CESifo WORKING PAPERS

9645 2022

March 2022

# Environmental, Redistributive and Revenue Effects of Policies Promoting Fuel Efficient and Electric Vehicles

*Patrick Bigler, Doina Radulescu*

**Impressum:**

CESifo Working Papers
ISSN 2364-1428 (electronic version)
Publisher and distributor: Munich Society for the Promotion of Economic Research - CESifo GmbH
The international platform of Ludwigs-Maximilians University's Center for Economic Studies and the ifo Institute
Poschingerstr. 5, 81679 Munich, Germany
Telephone +49 (0)89 2180-2740, Telefax +49 (0)89 2180-17845, email office@cesifo.de
Editor: Clemens Fuest
https://www.cesifo.org/en/wp
An electronic version of the paper may be downloaded
· from the SSRN website: www.SSRN.com
· from the RePEc website: www.RePEc.org
· from the CESifo website: https://www.cesifo.org/en/wp

CESifo *Working Paper No. 9645*

# Environmental, Redistributive and Revenue Effects of Policies Promoting Fuel Efficient and Electric Vehicles

## Abstract

We analyze welfare implications of policies promoting environmentally friendly vehicles employing rich Swiss micro-data on 23,000 newly purchased cars and their buyers. Our estimates reveal substantial income heterogeneity in price elasticity and electric vehicle (EV) adoption. While CO2 levies secure road financing revenue, emissions of the new car fleet only slightly decrease. In contrast, subsidies support EV uptake, and lead to a more pronounced emission reduction. Both instruments have redistributive implications. We compute optimal subsidy - fuel tax combinations subject to a pre-specified EV target and to securing road financing in the presence or absence of equity concerns.

JEL-Codes: C250, D120, H230, L620, Q480.

Keywords: electric vehicles, mixed logit, welfare, fuel tax, subsidies, $CO_2$ emissions.

*Patrick Bigler*
*KPM, University of Bern & Oeschger Centre for Climate Change Research*
*Bern / Switzerland*
*patrick.bigler@kpm.unibe.ch*

*Doina Radulescu*
*KPM, University of Bern & Oeschger Centre for Climate Change Research*
*Bern / Switzerland*
*doina.radulescu@kpm.unibe.ch*

The authors gratefully acknowledge the support of BKW Energie AG, Energie Wasser Bern, Energie Thun, the Tax Office of the Canton of Bern, the Swiss Federal Statistical Office, and Canton Bern's Road Traffic Office for providing us the necessary data. We thank Mark Jacobsen, Mathias Reynaert, Matti Liski and Ulrich Wagner as well as congress and seminar participants at the EEA 2020, Research Seminar in Neuchatel, ESS workshop 2020, Mannheim Energy Conference 2021, FSR conference 2021, IEW 2021, Bern Energy Economics Workshop 2021, EARIE 2021, VfS 2021 and the 2021 Summer School on economic foundations for energy and climate policies in Madrid for their valuable comments and feedback. .is paper is part of the project 'Household Preferences for Electric Vehicles and Renewable Energy and the Effect of These Technologies on Electricity Demand' financed by the Swiss National Science Foundation (Project-Nr. 100018 192554=1). Some calculations were performed on UBELIX (http://www.id.unibe.ch/hpc), the HPC cluster at the University of Bern.

# 1 Introduction

According to the International Energy Agency (IEA), the transport sector accounted for one quarter of global $CO_2$ 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 the last years, 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, 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 EV portfolio mandates. Despite the generous government support through 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 analyze households' car choice decision between combustion engine and alternative fuel vehicles to be able to better understand the factors that hinder or foster the diffusion of these technologies in the population (Xing, Leard, & Li 2021, Springel 2021). Furthermore, policies should also be assessed with regards to their impact on environmental outcomes (Bento, Jacobsen, Knittel, & Van Benthem 2020, Holland, Mansur, Muller, & Yates 2016) as well as their potential redistributive implications, which requires an in depth analysis of the effects of tax policy changes or subsidies across the income distribution (Sallee 2011, Durrmeyer 2021).

In this paper we estimate a stylised car choice model and address the welfare implications of a number of counterfactual policy scenarios for the overall sample and by income groups. We first analyze the effects of an additional $CO_2$ levy raised on fossil fuels and the implications of an up-front price subsidy for EVs. In a second step we compute the optimal subsidy-$CO_2$ levy combination from a social planner perspective under different constraints. In many countries, revenue raised by from fuel and motor vehicle taxation is used to fund road transport infrastructure. EVs are subject to preferential tax and tariff treatment while fuel efficient cars benefit from registration tax rebates. While this policy is meant to incentivise the adoption of EVs, hybrid and fuel efficient cars, it also raises equity concerns and may jeopardize the financing of the road infrastructure. Widespread adoption of fuel efficient cars, while desirable from an environmental perspective, may come at a cost in terms of lower public revenues to finance the road infrastructure (Davis & Sallee 2020). At the same time, generous support mechanisms, such as up-front price subsidies also require public outlays. It is thus important that a comprehensive welfare analysis accounts for additional dimensions beyond the change in consumer surplus, namely the impact on public finances and the effect on emissions. Furthermore, such policies may be regressive. Accounting for impacts along the income distribution allows us to address potential equity concerns.

We employ a discrete choice model with a control function approach following Petrin & Train (2010) to estimate households' preferences for new vehicles in the Swiss Canton of Bern

[1] The EU stipulates a fleet-wide emission reduction from new cars by 55% in 2030 compared to 2021.

observing all private new car purchases from January 2017 to June 2019. The perfect match between household and car ownership micro-data allows us to account for a large number of car as well as household specific attributes. In addition to unobserved heterogeneity through random coefficients, we can also control for observed heterogeneity in the valuation of certain car specific characteristics.

We find a strong negative impact of car prices after accounting for potential price endogeneity and significant heterogeneity in different income groups' price sensitivity. Households in our sample react significantly less to changes in variable costs than up-front prices. The average own-price elasticity amounts to -1.87. Our estimates imply substantial income heterogeneity with an average own-price elasticity of -2.18 for households in the lowest and of -1.37 for households in the highest income quartile. EV buyers tend to have more persistent preferences with a substantially higher EV to EV cross-price elasticity. Overall, we predict more than 2 out of 3 registered cars are gasoline driven, while the share of EVs and hybrid cars are relatively low with 1.77% and 4.7% respectively. Lower income households are almost 10 percentage points more likely to purchase a gasoline car than the highest income households. The pattern is reversed for the other fuel type categories. While a household in the lowest income group has a less than 1% probability to purchase an EV, agents in the highest income quartile are almost 2 percentage points or 150% more likely to do so.

The policy experiments reveal that the introduction of an additional $CO_2$ levy only slightly increases the average probability to purchase an EV or hybrid car and has little impact on emission reductions. Furthermore, consumer surplus decreases while the additional income generated by the levy increases public revenue. 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 for a simulated levy of CHF 0.12/l. Second, an EV price subsidy leads to a significant increase in EV uptake. For example, a CHF 4,000[2] subsidy leads to an 0.34 percentage point higher uptake of EVs and an overall increase in consumer surplus and more pronounced emission reductions. Overall subsidy costs are relatively low with less than CHF 1 million additional outlays. This policy also features redistributional effects, as the majority of subsidy payments go to higher income households. Furthermore, we assess the welfare implications of these policy changes. Public revenue impacts outweighs the effects on consumer surplus or emission reductions (all expressed in terms of their monetary equivalents), suggesting that subsidies cost more than they benefit while the revenue generated by additional fossil fuel taxes and the monetary equivalent of emission reductions exceed the reduction in consumer surplus.

The last counterfactual addresses the above mentioned trade-offs related to emission reduction, securing the financing of the road infrastructure and possible equity concerns. Hence, we estimate the optimal policy mix of $CO_2$ levy and EV subsidy from the perspective of a social planner that maximises changes in aggregate consumer surplus subject to generating enough revenue to finance the road infrastructure and achieving a pre-defined EV market share target in the presence or absence of equity concerns. Our results show that a combination of relatively high subsidies (CHF 10,000) and relatively low additional $CO_2$ levies (CHF 0.06 per

[2] 1 CHF $\approx$ 1 USD

l) maximises utilitaristic consumer welfare. If the social planner cares about equity and thus places a higher weight on the utility of lower income households, both subsidy and the levy are substantially lower at CHF 6,300 and CHF 0.03 per liter. This gap, however, narrows, if we allow households to adjust their annual mileage consumption based on higher driving costs. The optimal policy mix then features again a high subsidy (CHF 9,700) and a modest fossil fuel levy (CHF 0.05 per liter) while the emission reduction is almost twice as large. This optimal policy mix leads to substantial increases in the EV share of 34-66% with relatively small additional public outlays of CHF 1.4 to 2.7 millions.

We contribute to several related strands of the literature. First, the estimation of demand on the car market in general (Berry, Levinsohn, & Pakes 1995, Train & Winston 2007, Gillingham, Iskhakov, Munk-Nielsen, Rust, & Schjerning 2019) and agents' preferences for EVs and HVs in particular (Xing et al. 2021, Egnér & Trosvik 2018) with our work closely related to Huse & Koptyug (2021) from a methodological point of view. Second, the valuation of future variable costs relative to the valuation of up-front costs (Grigolon, Reynaert, & Verboven 2018, Gillingham, Houde, & Van Benthem 2021). Most empirical studies use fuel price variation to assess whether or not an energy paradox in the valuation of fuel costs exists. While Grigolon et al. (2018) find only slight undervaluation of fuel costs relative to vehicle prices in a structural estimation of purchases in Europe, Gillingham et al. (2021) use a quasi-experimental setting and find quite substantial consumer myopia. Similarly, Huse & Koptyug (2021) find that both future fuel costs and vehicle registration taxes are undervalued in comparison to upfront costs with registration taxes presenting the strongest undervaluation. Other empirical work on this topic shows mild to moderate undervaluation if any at all (Busse, Knittel, & Zettelmeyer 2013, Allcott & Wozny 2014, Leard, Linn, & Zhou 2021).

Furthermore, we contribute to the literature focusing on the impact of government policies such as subsidies, tax credits, fuel taxes and emission standards on the car market and emission abatement (Li, Linn, & Spiller 2013, Durrmeyer & Samano 2018, d'Haultfoeuille, Givord, & Boutin 2014, Bento et al. 2020) but also the specific market outcomes of policies promoting fuel efficient vehicles (Gallagher & Muehlegger 2011, Muehlegger & Rapson 2018, Chen, Hu, & Knittel 2021). Most studies find that government intervention supports the uptake of more fuel-efficient vehicles but at relatively high costs. Muehlegger & Rapson (2018) for example estimate that California's bill to reach the EV adoption goals by 2025 is quite high at USD 12-18 billion. Additionally, the type of instrument also plays a role, as for example, a sales tax waiver for hybrids is substantially more effective than income tax credits in promoting hybrid vehicles (Gallagher & Muehlegger 2011). Other studies highlight potential windfall gains of subsidies and tax credits since these may promote vehicle purchases by households that intended to buy an environmentally friendly vehicle anyway (Li et al. 2013, Xing et al. 2021, Muehlegger & Rapson 2020, Chen et al. 2021). Closely related is the analysis of the distributional impact of fossil fuel taxes and vehicle subsidies (Bento, Goulder, Jacobsen, & Von Haefen 2009, Sallee 2011, Durrmeyer 2021). Most papers find that subsidies are completely passed through to consumers (Sallee 2011, Muehlegger & Rapson 2018) but governmental interventions redistribute between income groups. Borenstein & Davis (2016) find that 90% of vehicle income tax credits were granted to the highest income quintile, while Durrmeyer (2021) finds that middle income households benefit the most from the French feebate policy. These papers are part of a broader and growing literature analysing distributional consequences of environmental policies (Bento 2013) in various fields such as carbon pricing in general (Ohlendorf, Jakob, Minx, Schröder, & Steckel 2021), electricity markets (Reguant 2019), private photovoltaic (Feger, Pavanini, & Radulescu 2022) and water conservation (Wolak 2016).

Our contribution to the above mentioned papers is manifold. First, our detailed micro-data with a perfect match between households and their newly registered cars features very detailed socio-demographic and car level characteristics. This allows an accurate assessment of the effects of different car characteristics across the income distribution and we are thus able to assess how car prices affect choice probabilities across income quartiles. The heterogeneity in the response to car prices by income group is novel and is important for the assessment of policies such as a subsidisation of EVs, as it allows for a thorough assessment of redistributive impacts. Furthermore, we can also assess cross-price elasticities by income quartile revealing how fuel type substitution patterns vary with income. Second, we compute optimal subsidy-fuel tax combination using a welfare maximisation approach subject to safeguarding the road infrastructure financing while simultaneously achieving a pre-specified environmental target. In addition, our detailed data allows us to compute this optimal policy mix in the presence of equity concerns where the government places a higher welfare weight on the utility of low income households.

The paper is structured as follows. Section 2 provides an overview of the institutional background and in Section 3 we present the empirical strategy. Section 4 provides an overview of the data and some descriptive statistics. Section 5 presents the regression results and is followed by a welfare analysis in Section 6. Finally Section 7 concludes.

## 2 Background and institutional setting

Our empirical analysis relies on data and information on car registrations in the Swiss Canton of Bern which, with an area of 6,000 $km^2$, is the second-largest Swiss canton with just over 1 million inhabitants. The different taxes and support schemes already in place are discussed in the following. Taxes, levies and support schemes in the passenger car sector have two main goals. On the one hand, they should address the various driving-related externalities such as local emissions, global carbon emissions, traffic and accident risks. On the other hand, they are designed as benefit taxes, meaning that the beneficiaries of the publicly provided infrastructure should bear the main share of its costs. Similar to most developed economies, Switzerland employs a wide policy mix to address these issues.

As a small open economy, Switzerland does not have any domestic car manufacturers and each vehicle registered here is imported at some point in time. Thus, vehicles are subject to a 4% import tariff. In order to promote EV adoption, the federal government exempts fully electric vehicles from this tariff. In addition, each imported car is subject to an attribute-based fuel economy standard which is a function of carbon emissions and its weight. Most car brands are represented by general importers which bring the majority of cars into Switzerland.[3] Once a company imports more than 50 cars annually, it has to pay a penalty if emission goals are

[3]Less than 1% of cars was imported by individuals in 2019.

not met. The penalty is calculated on the fleet-wide fuel economy instead of on the single car level.

Furthermore, vehicles are subject to an annual 40 CHF benefits levy that allows highway access. Switzerland has implemented a fuel tax per liter of fossil fuel, aimed at both financing the road infrastructure as well as internalising pollution externalities. In addition, fossil fuel selling companies are subject to a carbon compensation scheme and required to offset parts of their emissions. This rate is increased on an annual basis and amounts to 12% at the moment. Furthermore, regulations stipulate the amount of costs that can be passed through to consumers via the fuel price.

Switzerland is a federal country with 26 different cantons, and hence, various additional regulations exist on regional level. Most cantons levy an annual vehicle registration tax, with the main purpose to finance local road infrastructure. This tax is a function of a car's weight in the Canton of Bern. Fully electric vehicles as well as fuel efficient vehicles benefit from tax reductions during the first four years of car registration. Some cantons also implemented additional measures to promote the adoption of fuel efficient vehicles such as EV subsidies, income tax deductions for fuel efficient cars or support mechanisms for EV charging stations. The Canton of Bern currently has no price or income tax credit incentive in place to promote EVs. However, public charging stations are subsidised.

# 3 Empirical Analysis

In this paper we analyze households' new car choice behaviour in the Swiss Canton of Bern. We employ a unique dataset matching household specific characteristics with detailed information on car ownership and car specific attributes. Since our data includes extensive information on socio-demographic 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 agent specific attributes such as income, age, family size or urbanity.

Starting with the seminal work of Berry et al. (1995), most empirical studies estimating demand, substitution patterns and welfare effects of certain policies in the automobile market employ a random coefficients logit demand model (i.e. Grigolon et al. (2018) or Azarafshar & Vermeulen (2020)). However, due to lack of access to individual level data, these models usually aggregate individual decisions into market shares. One of our dataset's main advantage 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, & 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 & Winston (2007) and Xing et al. (2021) use survey data on household specific characteristics and second choice data to estimate substitution patterns in US car markets. The second choice data in these papers was crucial to precise estimates.

