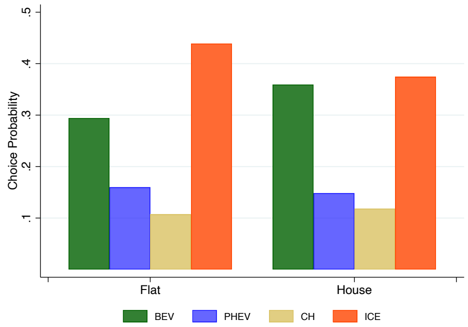
(b) Residential location



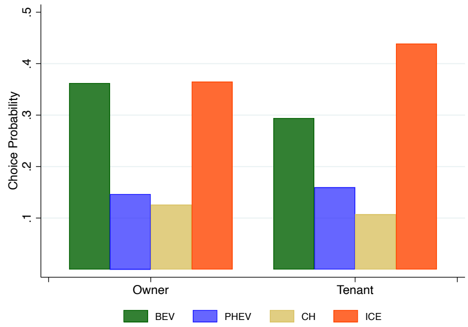
(c) Age group



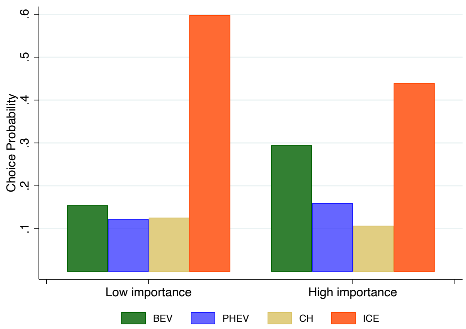
(d) Gender



(e) Dwelling type



(f) Dwelling tenancy



(g) Environmental values

Notes: Calculated from model (2).

E Municipalities used for synthetic control estimation (Chapter III)

Table E1: Group of one-station municipalities

Municipality code	Municipality name	County	Treatment quarter
135	Råde	Østfold	Q4 2016
227	Fet	Akershus	Q4 2013
239	Hurdal	Akershus	Q4 2015
418	Nord-Odal	Hedmark	Q4 2012
423	Grue	Hedmark	Q4 2014
425	Åsnes	Hedmark	Q4 2013
436	Tolga	Hedmark	Q1 2013
514	Lom	Oppland	Q3 2015
522	Gausdal	Oppland	Q4 2015
536	Søndre Land	Oppland	Q4 2013
619	Ål	Buskerud	Q1 2013
633	Nore og Uvdal	Buskerud	Q3 2012
814	Bamble	Telemark	Q4 2014
817	Drangedal	Telemark	Q4 2015
831	Fyresdal	Telemark	Q1 2017
833	Tokke	Telemark	Q2 2014
937	Evje og Hornnes	Aust-Agder	Q3 2015
1021	Marnardal	Vest-Agder	Q1 2014
1037	Kvinesdal	Vest-Agder	Q3 2013
1114	Bjerkreim	Rogaland	Q4 2016
1121	Time	Rogaland	Q4 2013
1127	Randaberg	Rogaland	Q3 2011
1135	Sauda	Rogaland	Q1 2016
1141	Finnøy	Rogaland	Q3 2015
1142	Rennesøy	Rogaland	Q4 2016
1222	Fitjar	Hordaland	Q4 2013
1231	Ullensvang	Hordaland	Q2 2016
1252	Modalen	Hordaland	Q1 2016
1264	Austrheim	Hordaland	Q2 2013
1417	Vik	Sogn og Fjordane	Q4 2016
1426	Luster	Sogn og Fjordane	Q3 2014
1516	Ulstein	Møre og Romsdal	Q2 2015
1535	Vestnes	Møre og Romsdal	Q4 2016
1551	Eide	Møre og Romsdal	Q2 2014
1822	Leirfjord	Nordland	Q3 2016
1828	Nesna	Nordland	Q4 2016
1850	Tysfjord	Nordland	Q4 2016
øy	Nordland	Q3 2016	
1871	Andøy	Nordland	Q1 2015
1913	Skånland	Troms	Q4 2016
2017	Kvalsund	Finnmark	Q3 2015
2019	Nordkapp	Finnmark	Q2 2014
5014	Frøya	Trøndelag	Q2 2015
5015	Ørland	Trøndelag	Q3 2012
5022	Rennebu	Trøndelag	Q1 2015
5025	Røros	Trøndelag	Q1 2015
5026	Holtålen	Trøndelag	Q1 2013

Notes: This table lists all municipalities included in the one-station municipality group. These have initially no charging infrastructure, until they installed a single charging station during the treatment quarter. After that, no more is installed.

