Welfare, Redistributive and Revenue Effects of Policies Promoting Fuel Efficient and Electric Vehicles*

Patrick Bigler†
Doina Radulescu‡

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Abstract

Worldwide, the road transport sector accounts for a large share of CO_2 emissions. However, despite generous government programs to subsidise electric and hybrid cars, their uptake continues to be very low. In this paper we employ a rich dataset including information on around 23,000 newly purchased cars in the Swiss Canton of Bern, as well as a large number of household socio-demographic characteristics and information on car attributes to analyse household choice behaviour towards hybrid and electric vehicles (EVs) as well as the welfare implications of policies to promote them. We scrutinize the effects of an EV subsidy, an increase in fossil fuel taxes or the introduction of a mileage dependent levy. The control function discrete choice model reveals a more pronounced reaction with respect to car prices than future driving costs. The mileage dependent charge generates public revenues to secure infrastructure finances, however it decreases the likelihood of EV adoption and thus increases CO_2 emissions. Fuel taxes do not significantly decrease CO_2 emissions of the new car fleet and feature like the mileage dependant charge substantial regressive effects across the income distribution. In contrast, subsidies support the uptake of EVs across all income quartiles, thus reducing CO_2 emissions, but require additional though not very high outlays.

JEL-classification: C25; L62; Q4

Keywords: Electric vehicles; discrete choice models; welfare; mileage tax; fuel tax; CO_2 emissions.

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†KPM,University of Bern and Oeschger Centre for Climate Change Research. E-mail: patrick.bigler@kpm.unibe.ch

‡KPM, University of Bern, Oeschger Centre for Climate Change Research and CESifo. E-mail: doina.radulescu@kpm.unibe.ch.

1 Introduction

According to the International Energy Agency (IEA), the transport sector accounted globally for one quarter of total CO_2 emissions in 2016, being 71% higher than in 1990. Road vehicles thereby represent nearly three-quarters of transport CO_2 emissions with 3.6 Gt CO_2 in 2018. Progress on reducing emissions from the transport sector lags behind. Even though global electric car sales rose in 2018, only 0.5% of the world's vehicles are electric (Bloomberg NEF Electric Vehicle Outlook 2019) and car buyers continue to purchase larger, heavier fossil fuel driven vehicles. For the transport sector to meet projected mobility and freight demand while reversing CO_2 emissions growth, energy efficiency measures such as promoting energy-efficient technologies for vehicles and the fuels that drive them will need to be deployed.

Policy makers design ambitious policies to combat rising emissions in the car sector. These range from strict limits on CO_2 emissions[1], fuel efficiency standards, subsidies, tax rebates or portfolio mandates for EVs. Furthermore, EVs can add flexibility to the renewable power sector by acting as a storage device and balancing periods of high and low energy production. Despite the generous government support instruments and regulations, households are still reticent when it comes to the adoption of non fossil fuel driven cars. As such, it is important to analyse households' car choice decision between combustion engine and hybrid cars or EVs to be able to better understand the factors that hinder or foster the diffusion of these technologies in the population. Furthermore, these policies have redistributive implications, requiring an in depth analysis of the effects of a subsidisation of these cars or increase in fuel taxes, across the income distribution.

In this paper we address the welfare implications of a number of policy scenarios. We first analyse the effects of implementing a CHF 0.12/l fuel levy on gasoline and diesel, which has been recently enacted by the Swiss parliament. Second, we simulate the effects of an up front price subsidy for EVs. The third instrument is the introduction of a mileage dependant charge, as an alternative to generate revenue to finance the road infrastructure. In Switzerland, the revenue derived from motor vehicle taxation is used to fund the local road transport infrastructure. This state-specific levy depends on vehicle weight and fuel efficiency category. EVs are subject to a preferential tax treatment and fuel efficient cars also benefit from tax rebates. While this policy is meant to incentivize the adoption of EVs, hybrid and fuel efficient cars, it also raises questions about the equity and efficiency of the current financing mechanism. Hence, one alternative is the introduction of levies that depend on the number of kilometres driven. Accordingly, these use based charges would ensure that all cars contribute to securing the financing of the infrastructure used.

We employ a discrete choice model with a control function approach to estimate households' choices for certain differentiated products in the car market. Our data allows us to account for a large number of car as well as household specific attributes. We find a strong negative impact of car prices, a negative impact of variable costs and a positive impact of car size and of engine power. We find little heterogeneity between different income groups in terms of average predicted probabilities to adopt EVs or hybrids. We do find

[1] The EU for instance decided to reduce emissions from new cars by 37.5% in 2030 compared to 2021.

a higher likelihood of EV adoption if the charging network in an agent's neighborhood is more dense, or in suburban areas and for cars registered in 2019 relative to 2017 or 2018.

Our policy experiments reveal that the introduction of an additional levy on fossil fuels of 0.12 CHF/l increases the overall probability to adopt an EV by 0.03 percentage points. Since most households own however combustion engine vehicles, overall consumer surplus decreases. Emissions of the new car fleet only insignificantly drop compared to the status quo. Even a much higher tax of 0.3 CHF would only lead to a 0.13% emission reduction of the new car fleet relative to the status quo. The tax has however regressive effects, since the share of annual tax payments to annual income is more than 4 times higher for households in the lowest compared to those in the highest income bracket. Second, a 4000 CHF subsidy leads to a 0.41 percentage point higher uptake of EVs and an overall increase in consumer surplus. The subsidy costs are relatively low with less than CHF 1 million and the average emissions decrease by 0.4%. For this policy we find little distributional effects, as all income groups are equally likely to adopt an EV and thus benefit from the subsidy. However, one caveat applies, as our analysis focuses on new car purchases, which in general are more likely among higher income households. Third, we simulate the implementation of a mileage dependent charge of 0.023 CHF/km. This charge raises the likelihood for gasoline driven cars to be chosen compared to the other fuel types. Consumer surplus decreases as driving costs increase. Emissions of the new car fleet increase by 0.35% or 53 tons and the incidence of the new tax is again almost 6 times higher for households in the lowest income quartile compared to those in the highest income quartile and thus such a levy is highly regressive.

The paper is structured as follows. Section 2 provides an overview of the literature and in Section 3 we present the empirical strategy. Chapter 4 gives an overview of the data and some descriptive evidence. Section 5 presents the regression results and a few model performance calculations and is followed by a welfare analysis in Section 6. Finally Section 7 concludes.

2 Literature

Our paper belongs to the more general body of literature which seeks to analyse the diffusion of electric vehicles in the population. Most articles focus however on analysing the impact of government policies such as subsidies, tax credits, tax rebates or the US 2009 Cash for Clunkers Program on adoption of electric and hybrid cars (Beresteanu and Li, 2011; Chandra, Gulati and Kandlikar, 2010; Gallagher and Muehlegger, 2011; Li, Linn and Spiller, 2013; Mian and Sufi, 2012 or Muehlegger and Rapson, 2018). Other studies analyse the incidence effects of these tax instruments (Gulati, McAusland and Sallee, 2017; Sallee, 2011) or focus on consumer attitudes and perceptions towards these technologies (Egbue and Long, 2012; Krause, Carley, Lane and Graham; 2013). A number of additional papers address the more general question of how gasoline taxes or fuel economy standards affect vehicle choice (Bento, Goulder, Jacobsen, von Haefen, 2009 and Bento, Knittel, Jacobsen, van Benthem, 2019).

Beresteanu and Li (2011) analyze the determinants of hybrid vehicle demand, focusing on gasoline prices and income tax incentives. They find that federal income tax deductions explained less than 5% of hybrid vehicle sales whereas more generous income tax credits accounted for about 20% of hybrid vehicles sales. Chandra, Gulati, and Kandlikar (2010) estimate the effects of tax rebates on sales of hybrid electric vehicles offered by Canadian Provinces. Their results reveal that 26% of the cars sold can be attributed to these rebates but they also find some crowding out effects. Some consumers were accordingly subsidized who would have bought fuel-efficient vehicles anyway. Gallagher and Muehlegger (2011) study the relative efficacy of state sales tax waivers, income tax credits, as well as non-tax incentives on the adoption of hybrid-electric vehicles. Their findings suggest that sales tax waivers are associated with more than a ten-fold increase in hybrid sales relative to income tax credits. Mian and Sufi (2012) and Li, Linn, and Spiller (2013) investigate the effects of the 'Cash for Clunkers' programme on new vehicle sales and the environment. The Cash-for-Clunkers was a USD 3 billion program that encouraged consumers to retire older vehicles and purchase fuel-efficient new vehicles. Mian and Sufi (2012) evaluate the short an medium-run responses of auto purchases. Their findings suggest a small positive short run effect while the medium run effects reveal a reversal. Fewer cars were bought in counties with high clunkers in the 10 months after the program expired. Using a difference- in-difference approach Li, Linn, and Spiller (2013) find that the program increased new vehicle sales only by about 0.37 million during July and August of 2009, such that around 45% of the spending went to consumers who would have purchased a new vehicle anyway. Muehlegger and Rapson (2018) estimate a subsidy elasticity of demand for electric vehicles of -3.9 exploiting a natural experiment that provides variation in subsidies targeted at low- and middle-income Californian households. Regarding the incidence aspect, Gulati, McAusland and Sallee (2017) investigate the subsidies of hybrid electric vehicles in Canada. Their findings suggest that prices rise by USD 570 for every USD 1000 increase in the subsidy. However, the authors conjecture that the pass-through estimate underestimates consumer gains because a majority of this price increase is due to increased product quality. More recent papers on EVs suggest that these actually replace relatively fuel efficient vehicles (Xing, Leard and Li, 2019; Muehlegger and Rapson, 2020). Xing, Leard and Li (2019) show that EVs replace gasoline vehicles with an average fuel economy of 4.2 mpg above the fleet average and more than 10% replace hybrid vehicles. Their findings also suggest that the awarded tax credits represent windfall gains for EV buyers, as 70% of the tax credits went to households that would have purchased EVs even in the absence of such credits. Muehlegger and Rapson (2020) also find that the incremental pollution abatement from EVs is rather smalle when compared to the correct reference vehicle, as EV buyers would have acquired environmentally friendly vehicles anyway. Regarding the efficiency of subsidies vs. bans, Holland, Mansur and Yates (2020) find that the optimal ban on the production of gasoline cars and the optimal purchase subsidy for EVs result in similar efficiency improvements.

Concerning consumer perceptions and attitudes, Egbue and Long (2012) identify potential socio-technical barriers to consumer adoption of EVs. Using survey data, they find that technology enthusiasts are likely to be early adopters of EVs only if they perceive them to be superior in performance compared to conventional vehicles. Krause, Carley, Lane, and Graham (2013) examine the extent of consumer knowledge about plug-in electric vehicles and the policies aimed to encourage their purchase. They show that more than 60% of the respondents provided incorrect answers to basic factual questions about EVs. Furthermore, a large majority of respondents were not aware of state incentives in place.

Concerning the more general question of how gasoline taxes affect car choice and hence gasoline consumption, Bento, Goulder, Jacobsen and von Haefen (2009) develop a model accounting for the new, used and scrapped vehicles markets to analyse the efficiency and distributional implications of such a tax. Using a highly elaborate framework and rich data their findings show that each cent-per-gallon increase in the price of gasoline reduces gasoline consumption by about 0.2%. The extent to which consumers correctly value fuel costs is the subject of Grigolon, Reynaert and Verboven (2018). The authors show that fuel taxes are effective in reducing fuel usage, despite a modest undervaluation of these costs.

Regarding the equity aspect, Borenstein and Davis (2016) use tax return data to examine the socio economic characteristics of recipients of US clean energy tax credits. Their findings reveal that the top income quintile received approximately 90% of tax credits related to electric vehicle purchases.

The above mentioned papers lack access to high quality detailed data on numerous household characteristics and a perfect match between household level and car data information. Furthermore, we also consider the revenue and welfare implications of a number of different policies. The recently expanding literature on EVs also considers the missing revenue to finance the transport infrastructure linked to the increased deployment of EVs. In the US for instance, gasoline taxes are used to finance highways, and in some states such as California, an increasing number of EVs implies less revenue from these levies. As such, an often mentioned reform envisages the introduction of mileage taxes. Davis and Sallee (2020) find that EVs have reduced gasoline tax revenues by USD 250 mn per year. They also derive the optimal mileage tax that accounts for the trade off between congestion externalities and the fact that gasoline is still underpriced and hence a negative mileage tax could encourage substitution towards more environmental friendly cars. In our counterfactual analysis we estimate how such a policy would change the composition of newly registered vehicles, and the effects across the income distribution.

3 Empirical Analysis

In this paper we analyse the car choice behaviour of households in the Swiss Canton of Bern. We employ a unique dataset matching household specific characteristics with detailed information on car ownership and car specific characteristics. Since our dataset includes extensive information on household specific characteristics, we are not only able to infer the effect of car-specific characteristics such as price, engine power and fuel economy on household utility but can also estimate how the valuation of these characteristics interacts with socio-demographic attributes such as income. Furthermore, previous studies mainly employ survey data with a low number of observations. Our data instead has the advantage of including a large number of households and their registered cars, thus capturing the aspect of revealed instead of stated preference.