Since we do not observe second choices and observe one market 'only', namely the Canton of Bern, the micro-BLP model is not the adequate approach. 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 would not be sufficient to achieve precise estimates. Hence, we resort to a standard discrete choice model based on an aggregated choice set and individual level socio-economic data, meaning we directly model a utility function and choice probabilities instead of aggregated market shares.

**Utility specification**

Households retrieve utility from owning and using a car, as well as from consumption of other commodities. Households have the choice between various distinct vehicle types with specific characteristics. To be more specific, we model the conditional indirect utility of household *i*, purchasing vehicle type *j* the following way:

$$u_{ij} = \beta_i^x x_j + \beta^z z_i x_j + \alpha_i(\log(p_j) + \gamma \log(G_{ij} + T_j)) + \sum_{l=2-4} \phi_l \log(p_j) d_i^l + \epsilon_{ij} \tag{1}$$

$x_j$ is a vector of car specific characteristics, such as engine power, height, weight and size and $\beta_i^x$ is a vector of coefficients that captures the (individual) valuations of those attributes.[4] The household specific characteristics are summarised by the vector $z_i$, including age, household size and location specific characteristics. We interact household attributes with car specific characteristics that are differently valued by different household types thus capturing observed heterogeneity preference patterns. $p_j$ denotes the price of vehicle type *j*, and $d_i^l$ is a dummy variable indicating if household $i$ belongs to income quartile $l$ ($l \in [2, 3, 4]$). Hence, we allow for heterogeneity in the marginal utility of income based on income level with $\alpha_1$ measuring the baseline log price sensitivity of the lowest income households and $\phi_l$ measuring each household quartiles average deviation from the baseline log price sensitivity. We follow Grigolon et al. (2018) and model the variable costs as present value of lifetime costs. $G_{ij}$ represents the present value of future fuel costs including fuel taxes, and $T_j$ the present value of future car registration taxes which are a function of weight and fuel efficiency. $\gamma$ denotes the future valuation of these costs respectively. It indicates 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. We define the present value of expected fuel costs and the present value of expected taxes as:

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

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

[4] We estimate a distribution of coefficients for various characteristics and thus allow households to individually deviate from the mean valuation of certain characteristics

where $m_i$ represents the annual kilometres 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 $\tau_{js}^g$ the fuel tax which is set to zero for the status quo and then raised to CHF 0.12 / Liter in the counterfactual.[5] 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, $t_{js}$ represents the annual car registration taxes that are levied based on a car's weight and 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 economy, which is in line with previous research (i.e. Bento et al. (2009) or West, Hoekstra, Meer, & Puller (2017)). Hence, mileage is decider specific but choice invariant. Furthermore, we follow the literature and model a household's expectation about future fuel prices to only depend on today's fuel price.[6] In a similar vein, we assume that households do not anticipate or do not have expectations about future tax system changes and only consider the current system when they decide on their car purchase. Following Grigolon et al. (2018), we define a capitalisation factor as

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

which allows us to simplify the two equations for $G_{ij}$ and $T_j$ to write the present value of fuel costs and taxes as

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

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

We can then substitute Equation 5 and Equation 6 into Equation 1 and derive the utility of household *i* from purchasing car type *j* as:

$$u_{ij} = \beta_i^x x_j + \beta^z z_i x_j + \alpha_i(\log(p_j) + \gamma\rho \log(m_i[e_j g_j(1+\tau_j^g)] + t_j)) + \sum_{l=2-4} \phi_l \log(p_j) d_i^l + \epsilon_{ij} \tag{7}$$

To simplify notification we define the deterministic part of utility as $V_{ij}$ and split the utility function into:

$$u_{ij} = V_{ij} + \epsilon_{ij} \tag{8}$$

with

$$V_{ij} = \beta_i^x x_j + \beta^z z_i x_j + \alpha_i(\log(p_j) + \gamma\rho \log(m_i[e_j g_j(1+\tau_j^g)] + t_j)) + \sum_{l=2-4} \phi_l \log(p_j) d_i^l \tag{9}$$

[5] 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 are part of the fuel price $g_{js}$ used to calculate the driving costs. The additionally introduced tax $\tau_{js}^g$ represents an extra levy on top of the already existing taxes.

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

**Estimation**

Inferring the choice probabilities allows us to investigate how households value certain car characteristics and later perform a number of counterfactual scenarios. The estimation of discrete choice 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. Assuming the non deterministic utility component $\epsilon_{ij}$ to be independent and identically distributed with a type 1 extreme value distribution, allows to derive standard logit functional forms for the choice probabilities. This models imply independence of irrelevant alternatives (IIA). In other words, the relative odds of two cars being chosen remain the same independent of the availability of another option (Train 2009). As Berry et al. (1995) point out, the automobile market is unlikely to follow such restrictive substitution patterns.

To overcome the potential bias following from a violation of the IIA assumption we specify the utility function more flexibly by introducing random coefficients. We thus allow for agent's heterogeneous valuation of certain car characteristics. Instead of a single point estimate, we estimate a distribution of certain coefficients. The mixing distribution f($\beta$;$\theta$) is specified for a number of coefficients with $\beta = (\beta_i^x, \alpha_i)$ and $\theta$ being mean and variance parameters to be estimated. Estimating a distribution of coefficients relaxes the independence assumption for the $\epsilon_{ij}$'s. Assuming type 1 extreme value distributed individual and vehicle type specific $\epsilon_{ij}$'s the following formula denotes the probability of household *i* choosing vehicle type *j* (McFadden & Train 2000):

$$P_{ij} = \int \frac{e^{V_{ij}}}{\sum_j e^{V_{ij}}} f(\beta|\theta) d\beta \tag{10}$$

Many candidates exists for the mixing distribution. We resort to a continuous one and assume a normal distribution. We estimate each random coefficient's mean and standard deviation, but no covariance terms between them. Many mixed logit applications use normally distributed coefficients and the heterogeneity in valuation is generally picked up comparably well. A notable exception are bi- or multimodal preference distributions (Train 2016, Bansal, Daziano, & Achtnicht 2018). Since we control for various observed heterogeneity patterns such as, for example, income related price sensitivity or age dependent engine power valuation, we think that potential bi-modal valuation structures are already captured by these and thus do not need to be modelled further in the mixing distribution.

We maximise the log likelihood function consisting of the sum of each household's log probability to purchase each vehicle type using simulated maximum likelihood estimation. We use 100 Halton draws for each individual to estimate the random coefficients.

**Identification**

In addition to the random deviations, the car market, as a differentiated product market, likely exhibits unobserved car specific characteristics correlated with household's derived utility. Those would be subsumed into $\epsilon_{ij}$ and lead to biased price coefficients, as researchers can expect car dealerships to observe such preference patterns. Hence, part of the error term is observed by both consumers and producers but not by the econometrician. Assuming that car manufacturers charge higher markups if they observe their products to have sought-after characteristics, such as, for example, high brand popularity, prices will be correlated with these unobserved product characteristics. Hence, price sensitivity estimates are upward biased. Berry et al. (1995) suggest an instrumental variable approach and Petrin & Train (2010) implement a control function approach to correct biased estimates. We follow the control function approach, but use BLP style instruments as well as a marginal cost shifter inspired by Swiss regulations. Formally we split the error terms into two components: $\epsilon_{ij} = \epsilon_{ij}^1 + \epsilon_{ij}^2$. In this setting, $\epsilon_{ij}^1$ is correlated with the price based on characteristics unobserved by the researcher while $\epsilon_{ij}^2$ is i.i.d extreme value. In a first step, we estimate a log linear pricing equation of the following form

$$\log(p_j) = \beta x_j + \lambda z_j + \mu_j \tag{11}$$

where $x_j$ denotes the car characteristics of vehicle $j$ and $z_j$ is a vector of marginal cost shifters 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 between prices and $\epsilon_{ij}^1$.

We propose as a marginal cost shifter the annual penalties for fleet wide fuel efficiency standards provided by Swiss law. All cars sold in Switzerland are imported and thus globally produced. As a small open economy, we do not expect Swiss consumers' demand to affect global conglomerates vehicle portfolio. Most brands either have a subsidiary company or a unique partner acting as general importer. Since 2012, the federal government has introduced $CO_2$ emission fleet standards for car importers. Firms that import more than 50 cars per year 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.[7]

Penalties are calculated based on the entire fleet imported by either the general importer or a pool of importers together.[8] Emission targets for one fleet are a function of a general target set by law (i.e. 130g $CO_2$ / km in 2019) and additional allowances based on the sales-weighted average weight in comparison to the average weight two years ago. For example, if the fleet is on average heavier (lighter) than the mean car two years before, then the fleet emission target is set higher (lower) than the initial general target. The target calculation thus depends on the weight of the car but also on the registration numbers of certain vehicles within the fleet. This could potentially harm the identification strategy, as the target may be related to demand patterns and pass through of potential penalties may not be identical within the car fleet if importers act strategically. In other words, if the general importer charges a higher share of the potential penalty to popular vehicle models than would be justified by this model's contribution to the deviation from the vehicle fleet goal. We argue that such strategic behaviour is less likely due to the following reasons: First, the general importer is (for most brands) not the only sales agent in the market. Several smaller and regional retail sellers also operate in the market and thus the general importer may not perfectly observe preference patterns for the different vehicle models at a given point in time. Second, the actual penalties are computed in retrospective once the complete vehicle fleet can be assessed, meaning that while the general

[7]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 (approximately 1% of average suggested retail price) or a total of CHF 35 Mn.

[8]Importing companies have the ability to form an emission pool and have their fleet assessed as one importer

importer may have an idea whether they are on track to meet the emission goal or not, they are unlikely to constantly assess the exact deviation. Nevertheless, we calculate the marginal cost shifter in different ways to account for potential concerns regarding strategic behavior.

First, we assume a complete pass through of the policy and the marginal cost increase for each individual car is identical to the amount it would be subject to, if the household imported it directly. In other words, we use the formula based penalty for each vehicle as marginal cost shifter. Hence, potential penalties are charged to consumers, even though at the end of the year, if the emission target is met, the penalty would be zero.[9] Second, importers may not behave strategically and pass on emission standard penalties based on the calculated formulas. We control for this issue, by using the lagged equally distributed penalty as a cost shifter.[10] Third, if importers behaved strategically and distributed expected penalties according to known, but by the econometrician unobserved, preference patterns for certain cars in their product portfolio, then the exclusion restriction would be violated. Hence, in addition to the marginal cost shifter, we also use the classic BLP-style instruments. These are constructed as the sum of characteristics from competitors' vehicle fleet and the sum of characteristics from the own vehicle fleet excluding the chosen option.[11] The relevance assumption is tested through first-stage F-tests.

**Sample and choice set**

We model the purchase decision of households conditional on buying a new car (in the spirit of Train & Winston (2007) as well as Xing et al. (2021)). The dataset includes more than 3,000 distinct make-model-trim-fuel combinations. We follow a common procedure in the literature (i.e. Bento et al. (2009)), and calculate average car characteristics on a level of make-model fuel type combination (i.e. VW Golf diesel or Audi A6 gasoline).[12] Our final choice set includes 489 distinct cars after excluding a few exotic options.[13] Some households have a lower number of options available since not all cars were available in all 3 years of observation.

[9]We tested different calculations of the penalty variables and the formula based is the best performing predictor in terms of $R^2$, AIC and BIC. Detailed regressions are available in Table 11 in the Appendix. We use sensitivity checks to address potential concerns about strategic behaviour of importers that could harm our identification strategy. The third way to calculate penalties assesses for each importer's fleet its specific weight based goal. Penalties are then assessed to each car based on its individual deviation from this fleet-specific goal. Another test is also the deviation from the lagged fleet-specific goal.

[10]For example, if in 2018, an importer was subject to a penalty of CHF 50 Mn. and imported 100,000 cars, we use the penalty of CHF 500 as instrument for each car in 2019.

[11]We also perform a sensitivity check, where we only use the BLP instruments.

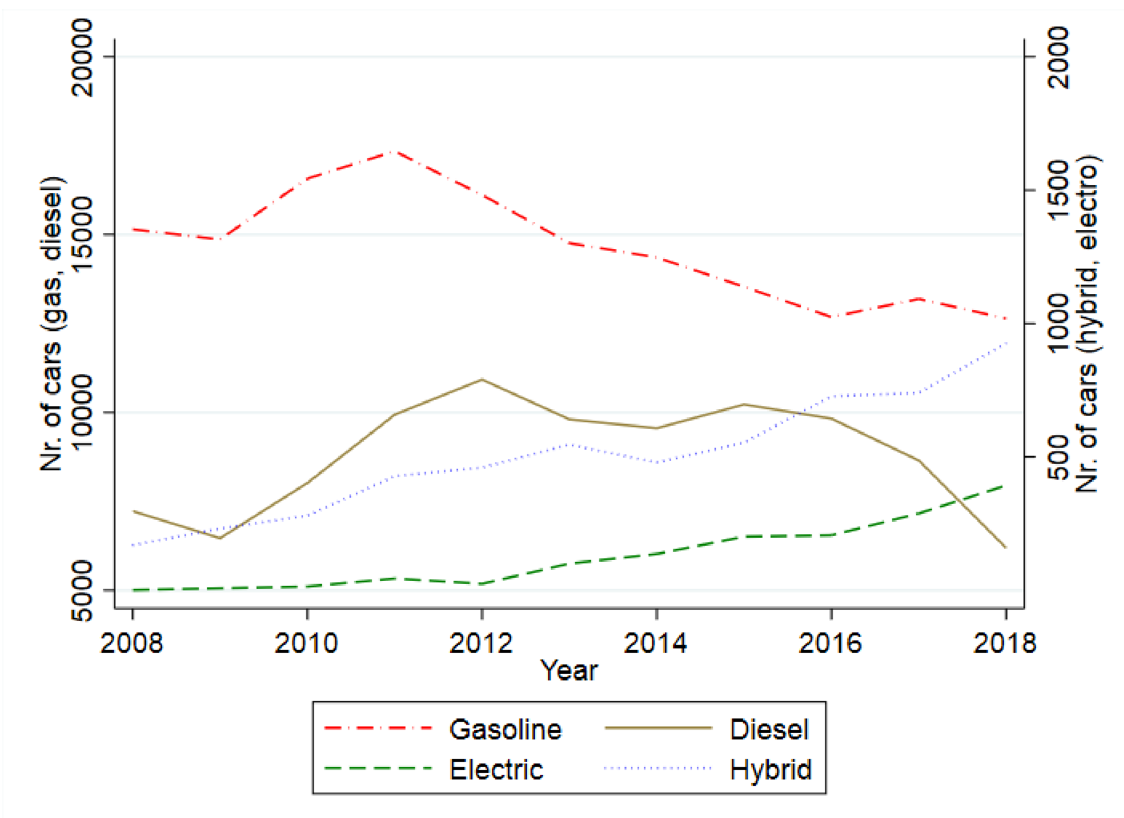
[12]To compute these average values we use actual registration data from all of Switzerland as weights for different vehicle types within the category and collapse the data on an annual basis.

[13]We exclude car options based on pre-defined rules. We exclude cars of brands with less than 5 registrations during our observed time frame overall as well as make - model combinations with 2 or less registrations in any given year. This ensures that results are not driven by outlier preferences. We do not apply those rules for EVs since they are of special interest in our analysis. Low registrations of certain EVs are probably more due to low overall market share than very special characteristics. The options excluded are mainly high priced cars of luxury brands such as Ferrari or Bentley.