Table E2: Group of multi-station municipalities

Municipality code	Municipality name	County	Treatment quarter
429	Åmot	Hedmark	Q1 2016
432	Rendalen	Hedmark	Q4 2016
515	Vågå	Oppland	Q1 2017
540	Sør-Aurdal	Oppland	Q4 2016
716	Re	Vestfold	Q2 2015
830	Nissedal	Telemark	Q1 2017
938	Bygland	Aust-Agder	Q2 2015
1211	Etne	Hordaland	Q4 2013
1228	Odda	Hordaland	Q3 2014
1422	Lærdal	Sogn og Fjordane	Q3 2016
1515	Herøy	Møre og Romsdal	Q3 2016
1524	Norddal	Møre og Romsdal	Q2 2014
1865	Vågan	Nordland	Q3 2014
1920	Lavangen	Troms	Q1 2017
1924	Målselv	Troms	Q1 2017
1931	Lenvik	Troms	Q1 2015
5011	Hemne	Trøndelag	Q4 2016

Notes: This table lists all municipalities included in the group of multi-station municipalities. These have initially no charging infrastructure, until they installed two or more charging station over a period of four consecutive quarters. In the table, treatment quarter refers to the first of the up to four consecutive quarters where charging stations are installed.

Table E3: Municipalities included in the donor pool

Municipality code	Municipality name	County
121	Rømskog	Østfold
234	Gjerdrum	Akershus
434	Engerdal	Hedmark
441	Os	Hedmark
541	Etnedal	Oppland
621	Sigdal	Buskerud
628	Hurum	Buskerud
632	Rollag	Buskerud
711	Svelvik	Vestfold
811	Siljan	Telemark
822	Sauherad	Telemark
827	Hjartdal	Telemark
912	Vegårshei	Aust-Agder
919	Froland	Aust-Agder
928	Birkenes	Aust-Agder
935	Iveland	Aust-Agder
1027	Audnedal	Vest-Agder
1029	Lindesnes	Vest-Agder
1034	Hægebostad	Vest-Agder
1111	Sokndal	Rogaland
1119	Hå	Rogaland
1129	Forsand	Rogaland
1130	Strand	Rogaland
1133	Hjelmeland	Rogaland
1144	Kvitsøy	Rogaland
1145	Bokn	Rogaland
1151	Utsira	Rogaland
1234	Granvin	Hordaland
1265	Fedje	Hordaland
1418	Balestrand	Sogn og Fjordane
1424	Årdal	Sogn og Fjordane
1428	Askvoll	Sogn og Fjordane
1438	Bremanger	Sogn og Fjordane
1441	Selje	Sogn og Fjordane
1511	Vanylven	Møre og Romsdal
1514	Sande	Møre og Romsdal
1526	Stordal	Møre og Romsdal
1529	Skodje	Møre og Romsdal
1531	Sula	Møre og Romsdal
1534	Haram	Møre og Romsdal
1543	Nesset	Møre og Romsdal
1545	Midsund	Møre og Romsdal
1546	Sandøy	Møre og Romsdal
1547	Aukra	Møre og Romsdal
1548	Fræna	Møre og Romsdal
1567	Rindal	Møre og Romsdal
1576	Aure	Møre og Romsdal
1811	Bindal	Nordland
1812	Sømna	Nordland
1815	Vega	Nordland
1816	Vevelstad	Nordland
1818	Herøy	Nordland

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Table E3 – *Continued from previous page*