Starting with the seminal work of Berry, Levinsohn and Pakes (1995) most empirical work estimating demand, substitution patterns and welfare effects of certain policies in the automobile market use a random coefficients logit demand model (i.e. Grigolon, Reynaert and Verboven, 2018 or Langford and Gillingham, 2019). However, due to lack of access to individual level data, these models usually aggregate individual decisions into market shares. One of the main advantages of our dataset is the extensive information of household characteristics, which allows us to control for a large number of observables and assess car choice probabilities across the income distribution. Previous research also incorporated household characteristics based on random draws from population surveys into a model with market shares. For example, the Micro-BLP model (Berry, Levinsohn and Pakes, 2004) employs individual level decisions of car buyers and their reported second-choice data to improve the estimation of substitution patterns in the car market. They thereby draw on information on the population distribution of certain socio-economic factors such as age and income. Similarly, Train and Winston (2007) use survey data on household specific characteristics and second choice data to estimate substitution patterns and explain decreasing market shares of US-American car producers.

In our data we do not observe second choices. To overcome this, one possibility would be to follow Berry, Levinsohn and Pakes (2004) who tried to estimate their model without the second-choice information. However, these estimations did not achieve conversion in the likelihood function in various different models. Furthermore, like them, we observe one market 'only', namely the Canton of Bern. Even though we could construct a time-series of market-shares spanning more than ten years, we believe that the variation in prices, fuel costs and available choices just based on one market within Switzerland would not be enough to employ the Micro-BLP framework. Hence, we resort to a standard choice model based on an aggregated choice set and individual level socio-economic data. Since our car characteristic data is detailed and specific we believe it is rather unlikely that each household considers almost 48k different vehicle make-model-trim combinations in deciding on which car they should buy.

We model the purchase decision of households conditional on purchasing a new car following Train and Winston (2007) and Xing, Leard and Li (2019). We assume that every car registered between 2017-2019 was originally purchased by the current holder. Even if we shrink the choice set to the actually registered vehicles, we still have more than 3,000 distinct types of cars, which makes a further aggregation step necessary. Hence, following a common procedure in the literature (Bento, Goulder, Jacobsen and van Haefen, 2009), we calculate average car characteristics on a level of make-model fuel type combination (i.e. VW Golf diesel or Audi A6 gasoline). In order to calculate the mean characteristics we use actual registration data from all of Switzerland as weights for different vehicle types within the category and collapse the data on an annual basis. To be more specific, the choice set includes 489 distinct cars after excluding a few exotic options [2] Some households have a lower number of options since not all cars existed in all 3 years of observation. All case invariant variables (i.e. all socio-demographic characteristics) remain the same as for the actual observation. The case-variant variables, namely the car characteristics, for the different options are calculated as the weighted average of the respective make-model fuel type combinations.

We employ a discrete choice model to estimate car choice behavior of the observed households. Households retrieve utility from owning and using a car, as well as from consumption of other commodities. Each household has the choice between acquiring a less environmental friendly (combustion engine) and a more environmental friendly (electric or hybrid) vehicle. To be more specific, we adopt a simplified version of the utility function by Grigolon, Reynaert and Verboven (2018). The conditional indirect utility of household i, purchasing vehicle type j can be expressed the following way:

$$u_{ij} = \beta^x x_j + \beta^z z_i x_j + \alpha_1(log(p_j) + \gamma(G_{ij} + T_j)) + \alpha_2 \frac{log(p_j)}{y_i} + \epsilon_{ij} \tag{1}$$

x_j is a vector of car specific characteristics, such as engine power, height, weight and size and β^x is a vector of coefficients that capture the valuations of those attributes. The household specific characteristics are summarized by the vector z_i, including age, household size and location specific characteristics. We interact attributes with a car specific characteristic that is likely differently appreciated by different household types. p_j is the price of vehicle type j, and y_i the household's income. Hence, we allow for heterogeneity in the marginal utility of income based on the income level with α_1 and α_2 measuring the price sensitivity. G_j represents the present value of future fuel costs including possible fuel taxes, and T_j the present value of future car registration taxes which are a function of weight and fuel efficiency. γ and δ measure the future valuation of these costs respectively. They indicate whether or not a household pays full attention to future costs associated with a purchase of a certain car type or if a future pay-off, for example in the form of a better fuel economy, is undervalued. Furthermore, we also include the possibility of future mileage dependent taxes, which are however set to 0 for the baseline case ($\tau_{js}^m = 0$). We define the present value of expected fuel costs and the present value of expected taxes as:

$$G_{ij} = E\left[\sum_{s=1}^{S} \frac{m_i[e_j g_{js}(1 + \tau_{js}^g) + \tau_{js}^m]}{(1+r)^s}\right] \tag{2}$$

[2] We exclude car options based on pre-defined rules. Cars of brands with less than 5 registrations in our timeframe of observation as well as make - model combinations with 2 or less registrations are excluded from our choice set. This ensures that results are not driven by outlier preferences. We do not apply those rules for EVs since wer are mainly interested in EV registrations and argue that low market shares for a certain EV make-model combination could be due to low overall market share and not caused by very specific car characteristics. The options excluded are mainly high priced cars of luxury brands such as Ferrari or Bentley.

$$T_j = E\left[\sum_{s=1}^{S} \frac{t_{js}}{(1+r)^s}\right] \tag{3}$$

where m_i represents the annual kilometers driven, which is a household specific variable, as we assume it does not vary by fuel type choice. e_j denotes the fuel economy of the car type (l or kWh per km), g_{js} is the expected price for a unit of car type j's fuel in period s and τ^g_{js} the fuel tax which is set to zero initially and then set to CHF 0.12 / Liter in the counterfactual [3]. S is the time horizon of the household, which can be thought of as the expected length of ownership but also the expected lifetime, r denotes the discount rate. In equation (3), t_j represents the annual car registration taxes that are levied based on certain car specific characteristics such as the weight and the fuel efficiency. EVs are subject to lower rates and both EVs as well as fuel efficient vehicles benefit from further reductions during the first four years of registration. We allow for consumer specific km driven but assume mileage is inelastic with respect to fuel prices, which is in line with previous research (i.e. Bento et al., 2009). Hence, mileage is decider specific but choice invariant. Furthermore, household's expectation about future fuel prices only depend on today's fuel price[4]. In a similar vein, we assume that households do not anticipate or do not have expectations about the future tax system changes and only consider the current system when they decide on their car purchase. Following Grigolon, Reynaert and Verboven (2018), we define a capitalization factor as

$$\rho = \sum_{s=1}^{S} \frac{1}{(1+r)^s} \tag{4}$$

which allows us to simplify the two equations for G_j and T_j to write the present value of fuel costs and taxes as

$$G_{ij} = \rho m_i[e_j g_j(1+\tau^g_j) + \tau^m_j] \tag{5}$$

$$T_j = \rho t_j \tag{6}$$

We can then substitute equations (5) and (6) into equation (1) and derive the utility of household i from purchasing car type j as:

$$u_{ij} = \beta^x x_j + \beta^z z_i x_j + \alpha_1 log(p_j) + \gamma\rho(m_i[e_j g_j(1+\tau^g_j) + \tau^m_j] + t_j) + \alpha_2 \frac{log(p_j)}{y_i} + \epsilon_{ij} \tag{7}$$

Assuming independent and identically Type 1 extreme value distribution of the error terms ϵ_{ij}, the probability that household i selects vehicle j can be expressed as:

$$P_{ij} = \frac{e^{\beta^x x_j + \beta^z z_i x_j + \alpha_1(log(p_j) + \gamma(G_{ij}+T_j)) + \alpha_2 \frac{log(p_j)}{y_i}}}{\sum_j e^{\beta^x x_j + \beta^z z_i x_j + \alpha_1(log(p_j) + \gamma(G_{ij}+T_j)) + \alpha_2 \frac{log(p_j)}{y_i}}} \tag{8}$$

[3] At the moment Switzerland imposes a tax on certain types of fuels such as gasoline and diesel. These taxes are paid by the importing companies of gasoline and diesel and we assume these taxes and the VAT to be part of the price that we use to calculate the driving costs. The additionally introduced tax τ^g_{js} represents an extra tax on top of the already existing tax.

[4] $E[g_{js}] = g_j$

Inferring the choice probabilities will allow us to investigate the effects of a reduction in the prices of EVs or an increase in the annual variable costs due to fuel taxes, or the effect of introducing a mileage dependent levy. The estimation of conditional logit models with individual level data and an exhaustive choice set is implemented by specifying a likelihood function based on each household's probability to choose a certain vehicle type. Furthermore, we also control for a set of car fixed effects such as car type (i.e. minivan, middle class...) and the brands' country of origin. [5] However, conditional logit models assume independence of irrelevant alternatives (IIA) and thus restrict substitution patterns between different products to be proportionate. In other words, the availability of an additional alternative on the market affects the choice probability of the remaining options to the same extent. As Berry, Levinsohn and Pakes (1995) point out, the automobile market is unlikely to follow such restrictive substitution patterns.

Hence, to relax this assumption we allow for random coefficients to control for heterogeneity in the valuation of the observed car characteristics. To be more specific, we allow for individual deviations in the valuation of certain car characteristics and estimate an entire distribution of coefficients instead of just one constant coefficient. In order to do so we assume a distribution, f(β;θ) for the some coefficients, $\beta = (\beta_i^x, \alpha_i)$, with θ being mean and (co)variance parameters to be estimated. On the condition that β is independent of the type 1 extreme value distributed individual and vehicle type specific ϵ_{ij} the following formula denotes the probability of household i choosing vehicle type j (McFadden and Train, 2000):

$$P_{ij} = \int \frac{e^{\beta_i^x x_j + \beta_i^z z_i x_j + \alpha_{i1}(log(p_j) + \gamma(G_{ij} + T_j)) + \alpha_{i2}\frac{log(p_j)}{y_i}}}{\sum_j e^{\beta_i^x x_j + \beta_{ij}^z z_i x_j + \alpha_{i1}(log(p_j) + \gamma(G_{ij} + T_j)) + \alpha_{i2}\frac{log(p_j)}{y_i}}} f(\beta|\theta) d\beta \tag{9}$$

Random coefficients allow the researcher to account for correlations in the unobservable factors that influence a household's car choice while also allowing for more flexible substitution patterns among vehicles (McFadden and Train, 2000).

The car market, as a differentiated product market, likely exhibits unobserved car specific characteristics correlated with the utility of households. Those would be subsumed into ϵ_{ij} and likely lead to potential endogeneity problems of the price coefficients, as researchers can expect that car producers also observe those characteristics and preferences for them. Thus they have the ability to charge higher markups. Berry, Levinsohn and Pakes (1995) suggest an instrumental variable approach to deal with this potential price endogeneity. We adopt a similar strategy using BLP style instruments as well as a marginal cost shifter. However, since we directly estimate the probabilities of buying a car and not market shares we follow the estimation method of Petrin and Train (2010) and use a control function approach. To be precise, we split the error terms in equation (7) into two components: $\epsilon_{ij} = \epsilon_{ij}^1 + \epsilon_{ij}^2$. In this setting, ϵ_{ij}^1 is correlated with the price

[5] We also tried to control for brand specific fixed effects. However, the likelihood function does not converge, which can be caused by a potential curse of dimensionality, since around 23k observations might not be enough to identify all 33 brand fixed effects in our sample.

based on characteristics unobserved by the researcher while ϵ_{ij}^2 is i.i.d extreme value. In a first step, we thus estimate a linear pricing equation of the following form

$$log(p_j) = \beta x_j + \lambda z_j + \mu_j \tag{10}$$

where x_j denotes the car characteristics of vehicle j and z_j is the marginal cost shifter of vehicle j. The estimated residuals from this pricing function $\hat{\mu_j}$ are used as an additional term in the utility function to control for the potential correlation of unobserved preferences and the price. Instruments should exhibit the properties of marginal cost shifter in order to be valid for this approach. We propose as a marginal cost shifter the annual penalties for fleet wide fuel efficiency standards based on Swiss environmental policy. All cars that are sold in Switzerland are imported from other countries and thus from global producers. As a small open economy, we do not expect Switzerland to affect the global car price of different brands. Most brands either have a subsidiary company that is the sole importer of their cars into Switzerland or operate with a unique partner (i.e. a general importer). Since 2012, the federal government has introduced CO_2 emission fleet standards for car importers. Companies importing more than 50 cars annually are subject to an assessment of the average fleet emission. If emission standards are not met, a substantial penalty based on the deviation is charged. Those penalties apply to all general importers and are significant enough to apply as cost shifters [6]. In addition to those fees and penalties we also use the typical BLP instruments of the sum of characteristics of own and competitors product characteristics.