# 4 Data

We draw on a unique panel data set on household income, wealth, and further characteristics for the Canton of Bern and the years 2008-2017 provided by the Tax Office of the Canton of Bern. These variables are matched to car registration data from the Canton Bern's Road Traffic Office 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 observe market penetration of the four different drive types (gasoline, diesel, electric or hybrid) over time. Figure 1 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 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



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[14] and we only keep those observations.[15] If a household owned more than one car registered in the last 2.5 years, we keep the car with the most recent registration date, since we consider this the most recent occurrence of revealed preferences.[16]

We collect additional vehicle characteristics such as the brand and type name, fuel economy, engine power and the size of the car from the Swiss Federal Road office. In addition, price data is retrieved from Eurotax, a company that collects historical suggested retail prices. Data is very disaggregated[17] 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...). Furthermore, we observe the import timespan and thus market availability. Since the car type record in the observed choice data is not always as distinct we employ a weighted string match algorithm to match the recorded registration with the closest price data available.[18]

We also include information on automobile taxes and motor vehicle registration taxes. We assume full pass-through and consider the 4% one-off import tariff (automobile tax) as part of the suggested retail price. In addition, vehicle owners pay a cantonal annual vehicle registration tax, which in Bern is a function of car weight, energy efficiency and vehicle age. EVs are subject to much lower rates. Further reductions for EVs and efficient vehicles are rewarded for the first 4 years of registration.[19] We assume a car longevity of 10 years[20] and compute the present discounted value of annual vehicle taxes for a period of 10 years. We follow the literature (Allcott & Wozny 2014, Grigolon et al. 2018, Cerruti, Alberini, & Linn 2019) and assume a discount rate of 6%.[21] The present value of registration tax payments varies between CHF 840 and CHF 5,462 , with a higher average value of CHF 3,312 for conventional cars and a much lower value of around CHF 1,357 CHF for EVs.[22]

[14]We collected vehicle registration data in June 2019 and hence we observe ownership status as of this date.

[15]Matched socio-demographic data is thus collapsed. Income and wealth represent averages. Age and household size are most recent observation.

[16]We do not lose much information by only including one car per household. Only 13% of the households in our entire cross-section (cars aged 0-12 years) own more than one car with vehicle registrations ranging from one to four per agent. Moreover, no household has multiple registered cars during the same year.

[17]The price information is available for around 48,000 distinct vehicle types in our time frame of observation.

[18]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 word 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.

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

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

[21]We also perform sensitivity checks with respect to these values and present the results in Table 12 in the Appendix.

[22]This corresponds to roughly 11% of the average vehicle price, with a much lower value of 3% for EVs.

We define a car's fuel economy as the costs per 100km driven. Fuel efficiency is retrieved from the Swiss Federal Roads Office's TARGA dataset. Efficiency estimates are based on both laboratory as well as driving tests. Fuel prices are measured as the annual average in the year of registration gathered from the Swiss Statistical Office. The Car Registration dataset also includes the number of driven kilometres for some cars. However, this information is not observed for the majority of our sample, since new cars did not have to attend the regular check-up's yet. Thus, we use odometer readings of older cars and different households and estimate a mileage consumption function to impute the average expected annual distance driven.[23] This procedure allows us to calculate the present value of future driving costs based on mileage, average efficiency and average fuel costs.[24]

In Table 1 we summarise 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[25] are less often encountered with 20 and 54 make - model combinations respectively. Taxes and driving costs are lower for EVs, whereas prices are on average similar across categories except for hybrid cars which are more expensive in this sample. The second panel presents the actually observed choices. Almost 70% of registrations are gasoline driven cars. EVs and HVs exhibit relatively low market shares. Gasoline cars display below average prices, weights, engine power and size. In contrast, EVs are on average CHF 20,000 more expensive than corresponding gasoline vehicles. EVs and hybrids feature considerably lower variable costs in terms of taxes and driving. The last panel presents the most frequently purchased vehicle per fuel category. The gasoline driven VW Polo was the most popular vehicle with 419 total registrations. 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.

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 & Long 2012, Egnér & Trosvik 2018). We download coordinates of all charging stations from LEMNET and count the numbers of charging stations within 5km of each household's address. Additionally, we compute the distance to the closest EV. Neighbors may influence adoption of new technology. For example, a constant visual exposure as well as one's neighbours customer experience can influence car choice (Jansson, Pettersson, Mannberg, Brännlund, & Lindgren 2017). The left panel of Figure 2 plots both the share of EVs in total car registrations whereas the number of charging stations per 100 registered vehicles per municipality is presented in the right panel. This allows a graphical assessment of clustering patterns as well as correlation between charging station diffusion and EV adoption. There is heterogeneity in terms of EV registration shares between the different municipalities but little concentration or clustering.

[23]We control for the added variation due to our approach in an additional robustness check. For example, (Alberini & 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.

[24]We again assume a discount rate of 6% and a vehicle holding period of 10 years.

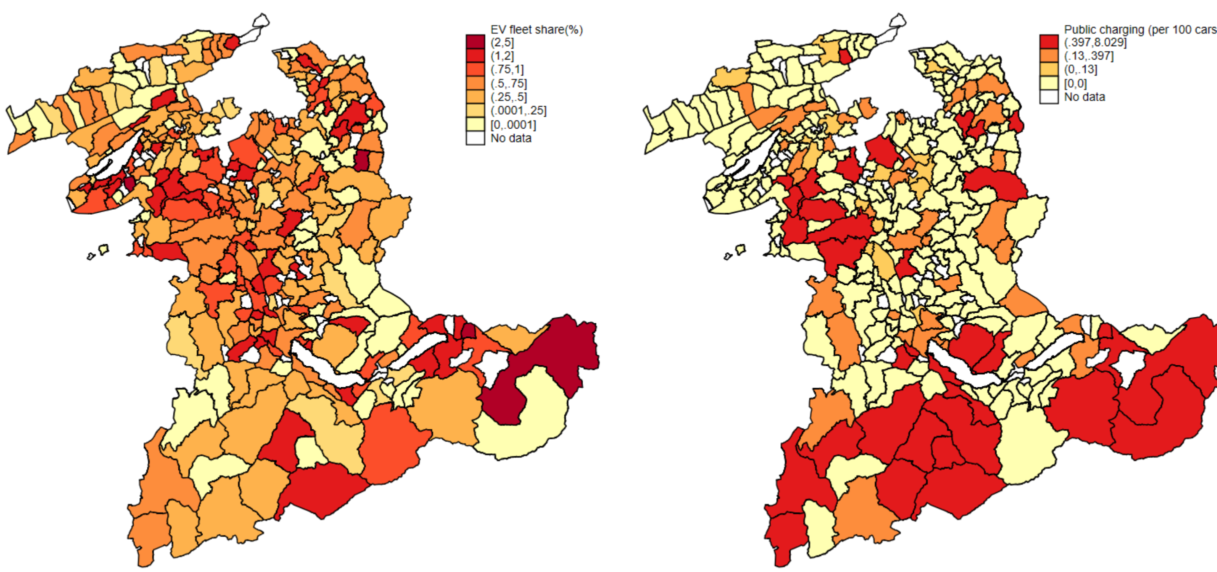
[25]Our dataset does not allow us to distinguish between plug-in Hybrid cars and standard hybrid vehicles and we thus aggregate them into one category.

Table 1: Choice set

| | N | Price (kCHF) | 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 denotes the number of cars per category, whereas the other columns represent 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 column presents the number of households that chose this particular car and the reported car characteristics are the actual values.

Figure 2: EV and charging station diffusion




*Notes:* The left panel shows the EV diffusion normalised by number of registered cars on a community level. The right map shows the number of public charging stations per 100 registered cars on a community level. Both maps were computed by the authors based on data from the Road Traffic Office of Bern as well as charging station data downloaded from LEMNET.

The map reveals that several high adoption municipalities are spread throughout the canton. Public charging stations are most prevalent in the urban centers (i.e. Bern city) as well as in the touristic regions in the South of the canton (i.e. Grindelwald or Gstaad).[26] Furthermore, we illustrate the distribution of households owning an EV and hybrid cars in Figure 5 in the Appendix. The distribution of vehicles throughout the canton roughly corresponds to the distribution of the population with little local concentration. Southern regions with low diffusion are mountainous and thus scarcely populated.

We use information from the Federal Department of Energy to calculate the marginal cost shifter. As mentioned above, each company importing more than 50 cars annually is subject to an average fleet emission assessment. An importer's individual emission target is a linear function of the average vehicle weight within the fleet.[27] Penalties are not based on a brand specific structure, but calculated on general importer information.[28] Overall penalties for each general importer are calculated in five different ways to create a marginal cost shifter for each vehicle in the choice set.[29]

Table 2 presents the summary statistics for some socio-economic and car characteristics for both our final sample of 23,074 households as well as for the subsamples divided by fuel type category.[30] Average household income amounts to CHF 114,000. The mean vehicle price lies at around CHF 35,000. Most variables feature considerable variation, as for instance vehicle prices vary between CHF 8,000 to CHF 210,000. Summary statistics are also presented by fuel type. Mean household income of EV owners is around 50% higher than overall average income. The average distance to an EV charging station is 1.32 km without any significant variability between the different fuel type households. On average agents drive 12,300 kilometres which is in line with previous estimates for Switzerland (i.e. Alberini & Bareit (2019)). However, mileage is quite heterogeneous and varies between 4,100 and almost 30,000 kilometres per year, with diesel car owners driving on average 4,000 kilometres more relative to other categories. 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 an electric vehicle's environmental benefit heavily depends on local factors of electricity production, especially on the energy mix (Holland et al. 2016). Nevertheless, we think in our setting zero emissions from EVs are a safe assumption, as Switzerland relies almost entirely on non-fossil fuel electricity production[31] and the three main providers in the Canton of Bern actually guarantee their customers a certain

[26]This seems plausible for public charging stations with availability in spaces where private parking is scarce (cities) and daily or touristic visits frequent.

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

[28]For example, all brands of the Volkswagen holding are assessed a common penalty, independent of the actual brand they belong to. We assume, that 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.

[29]Detailed calculation of the penalty is described in Section 3

[30]Some household characteristics might be compromised (i.e. 1900 birth year leading to maximum age of 119). We decided to keep those observations, as all socio-demographics are formalized as categorial variables (i.e. Age-group 60+) to prevent bias from outliers or measurement error, but maximise available choices.

[31]According to the Swiss overall energy statistics hydropower accounted for a share of 55% to 60%, while nuclear power accounted for another 30%- 35%. Thermal natural gas plants, as the only fossil fuel based production, accounted for less than 5%.

electricity mix, which does not contain any fossil fuel based electricity.[32]

[32]While this might overestimate the overall environmental benefit, we focus on exhaustion pipe emission, due to data availability. Thus, a consistent comparison should not take electricity emission into account.

## 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 |
| $CO_2$emission (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 & Domanski 2018). In a first step, we estimate maximum likelihood models based on the logit probabilities without allowing for random coefficients. According to Train (2009) a logit specification may capture average preferences fairly robust, even if tastes vary randomly between agents. Column (1) in Table 3 presents the conditional logit (CL) results. In column (2) we add the random deviations (RCL) for each household for three variables - the car price, height and weight. As shown by the estimated standard deviations of the coefficients and the log likelihood value of the specification, the random deviations add little additional explanatory power to the model. In column (3) we additionally control for car type (i.e. SUV) and car brand country of origin (i.e. Germany for Audi).[33] These additional dummies significantly improve the model fit, indicating that there seem to be unobserved brand or car type specific preferences in consumers' utilities. In the specifications presented in columns (4) and (5) we control for the potential price endogeneity by applying the control function approach introduced in Section 3. The estimate of the price coefficient increases in absolute terms compared to columns (1)-(3) which confirms the upward biased estimates if positive correlation between unobserved car characteristics and prices is not accounted for.[34]

Both the up front price as well as the future variable costs display a negative and highly significant coefficient. Moreover, the reaction to the vehicle price is more pronounced, which is in line with previous and recent findings on myopic car consumers (i.e. (Gillingham et al. 2021, Grigolon et al. 2018)). The discrepancy between the upfront cost valuation and the future variable cost valuation becomes more pronounced once we control for price endogeneity. We should note however, that we only examine a subsample of the population, namely new car buyers and hence, in contrast to the aforementioned papers, we cannot draw conclusions about general consumer myopia. Additionally, we do not only control for fuel costs but also for vehicle registration taxes and thus cost salience could be another potential explanation for the undervaluation, which has been found to be the case in Sweden (Huse & Koptyug 2021), the UK (Cerruti et al. 2019) and Germany (Andor, Gerster, Gillingham, & Horvath 2020). Vehicle registration tax is a function of weight with a reduced rate for electric and relatively efficient fossil fuel cars. These reductions are not publicly advertised and households may not be perfectly aware of them. Additionally, taxes are charged once per year in retrospective and new vehicle buyers may be less aware of potential cost savings. Differences between up-front cost and future expected variable cost valuations may also stem from the fact that households anticipate policy changes over the lifetime of their vehicle, such as for instance a future expiration of the temporary annual tax registration reduction. Thus, the undervaluation of variable

[33] We tried to control for brand dummies as well, but this absorbs substantial identifying variation.

[34] The reported standard errors correspond to the square root of the diagonal of the inverse hessian matrix. As elaborated by Petrin & Train (2010) the control function approach and hence the double usage of the data in estimation would require the standard errors to be corrected, as they could potentially be biased. We estimate our main specification RCL-Logit II with bootstrapped standard errors based on 100 random subsample draws of 25% of the sample with replacement. Due to computational limitations a larger sample draw or more replications appear infeasible. Results of the bootstrapped standard errors are available upon request, since the main results are consistent.

costs may be a combination of several factors such as salience, inattention and future policy or price expectations. Coefficients of the other control variables feature the expected sign. Households prefer more powerful, heavier and bigger cars. There is a general preference for gasoline cars and a negative taste for other fuel types such as electric, hybrid or diesel. We find little evidence for unobserved heterogeneity in the random coefficient logit models, as most estimated standard deviations do not significantly differ from zero and are quite small. This indicates that valuation of certain car characteristics seems to vary little between households.

Our detailed data also allows us to control for observed heterogeneity between households. We find significant income heterogeneity in terms of price sensitivity. The coefficients of the interaction terms between price and income groups are positive and increase with higher income quartiles. This translates into lower price sensitivities for households in higher income brackets. Furthermore, bigger households value larger cars to a stronger extent, as all interaction effects are positive and significantly different from zero. Similarly, younger agents prefer more powerful cars.

We also estimate various interaction effects of socio-economic characteristics with EV dummies, to gain a better understanding of EV adoption patterns. We control for the density of charging stations, and find significant positive effects. Households are more likely to buy an EV if there are more charging stations in the vicinity. Home ownership and solar panel ownership also feature positive and significant coefficients. This indicates three potential barriers for adoption. In order to acquire an EV, an agent needs access to a charging point. With an improved public charging infrastructure availability, households are more likely to adopt EVs, which is in line with previous research (i.e. (Springel 2021, Delacrétaz, Lanz, Van Dijk, et al. 2020)). However, the availability of charging infrastructure is not only a public but also a private issue. Households living in their own dwelling can easily install a charging point in their own garage, and thus depend to a lower extent on public charging networks. In addition, households owning a solar panel are significantly more likely to adopt an EV as well. In our opinion, potential synergies between cost efficient self-produced electricity and EV ownership are the likely explanation for this pattern. Moreover, the EV battery as a potential storage device may be another reason for higher adoption probabilities. As suggested by Figure 1, a car registered in 2019 is more likely an EV, than a car purchased in 2017 or 2018, which is confirmed 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. There is no evidence for significant urbanity patterns in terms of EV adoption, which is in line with the graphical analysis in Figure 2.

It is important to assess whether our results depend on model specification or assumptions. We therefore conduct a number of robustness checks. We mainly focus on the identification strategy and the calculation of the future variable costs.[35] Table 12 in the Appendix presents the six different robustness checks. Columns *Sens (1)* to *Sens (4)* correspond to sensitivity anal-

[35]We also test a number of additional technical assumptions. The mainly unchanged results, are available upon request. Further estimations include the following: Estimation with 200 instead of 100 Halton draws, re-defining of EV and Hybrid into the overall category 'alternative fuel vehicle', estimation with bootstrapped standard errors to correct for the double use of data in the control function approach.