Municipality code	Municipality name	County
1827	Dønna	Nordland
1834	Lurøy	Nordland
1835	Træna	Nordland
1836	Rødøy	Nordland
1837	Meløy	Nordland
1838	Gildeskål	Nordland
1839	Beiarn	Nordland
1848	Steigen	Nordland
1851	Lødingen	Nordland
1852	Tjeldsund	Nordland
1856	Røst	Nordland
1857	Værøy	Nordland
1859	Flakstad	Nordland
1866	Hadsel	Nordland
1867	Bø	Nordland
1868	Øksnes	Nordland
1874	Moskenes	Nordland
1911	Kvæfjord	Troms
1917	Ibestad	Troms
1919	Gratangen	Troms
1923	Salangen	Troms
1925	Sørreisa	Troms
1926	Dyrøy	Troms
1927	Tranøy	Troms
1928	Torsken	Troms
1929	Berg	Troms
1936	Karlsøy	Troms
1938	Lyngen	Troms
1940	Gáivuotna Kåfjord	Troms
1941	Skjervøy	Troms
1943	Kvænangen	Troms
2002	Vardø	Finnmark
2003	Vadsø	Finnmark
2011	Guovdageaidnu Kautokeino	Finnmark
2014	Loppa	Finnmark
2015	Hasvik	Finnmark
2021	Karasjohka Karasjok	Finnmark
2022	Lebesby	Finnmark
2023	Gamvik	Finnmark
2024	Berlevåg	Finnmark
2025	Deatnu Tana	Finnmark
2027	Unjargga Nesseby	Finnmark
2028	Båtsfjord	Finnmark
5012	Snillfjord	Trøndelag
5013	Hitra	Trøndelag
5019	Roan	Trøndelag
5020	Osen	Trøndelag
5029	Skaun	Trøndelag
5032	Selbu	Trøndelag
5038	Verdal	Trøndelag
5039	Verran	Trøndelag
5040	Namdalseid	Trøndelag
5043	Røyrvik	Trøndelag

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Table E3 – *Continued from previous page*

Municipality code	Municipality name	County
5046	Høylandet	Trøndelag
5048	Fosnes	Trøndelag
5049	Flatanger	Trøndelag
5050	Vikna	Trøndelag
5052	Leka	Trøndelag

Notes: This table lists all municipalities included in the donor pool. These have no charging infrastructure over the entire observation period.

F Control function estimation supplements (Chapter III)

Table F1: First-stage results for charging stations and charging points

	Charging stations (1)	Charging points (2)
IV	0.058***	0.111***
	(0.013)	(0.022)
ln(car price)	-3.01E-12	-9.54E-13
	(9.06E-12)	(1.58E-11)
ln(income)	0.196	0.189
	(0.388)	(0.643)
ln(income) x Time	-0.004	0.001
	(0.016)	(0.027)
ln(hybrids) x Time	0.003**	-0.0003
	(0.001)	(0.002)
Constant	-2.206	-5.958
	(4.575)	(8.603)
N	366,296	366,296
Adjusted within-R^2	0.393	0.355

Notes: This table reports first stage regression results for 2SLS and CF procedures. In column (1), the dependent variable is *ln(charging stations)*$_{mit}$. In column (2), the dependent variable is *ln(charging points)*$_{mit}$. See equation (2) for the definition of the instrumental variable (IV). All specifications include quarter and municipality-model fixed effects. Standard errors clustered at the municipality level reported in parentheses. *, ** and *** respectively denote significance at 10%, 5% and 1% levels.