4 Data

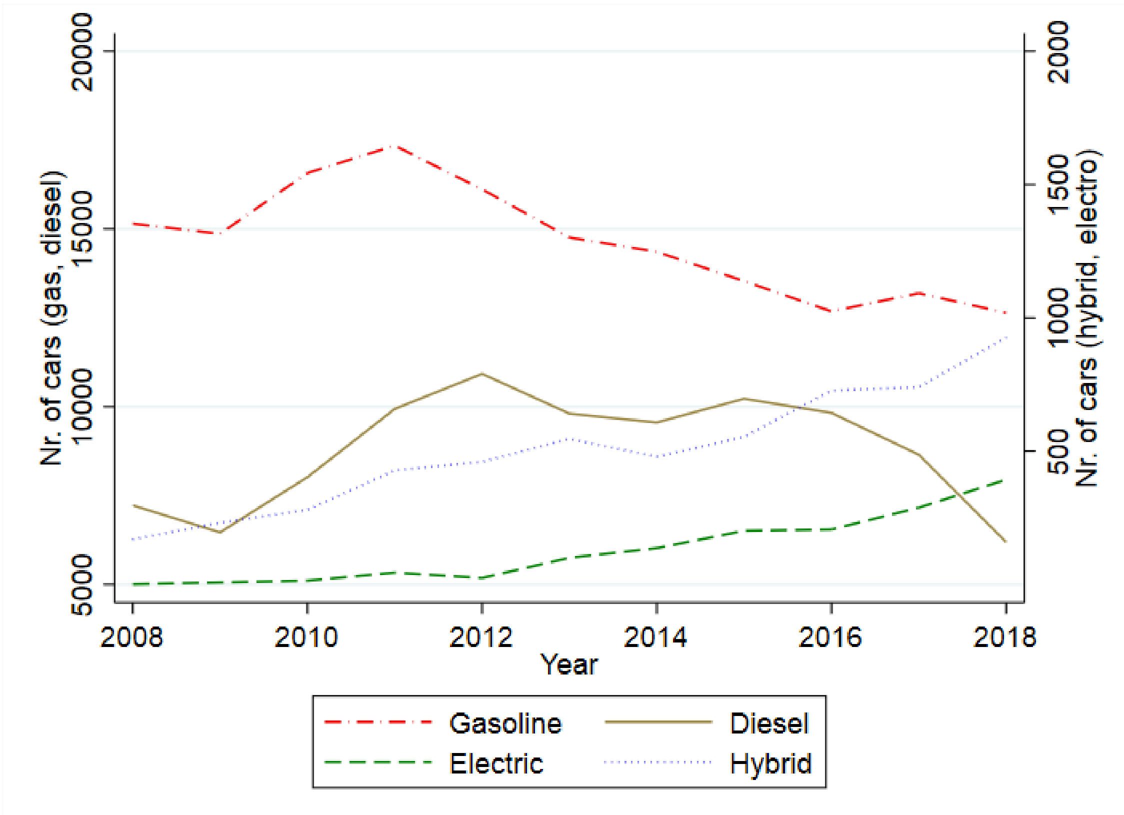
For this paper we draw on a unique panel data set on household income, wealth, and further household characteristics for the canton of Bern for the years 2008-2017. This data is provided by the Tax Office of the Canton of Bern.

We match this data with information on car registrations from the Road Traffic Office of the Canton of Bern observing every new car registration between 2008-2019. However, we only observe current vehicle ownership and thus cannot match the registrations with the tax information panel data, as it is unlikely, especially for older cars, that the current owner has also been the initial purchaser. Nevertheless, we can assess market penetration of the four different drive types (gasoline, diesel, electric or hybrid) over time. The following figure depicts the evolution of the annual number of registered cars divided into our categories of interest, namely gasoline, diesel, electric or hybrid cars. The figure shows a decline in the annual number of registered gasoline and diesel driven cars and an increase in the number of hybrid or electric cars. However, the absolute number of environmental friendly cars is still very low, as shown by the right hand axis in Figure 1. Accordingly, in 2018, there were around 1,000 newly registered hybrid and less than

[6] Penalties rose from CHF 3.5 Mn. in 2012 to more than CHF 78 Mn. in 2019. For example, the VW group as the biggest importer in 2019 had an average penalty per car of CHF 390 or a total of 35 Mn. CHF

500 electric cars in the Canton of Bern. The corresponding figures for gasoline and diesel amounted to around 13,000 and 6,000 respectively.

Figure 1: Evolution of registered cars by type between 2008 and 2018



If a household owned more than one car, we keep the car with the most recent registration date, since we consider this the most recent occurrence of revealed preferences by the household. However, only 13% of the households in our sample own more than one vehicle[7]. Furthermore, 74% of electric and 89% of hybrid cars, which represent our main category of interest, are owned by households with only one car. Hence, we do not lose much information by only including one car per household.

In addition to the date of first registration and the fuel type of the vehicle we also observe a number of vehicle characteristics such as the brand and type name, fuel economy, the energy efficiency category, engine power and the weight, size and height of the car. Price data is retrieved from Eurotax, a company that collects historical import prices for each distinct brand and type. Hence, the price we use in our regressions is not the transaction price but the price for which the respective car type is listed for by the

[7]The range is from one to four vehicles, but households owning more than two cars represent less than 1% of the sample.

importer. Since Switzerland does not manufacture any cars itself, all cars are imported at some point in time. The price information is available for around 68,000 different cars in total and around 48,000 cars in our timeframe of observation. These data are very disaggregated insofar as for instance VW Golf V, VW Golf VI, VW Golf VII are recorded as three different observations with even further distinction into the various types and models (i.e. GT, sport, TSI, TDI...). We also observe the number of years the respected car type was imported and thus available in Switzerland. Since the recording of car type in the data of observed choices is not always as distinct we employ a weighted string match algorithm to match the recorded registration with the closest price data available.[8]

We also include information on automobile taxes and motor vehicle taxes. In Switzerland, the automobile tax is a one-off tax on all imported cars levied at the federal level. It amounts to 4% of the car value, but electric vehicles are exempt from this tax. We do not add this tax to our price variable, as we consider the tax to be part of the suggested retail price. In addition, vehicle owners also have to pay an annual vehicle tax at the cantonal level. In the Canton of Bern the tax is a function of car weight, energy efficiency and the duration since the initial registration. Electric vehicles also pay much lower vehicle taxes. The tax reductions are awarded for the first four years only. [9]. We assume a car longevity of 10 years[10] and compute the present discounted value of annual vehicle taxes for a period of 10 years. We also follow the literature (Allcott and Wozny (2014); Grigolon, Reynaert and Verboven (2018); Cerruti, Alberini and Linn (2017)) and assume a discount rate of 6% [11]. The present value of these tax payments varies between 840 CHF and 5462 CHF, with a higher average value of 3312 CHF for conventional cars and a much lower value of around 1357 CHF for EVs. These figures represent 11% of the car price, with a much lower value of 3% for EVs.

We define the fuel economy of the car as the costs per 100km driven. This variable is computed as estimated car fuel usage times the average costs of the respective fuel in the year 2019. Fuel usage is retrieved from the TARGA dataset provided by the Swiss Federal Roads Office. Fuel prices represent the average for the year of purchase gathered from the Swiss Statistical Office. The Car Registration Office dataset also includes the number of driven kilometers for some cars. However, this information is not observed for the majority of our sample, since these new cars did not have to attend to these regular check up yet. Thus, we use odometer readings of older cars and different households and

[8] Make and time of observations need to match perfectly, then the type classification is further distinguished into various parts and a match score is calculated based on decreasing weights for the different specifications. For example, Golf as the second part of the registration of a VW Golf VII is higher weighted than the third part VII. By employing this weighted score and using a rather high match threshold we ensure that the actual price in the data is as close as possible to the actually valid price on the market.

[9] Details on the calculation of the tax can be found on the webpage of the Road Traffic Office for the Canton of Bern $https://www.svsa.pom.be.ch/svsa_{p}om/de/index/navi/index/rund-ums-fahrzeug/fahrzeugsteuer-berechnen.html$, found 30.04.2020

[10] This is at the lower end of Eurostat estimates but according to a COMPARIS questionnaire Swiss household's average holding period is 6 years for newly purchased cars and 5 years in general.

[11] We will in a later step add further robustness checks with lower discount rates of 3% and lower holding periods of 6 years

estimate a mileage consumption function. Based on the estimated coefficients we then extrapolate the predicted annual kilometers driven for the households in the dataset. [12]. This procedure allows us to calculate the present value of future driving costs based on the assumption of a discount rate of 6% and a car longevity of 10 years.

In Table 1 we summarise a few car characteristics based on three different samples. First, we present the choice set available to households. Roughly 50% are gasoline driven. More environmentally friendly cars such as EVs and hybrids are less often encountered with 20 and 54 make - model combinations respectively. Taxes as well as driving costs are lower for EVs. Prices are similar across categories except for hybrid cars which are more expensive in this sample. The second panel presents the actually observed choices. Here we see that almost 70% of all registrations represent gasoline driven cars. EVs and hybrids exhibit still relatively low market shares. The former category display below average prices, weights, engine power and size. In contrast, EVs are CHF 20,000 more expensive than corresponding gasoline driven car. EVs and hybrids feature considerably lower variable costs in terms of taxes and fuel related expenses. The last panel presents most frequently purchased vehicle in the four different fuel categories. With 419 registrations in the time frame of observation the gasoline driven VW Polo was the most popular vehicle. With a below average price and relatively high efficiency and low annual taxes within the category of gasoline driven cars it seems to be an attractive option. In terms of hybrids and EVs the most popular choices are Toyota Yaris and Renault Zoe.

Table 1: Choice set

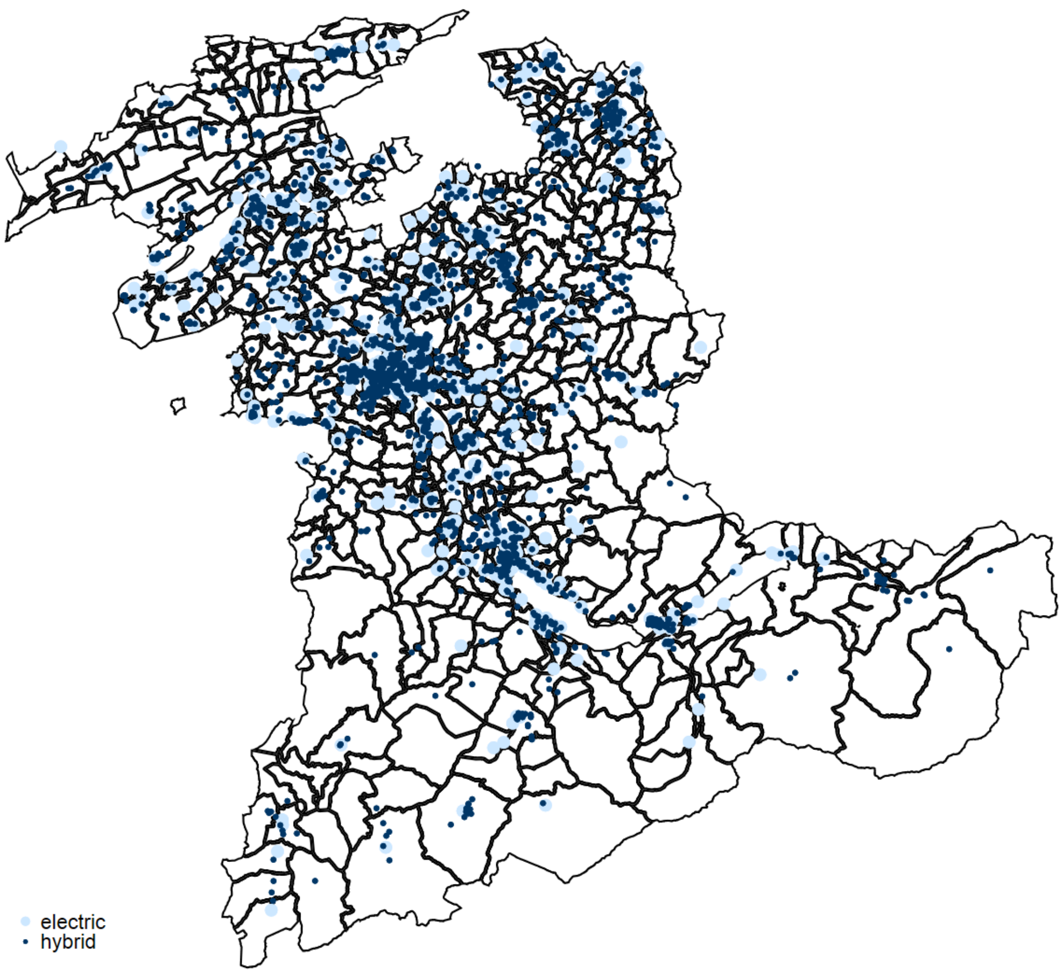
	N	**Price**	**Tax**	**KW**	**Weight (kg)**	**Height (m)**	**Size (m^2)**	**CHF / 100km**
Choice set								
Total	489	47	400	136	2,077	1.55	8.17	9.17
Gasoline	242	44	415	143	1,957	1.53	7.96	10.38
Diesel	173	45	420	123	2,202	1.59	8.43	8.52
Electric	20	48	90	145	2,020	1.55	7.44	3.6
Hybrid	54	62	384	142	2,232	1.52	8.55	7.87
Observed choices								
Total	23,074	35	382	112	1,929	1.55	7.83	8.94
Gasoline	16,005	31	372	108	1,815	1.53	7.59	9.28
Diesel	5,601	43	445	122	2,237	1.62	8.5	8.71
Electric	380	53	96	195	2,197	1.53	8.17	3.8
Hybrid	1,088	40	305	97	1,921	1.54	7.79	6.82
Most frequent choice								
VW Polo (gas)	419	23	226	80	1,608	1.43	7.09	7.78
Ford Kuga (diesel)	291	31	490	109	2,246	1.68	8.32	8.18
Renault Zoe (EV)	79	31	88	100	1,976	1.56	7.07	4.04
Toyota Yaris (Hybrid)	230	26	222	54	1,565	1.51	6.69	5.34

Note: The first Panel presents the summary statistics of the theoretically available choice set for each household. N measures the number of cars per category, whereas the other columns are the average car characteristics. In the second panel, the same variables are presented, but in terms of actually observed choices. The last panel presents the most frequently observed choice. Here the first columns measures the number of households that picked this car and the car characteristics are the actual values.

[12]We expand the existing literature here, by extrapolating household specific values. For example, Alberini and Bareit (2019) assume a constant mileage consumption of 16,000 km for diesel vehicles and a lower consumption rate of 12,000 km for other vehicles. We intend to control for the added variation due to our approach in an additional robustness check.

As we only observe current ownership we reduce the panel structure into a cross-sectional observation. We assume that cars that were newly registered between 2017 and 2019 are still owned by their respective initial purchasers in June 2019[13] and we only keep those observations. Hence, the matched socio-demograohic data is collapsed. Income and wealth represent averages over the sample period. Age is measured as current age [14], the variables married and size of household represent the most recent observations.