Table 3: Regression results

| | (CL) | (RCL) | (RCL-FE) | (RCL-Cont) | (RCL-Cont II) |
|---|---|---|---|---|---|
| Car price (log) | −0.682*** | −0.682*** | −0.481*** | −2.719*** | −2.482*** |
| | (0.04) | (0.04) | (0.04) | (0.04) | (0.11) |
| Variable costs (log pv) | −0.624*** | −0.626*** | −0.439*** | −0.327*** | −0.324*** |
| | (0.08) | (0.08) | (0.10) | (0.10) | (0.10) |
| Engine power (KW) | 0.001*** | 0.001*** | 0.001* | 0.009*** | 0.008*** |
| Car height | 0.459*** | 0.462*** | 0.502*** | −1.668*** | −1.445*** |
| Car weight | 0.000 | 0.000 | −0.001*** | 0.001*** | 0.001*** |
| Hybrid engine | −0.851*** | −0.846*** | −0.562*** | −0.273 | −0.341* |
| Electric engine | −2.637*** | −2.627*** | −1.97*** | −1.840*** | −1.852*** |
| Diesel engine | −0.762*** | −0.7625*** | −0.729*** | −0.560*** | −0.575*** |
| Car size | −0.032 | −0.032 | 0.067** | 0.082*** | 0.076** |
| *Price heterogeneity* | | | | | |
| 2nd inc. quartile | 0.319*** | 0.318*** | 0.321*** | 0.313*** | 0.314*** |
| | (0.04) | (0.04) | (0.04) | (0.04) | (0.04) |
| 3rd inc. quartile | 0.594*** | 0.594*** | 0.589*** | 0.590*** | 0.58*** |
| | (0.04) | (0.04) | (0.04) | (0.04) | (0.04) |
| 4th inc. quartile | 1.272*** | 1.272*** | 1.274 | 1.278*** | 1.259*** |
| | (0.04) | (0.04) | (0.04) | (0.04) | (0.04) |
| *Size heterogeneity* | | | | | |
| 2 Persons | 0.037*** | 0.037* | 0.048** | 0.048** | 0.052** |
| 3 Persons | 0.124*** | 0.145*** | 0.172*** | 0.175*** | 0.186*** |
| 4 Persons | 0.324*** | 0.324*** | 0.371*** | 0.369*** | 0.380*** |
| 5+ Persons | 0.527*** | 0.528*** | 0.595*** | 0.589*** | 0.599*** |
| *KW heterogeneity* | | | | | |
| 40-60 years old | −0.006*** | −0.006*** | −0.006*** | −0.006*** | −0.006*** |
| 60+ years old | −0.008*** | −0.008*** | −0.008*** | −0.008*** | −0.008*** |
| *EV effects* | | | | | |
| EV agglomeration | 0.159 | 0.147 | 0.114 | 0.148 | 0.143 |
| EV rural | −0.09 | −0.118 | −0.136 | −0.102 | −0.122 |
| Distance to EV | −0.019 | −0.02 | −0.052* | −0.02 | −0.016 |
| Nb. Charging (5km) | 0.008** | 0.008* | 0.001 | 0.008* | 0.008* |
| EV - Homeowner | 0.839*** | 0.854*** | 0.765*** | 0.826*** | 0.801*** |
| EV - Solar panel HH | 2.437*** | 2.456*** | 2.42*** | 2.429*** | 2.40*** |
| EV - 2018 | 0.133 | 0.134 | 0.04 | 0.147 | 0.12 |
| EV - 2019 | 1.357*** | 1.351*** | 1.254*** | 1.360*** | 1.306*** |
| *Rand. Coefficients* | | | | | |
| Car Price | | −0.001 | −0.001 | −0.001 | 0.0004 |
| Variable costs | | | | | 0.006 |
| Height | | 0.001 | 0.003 | 0.004 | 0.0006 |
| Weight | | 0.000 | 0.000 | 0.000 | |
| Hybrid | | | | | 0.005 |
| Diesel | | | | | 0.007 |
| Observations | 9,816,000 | 9,816,000 | 9,816,000 | 9,816,000 | 9,816,000 |
| Nr. of cases | 23,074 | 23,074 | 23,074 | 23,074 | 23,074 |
| Log Likelihood | −135,444.9 | −135,444.9 | −133,974.2 | −133,693.1 | −133,696.7 |
| Car type fe | No | No | Yes | Yes | Yes |
| Car brand (country) | No | No | Yes | Yes | Yes |
| Control function | No | No | No | Yes | Yes |

* $p<0.05$; ** $p<0.01$; *** $p<0.001$

Coefficients based on estimated mixed logit models. Estimated standard errors in parentheses for selected coefficients, but mainly suppressed to save space in the table. Model (1) features no random coefficients. Coefficients in Model (4) and (5) are based on the control function approach with estimation of the pricing equation in a separate model based on cost shifters in a first step.

ysis of the variable cost calculation. In column *Sens (1)* we apply a lower discount rate of 2%, since nominal interest rates were mostly close to zero or even negative between 2017-2019. In column *Sens (2)* and *Sens (3)* we calculate the net present value of future variable costs based on alternative holding periods. For column *Sens (2)* we employ a holding period of 6 years which corresponds to the average holding period of new vehicle buyers according to a Swiss survey and column *Sens (3)* employs the expected vehicle maximum lifetime of 25 years used in the literature (e.g. Huse & Koptyug (2021)). In column *Sens (4)* we use constant annual kilometre consumption instead of the imputed values. We employ a mileage of 16,000 km and 12,000 km for diesel and non-diesel cars respectively.[36] The results vary between the different specifications but are mainly consistent in terms of significance, sign and magnitude. The undervaluation of variable costs persists and varies between 7% and 17% with the baseline estimate at 13%. Other coefficients do not change between the different models. In columns *Sens (5)* and *Sens (6)* we conduct robustness checks with respect to the identification strategy. *Sens (5)* uses the lagged equally distributed penalty as well as the BLP instruments as cost shifters in the control function approach to address potential concerns of strategic import behaviour described in Section 3. In column *Sens (6)* we only use the typical BLP style instruments as cost shifters. The results vary slightly, as the coefficients of price and future variable costs differ, but the pattern of stronger up-front cost sensitivity continues to hold. Hence, we apply the coefficients of our preferred specification RCL Cont II in column (5) of Table 3 in the subsequent analysis.

First, we estimate the average predicted probability of a household to choose a certain car type based on the preferred control function specification. 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 1.77% and 4.73% respectively. There is quite substantial heterogeneity in terms of the income groups. A household in the highest income bracket is almost 10 percentage points less likely to buy a gasoline driven car than a household in the lowest income bracket. For the other fuel types, the pattern is reversed. With increasing income, households are more likely to buy a non-gasoline driven car. The difference in probability between the lowest and highest income bracket is around 1.8 percentage points for electric cars, 2 percentage points for hybrid cars and almost reaches 5 percentage points for diesel cars.

We apply a chi-square goodness of fit tests to evaluate how well the model fits the data. Since we do not apply alternative specific constants,[37] the model does not perfectly represent the observed shares in the data. Based on chi-square tests we compare the model predictions with the observed shares in the data. Table 13 in the Appendix presents the results. The model fits the data quite well with a chi-square test statistic of 3.17, if we test the model fit based on fuel types without differentiating between income quartiles. Hence, we can not reject the null hypothesis that the model prediction is significantly different from the observed shares in the population with 99% confidence. Furthermore, we evaluate how well we predict the fuel types based on the average predicted probabilities for each car combination and each income quartile. Our model captures the trend that lower income households are more likely to purchase gasoline vehicles, but not to a full extent. We slightly underestimate the share of gasoline driven cars in the first income quartiles. For the remaining income groups the predictions for

[36] This values were taken over from (Alberini & Bareit 2019) which are based on survey results for Switzerland

[37] Alternative specific constants would entail estimation of an additional 488 coefficients while also absorbing most variation in our data.

Table 4: Predicted probabilities

| | Overall | 1st inc. quartile | 2nd inc. quartile | 3rd inc. quartile | 4th inc. quartile |
|---|---|---|---|---|---|
| Gasoline | 69.56 | 73.51 | 70.86 | 68.69 | 65.17 |
| Diesel | 23.95 | 21.65 | 23.44 | 24.61 | 26.11 |
| Electric | 1.77 | .98 | 1.36 | 1.91 | 2.82 |
| Hybrid | 4.73 | 3.86 | 4.35 | 4.79 | 5.9 |

*Notes:* 1st quartile: income < 62.9 kCHF, 2nd quartile: 62.9<=income< 93.7 kCHF, 3rd quartile: 93.7<= income<131.9 kCHF and 4th quartile: income <= 131.9 kCHF. Estimation based on sample and specification (5) of Table 3.

gasoline cars work quite well and we cannot reject the null hypothesis that predicted numbers and observed numbers are significantly different from each other at the 1% level. The model fit is slightly less accurate for electric vehicles. While the adoption rates are quite well estimated for the lowest income quartile, we overestimate the adoption in the second and third income quartiles and underestimate the adoption rate for the highest income group. The main explanation for the comparably high chi-square statistics stems from the lowest and highest income quartiles, where deviations between predicted and observed variables are higher. In conclusion, our model fits the overall data quite well and there is no significant difference between the observed and the predicted overall market shares. However, if we differentiate between income groups, we slightly underestimate the emerging pattern of higher (lower) gasoline adoption in the lower (higher) income groups and lower (higher) adoption rates of non-gasoline vehicles in the lower (higher) income groups.

In addition, we compute mean own and cross-price elasticities for the whole sample as well as per income quartile. This allows us to compare our results to the relevant literature and to better understand the substitution patterns between the different vehicles and fuel categories. Table 5 presents the overall elasticities. All cross-price elasticities are smaller than -1 and vary between -1.55 and -2.13 with a mean of -1.87. It is important to note that initial probabilities of the four fuel types are quite heterogeneous. Furthermore, the number of options within one fuel type also differs. For instance, households can choose between more than 200 gasoline cars whereas the choice set contains only 20 EVs. The elasticities reflect the relative substitution patterns. For instance, a 1% price increase leads to a decrease in adoption probability of 1.9% for gasoline driven cars and just 1.7% for electric cars. Furthermore, relative substitution between the fuel types seems to be quite similar, albeit of small magnitude. These values are slightly lower than corresponding values from the literature. For example, Xing et al. (2021) estimate an own-price elasticity of 2.6 and Muehlegger & Rapson (2018) find EV own-price elasticities of -3.2 to -3.4. With respect to cross-price elasticities, Xing et al. (2021) estimate a gasoline to EV (to gasoline) average cross-price elasticity of 0.028 (0.029), whereas our estimates are smaller with 0.005 (0.006). Nevertheless, in line with Xing et al. (2021), we also find that EV buyers tend to have a distinct preference for EVs and thus display a substantially higher cross-price elasticity relative to EVs than to other fuel types. These differences in both own- and cross-price elasticity estimates have a number of explanations. First, our analysis focuses on new car buyers in a relatively higher income environment in Switzerland.[38] Furthermore, Xing et al. (2021) use data from 2014 and hence, we believe that the interchangeability between the different fuel types has further grown during more recent years (2017-2019) that are featured in our data. In addition, EV and hybrid car prices have further decreased over time. Range anxiety has also decreased over time and is less of a concern in Switzerland, as public charging network density is comparably high and average daily travel distance is comparably low.[39]

An important feature of our data is that it allows us to calculate the own- and cross-price elasticities also differentiated by income quartile, which is a novelty compared to existing papers. The results are depicted in Table 14 in the Appendix. We find quite substantial differences between income quartiles with an average own-price elasticity of -2.18 (-1.37) for the lowest (highest) income quartile. Lower income groups are substantially more price elastic with respect to combustion engine vehicles and less inelastic for alternative fuel vehicles (EVs and HEVs), whereas for higher income groups the own price elasticity is higher for EVs than for fossil fuel driven vehicles. The pattern of EV buyers having quite persistent preferences and mainly substituting to other EVs is observed for all income groups with higher cross-price elasticity estimates for EV-EV substitution in every income group. The lower own-price elasticities for fossil fuel cars in the higher income groups translate into lower within fuel group cross-price elasticities, meaning that the increase in the price of a specific gasoline driven car, leads to a lower substitution towards other gasoline cars, while most other cross-price elasticities do not change.

Table 5: Implied substitution patterns and elasticities

| | Own | Cross Gasoline | Cross Diesel | Cross Electric | Cross Hybrid |
|---|---|---|---|---|---|
| Gasoline | -1.896 | .006 | .005 | .005 | .005 |
| Diesel | -1.867 | .003 | .003 | .002 | .003 |
| Electric | -1.739 | .001 | .001 | .005 | .002 |
| Hybrid | -1.802 | .002 | .002 | .002 | .002 |

*Notes:* Estimations based on sample and specification (5) of Table 3. The table presents the estimated elasticities based on a 1% price increase, which corresponds to the mean own and cross-price elasticities. All measures are in percentages.

[38]Our estimates of own-price elasticities are close to Train & Winston (2007), who also focuse on buyers of new cars. Muehlegger & Rapson (2018) specifically focus on low- and middle income households.

[39]According to the most recent survey estimate from 2015, the average daily distance travelled by car amounts to 24 km.

# 6 Welfare and Counterfactuals

We simulate two policy changes based on the estimated coefficients. These two policies, namely an increase in the fossil fuel levy and an up-front price subsidy for EVs are common instruments policy makers have introduced in various countries to address the negative environmental externalities from the road transport sector. However, these policies also have heterogeneous effects across the income distribution as well as implications for the revenue raised to finance the road infrastructure. We assume that the annual number of private registered cars amounts to 9,230 in the Canton of Bern,[40] 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 these type of cars benefit from generous motor vehicle tax reductions (Davis & Sallee 2020) and also consume less or no fossil fuel and thus pay less or even no fuel taxes. Hence, besides assessing the effects on emissions, we also compute the change in consumer surplus and the revenue effects of these policies.

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

$$CS_i = \frac{1}{a_i} \max_j u_{ij} \tag{12}$$

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

$$E(CS_i) = \frac{1}{a_i} E[\max_j (V_{ij} + \epsilon_{ij})] \tag{13}$$

Assuming an iid extreme value distribution of the error term Small & Rosen (1981) have shown that the expected consumer surplus can be computed as

$$E(CS_i) = \frac{1}{a_i} \log(\sum_{j=1}^{J} e^{V_{ij}}) + C \tag{14}$$

with $C$ representing an unknown constant. Since we allow for heterogenous deviations from the mean valuation of certain characteristics, the above formula is slightly adapted since the unobserved random terms are integrated out (Train 2015). The change in consumer surplus following a policy change can be expressed as

$$\Delta E(CS_i) = \int \frac{1}{a_i} [\log(\sum_{j=1}^{J^1} e^{V_{ij}^1}) - \log(\sum_{j=1}^{J^0} e^{V_{ij}^0})] f(\alpha, \beta) d\alpha d\beta \tag{15}$$

where 1 and 0 represent the time period after and before the policy change respectively. The estimated price coefficient is usually employed as an estimate for the marginal utility of income,

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

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 allow for heterogeneity in the price sensitivity as described in Section 3 and thus the marginal utility of income is:

$$a_i = -\frac{\partial u_{ij}}{\partial p_j} = \frac{1}{p_j}(\alpha_i + \sum_{l=2-4} \phi_l d_i^l) \tag{16}$$

where $l \in [2, 3, 4]$ and $d_i^l$ is a dummy variable indicating whether or not a household belongs to a particular income quartile.

We assume that household characteristics and the choice set remain the same for both simulated policy changes. Furthermore, we assume that annual mileage is inelastic with respect to vehicle economy (i.e. West et al. (2017)). Similar to Grigolon et al. (2018), households do not change kilometres driven, when variable costs change. Hence, 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 effects of the simulated policies still take 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.