Table F2: Polynomial forms of robustness checks – charging stations

	No price (1)	2015 parking (2)	No neighbours (3)	Chargers x BEV (4)	Additional controls (5)	Chargers x time (6)	Chargers x urban (7)
ln(charging stations)	0.131***	0.155***	0.146***	0.133**	0.130***	–	–
	(0.045)	(0.041)	(0.050)	(0.053)	(0.050)		
ln(charging stations)^2	-0.036	-0.037	-0.036	-0.050	-0.036	–	–
	(0.032)	(0.032)	(0.032)	(0.038)	(0.031)		
ln(charging stations)^3	0.018**	0.019**	0.018**	0.023**	0.018**	–	–
	(0.009)	(0.009)	(0.009)	(0.011)	(0.009)		
ln(charging stations) x BEV	–	–	–	-0.004	–	–	–
				(0.026)			
ln(charging stations)^2 x BEV	–	–	–	0.031	–	–	–
				(0.029)			
ln(charging stations)^3 x BEV	–	–	–	-0.010	–	–	–
				(0.007)			
ln(charging stations) x early	–	–	–	–	–	0.194***	–
						(0.049)	
ln(charging stations)^2 x early	–	–	–	–	–	-0.055**	–
						(0.025)	
ln(charging stations)^3 x early)	–	–	–	–	–	0.023***	–
						(0.008)	
ln(charging stations) x late	–	–	–	–	–	0.144***	–
						(0.054)	
ln(charging stations)^2 x late	–	–	–	–	–	-0.034	–
						(0.032)	
ln(charging stations)^3 x late	–	–	–	–	–	0.019**	–
						(0.009)	
ln(charging stations) x urban	–	–	–	–	–	–	0.019
							(0.366)
ln(charging stations)^2 x urban	–	–	–	–	–	–	-0.008
							(0.165)
ln(charging stations)^3 x urban	–	–	–	–	–	–	0.015
							(0.028)
ln(charging stations) x town	–	–	–	–	–	–	0.182***
							(0.063)
ln(charging stations)^2 x town	–	–	–	–	–	–	-0.091*
							(0.050)
ln(charging stations)^3 x town	–	–	–	–	–	–	0.034**
							(0.013)
ln(charging stations) x rural	–	–	–	–	–	–	0.168***
							(0.039)
ln(charging stations)^2 x rural	–	–	–	–	–	–	-0.074***
							(0.025)
ln(charging stations)^3 x rural	–	–	–	–	–	–	0.027***
							(0.008)
ln(car price)	–	0.110***	0.110***	0.109***	0.110***	0.110***	0.110***
		(0.008)	(0.009)	(0.009)	(0.009)	(0.008)	(0.009)
ln(income)	-0.130	-0.136*	-0.134	-0.130	-0.122	-0.136*	-0.163**
	(0.077)	(0.092)	(0.078)	(0.084)	(0.073)	(0.075)	(0.082)
ln(income) x Time	0.003	0.003	0.003	0.003	0.002	0.003	0.004
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
ln(hybrids) x Time	0.006***	0.006***	0.006***	0.006***	0.006***	0.006***	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ln(population)	–	–	–	–	-0.082	–	–
					(0.096)		
Proportion of detached and duplex dwellings	–	–	–	–	0.001	–	–
					(0.002)		
First stage residual	-0.136***	-0.158***	-0.150***	-0.135***	-0.134***	-0.160***	-0.138***
	(0.033)	(0.037)	(0.038)	(0.035)	(0.041)	(0.047)	(0.037)
Constant	0.360	-1.081	-1.075	-1.044	-1.775	-1.238	-1.243
	(1.052)	(1.067)	(0.902)	(0.965)	(1.184)	(1.150)	(1.161)
N	366,296	366,296	366,296	366,296	366,296	366,296	366,296
Adjusted within-R^2	0.0806	0.0817	0.0817	0.0820	0.0817	0.0821	0.0820
1st-stage partial F-stat.	18.32	11.29	16.80	19.01	19.51	19.01	19.01

Notes: In all columns, the dependent variable is the log of new electric vehicle registrations ($ln(EV)_{mit}$). Column (1) omits the car price variable. Column (2) uses the number of parking spaces in 2015 to construct the instrument. Column (3) excludes neighboring municipalities to construct the instrument. In column (4), we interact the treatment variable with a dummy for battery-only EVs. Column (5) includes further control variables. In column (6), we estimate separate elasticities for observations in 2010-2013 and 2014-2017. [id=J]Column (7) estimates separate elasticities by municipal degree of urbanisation – urban/city, town/suburban, rural. All specifications are estimated with a control function approach and include quarter and municipality-model fixed effects. The 1st stage partial F-statistic for the instrumental variable is derived from first-stage regression results. Standard errors bootstrapped with 500 replications and clustered at the municipality level reported in parentheses. *, ** and *** respectively denote significance at 10%, 5% and 1% levels.