Figure 2: Map of electric and hybrid cars



In addition, we control for the availability of EV charging stations. Several previous studies found that the availability of public charging stations affects the diffusion of EVs (Egbue and Long, 2012; Egnér and Trosvik, 2018). We download coordinates of all charg-

[13]June 2019 is when our data collection of the vehicle registration data took place and thus indicates point of time where we know the ownership status

[14]By the end of 2019

ing stations from LEMNET and calculate first the minimum distance for each household to the closest charging station. Second we compute the density of these charging stations within the range of 5km from the household's location.

On top of that, we compute the distance to the closest EV. Adoption of a new technology may be driven by neighbours through various channels. For example, a constant visual exposure as well as positive or negative customer experiences of one's neighbours can influence the own decision (Jansson et al., 2017). Figure 2 plots the distribution of electric and hybrid vehicles in the Canton of Bern, in order to assess whether such a clustering of technology adoption is evident. We see that there is a slight concentration of vehicles in the three main centres of the Canton[15] which is the strongest along lake Thun. Nevertheless, the distribution of vehicles throughout the canton roughly corresponds with the distribution of the population. The southern region that almost has no EV or hybrid vehicles is also very scarcely populated, as it is a mountain region.

We use information from the Federal Department of Energy to calculate the marginal cost shifter. As mentioned above, each company that imports more than 50 cars annually is subject to an assessment of the emissions of its fleet. The individual emission target is thereby a linear function of the average vehicle weight within the fleet. [16] Penalties are not based on a brand specific structure.[17] We use five different calculations of the marginal cost shifter. First, we assume that the fines are equally split between all cars imported in a given year. Second, we assume an equal split, but based on the prior year's penalty, since a car importer may not have assessed the implications of its imported fleet over the year. Third, we compute a distinct fine for each imported vehicle. Such a procedure would apply if an agent decides to import the vehicle herself from abroad. Fourth, we assess the cost shifter based on a penalty per emission unit instead of per vehicle. We calculate the total penalty for an importer, assess the costs per unit of deviation and apply it to the car specific deviation. Fifth, we apply this last methodology as the price shifter for the subsequent year. We estimate all five specifications separately while also using the typical BLP cost shifters and accounting for numerous car specific observables. We determine by comparison of AIC and R^2 of the distinct methodologies the lagged equal distribution of the penalty as the preferred cost shifter.

Table 2 presents the summary statistics for some socio-economic and car characteristics of our final sample including 23,074 households in total as well as for the subsamples divided by fuel type category. On average, household income reaches around 114,000 CHF. The mean vehicle price amounts to 35,000 CHF. As suggested by the numbers in Table 2, the moments of the distribution of the control variables vary a lot since car prices can vary between 8,000 CHF to 210,000 CHF. We also present these summary statistics

[15]The cities Bern, Biel and Thun

[16]Details of the calculation scheme are available on the following homepage `https://www.bfe.admin.ch/bfe/en/home/efficiency/mobility/co2-emission-regulations-for-new-cars-and-light-commercial-vehicles.html`

[17]For example, all brands of the Volkswagen holding are assessed the penalty of the entire holding, independent of the actual brand they belong to. We assume, that the costs of the fines within the holding are equally assessed between for example Skoda and Audi even though the holding might serve different market segments with the different brands.

by fuel type category. Mean household income of electric car owners is around 50% higher than average household income in our overall sample. The average distance to an EV charging station is 1.32 km without any significant variability between the different fuel type households. The average number of kilometers driven is 12,300 which is in line with previous estimates for Switzerland (i.e. Alberini and Bareit, 2019). However, mileage is quite heterogeneous and varies between 4,100 and almost 30,000 kilometers per year, with diesel car owners driving on average 4,000 kilometers more relative to drivers of the other 3 fuel types. Exhaustion pipe CO_2 emissions are 0 for EVs but can vary between 88g/km and 359 g/km for gasoline driven cars. Previous research has shown that the environmental benefits of EVs and hybrid vehicle might depend on local factors of electricity production, especially on the local electricity mix (Holland et al., 2016). Nevertheless, we think in our setting zero emissions from EVs are a safe assumption. Switzerland relies almost entirely on non-fossil fuel electricity production[18] and the three main providers in the canton of Bern actually guarantee their customers a certain electricity mix, which do not contain any fossil fuel based electricity.

[18] According to the Swiss overall energy statistics hydro power has accounted for a share of 55% to 60% in the last 5 years, while nuclear power accounted for another 30 %- 35%. Fossil fuel electricity production in the form of thermal natural gas plant only accounted for less than 5% in that timeframe.

Table 2: Summary Statistics

Overall Sample

	N	Mean	Sd	Min.	Median	Max.
Household income (TCHF)	23,074	114	467	0	94	68,364
Household wealth (TCHF)	23,074	691	5,046	0	322	648,887
Age (main income source)	23,074	55	15	21	56	119
Suggested car price (TCHF)	23,074	35	20	8	32	210
Distance driven (KM/year)	23,074	12,342	2,875	4,132	11,961	29,715
Fuel Economy (CHF/100km)	23,074	9	2	3	9	25
CO_2 emission (g/km)	23,074	132	32	0	129	359
Distance to EV charging station (m)	23,074	1,320	1,300	1	789	9,679
Household size	23,074	2.1	1.11	1	2	5
Urbanity of home	23,074	1.91	.88	1	2	3

Gasoline

	N	Mean	Sd	Min.	Median	Max.
Household income (TCHF)	16,005	111	556	0	90	68,364
Household wealth (TCHF)	16,005	680	5,825	0	311	648,887
Age (main income source)	16,005	55	16	21	57	99
Suggested car price (TCHF)	16,005	31	20	8	28	210
Distance driven (KM/year)	16,005	11,259	2,084	4,132	11,183	29,715
Fuel Economy (CHF/100km)	16,005	9	2	6	9	25
CO_2 emission (g/km)	16,005	135	27	88	129	359
Distance to EV charging station (m)	16,005	1,317	1,292	1	787	9,679
Household size	16,005	2	1.05	1	2	5
Urbanity of home	16,005	1.91	.88	1	2	3

Diesel

	N	Mean	Sd	Min.	Median	Max.
Household income (TCHF)	5,601	117	95	0	101	3,698
Household wealth (TCHF)	5,601	618	2,456	0	303	144,041
Age (main income source)	5,601	52	13	21	52	94
Suggested car price (TCHF)	5,601	43	15	12	41	115
Distance driven (KM/year)	5,601	15,717	2,322	4,498	15,695	28,872
Fuel Economy (CHF/100km)	5,601	9	1	5	9	16
CO_2emission (g/km)	5,601	138	21	86	137	244
Distance to EV charging station (m)	5,601	1,323	1,328	3	784	9,296
Household size	5,601	2.38	1.23	1	2	5
Urbanity of home	5,601	1.93	.89	1	2	3

Hybrid

	N	Mean	Sd	Min.	Median	Max.
Household income (TCHF)	1,088	129	106	3	105	1,395
Household wealth (TCHF)	1,088	963	2,101	0	491	28,973
Age (main income source)	1,088	60	13	22	61	90
Suggested car price (TCHF)	1,088	40	20	18	35	160
Distance driven (KM/year)	1,088	11,418	2,125	6,337	11,228	27,692
Fuel Economy (CHF/100km)	1,088	7	2	4	6	15
CO_2 emission (g/km)	1,088	91	28	33	87	221
Distance to EV charging station (m)	1,088	1,352	1,282	7	829	6,617
Household size	1,088	2.06	1.01	1	2	5
Urbanity of home	1,088	1.9	.87	1	2	3

Electric

	N	Mean	Sd	Min.	Median	Max.
Household income (TCHF)	380	170	141	7	138	1,092
Household wealth (TCHF)	380	1,495	3,844	0	711	63,082
Age (main income source)	380	55	13	22	54	119
Suggested car price (TCHF)	380	53	25	24	46	104
Distance driven (KM/year)	380	10,838	2,181	4,466	10,663	23,351
Fuel Economy (CHF/100km)	380	4	1	3	4	6
CO_2 emission (g/km)	380	0	0	0	0	0
Distance to EV charging station (m)	380	1,313	1,310	37	791	7,482
Household size	380	2.47	1.2	1	2	5
Urbanity of home	380	1.84	.85	1	2	3

5 Regression Results

Discrete choice estimation, especially with large choice sets and random parameters are computationally demanding (von Haefen and Domanski, 2018). Hence, in a first step we estimate maximum likelihood models based on the logit probabilities of equation (8) and assume a well-specified utility function without individual unobserved heterogeneity. According to Train (2009) a logit specification may capture average preferences fairly robust, even if tastes vary randomly between agents. Thus, we use conditional logit models with an extensive set of different control variables to test out different specifications.

Households choose between 489 options. We distinguish between different model types. First, we define costs over the lifetime of the vehicle such as the total price, the present value of the driving costs and the present value of the variable costs (the sum of driving costs and taxes). Households are cost averse, meaning they prefer cars with lower prices and lower variable costs. Perhaps surprising, according to the first specifications presented in column (1) of Table 3 (and the first columns in Table 11 in the Appendix), future variable costs seem to count more compared to the upfront price, which differs from previous research on myopic car consumers (i.e. Gillingham, Houde and van Benthem, 2021; Grigolon, Reynaert and Verboven, 2018). However, it is important to note once again that we only examine a subsample of the population, namely new car buyers and hence, we cannot draw conclusions about general consumer myopia. In a next step we control for the sum of annual driving costs and annual taxes instead of lifetime costs (see Table 11 in the Appendix). Furthermore, we assess whether a specification based on annual instead of total costs is more suitable to capture the consumer's decisions. One can argue, that households optimise over an annual budget and depending on vehicle type between 30% to 75% of newly purchased cars are leased. We do so by specifying three different models. Again, we assume discount rates of 6% and a vehicle holding period of 10 years. We split prices evenly into an annual rent and add 6% interest as a leasing rate. The result persists, and households seem to value differences in variable costs more than differences in prices. Third, we add fixed effects. We control for the environmental category of vehicles (A-G based on efficiency), the vehicle type (i.e. Minivan, SUV, small and so on) and the brand's country of origin. Once, we include car type and environmental category fixed effects (column 8 in Table 11 in the Appendix), the coefficient on the car price is still negative and significant, but households seem to prefer higher driving costs within the category. So car buyers seem to appreciate more the environmental label than the actual driving costs. Once we also control for brand origin fixed effects, most results in terms of costs are no longer statistically significant.

Coefficients of the remaining control variables are quite consistent between the different specifications. Model (1) in Table 3 estimates car choice without including fixed effects. In Model (2) we add car type and brand country of origin fixed effects, while model (3) applies the control function approach based on the pricing equation to address potential endogeneity of the price variable due to correlation between unobserved car attributes and the price. As expected, the coefficient for car price increases in absolute value once we address this potential correlation. The results of this last specification are in line with previous research and agents seem to be myopic with respect to future variable costs.

We also include dummies for the four distinct fuel types to capture some general preferences for or against them. All three alternative fuel types are less attractive relative to gasoline driven cars. The results are consistent throughout all specifications, with the disutility from EVs being the strongest.

Our detailed data also allows us to control for observed heterogeneity between households. We find little observed heterogeneity in households' valuation of prices based on income. The coefficient is positive as expected meaning that households with higher income are less price sensitive. However, the coefficient is relatively small and only significantly different from zero at the 10% level.[19] We also control for different valuations of car size in terms of heterogeneous household size. The result show that bigger households value bigger cars to a stronger extent, as all interaction effects are positive and significantly different from zero. We also allow households to value engine power differently depending on their age. All interaction effects are negative and significantly different from zero indicating that relatively older households prefer less powerful cars.

Since our main interest lies in explaining the effect of different policies, we also estimate a few interaction effects of EV preferences, to better understand patterns of households adopting this new technology. We control for the density of charging stations, and find significant positive effects. Households more likely buy an EV if there are more charging stations in the vicinity. In terms of urbanity patterns, we observe that households living in an agglomeration are more likely to adopt an EV compared to households living in urban and rural areas. Furthermore, as suggested by Figure 1, a car registered in 2019 is more likely an EV, than a car purchased in 2017 or 2018 as shown by the statistically significant positive effect of the interaction term. We find no evidence of a peer effect, as households that live closer to someone owning an EV do not have a significantly higher probability than other agents to purchase an EV.

[19] Heterogeneity in terms of correlation between price sensitivity and wealth is also controlled for. The results in the appendix indicate that there is no significantly different valuation of prices once we control for wealth and income.