To assess the overall welfare impact of potential policy changes we first calculate the net present value of the annual emission savings and changes in public tax revenue over the assumed vehicle holding period of ten years and apply the discount rate of 6%. Second, we compute the sum of the monetary equivalents of the three welfare components - consumer surplus, change in emissions and public revenue. The change in consumer surplus is defined in Equation 15, the change in public revenue constitutes the net present value of the sum of fossil fuel tax, vehicle registration tax and vehicle tariffs as well as the additional income generated by the levy or subsidy outlays. Carbon emission reductions are expressed in monetary terms using a social cost of carbon (SCC) of CHF 175.[41]

[41] We acknowledge that this is a comparably high value, as for instance US policy currently employs USD 30 as social cost of carbon (SCC). In our opinion, the higher charge is justified on several grounds. First, combustion fuel engines produce additional harmful emissions that are not measured in our data and hence not accounted for (i.e. PM or NOx). A higher SCC captures these effects as well. Second, Switzerland currently charges CHF 96 per t $CO_2$ for heating fuels and is about to increase the charge to CHF 120. Third, more recent research emphasises that IAM models may underestimate the true social costs of emissions. Carleton & Greenstone (2021) estimate a SCC of USD 125 after adjusting discount rates, and point out several additional damages that currently are unaccounted for in the standard models. Pindyck (2019) uses a survey based calculation to estimate a SCC. The mean estimate on expert answers from economists is USD 171. Natural scientists estimate an even higher SCC, which is consistent with recent research. Ricke, Drouet, Caldeira, & Tavoni (2018) estimate the country level median SCC to USD 417. To assess the external costs of Swiss road traffic in 2015, the government employed a SCC of CHF 132.8 with a lower and upper bound of CHF 75.7 and CHF 233.7 respectively (`https://www.are.admin.ch/are/de/home/mobilitaet/grundlagen-und-daten/kosten-und-nutzen-des-verkehrs.html`). The German environmental agency suggests an SCC of EUR 199 for 2020 (`https://www.umweltbundesamt.de/daten/umwelt-wirtschaft/gesellschaftliche-kosten-von-umweltbelastungen#gesamtwirtschaftliche-bedeutung-der-umweltkosten`). In our opinion, the SCC of CHF 175 reflects the more recent developments in the literature. It may be slightly higher, but it also accounts for unmeasured local air pollution effects.

## 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. Furthermore, gas importers are required to compensate a substantial amount of fossil fuel based carbon emissions with different projects. In September 2020, the revision of the $CO_2$ law envisaged further increases in those compensation schemes.[42] Pass through of $CO_2$ compensation was meant to be capped at CHF 0.12 per litre and constitutes our main policy scenario. We also simulate the welfare effects of an increase up to CHF 0.25/l.

Table 6 presents the changes in adoption probabilities for the four fuel categories and the distribution across the income quartiles. Perhaps surprising, the likelihood 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 0.03 and 0.02 percentage points respectively. This increase is slightly more pronounced for EVs and slightly less pronounced for hybrids in the case of richer households. Households substitute away from gasoline driven cars, but the reaction is less than 0.1 percentage points overall, with higher income households more likely to substitute, but at comparable low levels. Overall, the response to the hike in fuel taxes is extremely low, as households value future driving costs to a low extent.

Table 6: $CO_2$ levy - Change in probabilities

| | Overall | $1^{st}$ inc. quartile | $2^{nd}$ inc. quartile | $3^{rd}$ inc. quartile | $4^{th}$ inc. quartile |
|---|---|---|---|---|---|
| Gasoline | -.0693 | -.0552 | -.0631 | -.0719 | -.0869 |
| Diesel | .0253 | .0273 | .0268 | .025 | .0219 |
| Electric | .0279 | .0163 | .0221 | .0305 | .0429 |
| Hybrid | .0161 | .0116 | .0142 | .0164 | .0222 |

*Notes:* $1^{st}$ quartile: income $<$ 62.9 kCHF, $2^{nd}$ quartile: 62.9$<=$income$<$ 93.7 kCHF, $3^{rd}$ quartile: 93.7$<=$ income$<$131.9 kCHF and $4^{th}$ quartile: income $<=$ 131.9 kCHF. Estimation based on sample and specification (5) of Table 3. These numbers reflect percentage point changes.

In Table 7 we summarise the welfare implications of this counterfactual scenario. The fuel levy leads to a decline in consumer surplus of CHF 3.06 millions in absolute terms or approximately 0.12% relative to the status quo. The decrease in both absolute as well as relative terms is stronger for higher income households. We calculate the changes in public revenue accounting for the additional $CO_2$ levy and the changes in vehicle registration taxes, fuel levies and vehicle tariffs for the hypothetically newly purchased cars. Vehicle registration tax, fossil fuel tax and vehicle tariff revenue slightly decrease, as consumers shift to relatively more

[42] The actual referendum did not pass the public vote in June 2021, such that the implementation of further policy changes is uncertain.

efficient models. The $CO_2$ levy is regressive since lower income households pay a higher share of their income in terms of levies, even though in absolute terms we find little heterogeneity between income groups. Nevertheless, we should note that in reality, the $CO_2$ levy would be 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 760,000 projected here. On average, the policy change leads to a very small 0.05% drop in the new car fleet's annual $CO_2$ emissions. The decrease is stronger among wealthier households. Overall, the welfare effect of the policy change is positive with an estimated NPV effect of around CHF 2.6 millions. As the achieved emission reductions from the new car fleet are very small, the overall effect stems from the fact that additional tax revenue outweighs reductions in consumer surplus, especially for lower income households.

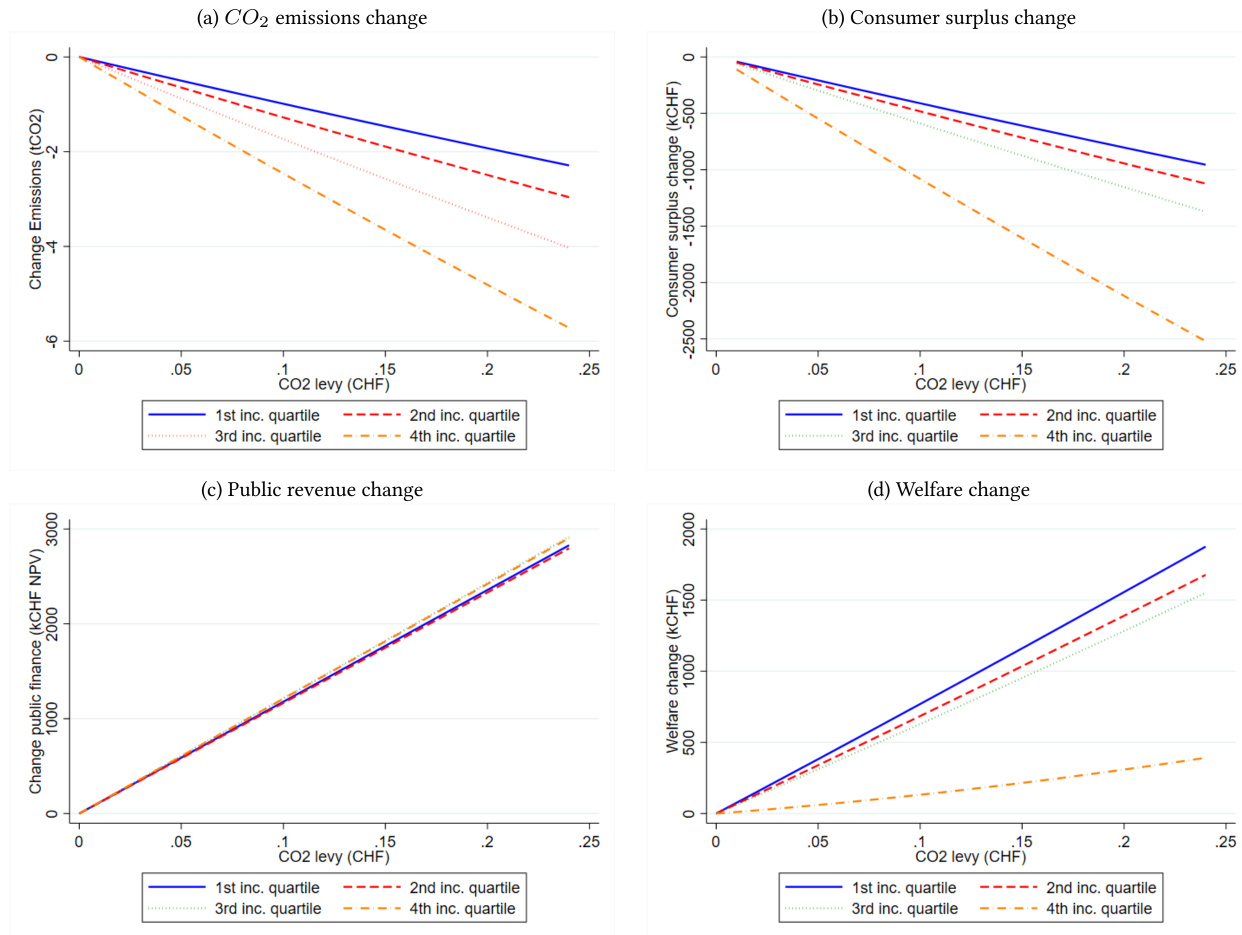
Table 7: $CO_2$ LEVY - WELFARE

| | $1^{st}$ inc. quartile | $2^{nd}$ inc. quartile | $3^{rd}$ inc. quartile | $4^{th}$ inc. quartile | Overall |
|---|---|---|---|---|---|
| Cons. surplus (kCHF) | -490.249 | -576.05 | -704.013 | -1,292.58 | -3,062.89 |
| Change Cons. surplus (%) | -.078 | -.093 | -.112 | -.21 | -.123 |
| $CO_2$ levy (kCHF p.a.) | 192.727 | 190.765 | 199.342 | 198.978 | 782.351 |
| Levy incidence (%) | .201 | .106 | .078 | .038 | .074 |
| Fuel levy (CHF p.a) | -404.682 | -513.027 | -686.387 | -958.25 | -2,576.72 |
| Car registration taxes (CHF p.a) | -113.396 | -165.081 | -236.63 | -362.973 | -878.534 |
| Vehicle tariffs (CHF) | -170.42 | -434.249 | -876.195 | -1,952.29 | -3,436.61 |
| $CO_2$ change (t p.a.) | -1.179 | -1.524 | -2.072 | -2.94 | -7.76 |
| $CO_2$ change (%) | -.031 | -.041 | -.053 | -.075 | -.05 |
| $CO_2$ change (CHF) | 206.385 | 266.699 | 362.544 | 514.556 | 1,358.08 |
| Overall Welfare effect (kCHF) | 925.772 | 824.532 | 758.161 | 164.027 | 2,676.41 |
| Welfare incidence (%) | .131 | .062 | .04 | .004 | .034 |

*Notes:* $1^{st}$ quartile: income $<$ 62.9 kCHF, $2^{nd}$ quartile: 62.9$<=$income$<$ 93.7 kCHF, $3^{rd}$ quartile: 93.7$<=$ income$<$131.9 kCHF and $4^{th}$ quartile: income $<=$ 131.9 kCHF. Estimation based on sample and specification (5) of Table 3. Consumer surplus based on Equation 15. Welfare impact assumes a vehicle lifetime of 10 years and discount rate of 6% to calculate the NPV of public revenue changes and emission reductions. Global social cost of carbon applied is CHF 175 per t $CO_2$.

In a next step we simulate how a variation in the $CO_2$ levy affects the outcomes of interest. We increase the levy progressively from 0 to CHF 0.25/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 (upper left panel). Wealthier households react stronger to changes in variable costs and the recorded emission reductions within this group is higher. In contrast, public revenue increases linearly and changes are evenly distributed between the income groups as presented in the lower left panel. As the upper right panel in Figure 3 shows, consumer surplus is negatively affected by the increase in fossil fuel levies with higher income households exhibiting the most pronounced loss. Overall, the additional public revenue raised outweighs the consumer surplus and emission reduction and hence welfare, defined as the sum of the three components, increases. However, the contribution to public revenues increases homogeneously across income quartiles. This reflects the regressivity of the levy, as lower income households pay a higher share of their income in terms of taxes.

Figure 3: $CO_2$ LEVY - WELFARE SIMULATION




*Notes:* 1st quartile: income $<$ 62.9 kCHF, 2nd quartile: 62.9$<=$income$<$ 93.7 kCHF, 3rd quartile: 93.7$<=$ income$<$131.9 kCHF and 4th quartile: income $<=$ 131.9 kCHF. Estimation based on sample and specification (5) of Table 3.

This analysis shows that increasing fossil fuel levies is a viable way to secure road infrastructure financing, but has little impact on a hypothetical new car fleet's carbon emissions. However, the emission reduction may be higher than estimated if the elasticity of driving is different from zero (Gillingham 2014). Furthermore, increasing fuel levies may lead to earlier retirement of old, fuel-inefficient cars. However, such dynamics are not part of our analysis of new vehicle purchase decisions and are not captured by our estimates.

## 6.2 Subsidy

The results of the empirical analysis in Section 5 reveal that households are more sensitive with respect to vehicle up-front prices than variable costs. In this counterfactual we simulate the effects of an EV up-front price subsidy that could complement 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.[43] Furthermore, it is important to properly account for the substitution patterns induced, as they may involve windfall gains for households that would have purchased a relatively fuel efficient vehicle anyway (Xing et al. 2021, Chen et al. 2021).

Table 8 presents the changes in probabilities, following the introduction of the subsidy. The likelihood to acquire an EV increases by 0.34 percentage points overall, whereas all other fuel types are less likely chosen. The substitution mainly stems from gasoline vehicles that have a 0.24 percentage point lower probability of being chosen. Households belonging to the highest and lowest income quartile feature slightly lower adoption probability changes. This is due to the higher price sensitivity of lower income households and the already substantially higher EV adoption rates of highest 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 1.77%. An increase by 0.34 percentage points translates into an average predicted probability of 2.11%, which corresponds to an EV market share increase of almost 20%. Our findings show that the subsidy leads to adoption probability increases across all income groups and not only for richer households.

Table 8: EV subsidy - probabilities

| | Overall | $1^{st}$ inc. quartile | $2^{nd}$ inc. quartile | $3^{rd}$ inc. quartile | $4^{th}$ inc. quartile |
|---|---|---|---|---|---|
| Gasoline | -.2417 | -.2294 | -.2525 | -.2754 | -.2097 |
| Diesel | -.0775 | -.0625 | -.0774 | -.0912 | -.0787 |
| Electric | .3359 | .304 | .3455 | .3861 | .308 |
| Hybrid | -.0167 | -.0121 | -.0156 | -.0194 | -.0196 |

$1^{st}$ quartile: income $<$ 62.9 kCHF, $2^{nd}$ quartile: 62.9$<=$income$<$ 93.7 kCHF, $3^{rd}$ quartile: 93.7$<=$ income$<$131.9 kCHF and $4^{th}$ quartile: income $<=$ 131.9 kCHF. Estimation based on sample and specification (5) of Table 3. All changes depicted in percentage points.

Table 9 presents the counterfactual welfare effects. The subsidy leads to a slight increase in consumer surplus of 0.027% relative to the status quo. Overall the subsidy costs around CHF 776,000 with a fairly heterogenous distribution between the income quartiles. Agents in the highest income quartile receive more than twice the subsidy payments compared to the ones in the lowest income quartile, because wealthier households have an initially higher propensity to purchase an EV. At the same time, the changed composition of the hypothetical new car fleet decreases vehicle registration tax revenue by a negligible amount of CHF 9,400. In contrast,

[43] An overview of further support mechanisms can be found here: `https://www.swiss-emobility.ch/de/elektromobilitaet/Foerdermassnahmen/#anchor_b8547d00_Accordion-Kantone`. Similar subsidies are also in place in the Cantons of Valais and Thurgau, but to a slightly smaller extent.