Table F3: Polynomial forms of robustness checks – charging points

	No price (1)	2015 parking (2)	No neighbours (3)	Chargers x BEV (4)	Additional controls (5)	Chargers x time (6)	Chargers x urban (7)
ln(charging points)	0.132***	0.153***	0.136***	0.152***	0.131***	–	–
	(0.020)	(0.023)	(0.021)	(0.017)	(0.020)		
ln(charging points)^2	-0.055***	-0.056***	-0.055***	-0.073***	-0.055***	–	–
	(0.008)	(0.009)	(0.009)	(0.009)	(0.008)		
ln(charging points)^3	0.012***	0.012***	0.012***	0.015***	0.012***	–	–
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)		
ln(charging points) x BEV	–	–	–	-0.048***	–	–	–
				(0.016)			
ln(charging points)^2 x BEV	–	–	–	0.041***	–	–	–
				(0.011)			
ln(charging points)^3 x BEV	–	–	–	-0.007***	–	–	–
				(0.002)			
ln(charging points) x early	–	–	–	–	–	0.147***	–
						(0.026)	
ln(charging points)^2 x early	–	–	–	–	–	-0.053***	–
						(0.018)	
ln(charging points)^3 x early	–	–	–	–	–	0.012***	–
						(0.003)	
ln(charging points) x late	–	–	–	–	–	0.134***	–
						(0.019)	
ln(charging points)^2 x late	–	–	–	–	–	-0.054***	–
						(0.011)	
ln(charging points)^3 x late	–	–	–	–	–	0.012***	–
						(0.002)	
ln(charging points) x urban	–	–	–	–	–	–	0.080
							(1.045)
ln(charging points)^2 x urban	–	–	–	–	–	–	-0.041
							(0.243)
ln(charging points)^3 x urban	–	–	–	–	–	–	0.011
							(0.019)
ln(charging points) x town	–	–	–	–	–	–	0.149***
							(0.031)
ln(charging points)^2 x town	–	–	–	–	–	–	-0.068***
							(0.018)
ln(charging points)^3 x town	–	–	–	–	–	–	0.015***
							(0.003)
ln(charging points) x rural	–	–	–	–	–	–	0.102***
							(0.021)
ln(charging points)^2 x rural	–	–	–	–	–	–	-0.028**
							(0.013)
ln(charging points)^3 x rural	–	–	–	–	–	–	0.006**
							(0.003)
ln(car price)	–	0.110***	0.110***	0.109***	0.110***	0.110***	0.110***
		(0.008)	(0.008)	(0.006)	(0.008)	(0.010)	(0.007)
ln(income)	-0.108	-0.113	-0.109	-0.107	-0.105	-0.112	-0.119
	(0.070)	(0.066)	(0.069)	(0.099)	(0.067)	(0.082)	(0.083)
ln(income) x Time	0.002	0.002	0.002	0.002	0.002	0.003	0.003
	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
ln(hybrids) x Time	0.006***	0.006***	0.006***	0.006***	0.006***	0.006***	0.006***
	(0.0005)	(0.001)	(0.0004)	(0.0004)	(0.001)	(0.0004)	(0.001)
ln(population)	–	–	–	–	0.057	–	–
					(0.098)		
Proportion of detached and duplex dwellings	–	–	–	–	0.001	–	–
					(0.002)		
First stage residual	-0.079***	-0.099***	-0.083***	-0.079***	-0.079***	-0.088***	-0.078***
	(0.018)	(0.023)	(0.018)	(0.017)	(0.015)	(0.017)	(0.016)
Constant	0.303	-1.142	-1.123	-1.112	-1.651	-1.347	-1.108
	(1.017)	(0.811)	(1.145)	(0.946)	(1.411)	(1.014)	(1.072)
N	366, 296	366, 296	366, 296	366, 296	366, 296	366, 296	366, 296
Adjusted within-R^2	0.0815	0.0826	0.0826	0.0830	0.0826	0.0828	0.0830
1st-stage partial F-stat.	24.57	14.17	23.73	25.54	23.04	25.54	25.54

Notes: In all columns, the dependent variable is the log of new electric vehicle registrations ($ln(EV)_{mit}$). Column (1) omits the car price variable. Column (2) uses the number of parking spaces in 2015 to construct the instrument. Column (3) excludes neighboring municipalities to construct the instrument. In column (4), we interact the treatment variable with a dummy for battery-only EVs. Column (5) includes further control variables. In column (6), we estimate separate elasticities for observations in 2010-2013 and 2014-2017. [id=J]Column (7) estimates separate elasticities by municipal degree of urbanisation – urban/city, town/suburban, rural. All specifications are estimated with a control function approach and include quarter and municipality-model fixed effects. The 1st stage partial F-statistic for the instrumental variable is derived from first-stage regression results. Standard errors bootstrapped with 500 replications and clustered at the municipality level reported in parentheses. *, ** and *** respectively denote significance at 10%, 5% and 1% levels.

Table F4: First-stage results for robustness checks – charging stations

	No price (1)	2015 parking (2)	No neighbours (3)	Chargers x BEV (4)	Additional controls (5)	Chargers x time (6)	Chargers x urban (7)
IV	0.058^{***}	–	–	0.058^{***}	0.057^{***}	0.058^{***}	0.058^{***}
	(0.014)			(0.013)	(0.013)	(0.013)	(0.013)
IV-parking 2015	–	0.049^{***}	–	–	–	–	–
		(0.015)					
IV-no neighbors	–	–	0.055^{***}	–	–	–	–
			(0.014)				
ln(car price)	–	-2.05E-12	-3.17E-12	-3.01E-12	-5.64E-12	-3.01E-12	-3.01E-12
		(8.76E-12)	(8.75E-12)	(9.06E-12)	(9.09E-12)	(9.06E-12)	(9.06E-12)
ln(income)	0.196	0.170	0.205	0.196	0.307	0.196	0.196
	(0.374)	(0.396)	(0.373)	(0.388)	(0.402)	(0.388)	(0.388)
ln(income) x Time	-0.004	-0.002	-0.004	-0.004	-0.008	-0.004	-0.004
	(0.016)	(0.015)	(0.015)	(0.016)	(0.016)	(0.016)	(0.016)
ln(hybrids) x Time	0.003^{**}	0.003^{**}	0.003^{**}	0.003^{**}	0.003^{**}	0.003^{**}	0.003^{**}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ln(population)	–	–	–	–	0.446^{***}	–	–
					(0.586)		
Proportion of detached and duplex dwellings	–	–	–	–	-0.003	–	–
					(0.009)		
Constant	-2.206	-2.231	-2.076	-2.206	-5.280	-2.206	-2.206
	(4.270)	(4.398)	(4.263)	(4.575)	(6.324)	(4.575)	(4.575)
N	366, 296	366, 296	366, 296	366, 296	366, 296	366, 296	366, 296
Adjusted within-R^2	0.393	0.390	0.392	0.393	0.394	0.393	0.393