Table 3: Regression results

	(1)	(2)	(3)
Car price (log)	$-0.227***$	-0.034	$-2.116***$
	(0.03)	(0.04)	(0.11)
Price (log) / income	0.002+	0.003+	0.002+
	(0.00)	(0.00)	(0.00)
Variable costs (log pv)	$-0.684***$	$-0.520***$	$-0.350***$
	(0.08)	(0.10)	(0.10)
Engine power (KW)	-0.000	$-0.001+$	$0.007***$
	(0.00)	(0.00)	(0.00)
Car height	$0.453***$	$0.466***$	$-1.550***$
	(0.09)	(0.13)	(0.16)
Car weight	0.000	$-0.001***$	$0.001***$
	(0.00)	(0.00)	(0.00)
Hybrid engine	$-0.751***$	$-0.690***$	-0.205
	(0.16)	(0.16)	(0.16)
Electric engine	$-1.983***$	$-1.731***$	$-1.178***$
	(0.23)	(0.24)	(0.24)
Diesel engine	$-0.760***$	$-0.732***$	$-0.567***$
	(0.02)	(0.02)	(0.02)
Car size	$-0.127***$	-0.033	-0.006
	(0.02)	(0.02)	(0.02)
Size heterogeneity			
2 Persons	$0.163***$	$0.187***$	$0.184***$
	(0.02)	(0.02)	(0.02)
3 Persons	$0.315***$	$0.362***$	$0.359***$
	(0.03)	(0.03)	(0.03)
4 Persons	$0.516***$	$0.582***$	$0.577***$
	(0.02)	(0.03)	(0.03)
5+ Persons	$0.714***$	$0.793***$	$0.785***$
	(0.04)	(0.04)	(0.04)
KW heterogeneity			
40-60 years old	$-0.003***$	$-0.003***$	$-0.003***$
	(0.00)	(0.00)	(0.00)
60+ years old	$-0.005***$	$-0.005***$	$-0.005***$
	(0.00)	(0.00)	(0.00)
EV effects			
EV agglomeration	$0.311*$	$0.311*$	$0.310*$
	(0.14)	(0.14)	(0.14)
EV rural	-0.023	-0.025	-0.026
	(0.15)	(0.15)	(0.15)
Distance to EV	-0.030	-0.029	-0.029
	(0.02)	(0.02)	(0.02)
Nb. Charging (5km)	$0.007*$	$0.007*$	$0.007*$
	(0.00)	(0.00)	(0.00)
EV 2018	0.133	0.088	0.123
	(0.14)	(0.14)	(0.14)
EV 2019	$1.357***$	$1.307***$	$1.359***$
	(0.13)	(0.13)	(0.13)
Control function	*No*	*No*	*Yes*
Observations	9,816,000	9,816,000	9,816,000
Nr. of cases	23,074	23,074	23,074
Log Likelihood	$-136,093.3$	$-134,604$	$-134,380.7$
Car type fe	*No*	*Yes*	*Yes*
Car brand (country)	*No*	*Yes*	*Yes*

+p<0.1; * p<0.05; ** p<0.01; *** p<0.001
Coefficients based on estimated conditional and mixed logit model. Estimated standard errors in parentheses. Model (1) - (3) do not have random coefficients. Coefficients in Model (1) and (5) are based on control function approach with estimation of the pricing equation in a separate model based on cost shifters in a first step.

We estimate the average predicted probability of a household to choose a certain car type based on the estimated control function approach in column (3) of Table 3. We determine the average predicted probability by fuel type and income quartile. Table 4 depicts the results. Overall, we predict 2 out of 3 chosen cars to be gasoline driven. The share of electric and hybrid vehicles is comparably low with 1.7% and 5.04% respectively. Low income households are even more likely to buy a gasoline driven car, while households with income in excess of 62,900 CHF are more likely to choose diesel or hybrid cars.

Table 4: Predicted probabilities

	Overall	1^{st} inc. quartile	2^{nd} inc quartile	3^{rd} inc quartile	4^{th} inc quartile
Gasoline	0.6719	0.6883	0.6744	0.6645	0.6606
Diesel	0.2610	0.2463	0.2594	0.2679	0.2703
Electro	0.0167	0.0175	0.0162	0.0162	0.0170
Hybrid	0.0504	0.0479	0.0514	0.0514	0.0522

Notes: 1^{st} quartile: income < 62.9 kCHF, 2^{nd} quartile: 62.9>=income< 93.67 kCHF, 3^{rd} quartile: 93.67>= income<131.7 kCHF and 4^{th} quartile: income >= 131.7 kCHF. Estimation based on sample and specification (3) of Table 3.

We apply a chi-square goodness of fit test to evaluate how well the model fits the data. Since we do not apply alternative specific constants, our model does not perfectly represent the observed shares in the data. We evaluate how well we predict the fuel types gasoline and electric based on the average predicted probabilities for each car combination and each income quartile separately. Table 5 presents the results. Overall, there is no perfect fit especially since in the lower income quartile the share of gasoline vehicles is drastically underestimated while the share of EVs is overestimated. For the second and third income quartile the model fits the data quite well for gasoline cars and we cannot reject the null hypothesis that predicted numbers and observed numbers are significantly different from each other at the 5% level. Taking into account the other two fuel types that are not illustrated in the table, does not significantly improve the model's prediction performance. Without differentiating between income groups, the χ^2 statistic is 50 and we mainly have prediction errors between diesel and gasoline cars and almost perfectly predict the shares of EVs and hybrids in the overall population. If we account for the different income groups, the presented pattern of Table 6 also appears for the complete sample of fuel types. In the lowest income bracket we significantly underestimate the number of gasoline cars and significantly overestimate the other fuel types. For all other income brackets the prediction of the model for diesel and hybrid adoption is quite accurate and not significantly different from the observed market penetration (Table presented in Appendix).

Table 5: Prediction evaluation

Income	Gasoline predicted (N)	Gasoline actual (N)	EV predicted (N)	EV actual (N)
1st inc. quartile	3,971	4,450	100	52
2nd inc quartile	3,890	4,045	93	55
3rd inc quartile	3,833	3,853	93	68
4th inc quartile	3,810	3,648	97	205
Overall χ^2_3	65.49		Overall χ^2_3	136.61
2nd & 3rd quartile χ^2_1	6.74		2nd & 3rd quartile χ^2_1	35.45

Notes: 1st quartile: income < 62.9 kCHF, 2nd quartile: 62.9>=income< 93.67 kCHF, 3rd quartile: 93.67>= income<131.7 kCHF and 4th quartile: income >= 131.7 kCHF. Predictions based on sample and specification (3) of Table 3. The critical values are 7.815 and 3.841 for the χ^2_3 and χ^2_1 with a 95% significance level and 11.345 and 6.635 with a 99% significance level respectively.

6 Welfare and Counterfactuals

We simulate three policy changes that are currently debated based on the estimated coefficients. These changes are further described in the following subchapters. We compute the change in consumer surplus as well as the change in the predicted average adoption probabilities. We assume that the annual number of private registered cars amounts to 9,230 in the Canton of Bern[20], and assess the changes in tax revenue as well as emissions and the particular implications of each policy change. A major concern related to the spread of fuel efficient cars in general and EVs in particular, relates to the missing tax revenue to finance the road infrastructure. This is the case, since they benefit from generous motor vehicle tax reductions (see also Davis and Sallee, 2019) and also consume less or no fossil fuel and thus pay less or even no fuel taxes. Hence, for each policy, we also calculate the implications for the revenue raised.

Following Small and Rosen (1981), we define consumer surplus as:

$$CS_i = \frac{1}{a_i} max_j U_{ij} \tag{11}$$

where $a_i = \frac{dU_i}{dY_i}$ is the marginal utility of income for household i (see Train, 2009). The researcher only observes the deterministic part of utility V_{ij} and hence expected consumer surplus can be defined as

$$E(CS_i) = \frac{1}{a_i} E[max_j(V_{ij} + \epsilon_{ij})] \tag{12}$$

Assuming an iid extreme value distribution of the error term Small and Rosen (1981)

[20]We calculate this number based on our sample and registrations in the last 3 years.

have shown that the expected consumer surplus can be computed as

$$E(CS_i) = \frac{1}{a_i} ln(\sum_{j=1}^{J} e^{V_{ij}}) + C \tag{13}$$

with C representing an unknown constant. The change in consumer surplus following a policy change can be expressed as

$$\Delta E(CS_i) = \frac{1}{a_i}[ln(\sum_{j=1}^{J^1} e^{V_{ij}^1}) - ln(\sum_{j=1}^{J^0} e^{V_{ij}^0})] \tag{14}$$

where 1 and 0 represent the time period after and before the policy change. The estimated price coefficient is usually employed as an estimate for the marginal utility of income, based on the assumption that an increase in the price leads to a decrease in the consumer's available income to purchase other goods (Train, 2009). We additionally allow for heterogeneity in the price sensitivity and thus the marginal utility of income, defined as the partial derivative of the utility function with respect to price is :

$$a_i = -\frac{\partial U_{ij}}{\partial p_j} = \frac{1}{p}(\alpha_1 - \frac{\alpha_2}{y}) \tag{15}$$

In all three simulated policy changes we assume that household characteristics and the choice set remain the same. Furthermore, at the moment we assume that annual mileage is inelastic with respect to changes in driving costs. However, there is some empirical evidence that mileage is indeed inelastic (i.e. Bento et al., 2009). Similar to Grigolon, Reynaert and Verboven (2018) we argue that our approach is an estimate of an upper bound in terms of revenue and a lower bound in terms of CO_2 reduction. Even if households are not perfectly inelastic in their mileage demand, the desired effects of our simulated policies are still taking place. Agents who reduce their mileage demand as a reaction to higher driving costs may substitute at a slightly lower rate than our model predicts, but the predicted effects of lower emissions or higher tax revenue still occur.

6.1 Fuel Tax

Switzerland already levies a CO_2 tax ('Mineralölsteuer'). Imports of gasoline and diesel are subject to this levy which constitutes an important part of the end user fossil fuel price. In September 2020, the revision of the CO_2 law envisaged further increases in these levies. [21] For the time being, future increases are capped at CHF 0.12 per l of fossil fuel. Hence, we mainly simulate the change in the gasoline and diesel price based on this increase but also simulate the welfare effects of an increase up to CHF 0.3 per l.

Table 6 presents the changes in the adoption probabilities of the four fuel categories and the distribution across the four income quartiles. Perhaps surprising, the likelihood

[21] The actual referendum for this policy takes place on June 13th 2021

to choose a diesel driven car increases, despite higher diesel prices. This effect arises as people substitute from gasoline to diesel driven cars, since the relative increase in driving costs is lower for the latter as these are usually more fuel efficient. Overall, the adoption probability of electric and hybrid cars increases by 0.0003 and 0.0002 respectively. For richer households this increase is slightly more pronounced for hybrids and slightly less pronounced for EVs.

Table 6: CO_2 levy - Change in probabilities

	Overall	1st inc. quartile	2nd inc quartile	3rd inc quartile	4th inc quartile
Gasoline	-0.00077	-0.00077	-0.00076	-0.00077	-0.00078
Diesel	0.00028	0.00027	0.00028	0.00028	0.00028
Electro	0.00030	0.00031	0.00029	0.00029	0.00030
Hybrid	0.00020	0.00019	0.00020	0.00021	0.00021

Notes: 1st quartile: income < 62.9 kCHF, 2nd quartile: 62.9>=income< 93.67 kCHF, 3rd quartile: 93.67>= income<131.7 kCHF and 4th quartile: income >= 131.7 kCHF. Estimation based on sample and specification (3) of Table 3.

In Table 7 we summarise the welfare implications of this counterfactual scenario. The fuel levy leads to a decline in consumer surplus of CHF 6.87 millions in absolute terms or 0.1% relative to the status quo. The relative decrease is stronger for higher income households. We calculate the additional tax revenue and the reduction in the vehicle registration taxes for the hypothetically newly purchased cars. Additional, fuel tax revenue of CHF 773,560 compensates by far for the almost unchanged vehicle taxes of around CHF 900. The levy is regressive since lower income households pay a higher share of their income in terms of this levy, even though in absolute terms we find little heterogeneity between the income groups. Nevertheless, we should note that the new CO_2 levy is charged to any existing vehicle in the car fleet and not only to newly purchased vehicles. Thus the additional tax revenue is significantly higher than the CHF 800,000 projected here. On average, the policy change leads to a very small 0.053% drop in annual CO_2 emissions of the new car fleet. The decrease is again more or less equally distributed between the different income groups.