$CO_2$ emissions of the new car fleet are 0.34% lower and the decrease is distributed evenly between the income groups. The subsidy accounts for a decrease of 52 tons of $CO_2$ annually, which corresponds to a monetary value of almost CHF 9,200 applying the social cost of carbon of CHF 175/t$CO_2$. The public budget changes contain the net present value of reductions in annual vehicle registration taxes as well as fossil fuel tax revenues, but also the one-off subsidy payments and reduction in vehicle tariff income.[44] The overall welfare impact amounts to CHF -283,273 and is the sum of consumer surplus changes, NPV of emission reductions and NPV of public budget changes. Thus, similar to the fossil fuel levy counterfactual, public revenue changes dominate both consumer surplus increases and annual emission reductions.

Table 9: EV SUBSIDY - WELFARE

| | $1^{st}$ inc. quartile | $2^{nd}$ inc. quartile | $3^{rd}$ inc. quartile | $4^{th}$ inc. quartile | Overall |
|---|---|---|---|---|---|
| Cons. surplus (kCHF) | 92.973 | 124.538 | 174.326 | 270.7 | 662.537 |
| Change Cons. surplus (%) | .015 | .02 | .028 | .044 | .027 |
| Total subsidy (kCHF) | 118.709 | 157.095 | 211.54 | 288.739 | 776.515 |
| Fuel levy (CHF p.a) | -3,628.67 | -4,086.55 | -4,796.65 | -3,852.28 | -16,362.7 |
| Car registration taxes (CHF p.a) | -1,981.71 | -2,340.03 | -2,730.89 | -2,366.78 | -9,421.43 |
| Vehicle tariffs (CHF) | -8,977.79 | -11,084.3 | -13,628.4 | -13,382 | -47,086.4 |
| $CO_2$ change (t p.a.) | -11.598 | -13.091 | -15.387 | -12.384 | -52.457 |
| $CO_2$ change (%) | -.306 | -.348 | -.391 | -.314 | -.34 |
| $CO_2$ change (CHF) | 2,029.68 | 2,290.98 | 2,692.69 | 2,167.28 | 9,180 |
| Overall Welfare effect (kCHF) | -61.069 | -74.08 | -86.427 | -61.242 | -283.273 |
| Welfare incidence (%) | -.009 | -.006 | -.005 | -.002 | -.004 |

*Notes:* $1^{st}$ quartile: income $<$ 62.9 kCHF, $2^{nd}$ quartile: 62.9$<=$income$<$ 93.7 kCHF, $3^{rd}$ quartile: 93.7$<=$ income$<$131.9 kCHF and $4^{th}$ quartile: income $<=$ 131.9 kCHF. Estimation based on sample and specification (5) of Table 3. Consumer surplus based on Equation 15. Welfare impact assumes a vehicle lifetime of 10 years and discount rate of 6% to calculate the NPV of public revenue changes and emission reductions. Global social cost of carbon applied is CHF 175 per t $CO_2$.

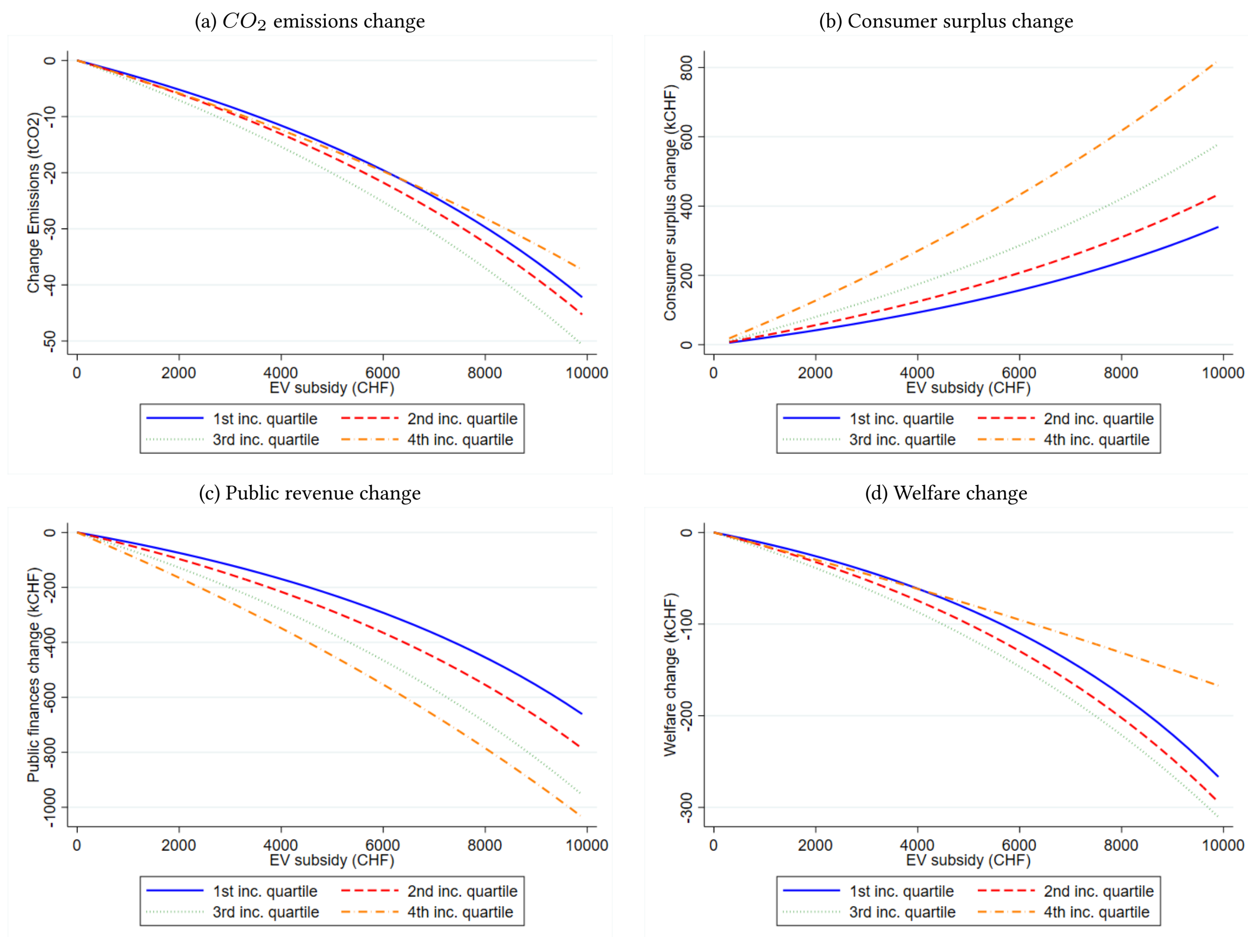
In Figure 4 we depict the effects by varying the subsidy from zero to CHF 10,000. With higher subsidies, the emission reductions grow exponentially, suggesting that higher subsidies lead to higher EV adoption probabilities at an increasing rate, especially for middle income brackets. Consumer surplus increases non-linearly with a more pronounced reaction for higher income groups. At the same time, revenues raised from the different taxes[45] decreases non-linearly and at a higher rate for higher income households. This heterogeneous effect is mainly driven by the higher propensity to purchase EVs by high income households, which makes them more likely to collect subsidy payments. The lower reduction in public revenues (lower left panel of Figure 4) for the lower income groups, indicates that the contribution to road financing from lower income households changes less, while they simultaneously receive less subsidy payments. Hence, the subsidy also raises redistributive concerns. One should note

[44]Revenues from vehicle tariffs are also lower since EVs are exempt from the 4% tariff and due to the subsidy now more likely to be bought.

[45]The curve depicts the sum of the one-time subsidy payment and reduction in vehicle tariff income as well as the net present value of the annual reduction in fossil fuel and vehicle registration tax income.

however, that in absolute terms the contribution of higher income agents is still higher, since they tend to have more expensive, heavier and less-fuel efficient vehicles leading to higher overall public revenue contributions. In total the subsidy features negative welfare effects since the negative repercussions on public revenue outweigh changes in emissions and consumer surplus.

Figure 4: EV SUBSIDY - WELFARE SIMULATION




*Notes:* 1st quartile: income < 62.9 kCHF, 2nd quartile: 62.9<=income< 93.7 kCHF, 3rd quartile: 93.7<= income<131.9 kCHF and 4th quartile: income <= 131.9 kCHF. Estimation based on sample and specification (5) of Table 3. Subsidy increased from 0 to CHF 10,000.

However, in terms of emission reduction of the new car fleet the subsidy is relatively more effective than the increased fuel levy, as households react stronger to up-front vehicle prices than to variable costs. For instance, the simulated carbon emission reduction of roughly 8 t $CO_2$ with the CHF 0.12 fossil fuel levy would be achieved by a subsidy as low as CHF 700. Nevertheless, subsidies require additional government outlays and come at relatively high costs. Abatement costs amount to CHF 2,011 per t $CO_2$ if only emission reductions are taken into account. If all public revenue changes and consumer surplus changes are accounted for, the abatement costs are considerably lower at CHF 908, which is comparable to the costs implied by the income tax credit in California (Xing et al. 2021) but still substantially higher than for example EU ETS prices, which amounted to EUR 25 in 2019.[46] Furthermore, subsidies have redistributive implications, as higher income households are the main beneficiaries, due to their higher initial propensity of EV adoption. Furthermore, the increased electrification of the vehicle fleet leads to lower public revenues, as the annual overall fossil fuel consumption decreases, which also decreases annual fuel tax income (Davis & Sallee 2020).[47]

## 6.3 Optimal policy under constraints

The two instruments involve trade-offs with regard to potential policy goals such as achieving emission reductions while safeguarding road infrastructure financing and accounting for equity concerns. Hence, we compute the optimal subsidy-fuel levy combination from the perspective of a social planner that maximises welfare subject to achieving a pre-specified EV registration share and securing enough revenue to finance the road infrastructure. Furthermore, we also account for potential equity concerns by assigning a higher welfare weight to consumer surplus changes of lower income households. To be more specific, we solve the following optimization problem under various constraints:

$$\max_{\tau_j^g, \eta_j^g} = \sum_{i=1}^{N} \left(\frac{1}{y_i}\right)^{\kappa} \int \frac{1}{a_i}[\log(\sum_{j=1}^{J^1} e^{V_{ij}^1}) - \log(\sum_{j=1}^{J^0} e^{V_{ij}^0})] f(\alpha, \beta) d\alpha d\beta \tag{17}$$

where $\tau_j^g$ denotes the level of fossil fuel levy for vehicle $j$ of fuel type $g$ and $\eta_j^g$ is subsidy for vehicle $j$ of fuel type $g$. $y_i$ is household $i$'s income in CHF and $\kappa \in [0; 1]$ indicates whether the social planner cares about redistribution ($\kappa = 1$) or not ($\kappa = 0$) (Saez 2002). We maximise the (un-)weighted sum of consumer surplus changes of all households $N$,[48] choosing from all vehicles $j$ as a function of the subsidy $\eta_j^g$ and the fossil fuel levy $\tau_j^g$, in comparison to the status quo (state 0), where both parameters $(\eta_j^g, \tau_j^g)$ are equal to zero. Both policy instruments are constrained at zero and capped at CHF 10,000 for the subsidy and CHF 0.25/l for the fossil fuel tax. Policies are simulated in increments of CHF 100 for the subsidy and CHF 0.01 for the tax respectively. These range constraints ensure that we do not extrapolate too far away from the actually observed variation in our estimates and thus we stipulate realistic policy boundaries. Additionally, two formal constraints represent policy targets and restrict the set of potential optimal policy combinations.

First, we set an environmental target as an EV market share, which corresponds to often stipulated and communicated policy targets or milestones.[49] The share of electric vehicles in

[46] These numbers correspond to the simulated subsidy of CHF 4,000 and emission abatement of 52 t $CO_2$

[47] This effect is stronger for higher income households, as they are the major EV adopters and thus the main beneficiaries of car taxes and tariff rate reductions and fossil fuel tax exemptions.

[48] N denotes the number of households purchasing a new car in a given year. As previously N thus is 9,230. As we observe choices over several years, individual outcomes are calculated and averaged to then being assessed for the hypothetical fleet. In terms of consumer surplus all household's are weighted equally but the outcome is reduced to the hypothetical fleet size.

[49] Another potential target are fleet wide average emissions, such as the official Swiss target of 130g $CO_2$/km

new car registrations for a given year $s$ is a function of vehicle type adoption probabilities $P_{ij}$ (as defined in Equation 10). Hence,

$$S_s^{EV} = \frac{1}{N}\sum_{i=1}^{N}\sum_{j}^{K} \mathbb{1}_{g=EV} P_{ij} \tag{18}$$

$N$ denotes the sample size and $\mathbb{1}_{g=EV}$ is equal to 1 for BEVs and zero otherwise. $K$ denotes the set of available vehicles.

The Swiss 'Roadmap Elektromobilität' stipulates that 15% of newly registered vehicles should be EVs in 2022.[50] This target also includes plug in hybrids. Thus if we only consider battery electric vehicles (BEVs) the target amounts to 8.25%.[51] Such a BEV registration share in 2022 is attainable with an annual registration share growth rate of 0.43. However, in most recent years, growth has been smaller. Thus, to attain the 2022 policy goal of 8.25% and assuming a constant growth rate[52], the target of EVs in newly registered cars is set to 2.31% for the year 2018. In other words, if the share of EVs in newly registered cars was 0.0231 in 2018, and registration shares continued to grow at the observed average growth rate of 0.375, the goal of 8.25% share of BEVs in annual registrations is met in 2022. Formally, the first constraint stipulates that:

$$S_{2018}^{EV^1} \geq 0.0231 \tag{19}$$

Second, we formulate a public revenue target. One main goal of Swiss road transport policy is to secure stable road infrastructure financing through benefit taxation. Hence, the second constraint requires non-decreasing public revenues. Formally, we define $\Delta T_s$ as the difference between the net present value of public revenue in the presence of subsidies and additional $CO_2 levies$($T_s^1$) and in the status quo ($T_s^0$). Hence, the public revenue target is specified as:

$$\Delta T_s = T_s^1 - T_s^0 \geq 0 \tag{20}$$

with

$$T_s^c = \sum_{i=1}^{N}\sum_{j=1}^{K} P_{ij}\{-\eta_j^g \mathbb{1}_{g=EV} + \mathbb{1}_{g\neq EV} p_j \tau_j^{imp} + \rho[t_j + m_{ij} e_j(\tau_j^g + \psi_j^g)]\} \tag{21}$$

$P_{ij}$ represents household $i$'s predicted probability to purchase vehicle $j$. $\eta_j^g$, $\tau_j^{imp}$, $\tau_j^g$, $\psi_j^g$ and $t_j$ denote the EV subsidy, vehicle import tariff, $CO_2$ levy, fossil fuel tax and vehicle registration

---

in 2019. However, this target is often not met by importers and they opt to pay fines instead. Furthermore, in our opinion, the EV target is a more appropriate indicator, since in reality up-front subsidies are mostly paid out in particular to EVs and not to fuel efficient cars in general.

[50] More information can be found here: `https://www.weu.be.ch/de/start/themen/energie/energiestrategie.html`. Overall, the Swiss mobility roadmap stipulates that at least 10% of the overall vehicle fleet should possess a non-fuel combustion engine in 2035 with the intermediary milestone for 2023 set at 3.6%.

[51] Assuming that BEVs continue to represent 55% (average) of the newly registered electric vehicles (BEVs + plug-in's) as it has been the case during 2016-2018 in Switzerland. We furthermore estimate a scenario with a stricter environmental target assuming BEVs represent a share of 64% (maximum). Results are not further discussed but available upon request.

[52] We set the growth rate to 0.375 which corresponds to the observed values for 2013 to 2018.

tax respectively. $\mathbb{1}$ is an indicator function and is equal to 1 if the respective condition is met and zero otherwise. This is important since only EVs benefit from subsidies and they are also exempt from the import tariff. The discount factor $\rho$ is defined in Equation 4 and translates annual tax and levy payments into the corresponding net present value[53]

In contrast to the previous sections we also allow for non-zero mileage elasticities. Hence, household mileage is no longer constant between options, but now expressed as $m_{ij}$ in Equation 20. Choice probabilities and consumer surplus are also now computed accounting for elastic mileage. We allow households to reduce the number of kilometers driven after the implementation of higher levies. We estimate three scenarios. The status quo assumes a mileage elasticity of 0. Furthermore, we follow the literature and employ a low elasticity of 0.1 and a higher elasticity of 0.3. The literature review by Gillingham, Rapson, & Wagner (2020) shows that most elasticities lie between 0.05 and 0.4 and a more recent study for Denmark estimates a medium-run average elasticity of 0.3 (Gillingham & Munk-Nielsen 2019).