Notes: This table reports first stage regression results for robustness checks. In all columns, the dependent variable is *ln(charging stations)*$_{mit}$. See equation (2) for the definition of the instrumental variable (IV). All specifications include quarter and municipality-model fixed effects. Standard errors clustered at the municipality level reported in parentheses. *, ** and *** respectively denote significance at 10%, 5% and 1% levels.

Table F5: First-stage results for robustness checks – charging points

	No price (1)	2015 parking (2)	No neighbours (3)	Chargers x BEV (4)	Additional controls (5)	Chargers x time (6)	Chargers x urban (7)
IV	0.111^{***}	–	–	0.110^{***}	0.108^{***}	0.110^{***}	0.110^{***}
	(0.022)			(0.022)	(0.023)	(0.022)	(0.022)
IV-parking 2015	–	0.089^{***}	–	–	–	–	–
		(0.024)					
IV-no neighbours	–	–	0.109^{***}	–	–	–	–
			(0.020)				
ln(car price)	–	5.70E-13	-1.53E-12	1.18E-12	-6.45E-12	1.18E-12	1.18E-12
		(1.67E-11)	(1.60E-11)	(1.03E-11)	(1.73e-11)	(1.03E-11)	(1.03E-11)
ln(income)	0.189	0.135	0.208	0.134	0.425	0.134	0.134
	(0.688)	(0.729)	(0.671)	(0.646)	(0.775)	(0.646)	(0.646)
ln(income) x Time	0.001	0.004	0.0004	0.006	-0.008	0.006	0.006
	(0.029)	(0.029)	(0.028)	(0.028)	(0.030)	(0.028)	(0.028)
ln(hybrids) x Time	-0.0003	0.0004	-0.0003	-0.001	-0.001	-0.001	-0.001
	(0.002)	(0.002)	(0.028)	(0.002)	(0.002)	(0.002)	(0.002)
ln(population)	–	–	–	–	0.882^{*}	–	–
					(0.1.074)		
Proportion of detached and duplex dwellings	–	–	–	–	-0.008	–	–
					(0.030)		
Constant	-5.958	-5.494	-5.731	-5.438	-11.824	-5.438	-5.438
	(8.391)	(9.238)	(8.567)	(7.620)	(12.546)	(7.620)	(7.620)
N	366, 296	366, 296	366, 296	366, 296	366, 296	366, 296	366, 296
Adjusted within-R^2	0.355	0.349	0.354	0.355	0.355	0.355	0.355

Notes: This table reports first stage regression results for robustness checks. In all columns, the dependent variable is *ln(charging points)*$_{mit}$. See equation (2) for the definition of the instrumental variable (IV). All specifications include quarter and municipality-model fixed effects. Standard errors clustered at the municipality level reported in parentheses. *, ** and *** respectively denote significance at 10%, 5% and 1% levels.

G Synthetic control method supplements (Chapter III)

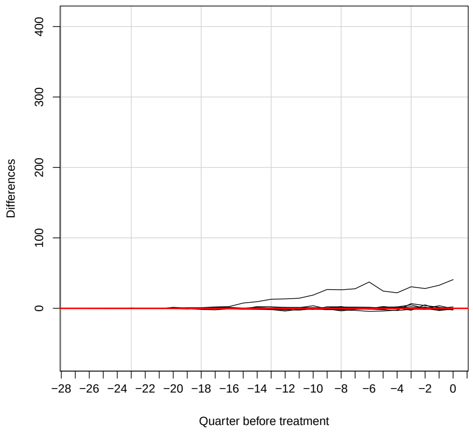
As outlined in section 2.3, the ridge-augmented SCM from Ben-Michael et al. (2021) offers an improvement in SCM case study analysis by allowing for a more precise matching and hence lower MSPE. In Figure G1, we compare a traditional SCM matching algorithm (Abadie and Gardeazabal, 2003; Abadie et al., 2010) to the ridge-augmented SCM results presented in the main text.