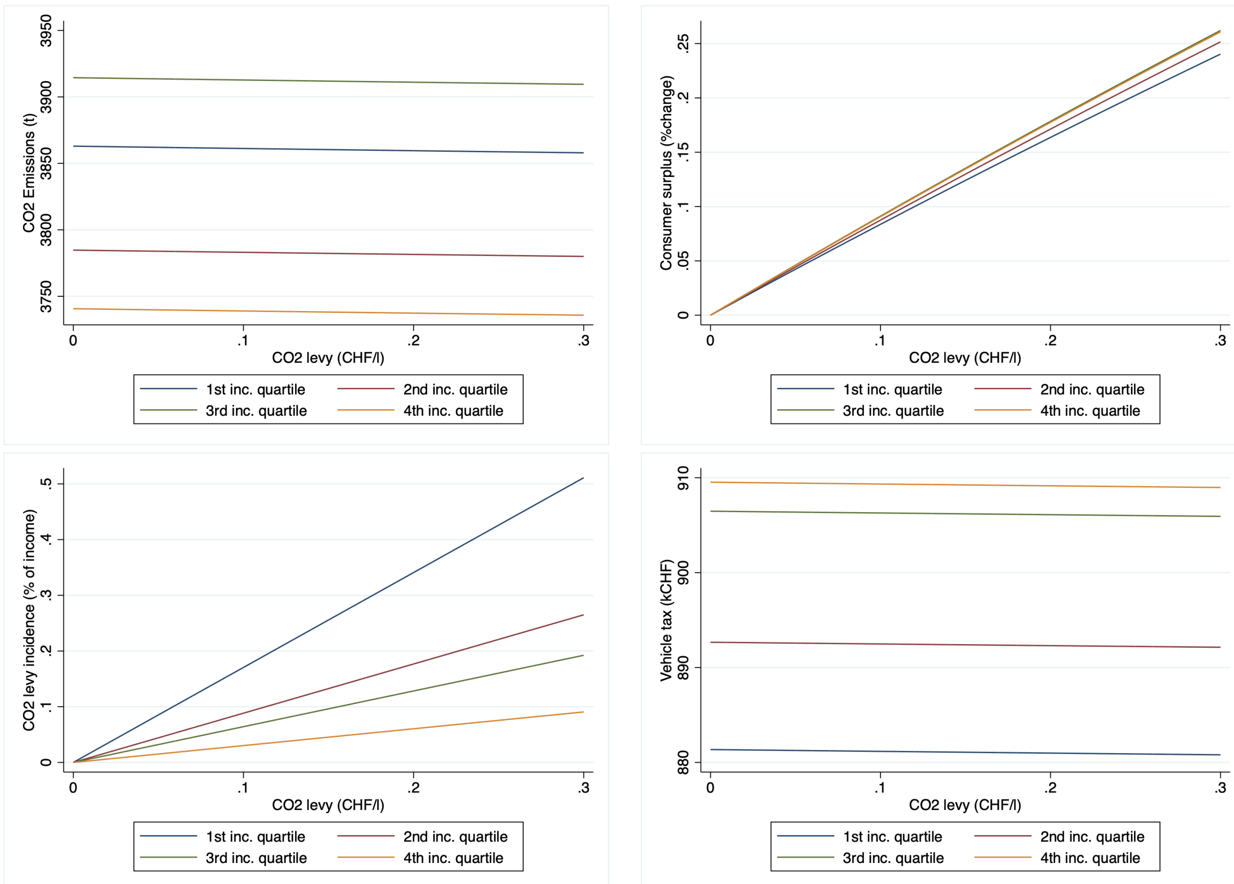
Table 7: CO_2 LEVY - WELFARE

	Cons. surplus (MCHF)	CS (% change)	CO_2 levy (kCHF)	Levy incidence (%)	Car taxes (CHF)	CO_2 (t)	CO_2 (% change)
1st inc quartile	-1.530	-0.0999	195.65	0.204	-228.33	-2.084	-0.054
2nd inc quartile	-1.585	-0.105	191.34	0.106	-217.40	-1.978	-0.052
3rd inc quartile	-1.710	-0.109	197.7	0.077	-223.07	-2.079	-0.055
4th inc quartile	-2.044	-0.108	188.89	0.036	-231.23	-2.027	-0.054
Total	-6.870	-0.106	773.56	0.073	-900.02	-8.171	-0.053

Notes: 1st quartile: income < 62.9 kCHF, 2nd quartile: 62.9>=income< 93.67 kCHF, 3rd quartile: 93.67>= income<131.7 kCHF and 4th quartile: income >= 131.7 kCHF. Estimation based on sample and specification (3) of Table 3. Consumer surplus based on logsum formula.

In a next step we simulate how a variation in the CO_2 levy affects the outcomes of interest. We let the levy vary from 0 to CHF 0.3 per l of fossil fuel and present the average reactions by income quartiles in Figure 3. As expected, the higher the levy, the higher the emission reduction, even though the decline is linear and at a very low rate. In contrast, the incidence of the CO_2 levy linearly increases with a higher tax rate and taxes paid as a share of income are almost three times higher for the poorest compared to the richest households. Higher fuel taxes lead to slightly declining vehicle registration taxes and consumer surplus. Consumer surplus decreases in a similar fashion across income groups.

Figure 3: CO_2 levy - Welfare simulation



Notes: 1^{st} quartile: income < 62.9 kCHF, 2^{nd} quartile: 62.9>=income< 93.67 kCHF, 3^{rd} quartile: 93.67>= income<131.7 kCHF and 4^{th} quartile: income >= 131.7 kCHF.

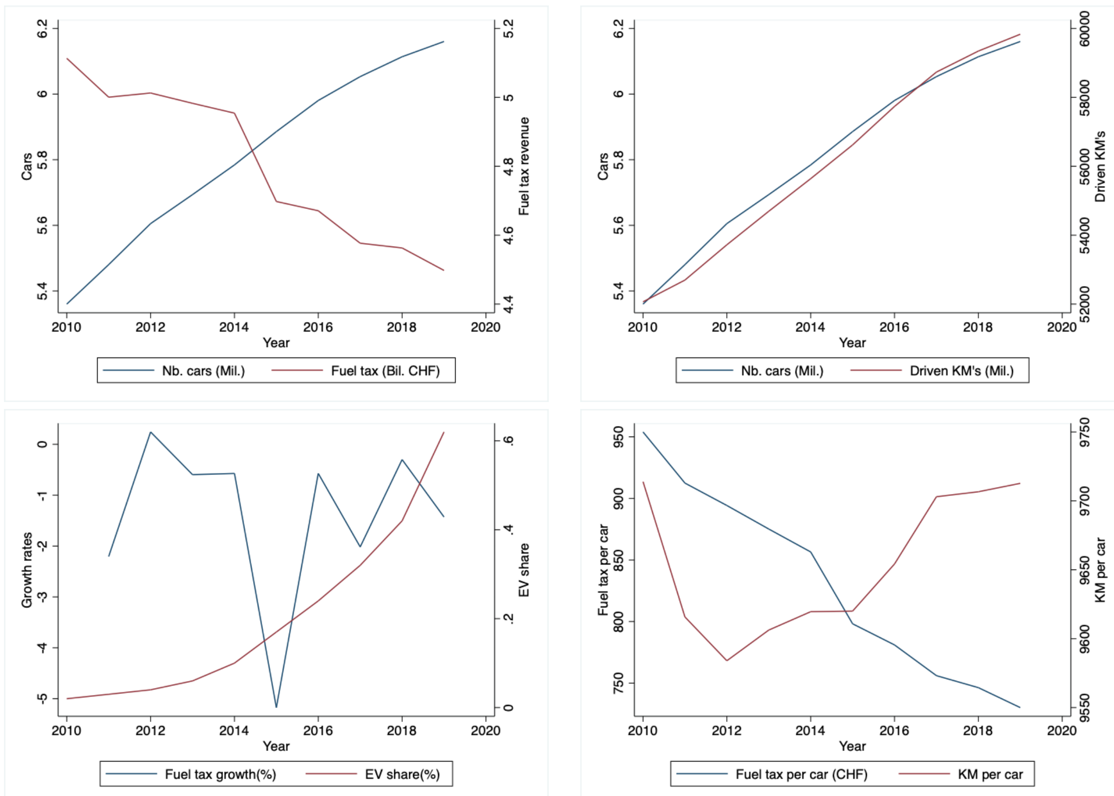
6.2 Mileage Dependent Charge

As mentioned above, an increased adoption of EVs challenges the financing of the road infrastructure (Davis and Sallee, 2019). Many countries use the revenue generated by fossil fuel levies and motor taxes to secure investments in the road infrastructure. However, with increased fuel efficiency, revenues decline. Furthermore, EVs do not consume any fossil fuels and thus do not contribute at all, even though they also need roads and highways. As the top panel in Figure 4 shows, in Switzerland, the overall as well as per car revenue from fuel taxation has been decreasing during the last years, even though the number of registered cars and the amount of total kilometers driven have steadily increased during the same time frame. This has two reasons: First, a higher fuel efficiency [22] and second,

[22] As shown in the lower right panel of figure 4, km driven per car are nearly constant, while tax revenue per car is decreasing. This suggests that cars need less fuel to drive the same distance.

an increasing share of EVs in the total car fleet. Both trends may be desirable from an environmental perspective, however they challenge the security of infrastructure financing. This problem is aggravated if mainly EV owners benefit from preferential tax schemes.

Figure 4: Mileage charge - Motivation



Notes: Based on several statistics from the Swiss department of statistics.

One suggested solution is the introduction of a so-called mileage-dependent charge that either replaces the current motor vehicle tax[23] or the fossil fuel charge or may even complement those. In our counterfactual we assume that the current policy mix is maintained, but the fuel tax revenue per car should correspond to the 2010 level. First, we compute today's hypothetical overall revenue based on this level and the observed growth rate in car registrations. The difference between this simulated and the actual revenue is divided by the overall number of km driven. The annual mileage charge for the year 2019 would amount to 0.023 CHF/km.

Table 8 shows an overall substitution towards gasoline driven cars if such a mileage tax is introduced. The probability to acquire a gasoline driven car increases by 0.18 percentage across all income groups. Households substitute away from the remaining fuel types. The strongest decrease in purchase probability is exhibited for EVs. While in

[23]In the Canton of Bern, this charge is a function of fuel efficiency, fuel type and weight of the vehicle.

percentage points the decrease seems relatively small at 0.0012, in absolute terms the decrease is still quite substantial with 7.2%. This is caused by the increase in driving costs that apply to all vehicles alike. Hence, the relative advantage of EVs in terms of driving costs is lower in this setting.

Table 8: Mileage charge - probability changes

	Overall	1st inc. quartile	2nd inc quartile	3rd inc quartile	4th inc quartile
Gasoline	0.0018	0.0018	0.0018	0.0018	0.0018
Diesel	-0.0002	-0.0002	-0.0002	-0.0002	-0.0002
Electro	-0.0012	-0.0012	-0.0011	-0.0011	-0.0012
Hybrid	-0.0004	-0.0004	-0.0004	-0.0005	-0.0005

Notes: 1st quartile: income < 62.9 kCHF, 2nd quartile: 62.9>=income< 93.67 kCHF, 3rd quartile: 93.67>= income<131.7 kCHF and 4th quartile: income >= 131.7 kCHF. Estimation based on sample and specification (3) of Table 3.

These substitution patterns have welfare implications. Overall consumer surplus decreases by almost CHF 23 millions or 0.35% relative to the status quo. CO_2 emissions increase by 0.35% relative to the status quo (again calculated for a hypothetical annual new car fleet), since more gasoline driven cars are bought. In contrast, both mileage tax as well as car registration tax revenue increase. Furthermore, annual fossil fuel tax revenue also rises since more gasoline driven cars are registered. The numbers presented below only refer to the hypothetical new car fleet. However, all cars would be subject to the mileage dependent charge and accordingly the generated revenue substantially exceeds the presented numbers. The charge is regressive as shown by the higher fraction of taxes paid relative to income for the lowest income households (0.69% vs. 0.25% on average).

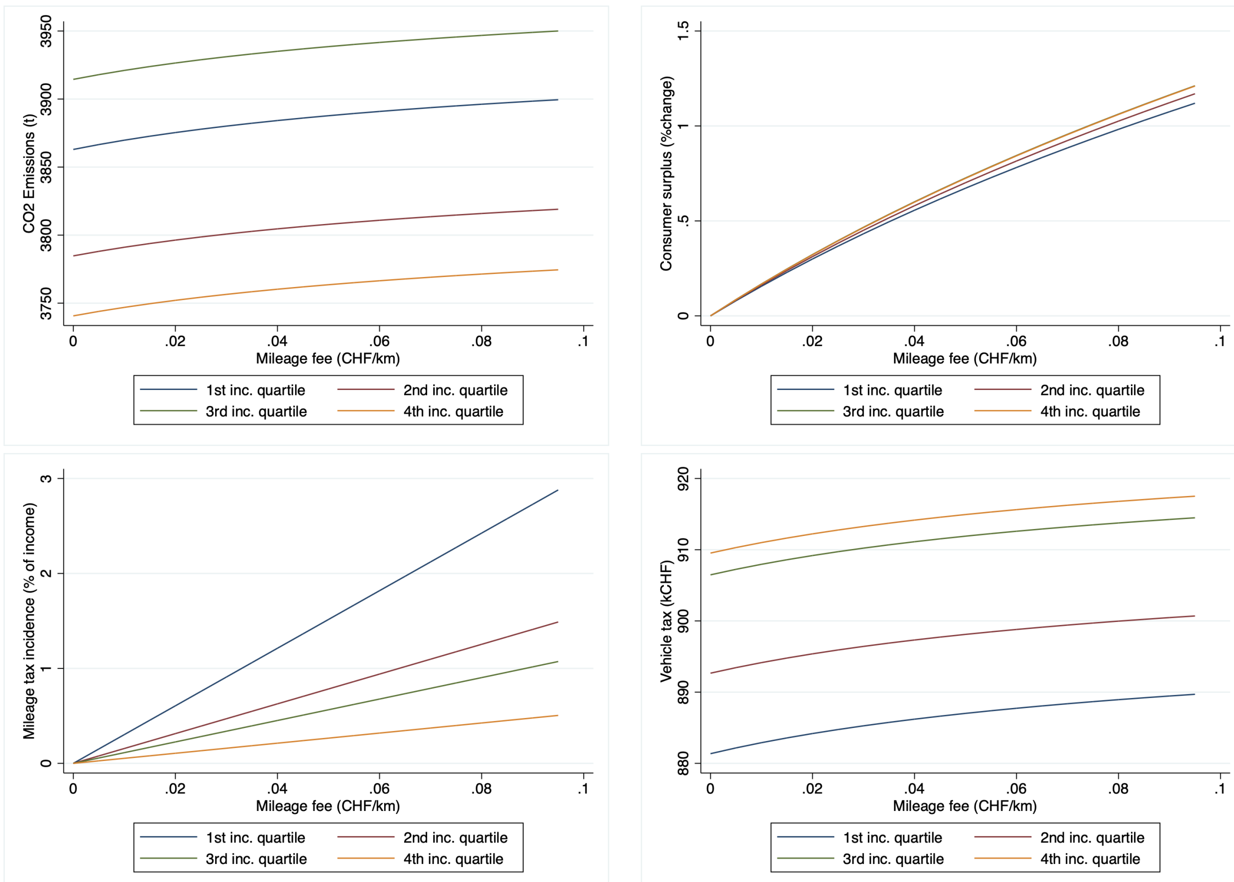
Table 9: Mileage charge - Welfare

	Cons. surplus (MCHF)	CS (% change)	Mileage tax (kCHF)	Incidence (%)	Car taxes (CHF)	CO_2 (t)	CO_2 (% change)
1st inc quartile	-5.212	-0.340	666.69	0.696	3,172	13.924	0.360
2nd inc quartile	-5.375	-0.355	650.21	0.360	3,046	13.004	0.344
3rd inc quartile	-5.764	-0.367	666.65	0.260	3,039	13.478	0.344
4th inc quartile	-6.901	-0.367	636.39	0.122	3,023	12.807	0.342
Total	-23.252	-0.358	2,619.92	0.248	12,279	53.213	0.348

1st quartile: income < 62.9 kCHF, 2nd quartile: 62.9>=income< 93.67 kCHF, 3rd quartile: 93.67>= income<131.7 kCHF and 4th quartile: income >= 131.7 kCHF. Estimation based on sample and specification (3) of Table 3. Consumer surplus based on logsum formula.