Table 10: Optimal policy outcomes

| | **Inelastic mileage** | | **Low elasticity (0.1)** | | **High elasticity (0.3)** | |
|---|---|---|---|---|---|---|
| | $\kappa = 0$ | $\kappa = 1$ | $\kappa = 0$ | $\kappa = 1$ | $\kappa = 0$ | $\kappa = 1$ |
| *Overall effects* | | | | | | |
| Subsidy level (CHF) | 9,600 | 6,500 | 10,000 | 6,300 | 10,000 | 6,800 |
| $CO_2$ levy (CHF / l) | 0.07 | 0.04 | 0.08 | 0.04 | 0.09 | 0.05 |
| Consumer Surplus (kCHF) | 281.50 | 166.02 | 377.25 | 223.46 | 632.60 | 380.08 |
| $CO_2$ reduction (t p.a.) | 173.12 | 98.95 | 261.05 | 133.28 | 442.06 | 248.82 |
| $CO_2$ reduction (% p.a.) | 1.12 | 0.64 | 1.69 | 0.86 | 2.87 | 1.61 |
| Public revenue change (kCHF) | 0.64 | 23.97 | 52.95 | 9.40 | 63.10 | 31.25 |
| $CO_2$ levy (kCHF p.a.) | 451.45 | 259.23 | 512.97 | 258.65 | 570.20 | 320.87 |
| Subsidy paid (kCHF) | 2,541.0 | 1,437.26 | 2,714.26 | 1,377.82 | 2,710.74 | 1,526.55 |
| EV share (%) | 2.867 | 2.396 | 2.941 | 2.37 | 2.937 | 2.432 |
| *Distributive effects* | | | | | | |
| Subsidy share 1$^{st}$ inc. quartile (%) | 17.89 | 16.34 | 18.12 | 16.25 | 18.12 | 16.47 |
| Subsidy share 4$^{th}$ inc. quartile (%) | 32.67 | 35.30 | 32.31 | 35.46 | 32.31 | 35.06 |
| $CO_2$ levy share 1$^{st}$ inc. quartile (%) | 24.66 | 24.66 | 24.65 | 24.66 | 24.65 | 24.66 |
| $CO_2$ levy share 4$^{th}$ inc. quartile (%) | 25.50 | 25.47 | 25.50 | 25.47 | 25.51 | 25.48 |

*Notes:* 1$^{st}$ quartile: income $<$ 62.9 kCHF and 4$^{th}$ quartile: income $>=$ 131.9 kCHF. Estimation based on sample and specification (5) of Table 3. Results of constrained maximisation of Equation 17 with constraints Equation 19 and Equation 20. Consumer surplus based on Equation 15. We assume a vehicle lifetime of 10 years and a discount rate of 6% to calculate the NPV of public revenue changes. $\kappa$ indicates if welfare function is income weighted (=1) or not (=0).

Table 10 presents the results of the optimisation exercise. The table distinguishes between the different driving elasticities and the two welfare goals of weighted ($\kappa = 1$) or unweighted ($\kappa = 0$) changes in consumer surplus. Overall, a pattern of high subsidies and moderate fossil

[53]We continue to assume a vehicle holding period of 10 years and a discount rate of 6%.

fuel levies emerges. In the absence of equity concerns ($\kappa = 0$), the optimal subsidy is set at or close to the maximum of CHF 10,000. In the presence of equity concerns ($\kappa = 1$) and inelastic mileage the optimal subsidy is considerably lower, but also requires a lower fossil fuel levy to achieve revenue neutrality. The lowest increase in consumer surplus is recorded in a scenario with equity concerns and inelastic driving with subsidies set at CHF 6,500 and levies at CHF 0.04/l. Emission reductions of the new car fleet are also the lowest in this scenario at approximately 99 tons per year or 0.6% relative to the baseline scenario. Although the overall amount of subsidies paid is more than 1 million lower than in the scenario without equity concerns, the share of payments to high income agents is actually higher with 35.3% compared to 32.6% in the optimal outcome absent equity concerns.

Allowing for an elastic driving behaviour has two consequences. The emission reductions are substantially larger, as households not only buy more fuel-efficient cars but also use them less. However, in order to be able to finance the high subsidies, also higher fossil fuel levies are necessary. Absent equity concerns, the maximum subsidy of CHF 10,000 is paid out, but requires a higher tax rate of CHF 0.08 in the low elasticity case and even CHF 0.09 in the higher elasticity case indicating that the public revenue target becomes more stringent if households adapt their driving behaviour.

In most scenarios, an EV share of around 2.4% to 2.9% is attained. Absent equity concerns the environmental target is surpassed by almost 0.7 percentage points. These results illustrate that a combination of high subsidies for BEVs and moderate additional levies on fossil fuels can attain emission reductions without jeopardizing revenues required to finance the road infrastructure. The emission reductions are a manifold of the ones achieved if solely a fossil fuel levy or a subsidy is implemented. If the social planner caters to equity concerns, optimal subsidies and fuel levies tend to be lower. Interestingly the relative share of subsidy payments received by the lowest income group is higher absent equity concerns. This illustrates that up front vehicle prices represent a more substantial EV adoption barrier for lower income households. Implementing a higher subsidy leads to relatively more additional adopters among the lower income groups.

# 7 Conclusion

The increasing $CO_2$ emissions from the road transport sector and the still rather cautious uptake of fuel-efficient cars 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 households and their newly purchased vehicles. Using random coefficient models and accounting for possible price endogeneity, our findings reveal that households are considerably more sensitive with respect to the purchase price than with respect to future variable costs. Furthermore, we find substantial differences in price sensitivity between income groups with lower income households featuring a considerably higher price elasticity. We find comparably low own price elasticities of 1.9 for gasoline and 1.7 for EVs with again substantial income heterogeneity. Similar to previous findings, we can confirm that EV preferences tend to be persistent, as EV buyers display higher cross-price elasticities relative to other EVs than to different fuel types. Richest households are more than 2.5 times likelier to purchase an EV than the poorest. Lower income households feature an almost 10 percentage points higher likelihood to buy a gasoline driven car compared to households in the highest income bracket.

We simulate two counterfactual policy experiments based on the estimated demand model. First, we vary an additional $CO_2$ levy on fossil fuels up to CHF 0.25/l. This scenario leads to overall little substitution between different fuel types and negligible emission reductions of the new car fleet but secures the revenue for road infrastructure financing. For instance, a CHF 0.12/l levy reduces annual carbon emissions by only 7.7 tons. The net welfare impact is positive and the fuel tax is regressive. Second, we simulate the introduction of EV price subsidies up to CHF 10,000. EV adoption probabilities significantly increase leading to more pronounced decreases in annual $CO_2$ emissions of the new car fleet. Overall, the subsidy introduction has negative welfare effects, as reductions in public revenue outweigh the positive impact derived from consumer surplus increases and emission reductions.

These counterfactual exercises illustrate a number of challenges and important trade-offs that policy makers face. On the one hand, increasing adoption of EVs can be supported through pricing carbon or through price subsidies. Higher EV adoption leads to lower $CO_2$ emissions. On the other hand, an increased adoption of fuel efficient vehicles erodes public revenue needed to finance the road infrastructure. Furthermore, carbon tax instruments usually exhibit regressive features, causing higher relative costs for lower income households. At the same time, upfront subsidies are more likely paid to higher income households, due to their higher initial adoption probability and higher propensity to act on the new vehicle market, which exacerbates the redistributive concerns of environmental policies.

Thus, we also compute the optimal policy mix from a social planner perspective maximising overall consumer surplus subject to achieving a pre-specified EV share in new vehicle registrations and raising enough revenue to finance the road infrastructure. We also allow the social planner to take equity concerns into account. We find that high subsidies paired with relatively modest additional $CO_2$ levies are the optimal policy mix to substantially increase EV shares while generating sufficient revenue to finance the road infrastructure in the absence of equity concerns. The optimal subsidy-levy combination is lower in the presence of equity concerns illustrating that higher income households are more likely to be the main beneficiaries of subsidy payments. At the same time, achieved emission reductions are lower when equity is taken into consideration. Furthermore, emission reductions vary significantly based on assumed mileage elasticity. This suggests that additional fossil fuel levies rather influence driving behaviour than the choice of more fuel efficient cars. Our analysis comes with a few caveats. We focus on new car registrations only, thus ignoring policy impacts on second-hand vehicle markets and distributional consequences for the poorest households that may be less likely to purchase new vehicles frequently. Our estimates, nevertheless, indicate potential hurdles and avenues to higher electric vehicle adoption and reductions in overall private road transport carbon emissions. We take both redistribution and concerns about sufficient public budget for road infrastructure into account on a micro level. We can thus illustrate a path for policy makers to accommodate the trade-off between environmental and equity concerns without jeopardizing the financing of the road infrastructure.

## References


Alberini, A., & Bareit, M. (2019). The effect of registration taxes on new car sales and emissions: Evidence from switzerland. *Resource and Energy Economics*, *56*, 96–112.

Allcott, H., & Wozny, N. (2014). Gasoline prices, fuel economy, and the energy paradox. *Review of Economics and Statistics*, *96*(5), 779–795.

Andor, M. A., Gerster, A., Gillingham, K. T., & Horvath, M. (2020). Running a car costs much more than people think—stalling the uptake of green travel. *Nature*, *580*, 453-455.

Azarafshar, R., & Vermeulen, W. N. (2020). Electric vehicle incentive policies in canadian provinces. *Energy Economics*, *91*, 104902.

Bansal, P., Daziano, R. A., & Achtnicht, M. (2018). Comparison of parametric and semiparametric representations of unobserved preference heterogeneity in logit models. *Journal of choice modelling*, *27*, 97–113.

Bento, A. M. (2013). Equity impacts of environmental policy. *Annu. Rev. Resour. Econ.*, *5*(1), 181–196.

Bento, A. M., Goulder, L. H., Jacobsen, M. R., & Von Haefen, R. H. (2009). Distributional and efficiency impacts of increased us gasoline taxes. *American Economic Review*, *99*(3), 667–99.

Bento, A. M., Jacobsen, M. R., Knittel, C. R., & Van Benthem, A. A. (2020). Estimating the costs and benefits of fuel-economy standards. *Environmental and Energy Policy and the Economy*, *1*(1), 129–157.

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

Berry, S., Levinsohn, J., & 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.

Borenstein, S., & Davis, L. W. (2016). The distributional effects of us clean energy tax credits. *Tax Policy and the Economy*, *30*(1), 191–234.

Busse, M. R., Knittel, C. R., & Zettelmeyer, F. (2013). Are consumers myopic? evidence from new and used car purchases. *American Economic Review*, *103*(1), 220–56.

Carleton, T., & Greenstone, M. (2021). Updating the united states government's social cost of carbon. *University of Chicago, Becker Friedman Institute for Economics Working Paper*(2021-04).

Cerruti, D., Alberini, A., & Linn, J. (2019). Charging drivers by the pound: How does the uk vehicle tax system affect co 2 emissions? *Environmental and Resource Economics*, *74*(1), 99–129.

Chen, C.-W., Hu, W.-M., & Knittel, C. R. (2021). Subsidizing fuel-efficient cars: Evidence from china's automobile industry. *American Economic Journal: Economic Policy*, *13*(4), 152–84.

Davis, L. W., & Sallee, J. M. (2020). Should electric vehicle drivers pay a mileage tax? *Environmental and Energy Policy and the Economy*, *1*(1), 65–94.

Delacrétaz, N., Lanz, B., Van Dijk, J., et al. (2020). The chicken or the egg: Technology adoption and network infrastructure in the market for electric vehicles. *IRENE working paper*.

d'Haultfoeuille, X., Givord, P., & Boutin, X. (2014). The environmental effect of green taxation: the case of the french bonus/malus. *The Economic Journal*, *124*(578), F444–F480.

Durrmeyer, I. (2021). Winners and losers: The distributional effects of the french feebate on the automobile market. *The Economic Journal*.

Durrmeyer, I., & Samano, M. (2018). To rebate or not to rebate: Fuel economy standards versus feebates. *The Economic Journal*, *128*(616), 3076–3116.

Egbue, O., & Long, S. (2012). Barriers to widespread adoption of electric vehicles: An analysis of consumer attitudes and perceptions. *Energy policy*, *48*, 717–729.

Egnér, F., & Trosvik, L. (2018). Electric vehicle adoption in sweden and the impact of local policy instruments. *Energy policy*, *121*, 584–596.

Feger, F., Pavanini, N., & Radulescu, D. (2022). Welfare and redistribution in residential electricity markets with solar power. *Review of Economic Studies*, *forthcoming*.

Gallagher, K. S., & Muehlegger, E. (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. (2014). Identifying the elasticity of driving: evidence from a gasoline price shock in california. *Regional Science and Urban Economics*, *47*, 13–24.

Gillingham, K., Houde, S., & Van Benthem, A. A. (2021). Consumer myopia in vehicle purchases: evidence from a natural experiment. *American Economic Journal: Economic Policy*, *13*(3), 207–38.

Gillingham, K., Iskhakov, F., Munk-Nielsen, A., Rust, J. P., & Schjerning, B. (2019). *Equilibrium trade in automobile markets* (Tech. Rep.). National Bureau of Economic Research.

Gillingham, K., & Munk-Nielsen, A. (2019). A tale of two tails: commuting and the fuel price response in driving. *Journal of Urban Economics*, *109*, 27–40.

Gillingham, K., Rapson, D., & Wagner, G. (2020). The rebound effect and energy efficiency policy. *Review of Environmental Economics and Policy*.

Grigolon, L., Reynaert, M., & Verboven, F. (2018). Consumer valuation of fuel costs and tax policy: Evidence from the european car market. *American Economic Journal: Economic Policy*, *10*(3), 193–225.

Holland, S. P., Mansur, E. T., Muller, N. Z., & Yates, A. J. (2016). Are there environmental benefits from driving electric vehicles? the importance of local factors. *American Economic Review*, *106*(12), 3700–3729.

Huse, C., & Koptyug, N. (2021). Salience and policy instruments: Evidence from the auto market. *Journal of the Association of Environmental and Resource Economists*, forthcoming.

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

Leard, B., Linn, J., & Zhou, Y. C. (2021). How much do consumers value fuel economy and performance? evidence from technology adoption. *The Review of Economics and Statistics*, 1–45.

Li, S., Linn, J., & Spiller, E. (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., & Train, K. (2000). Mixed mnl models for discrete response. *Journal of applied Econometrics*, *15*(5), 447–470.

Muehlegger, E., & Rapson, D. (2018). Subsidizing mass adoption of electric vehicles: Quasi-experimental evidence from california. *NBER Working Paper*(w25359).

Muehlegger, E., & Rapson, D. S. (2020). Measuring the environmental benefits of electric vehicles (relative to the car that wasn't bought). *NBER Working Paper*.

Ohlendorf, N., Jakob, M., Minx, J. C., Schröder, C., & Steckel, J. C. (2021). Distributional impacts of carbon pricing: A meta-analysis. *Environmental and Resource Economics*, *78*(1), 1–42.

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

Pindyck, R. S. (2019). The social cost of carbon revisited. *Journal of Environmental Economics and Management*, *94*, 140–160.

Reguant, M. (2019). The efficiency and sectoral distributional impacts of large-scale renewable energy policies. *Journal of the Association of Environmental and Resource Economists*, *6*(S1), S129–S168.

Ricke, K., Drouet, L., Caldeira, K., & Tavoni, M. (2018). Country-level social cost of carbon. *Nature Climate Change*, *8*(10), 895–900.

Saez, E. (2002). Optimal income transfer programs: intensive versus extensive labor supply responses. *Quarterly Journal of Economics*, *3*(117), 1039-1073.