Results suggest that the pre-treatment residuals (panels G1a and G1b) are significantly larger and display more variability as compared to our main results. This lower fit of the synthetic municipalities confirms that the ridge-augmented SCM approach provides a more accurate estimate of the counterfactual, and in turn the treatment effects.

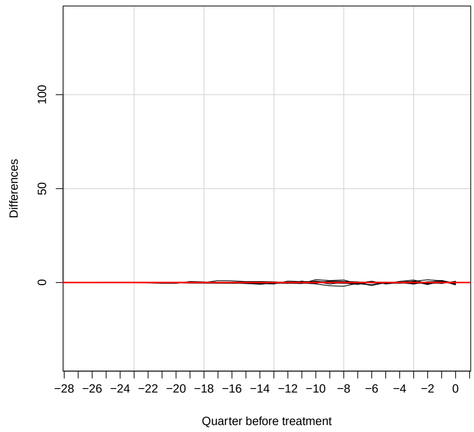
Nevertheless, Figure G1 panels G1c and G1d show that the estimated post-treatment differences are qualitatively similar using both approach. As expected, larger MPSE implies additional variability in early post-treatment quarters. However, overall, the average treatment effect is very similar with both approaches. This is also illustrated in Table G1, which provides the mean and median treatment effect for each quarter associated with a traditional SCM.

Figure G1: Results from the traditional synthetic control method

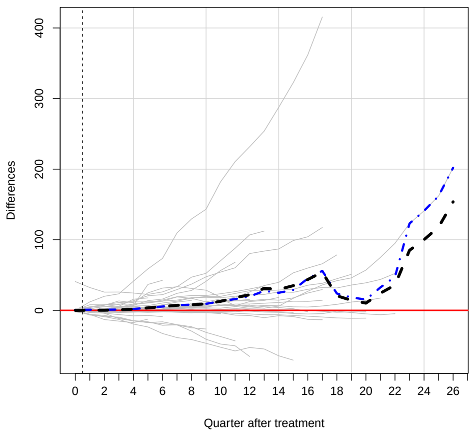
(a) One-station municipalities: matching periods



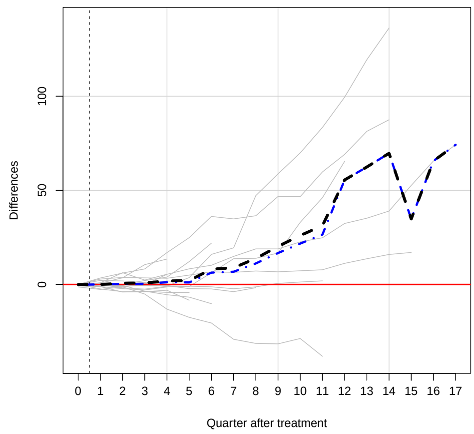
(b) Multi-station municipalities: matching periods



(c) One-station municipalities: treatment effect



(d) Multi-station municipalities: treatment effect



Notes: The solid gray lines represent the SCM estimated differences between each treated municipality and its synthetic counterpart. The dashed-dotted lines present the mean differences across treated units. The dashed lines provide the mean difference estimated from the ridge-augmented SCM approach reported in Figure 4.

Table G1: Summary results for the traditional synthetic control method

Quarter post-treatment	One-station municipalities			Multi-station municipalities		
	Obs.	Mean	Median	Obs.	Mean	Median
1	47	0.87	-0.06	17	0.04	-0.08
2	47	0.84	0.04	17	0.28	-0.27
3	47	1.14	0.50	17	0.35	-0.10
4	47	1.89	0.52	17	1.19	-0.58
5	46	3.68	0.86	13	1.08	-0.93
6	38	5.42	2.64	10	6.28	6.44
7	36	7.19	4.16	8	6.76	10.05
8	35	8.14	4.02	8	11.17	10.52
9	33	9.24	5.64	7	16.68	16.70
10	30	12.79	7.07	7	21.71	22.60
11	26	15.96	6.61	7	26.52	24.80
12	24	19.67	7.40	5	55.52	65.40
13	20	27.57	8.55	4	62.39	58.27
14	18	24.88	6.26	4	69.67	63.25
15	17	28.89	4.98	2	34.80	34.80
16	14	45.15	18.62	1	65.60	65.60
17	13	55.89	29.49	1	74.20	74.20
18	8	23.84	20.11			
19	7	18.28	11.76			
20	6	15.28	5.88			
21	4	32.51	30.62			
22	3	47.48	52.23			
23	1	123.00	123.00			
24	1	141.00	141.00			
25	1	162.00	162.00			
26	1	202.00	202.00			

Notes: This table summarizes results for the post-treatment gap in cumulative EV stock between treated municipalities and synthetic controls. Mean and median reported refer to the distribution of treatment effects estimated from the traditional SCM.