Below, we depict the effects for a mileage dependent charge between 0 and CHF 0.1 per km. As indicated in Figure 5, overall emissions increase, but at a decreasing growth rate. In terms of income, mileage taxes paid can even be as high as 2 per cent for households with annual income less than CHF 63,000. The decrease in consumer surplus is almost linear and strongest for the highest income households. Revenue from annual vehicle registration taxes increases, since it becomes relatively less attractive to buy more efficient cars.

Figure 5: Mileage charge - Welfare simulation



Notes: 1^{st} quartile: income < 62.9 kCHF, 2^{nd} quartile: 62.9>=income< 93.67 kCHF, 3^{rd} quartile: 93.67>= income<131.7 kCHF and 4^{th} quartile: income >= 131.7 kCHF.

6.3 Subsidy

The results of the empirical analysis presented in Section 4 above reveal that households are more sensitive with respect to vehicle prices than variable costs. In this counterfactual we simulate the effects of an EV subsidy that complements the existing support mechanisms in the Canton of Bern. The most generous subsidies in Switzerland are paid in the Canton of Ticino and amount to CHF 4,000 per EV purchase. Hence, we show the potential effects of the introduction of such up front price subsidies.

Table 10 presents the changes in probabilities. The likelihood to acquire an EV increases by 0.4 percentage points, whereas all other fuel types are less likely chosen. The substitution mainly stems from gasoline vehicles that have a 0.29 percentage point lower probability of being chosen on average. Lower income households feature slightly higher adoption probabilities, than higher income households. This is likely due to the higher price sensitivity of lower income households. Albeit a relatively weak reaction, it is important to keep in mind the low base level of EV adoption. Our model predicts an average probability of 1.67%. An increase by 0.41 percentage points translates into an average predicted probability of 2.08%, which corresponds to an increase in the number of EVs by almost 25%. Our findings show that the subsidy benefits all income groups and not richer households exclusively. An important caveat applies here though. We model in our framework new vehicle purchase decisions, and the low income group is likely still a relatively well-off sample.

Table 10: EV SUBSIDY - PROBABILITIES

	Overall	1^{st} inc. quartile	2^{nd} inc quartile	3^{rd} inc quartile	4^{th} inc quartile
Gasoline	-0.0029	-0.0031	-0.0028	-0.0027	-0.0028
Diesel	-0.0010	-0.0010	-0.0010	-0.0010	-0.0010
Electro	0.0041	0.0043	0.0040	0.0039	0.0041
Hybrid	-0.0002	-0.0002	-0.0002	-0.0002	-0.0002

1^{st} quartile: income < 62.9 kCHF, 2^{nd} quartile: 62.9>=income< 93.67 kCHF, 3^{rd} quartile: 93.67>= income<131.7 kCHF and 4^{th} quartile: income >= 131.7 kCHF. Estimation based on sample and specification (3) of Table 3.

In Table 11 we present the welfare implications of this counterfactual scenario. The subsidy leads to a slight increase in consumer surplus of 0.025% relative to the status quo. Overall the subsidy costs around CHF 768,000 with a fairly even distribution between the income quartiles. The lowest and the highest income quartiles benefit slightly more than the middle class. At the same time, the changed composition of the hypothetical new car fleet decreases vehicle registration tax revenue by around CHF 11,500. In contrast, CO_2 emissions of the new car fleet are 0.41% lower. This decrease is distributed evenly between the income groups. The subsidy accounts for a decrease of 63 tons of CO_2 or equivalently 0.41% relative to the status quo.

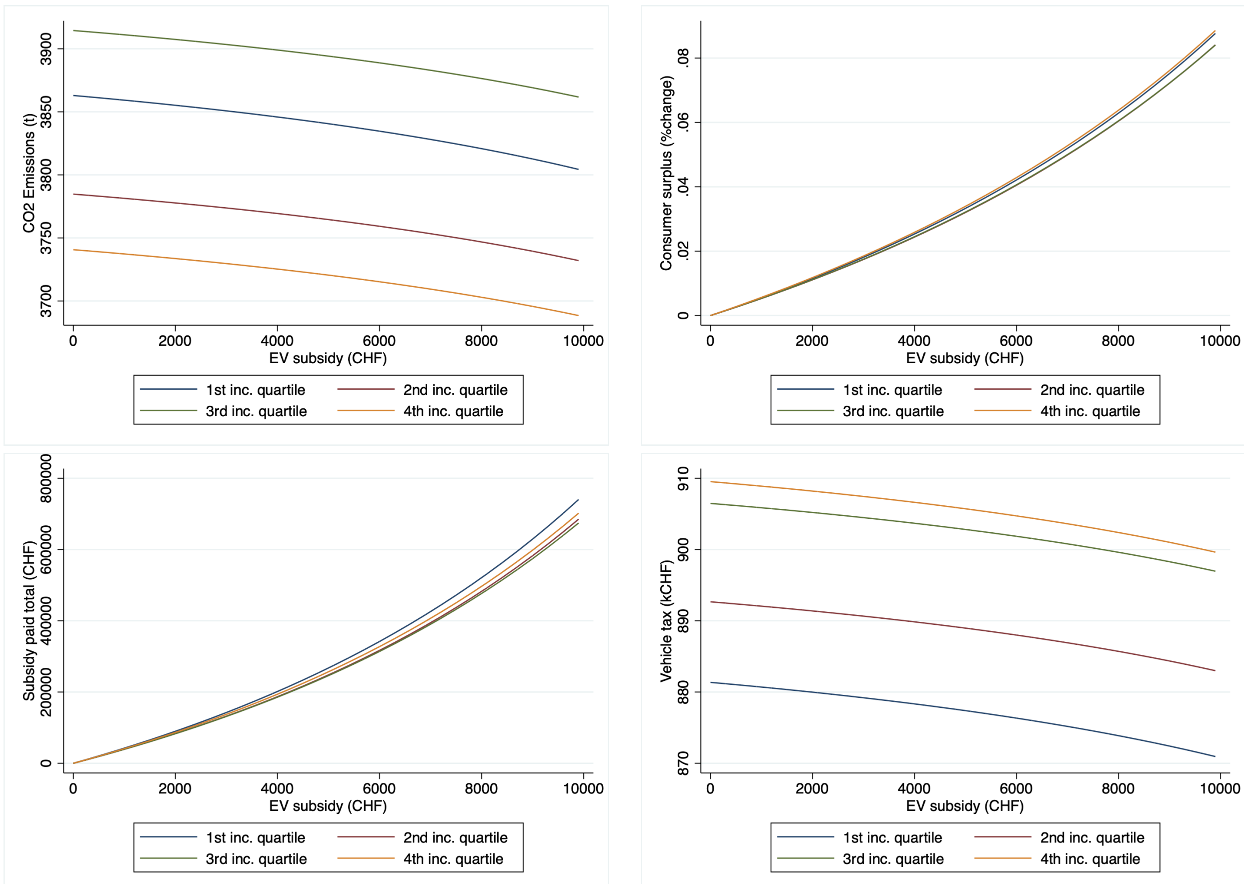
Table 11: EV subsidy - Welfare

	Cons. surplus (kCHF)	CS (% change)	Total subsidy (kCHF)	Car taxes (kCHF)	CO_2 emission (t)	CO_2 (% change)
1st inc quartile	387.93	0.025	201.53	-3.021	-17.057	-0.44
2nd inc quartile	369.37	0.024	186.90	-2.813	-15.376	-0.406
3rd inc quartile	384.51	0.025	185.64	-2.785	-15.485	-0.396
4th inc quartile	487.83	0.026	193.85	-2.905	-15.370	-0.411
Total	1,629.63	0.025	767.91	-11.524	-63.289	-0.414

1st quartile: income $<$ 62.9 kCHF, 2nd quartile: 62.9>=income< 93.67 kCHF, 3rd quartile: 93.67>= income<131.7 kCHF and 4th quartile: income >= 131.7 kCHF. Estimation based on sample and specification (3) of Table 3. Consumer surplus based on logsum formula.

In Figure 6 we depict the effects by varying the degree of subsidy. With higher subsidies, the total amount of subsidy paid grows exponentially, suggesting that higher subsidies lead to higher adoption probabilities. The amounts paid are relatively evenly distributed between the different income groups. At the same time, emissions and vehicle registration tax revenue decrease non-linearly. Lowest income households pay the lowest registration taxes and exhibit the strongest decrease in these taxes with an increasing subsidy. Consumer surplus increases exponentially.

Figure 6: EV subsidy - Welfare simulation



Notes: 1st quartile: income < 72.5 kCHF, 2nd quartile: 72.5>=income< 101.6 kCHF, 3rd quartile: 101.6>= income<138.6 kCHF and 4th quartile: income >= 138.6 kCHF.

7 Conclusion

The increasing CO_2 emissions from the road transport sector and the still very low uptake of EVs call for an in depth analysis of factors that may foster or hinder their adoption. In comparison to previous research we have access to a perfect match between household level data and their cars. Our dataset includes numerous characteristics of the actual registered cars and many observed household socio-demographic variables. Using discrete choice models that account for possible price endogeneity, our findings reveal that households are sensitive with respect to the upfront purchase price and less so with respect to future variable costs. We predict an average probability to purchase an EV of around 1.67% and find little heterogeneity based on income. Furthermore, households living in urban areas and those with a high density of charging stations in their neighbourhood are significantly more likely to purchase an EV.

We simulate several counterfactual policy experiments based on the estimated structural demand model. First, we simulate an increase in the fuel tax by CHF 0.12, which leads to overall little effects in terms of substitution between different fuel types with an 0.03 percentage points higher uptake of EVs but also a higher uptake of diesel driven cars. The increased fuel tax has a negative impact on consumers with a 0.1% reduction in consumer surplus and reduced vehicle taxation revenue and only a small positive environmental impact in terms of a lower emission footprint of the new vehicle fleet of 8 tons. Overall, the reduction in emission is very low and the substitution effects between different fuels are almost negligible. Second, the introduction of a mileage dependent charge increases the uptake of gasoline driven cars at the expense of all other fuel types. The strongest substitution towards gasoline fuelled cars stems from agents that previously chose an EV. Consequently, the CO_2 emissions of the new vehicle fleet also increase by 0.35% or 53 tons respectively. At the same time, consumer surplus decreases by approximately 0.36%, whereas mileage tax and vehicle registrations tax revenue increase. If driving costs now increase for all vehicle types according to their mileage, the previous relative attractiveness of EVs is diluted. Third, we simulate the introduction of a CHF 4,000 price subsidy for EVs. At a total cost of around CHF 1 million, the average probability to acquire an EV increases by 0.41 percentage points, which causes a 0.41% decrease in CO_2 emissions.

These counterfactual exercises illustrate two challenges and an important trade-off that policy makers face. On the one hand, increasing adoption of EVs can be supported through pricing carbon and hence increasing the price of fossil fuels or by subsidies or tax breaks. The increased adoption leads to decreasing negative externalities in terms of CO_2 emissions. On the other hand, increased fuel efficiency and adoption of EVs endangers the revenue needed to finance the road infrastructure. A distribution of the financing burden based on usage could cover the required revenue, however at the cost of impeding future adoption of environmentally friendly cars and hence reduced CO_2 emissions. Furthermore, all tax policy instruments usually exhibit regressive features, causing higher relative costs for lower income households than for higher income households. While we do not find redistributive consequences for the simulated EV subsidy, we should note that the sample of new vehicle buyers likely does not represent the overall population of the canton. The regressive effects may be even stronger than documented, since the demand for new vehicles is a market where higher income households are more likely to participate in[24].

References

Allcott, H. and N. Wozny (2014), Gasoline Prices, Fuel Economy and the Energy Paradox, *Review of Economics and Statistics*, 96(5) , 779-795.

Alberini, A. and M. Bareit (2019), The effect or registration taxes on new car sales and emis-

[24]The cut-off value of CHF 62,900 annual income for the lowest income quartile in the sample of new vehicle buyers is close to the median income in the region of Bern in 2017 in the overall tax population and the median income of CHF 78,000 in the population of car owners.

sions: Evidence from Switzerland, *Resource and Energy Economics*, 56 , 96-112.

Bento, A. M., L.H. Goulder, M.R. Jacobsen and R.H. von Haefen (2009), Distributional and Efficiency Impacts of Increased US Gasoline Taxes, *American Economic Review*, 99(3) , 667-699.

Beresteanu, A. and S. Li (2011), Gasoline Prices, Government Support, and the Demand for Hybrid Vehicles in the United States, *International Economic Review*, 52(1), 161-182.

Berry, S., Levinsohn, J., and Pakes, A. (1995), Automobile prices in market equilibrium, *Econometrica: Journal of the Econometric Society*, 841-890.