Sallee, J. M. (2011). The surprising incidence of tax credits for the toyota prius. *American Economic Journal: Economic Policy*, *3*(2), 189–219.

Small, K. A., & Rosen, H. S. (1981). Applied welfare economics with discrete choice models. *Econometrica: Journal of the Econometric Society*, 105–130.

Springel, K. (2021). Network externality and subsidy structure in two-sided markets: Evidence from electric vehicle incentives. *American Economic Journal: Economic Policy*, *13*(4), 393–432.

Train, K. (2009). *Discrete choice methods with simulation.* Cambridge university press.

Train, K. (2015). Welfare calculations in discrete choice models when anticipated and experienced attributes differ: A guide with examples. *Journal of choice modelling*, *16*, 15–22.

Train, K. (2016). Mixed logit with a flexible mixing distribution. *Journal of choice modelling*, *19*, 40–53.

Train, K., & Winston, C. (2007). Vehicle choice behavior and the declining market share of us automakers. *International economic review*, *48*(4), 1469–1496.

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

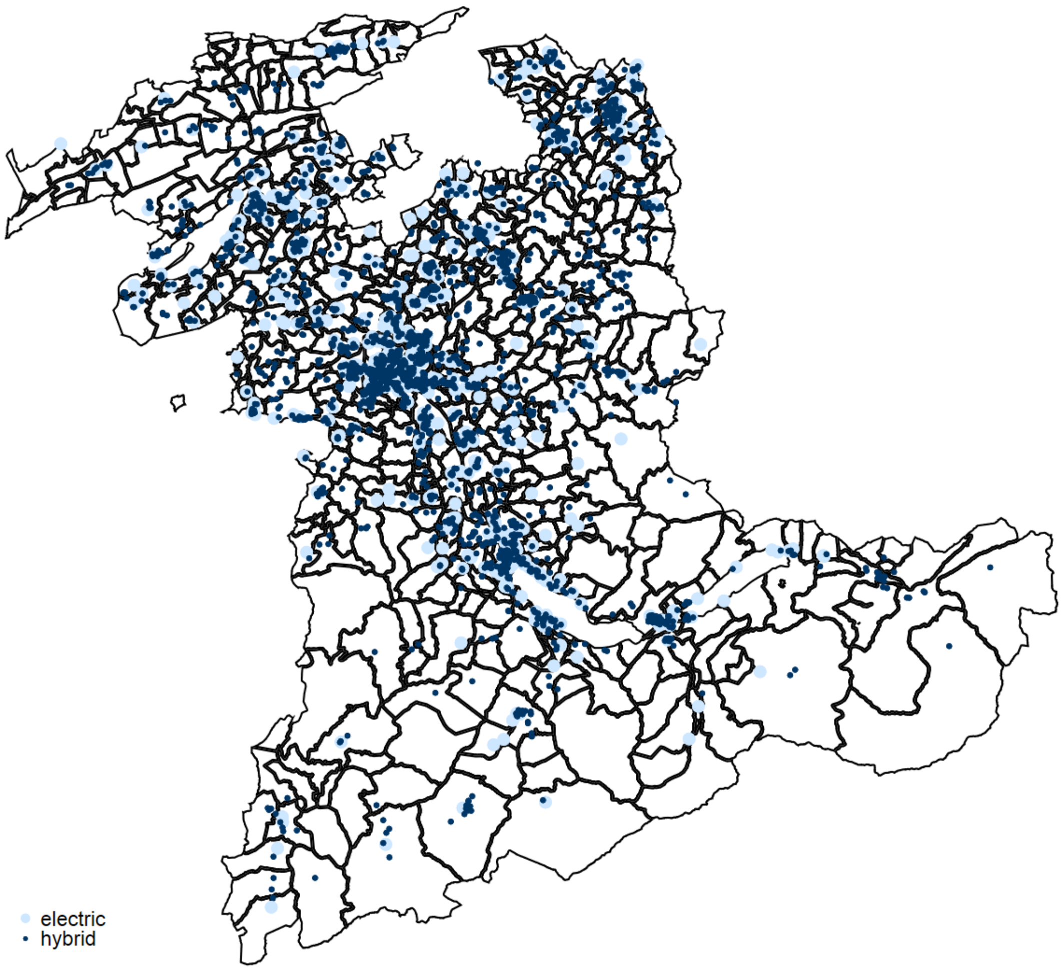
West, J., Hoekstra, M., Meer, J., & Puller, S. L. (2017). Vehicle miles (not) traveled: Fuel economy requirements, vehicle characteristics, and household driving. *Journal of public Economics*, *145*, 65–81.

Wolak, F. A. (2016). *Designing nonlinear price schedules for urban water utilities to balance revenue and conservation goals* (Tech. Rep.). National Bureau of Economic Research.

Xing, J., Leard, B., & Li, S. (2021). What does an electric vehicle replace? *Journal of Environmental Economics and Management*, *107*, 102432.

# Appendix

Figure 5: Map of electric and hybrid cars



## Table 11: Control functions

| | (1) lPrice | (2) lPrice | (3) lPrice | (4) lPrice | (5) lPrice |
|---|---|---|---|---|---|
| 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) |
| Variable driving costs | $-0.023***$ | $-0.021**$ | $-0.045***$ | $-0.020**$ | $-0.022**$ |
| | (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 |
| $R^2$ | .9038 | .9039 | .9042 | .9031 | .9024 |
| AIC | $-786.3626$ | $-787.1741$ | $-790.5846$ | $-718.8084$ | $-741.8232$ |
| 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 11. 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 3. All first stage F-test statistics exceed 200.

## Table 12: Regression results - Sensitivity

| | (RCL-Cont II) | (Sens (1)) | (Sens (2)) | (Sens (3)) | (Sens (4)) | (Sens (5)) | (Sens (6)) |
|---|---|---|---|---|---|---|---|
| Car price (log) | −2.482*** | −2.481*** | −2.484*** | −2.499*** | −2.483*** | −2.412*** | −2.541*** |
| | (0.11) | (0.11) | (0.11) | (0.11) | (0.11) | (0.11) | (0.11) |
| Variable costs (log pv) | −0.324*** | −0.283** | −0.194* | −0.430*** | −0.266*** | −0.352*** | −0.424*** |
| | (0.10) | (0.09) | (0.09) | (0.10) | (0.09) | (0.10) | (0.10) |
| Engine power (KW) | 0.008*** | 0.008*** | 0.008*** | 0.009*** | 0.008*** | 0.008*** | 0.009*** |
| Car height | −1.445*** | −1.446*** | −1.447*** | −1.442*** | −1.446*** | −1.455*** | −1.470*** |
| Car weight | 0.001*** | 0.001*** | 0.001*** | 0.001*** | 0.001*** | 0.001*** | 0.001*** |
| Hybrid engine | −0.341* | −0.346* | −0.352* | −0.323* | −0.347* | −0.376* | −0.316* |
| Electric engine | −1.852*** | −1.846*** | −1.839*** | −1.869*** | −1.845*** | −1.823*** | −1.878*** |
| Diesel engine | −0.575*** | −0.571*** | −0.560*** | −0.584*** | −0.568*** | −0.579*** | −0.591*** |
| Car size | 0.076** | 0.075** | 0.073** | 0.078*** | 0.074** | 0.086*** | 0.087*** |
| *Price heterogeneity* | | | | | | | |
| $2^{nd}$ inc. quartile | 0.314*** | 0.314*** | 0.319*** | 0.323*** | 0.315*** | 0.253*** | 0.328*** |
| | (0.04) | (0.04) | (0.04) | (0.04) | (0.04) | (0.04) | (0.04) |
| $3^{rd}$ inc. quartile | 0.58*** | 0.581*** | 0.585*** | 0.588*** | 0.582*** | 0.528*** | 0.593*** |
| | (0.04) | (0.04) | (0.04) | (0.04) | (0.04) | (0.04) | (0.04) |
| $4^{th}$ inc. quartile | 1.259*** | 1.259*** | 1.264*** | 1.265*** | 1.260*** | 1.221*** | 1.273*** |
| | (0.04) | (0.04) | (0.04) | (0.04) | (0.04) | (0.04) | (0.04) |
| *Size heterogeneity* | | | | | | | |
| 2 Persons | 0.052** | 0.052** | 0.051** | 0.051** | 0.051** | 0.052** | 0.051** |
| 3 Persons | 0.186*** | 0.185*** | 0.186*** | 0.187*** | 0.186*** | 0.183*** | 0.187*** |
| 4 Persons | 0.380*** | 0.380*** | 0.380*** | 0.380*** | 0.380*** | 0.381*** | 0.382*** |
| 5+ Persons | 0.599*** | 0.599*** | 0.599*** | 0.601*** | 0.599*** | 0.590*** | 0.605*** |
| *KW heterogeneity* | | | | | | | |
| 40-60 years old | −0.006*** | −0.006*** | −0.006*** | −0.006*** | −0.006*** | −0.006*** | −0.006*** |
| 60+ years old | −0.008*** | −0.008*** | −0.008*** | −0.008*** | −0.008*** | −0.008*** | −0.008*** |
| *EV effects* | | | | | | | |
| EV agglomeration | 0.143 | 0.145 | 0.148 | 0.138 | 0.146 | 0.152 | 0.135 |
| EV rural | −0.122 | −0.119 | −0.115 | −0.130 | −0.119 | −0.111 | −0.134 |
| Distance to EV | −0.016 | −0.014 | −0.009 | −0.021 | −0.012 | −0.015 | −0.022 |
| Nb. Charging (5km) | 0.008* | 0.009** | 0.010** | 0.008* | 0.009** | 0.007* | 0.008** |
| EV - Homeowner | 0.801*** | 0.805*** | 0.811*** | 0.790*** | 0.806*** | 0.814*** | 0.784*** |
| EV - Solar panel HH | 2.40*** | 2.401*** | 2.402*** | 2.399*** | 2.401*** | 2.399*** | 2.292*** |
| EV - 2018 | 0.12 | 0.11 | 0.125 | 0.115 | 0.123 | 0.136 | 0.096 |
| EV - 2019 | 1.306*** | 1.309*** | 1.313*** | 1.303*** | 1.310*** | 1.300*** | 1.312*** |
| *Rand. Coefficients* | | | | | | | |
| Car Price | 0.000 | 0.001 | 0.001 | 0.000 | 0.000 | 0.000 | 0.000 |
| Variable costs | 0.006 | 0.003 | 0.004 | 0.007 | 0.006 | 0.001 | 0.007 |
| Height | 0.001 | 0.001 | 0.001 | 0.000 | 0.001 | 0.000 | 0.001 |
| Hybrid | 0.005 | 0.002 | 0.002 | 0.006 | 0.005 | 0.000 | 0.006 |
| Diesel | 0.007 | 0.002 | 0.002 | 0.007 | 0.007 | 0.001 | 0.008 |
| Observations | 9,816,000 | 9,816,000 | 9,816,000 | 9,816,000 | 9,816,000 | 9,816,000 | 9,816,000 |
| Nr. of cases | 23,074 | 23,074 | 23,074 | 23,074 | 23,074 | 23,074 | 23,074 |
| Log Likelihood | −133,696.7 | −133,699.22 | −133,702.68 | −133,688.21 | −133,700.52 | −133,745.36 | −133,710.54 |
| Car type fe | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Car brand (country) | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Control function | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

* p<0.05; ** p<0.01; *** p<0.001

Coefficients based on estimated mixed logit models. Estimated standard errors in parentheses for selected coefficients, but mainly suppressed to save space in the table. Model (1) corresponds to the preferred specification in Column (5) of Table 3. Sens (1) to Sens (4) have different calculations of the future variable costs: Sens(1) corresponds to a discount rate of 2%, Sens (2) to a shorter holding period of 6 years, Sens (3) to a longer holding period of 25 years and Sens (4) to constant mileage consumption of households (12,000 km p.a. for non-diesel households and 16,000 km p.a. for diesel households). Sens (5) and Sens (6) are robustness checks for the identification strategy. Sens (5) corresponds to the lagged equally distributed carbon penalty as marginal cost shifter in combination with the BLP style instruments and Sens (6) employs just the BLP style instruments as cost shifters in the control function.

Table 13: Prediction evaluation

| Income | Gas predicted (N) | Gas actual (N) | EV predicted (N) | EV actual (N) |
|---|---|---|---|---|
| Overall | 16,049 | 16,005 | 408 | 380 |
| $1^{st}$ inc. quartile | 4,241 | 4,450 | 57 | 52 |
| $2^{nd}$ inc quartile | 4,087 | 4,045 | 78 | 55 |
| $3^{rd}$ inc quartile | 3,963 | 3,853 | 110 | 68 |
| $4^{th}$ inc quartile | 3,759 | 3,648 | 163 | 205 |
| **Income** | **Diesel predicted (N)** | **Diesel actual (N)** | **Hybrid predicted (N)** | **Hybrid actual (N)** |
| Overall | 5,527 | 5,601 | 1,091 | 1,088 |
| $1^{st}$ inc. quartile | 1,249 | 1,080 | 223 | 187 |
| $2^{nd}$ inc quartile | 1,352 | 1,375 | 251 | 272 |
| $3^{rd}$ inc quartile | 1,419 | 1,559 | 276 | 289 |
| $4^{th}$ inc quartile | 1,506 | 1,587 | 340 | 340 |
| Overall fit $\chi^2_3$ | 3.170 | | | |
| Gas by quartile $\chi^2_3$ | 16.6 | | EV by quartile $\chi^2_3$ | 44.6 |
| Diesel by quartile $\chi^2_3$ | 43.54 | | HEV by quartile $\chi^2_3$ | 9.14 |
| All income quartile: $\chi^2_{15}$ | 113.92 | | | |

*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 (5) of Table 3. The critical values are 24.996, 7.815 and 3.841 for the $\chi^2_{15}$, $\chi^2_3$ and $\chi^2_1$ with a 95% significance level and 30.578, 11.345 and 6.635 with a 99% significance level respectively.

Table 14: Implied substitution patterns and elasticities

(a) Mean Elasticities - 1st income quartile

| | Own | Cross Gasoline | Cross Diesel | Cross Electric | Cross Hybrid |
|---|---|---|---|---|---|
| Gasoline | -2.376 | .008 | .007 | .004 | .006 |
| Diesel | -2.117 | .003 | .003 | .002 | .002 |
| Electric | -1.397 | .001 | .001 | .002 | .001 |
| Hybrid | -1.796 | .002 | .002 | .001 | .001 |

(b) Mean Elasticities - 2nd income quartile

| | Own | Cross Gasoline | Cross Diesel | Cross Electric | Cross Hybrid |
|---|---|---|---|---|---|
| Gasoline | -2.087 | .006 | .006 | .005 | .006 |
| Diesel | -2.051 | .003 | .003 | .002 | .003 |
| Electric | -1.665 | .001 | .001 | .003 | .001 |
| Hybrid | -1.844 | .002 | .002 | .001 | .002 |

(c) Mean Elasticities - 3rd income quartile

| | Own | Cross Gasoline | Cross Diesel | Cross Electric | Cross Hybrid |
|---|---|---|---|---|---|
| Gasoline | -1.862 | .005 | .005 | .006 | .005 |
| Diesel | -1.93 | .003 | .003 | .003 | .003 |
| Electric | -2.018 | .002 | .002 | .006 | .002 |
| Hybrid | -1.901 | .002 | .002 | .002 | .002 |

(d) Mean Elasticities - 4th income quartile

| | Own | Cross Gasoline | Cross Diesel | Cross Electric | Cross Hybrid |
|---|---|---|---|---|---|
| Gasoline | -1.26 | .003 | .004 | .005 | .004 |
| Diesel | -1.373 | .002 | .002 | .003 | .002 |
| Electric | -1.874 | .002 | .002 | .008 | .002 |
| Hybrid | -1.668 | .001 | .001 | .002 | .002 |

*Notes:* Estimations based on sample and specification (5) of Table 3. All elasticities are mean own- and cross-price elasticities presented in percent. Results based on simulated price increase of 1%. Sample distinguished into 4 income groups. 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.