Table G2: Summary results for the temporal placebo tests

Quarter post-treatment	One-station municipalities			Multi-station municipalities		
	Obs.	Mean	Median	Obs.	Mean	Median
1	46	0.61	-0.06	16	0.47	0.10
2	46	0.69	-0.04	16	0.17	-0.18
3	46	0.54	-0.10	16	0.99	1.03
4	46	0.78	-0.13	16	1.08	1.31
5	46	0.83	0.18	16	1.31	1.67
6	46	0.68	0.52	16	2.03	1.81
7	46	1.50	0.48	16	2.85	1.93
8	46	2.22	0.48	16	4.69	2.59
9	45	4.09	0.89	12	4.59	2.65
10	37	8.69	2.34	9	11.94	8.86
11	35	11.18	7.57	7	14.19	16.22
12	34	12.83	6.55	7	19.18	16.10
13	32	15.40	9.18	6	24.80	19.32
14	29	18.88	4.50	6	29.81	28.98
15	25	20.64	13.05	6	36.77	36.16
16	23	28.24	21.22	5	54.30	63.63
17	19	31.63	21.89	4	60.49	59.13
18	17	29.05	4.67	4	66.55	63.09
19	16	32.85	4.63	2	30.39	30.39
20	13	45.06	10.50	1	65.80	65.80
21	12	53.21	8.97	1	74.45	74.45
22	7	20.05	5.67			
23	6	8.88	2.18			
24	5	2.36	-6.30			
25	3	16.17	13.58			
26	2	22.11	22.11			

Notes: This table summarizes results for the post-treatment gap in cumulative EV stock for non-treated municipalities subject to placebo treatments 4-quarter before treatment, and synthetic controls. We report mean and median placebo treatment effects.

Table G3: City-proximate donor pool municipalities

Municipality code	Municipality name	County
234	Gjerdrum	Akershus
711	Svelvik	Vestfold
1119	Hå	Rogaland
1129	Forsand	Rogaland
1130	Strand	Rogaland
5029	Skaun	Trøndelag

Notes: This table lists all municipalities included in the donor pool that have been calculated to have a one hour or less driving time from their population-weighted geographical centre to that of a city or urban municipality.

Table G4: Summary of post-treatment synthetic control results under "leave-one-out" test

Quarter post-treatment	One-station municipalities			Multi-station municipalities		
	Obs.	Mean	Median	Obs.	Mean	Median
1	47	-0.34	-0.15	17	0.00	-0.01
2	47	-0.30	-0.09	17	0.36	-0.05
3	47	0.10	0.36	17	0.50	-0.10
4	47	0.88	0.52	17	1.49	-0.14
5	46	2.57	0.71	13	1.62	-0.17
6	38	3.61	1.56	10	7.20	6.08
7	36	5.27	4.22	8	8.00	9.38
8	35	5.74	3.61	8	12.88	9.63
9	33	7.29	5.64	7	18.55	14.28
10	30	10.26	4.94	7	24.03	22.60
11	26	14.92	6.63	7	29.58	24.80
12	24	19.15	10.71	5	54.68	60.80
13	20	27.76	14.90	4	62.61	60.89
14	18	25.17	12.83	4	69.51	66.17
15	17	29.08	12.91	2	34.80	34.80
16	14	39.69	18.75	1	65.60	65.60
17	13	48.35	29.78	1	74.20	74.20
18	8	39.62	20.11			
19	7	38.67	11.76			
20	6	39.94	5.88			
21	4	71.59	30.62			
22	3	103.16	52.23			
23	1	298.83	298.83			
24	1	316.45	316.45			
25	1	356.75	356.75			
26	1	414.40	414.40			

Notes: This table summarizes results for the post-treatment gap in cumulative EV stock between treated municipalities and synthetic controls under the "leave-one-out" test. Mean and median reported refer to the distribution of treatment effects estimated from the ridge-augmented SCM.

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