Berry, S., Levinsohn, J., and Pakes, A. (2004), Differentiated products demand systems from a combination of micro and macro data: The new car market, *Journal of political Economy*, 112(1), 68-105.

Cerutti,D., A. Alberini and J. Linn (2017), Charging Drivers by the Pound: The Effects of the UK Vehicle Tax System, CERETH Economics working paper series 17/271, CER-ETH - Center of Economic Research (CER-ETH) at ETH Zurich.

Chandra, A., S. Gulati and M. Kandlikar (2010), Green Drivers or Free Riders? An Analysis of Tax Rebates for Hybrid Vehicles, *Journal of Environmental Economics and Management*, 60(2), 78-93.

Davis, L.W. and J. M. Sallee (2019), Should Electric Vehicles Pay a Mileage Tax, *NBER Working Paper*, No. 26072.

Egbue, O. and S. Long (2012), Barriers to Widespread Adoption of Electric Vehicles: An Analysis of Consumer Attitudes and Perceptions, *Energy Policy*, 48, 717-729.

Egnér, Filippa, and L. Trosvik (2018), Electric vehicle adoption in Sweden and the impact of local policy instruments, *Energy Policy*, 121, 584-596.

Gallagher, K.S. and E. Muehlegger (2011), Giving Green to Get Green? Incentives and Consumer Adoption of Hybrid Vehicle Technology, *Journal of Environmental Economics and Management*, 61(1), 1-15.

Gillingham, K., Houde, S. and A. van Benthem (2021) Consumer Myopia in Vehicle Purchases: Evidence from a Natural Experiment, *American Economic Journal: Economic Policy*, forthcoming

Greene, D., A. Hossain, J.Hofmann, G.Helfland and R.Beach (2018) Consumer Willingness to Pay for Vehicle Attributes: What Do We Know?, *Transportation Research Part A Policy Practice*, 118, 258-279.

Goldberg, P.K. and F.Verboven (2001) The Evolution of Price Dispersion in the European Car Market, *Review of Economic Studies*, 68(4), 811-848.

Grigolon, L., M. Reynaert and F. Verboven (2018) Consumer Valuation of Fuel Costs and Tax Policy: Evidence from the European Car Market, *American Economic Journal: Economic Policy*, 118, 258-279.

Holland, S.P., E.T. Mansur and A.J. Yates (2020), The Electric Vehicle Transition and the Economics of Banning Gasoline Vehicles, *NBER Working Paper*, No. 26804.

Jansson, J., Pettersson, T., Mannberg, A., Brännlund, R., and Lindgren, U. (2017), Adoption of alternative fuel vehicles: Influence from neighbors, family and coworkers. *Transportation Research Part D: Transport and Environment*, 54, 61-73.

Krause, R.M., S.C. Carley, B.W. Lane and J.D. Graham (2013), Perception and Reality: Public Knowledge of Plug-In Electric Vehicles in 21 US Cities, *Energy Policy*, 63, 433-440.

Li, S., J. Linn and E. Spiller (2013), Evaluating Cash-for-Clunkers: Program Effects on Auto Sales and the Environment, *Journal of Environmental Economics and Management*, 65(2), 175-193.

McFadden, D. and K. Train (2000), Mixed MNL Models for Discrete Response, *Journal of Applied Econometrics*, 15(5), 447-70.

Mian, A. and A. Sufi (2012), The Effects of Fiscal Stimulus: Evidence from the 2009 Cash for Clunkers Program, *The Quarterly Journal of Economics*, 1107-1142.

Muehlegger E. and D.S. Rapson(2020), Measuring the Environmental Benefits of Electric Vehicles (Relative to the Car That Wasn't Bought, *NBER Working Paper*, No. 27197.

Muehlegger E. and D.S. Rapson (2018), Subsidizing Mass Adoption of Electric Vehicles: Quasi-Experimental Evidence from California, working paper

Petrin, A., and Train, K. (2010), A control function approach to endogeneity in consumer choice models. *Journal of marketing research*, 47(1), 3-13.

Sallee, J.M. (2011), The Surprising Incidence of Tax Credits for the Toyota Prius, *American Economic Journal: Economic Policy*, 189-219.

Small, K.A. and H.S. Rosen (1981), Applied Welfare Economics With Discrete Choice Models, *Econometrica*, 49, 105-130.

Train, K. (2009), Discrete Choice Models With Simulation, Cambridge University Press; 2nd edition.

Train, K. and M. Weeks(2005), Discrete Choice Models in Preference Space and Willingness-To-Pay Space, in Scarpa R.and A. Alberini Eds. *Applications of Simulation Methods in Environmental and Resource Economics. The Economics of Non-Market Goods and Resources*; Vol. 6; Springer.

Train, K. and C. Winston (2007), Vehicle choice behavior and the declining market share of US automakers, *International economic review*, 48.4, 1469-1496.

Xing, J., B. Leard and S. Li (2019), What Does an Electric Vehicle Replace?, *NBER Working Paper*, 25771.

von Haefen, R. H., and Domanski, A. (2018), Estimation and welfare analysis from mixed logit models with large choice sets. *Journal of Environmental Economics and Management*, 90, 101-118.

Appendix

Table 12: Conditional logit estimation

	Total costs				Annual costs		fixed effects			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Car price (log)	−0.232***	−0.232***	−0.232***	−0.227***			−0.133***	−0.130***	−0.111***	−0.022
	(0.03)	(0.03)	(0.03)	(0.03)			(0.03)	(0.03)	(0.03)	(0.04)
Price (log) / income		0.002+						0.003+	0.002+	0.002+
		(0.00)						(0.00)	(0.00)	(0.00)
Price(log) / Wealth								0.000	0.000	0.000
								(0.00)	(0.00)	(0.00)
Driving costs (log pv)	−0.301***	−0.300***	−0.300***				−0.520***	0.790***	−0.032	−0.105
	(0.06)	(0.06)	(0.06)				(0.07)	(0.11)	(0.07)	(0.07)
Variable costs (log pv)				−0.684***						
				(0.08)						
Price (annual)					−0.224***					
					(0.03)					
Variable costs (annual log)					−0.357***					
					(0.06)					
Annual costs (log)						−0.560***				
						(0.04)				
Engine power (KW)	−0.001+	−0.001+	−0.001+	−0.000	−0.001*	−0.000	−0.000	0.003***	−0.002***	−0.001**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Car height	0.367***	0.367***	0.367***	0.453***	0.383***	0.122	0.037	0.701***	0.473***	0.363**
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.08)	(0.12)	(0.13)	(0.09)	(0.13)
Car weight	−0.000	−0.000	−0.000	0.000	−0.000	0.000	−0.000***	−0.000***	−0.000***	−0.001***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Hybrid engine	−0.917***	−0.917***	−0.683***	−0.981***	−0.932***	−0.781***	−1.058***	−0.877***	−0.802***	−0.829***
	(0.21)	(0.21)	(0.16)	(0.21)	(0.21)	(0.21)	(0.21)	(0.21)	(0.21)	(0.21)
Electric engine	−1.635***	−1.635***	−1.626***	−1.988***	−1.727***	−1.342***	−1.745***	−0.820**	−1.367***	−1.349***
	(0.24)	(0.24)	(0.23)	(0.24)	(0.24)	(0.23)	(0.24)	(0.25)	(0.24)	(0.24)
Diesel engine	−0.718***	−0.718***	−0.718***	−0.760***	−0.727***	−0.665***	−0.744***	−0.718***	−0.675***	−0.677***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Car size	−0.143***	−0.143***	−0.143***	−0.127***	−0.135***	−0.149***	−0.049*	−0.102***	−0.157***	−0.041+
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
<u>Size heterogeneity</u>										
2 Persons	0.163***	0.163***	0.163***	0.163***	0.163***	0.162***	0.187***	0.194***	0.163***	0.187***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
3 Persons	0.317***	0.317***	0.317***	0.315***	0.315***	0.316***	0.361***	0.372***	0.317***	0.363***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
4 Persons	0.519***	0.520***	0.519***	0.516***	0.517***	0.518***	0.580***	0.595***	0.522***	0.584***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)
5+ Persons	0.718***	0.719***	0.719***	0.714***	0.715***	0.716***	0.789***	0.808***	0.724***	0.796***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
<u>KW heterogeneity</u>										
40-60 years old	−0.003***	−0.003***	−0.003***	−0.003***	−0.003***	−0.003***	−0.003***	−0.003***	−0.003***	−0.003***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
60+ years old	−0.005***	−0.005***	−0.005***	−0.005***	−0.005***	−0.005***	−0.005***	−0.006***	−0.005***	−0.005***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
<u>EV effects</u>										
EV agglomeration	0.195	0.195	0.312*	0.195	0.196	0.192	0.195	0.195	0.195	0.196
	(0.13)	(0.13)	(0.14)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)
EV rural	−0.202	−0.202	−0.022	−0.202	−0.199	−0.206	−0.204	−0.210+	−0.201	−0.202
	(0.13)	(0.13)	(0.15)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)
Distance to charge	0.053+	0.053+		0.052+	0.053+	0.052+	0.053+	0.053+	0.053+	0.053+
	(0.03)	(0.03)		(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Distance to EV	−0.048*	−0.048*	−0.029	−0.049*	−0.048*	−0.049*	−0.048+	−0.047+	−0.048*	−0.048+
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Nb. Charging (5km)			0.007*							
			(0.00)							
EV 2018	0.138	0.138	0.141	0.129	0.138	0.138	0.063	0.073	0.164	0.100
	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)
EV 2019	1.351***	1.351***	1.355***	1.353***	1.352***	1.337***	1.287***	1.190***	1.345***	1.307***
	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)
Observations	9816000	9816000	9816000	9816000	9816000	9816000	9816000	9816000	9816000	9816000
Nr. of cases	23074	23074	23074	23074	23074	23074	23074	23074	23074	23074
Log Likelihood	−136118.9	−136117	−136118.4	−136095.7	−136114.5	−136071.2	−134941.7	−134360.4	−135830.8	−134617.6
Car type fe	*No*	*No*	*No*	*No*	*No*	*No*	*Yes*	*Yes*	*No*	*Yes*
Car brand fe	*No*	*No*	*No*	*No*	*No*	*No*	*No*	*No*	*Yes*	*Yes*
Environmental category fe	*No*	*No*	*No*	*No*	*No*	*No*	*No*	*Yes*	*No*	*No*

<u>Notes:</u> The presented results represent our estimates based on a maximum likelihood estimation of equation (7). The regression coefficients represent the effect of a change in the variable on the probability that a certain option was chosen. Standard errors are presented in brackets.
* p<0.05; ** p<0.01; *** p<0.001

Table 13: Control functions

	(1)	(2)	(3)	(4)	(5)
Equal fine	0.000 **				
	(0.00)				
Equal fine (lag)		0.000 **			
		(0.00)			
Fine formula			0.000 ***		
			(0.00)		
Fine deviation				0.000*	
				(0.00)	
Fine deviation (lag)					0.000
					(0.00)
Engine power (KW)	0.004 ***	0.003 ***	0.003 ***	0.004 ***	0.003 ***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Car height	−0.468	−0.533	−0.452	0.115	−0.549
	(0.50)	(0.50)	(0.49)	(0.72)	(0.50)
Car weight	0.000	0.000	0.000	0.000	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Car size	−0.118	−0.113	−0.109	−0.186*	−0.134
	(0.08)	(0.08)	(0.08)	(0.09)	(0.09)
drive_cost	−0.023 ***	−0.021 **	−0.045 ***	−0.020 **	−0.022 **
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Diesel engine	0.076 ***	0.077 ***	0.059 ***	0.078 ***	0.076 ***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Electric engine	0.152 **	0.160 ***	0.056	0.166 ***	0.163 ***
	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)
Hybrid engine	0.217 ***	0.217 ***	0.181 ***	0.219 ***	0.224 ***
	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)
BLP instruments	Yes	Yes	Yes	Yes	Yes
Registration year	Yes	Yes	Yes	Yes	Yes
Observations	1240	1240	1240	1122	1201
R^2	0.904	0.904	0.904	0.903	0.902
Brand country	Yes	Yes	Yes	Yes	Yes
Car type	Yes	Yes	Yes	Yes	Yes
Environmental category	Yes	Yes	Yes	Yes	Yes

+p<0.1; * p<0.05; ** p<0.01; *** p<0.001

Coefficients based on pricing equation. Dependent variable is the natural logarithm of price. Estimated standard errors in parentheses. Different specifications based on different calculations methods for the CO_2 standard penalties for vehicle importers. For details of the penalty calculation see section 4.

Table 14: Prediction evaluation - Diesel & Hybrid

Income	Diesel predicted (N)	Diesel actual (N)	Hybrid predicted (N)	Hybrid actual (N)
1^{st} inc. quartile	1,420	1,080	277	187
2^{nd} inc quartile	1,496	1,375	289	272
3^{rd} inc quartile	1,545	1,559	298	289
4^{th} inc quartile	1,559	1,587	302	340
Overall χ^2_3	118.31		Overall χ^2_3	48.91
2^{nd} - 4^{th} quartile χ^2_2	11.27		2^{nd} - 4^{th} quartile χ^2_2	5.59

Notes: 1^{st} quartile: income < 62.9 kCHF, 2^{nd} quartile: 62.9>=income< 93.67 kCHF, 3^{rd} quartile: 93.67>= income<131.7 kCHF and 4^{th} quartile: income >= 131.7 kCHF. Predictions based on sample and specification (3) of Table 3. The critical values are 7.815 and 5.991 for the χ^2_3 and χ^2_2 with a 95% significance level and 11.345 and 9.21 with a 99% significance level respectively.