Electric Vehicle Market Response to Discounting Incentives

The Impact of Electric Vehicle Purchase Premiums on Vehicle Markets in Switzerland

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May 3rd, 2022

Abstract

I investigate the impact of direct-discount (a.k.a. purchase premium) incentives on the registration of new fully electric vehicles in Switzerland using nationwide new registration data between 2016 and 2021. When controlling for a variety of fixed and time-varying factors, I find that a 1000 Swiss Franc increase in purchase premiums corresponds with an 8.6% increase in electric vehicle purchases or a 9.9% increase in the market share of newly registered vehicles that are fully electric. A purchase premium of this size leads to a 0.8% decrease in the average carbon dioxide CO_2 g/km tailpipe emissions for vehicles on the road, and a statistically insignificant reduction in total vehicle registrations, mitigating concerns over negative externalities associated with a fleet-size leakage effect. This research highlights the success of purchase premium policies in Switzerland and can provide some guidance for policymakers aiming to decrease the impact of climate change.

Special thanks to Davidson College's Economics Department and the Robert C. Whitton Mentoring Fund for making this project possible

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I. Introduction

The transportation sector accounts for 25% of global CO_2 emissions (Ge & Wang, 2019). By 2070, the International Energy Agency expects car ownership rates to increase by 60% and global road transportation density (measured in passenger-kilometers) to double. In Switzerland, the region of interest for my research, 41% (16 megatons) of CO_2 emissions come from road transportation each year, making it the largest source of pollution (OECD, 2019).[1] Many developed countries have been able to shift their reliance away from highly-polluting manufacturing techniques, but as population and vehicle ownership rates increase, road transportation has progressively accounted for a more significant proportion of global CO_2 emissions. These alarming statistics have encouraged companies, consumers, and politicians alike to look toward the benefits offered by the rapidly growing electric vehicle market.

Electric vehicle (EV) incentive programs exist to address positive and negative externalities in the free market. The primary objective that policymakers hope to realize with an EV incentive program is decreasing tailpipe emissions from vehicles on the road. Gas-powered automobiles emit greenhouse gases (GHG) like carbon dioxide, hydrocarbons, and other nitrous oxides (Brinson & Guzman, 2021). Too many pollutant particles in the atmosphere cause problems globally and locally; globally, the effects of climate change, rising tides, and the depletion of the ozone layer are examples of the many negative international externalities that arise from GHG emissions; locally, concentrated pollution in the atmosphere can cause respiratory illnesses and become carcinogenic in large quantities (U.S. Energy Information Administration, 2021). Battery electric vehicles (BEV) or plug-in hybrid vehicles (PHEV) can substitute for gas/diesel-powered vehicles and, when implemented on a large scale, can work to reduce overall GHG emissions.[2] However, reducing GHG emissions is not the only reason policymakers promote the electric vehicle market, and a variety of secondary positive externalities exist as well.

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[1] Additionally, in 2019, newly registered Swiss vehicles had the highest CO_2 emissions in all EU-EFTA countries.

[2] Assuming energy sources for these electric vehicles come from green sources like nuclear, wind, solar, etc.

Some politicians argue that electric vehicle subsidies can create employment geared towards reducing emissions ('green jobs') while crowding out oil and coal labor dependency (Clifford, 2021). In this sense, EV incentive programs can shift the labor market away from jobs seen as negative externalities in the market (Dell'Anna, 2021). This is a long-term focus, as new laborers about to enter the market can find and build careers in the EV industry that will continue to be increasingly employable.[3] Eventually, policymakers hope that a successfully implemented subsidy will provide spillover effects to other areas of the technology sector (European Commission, 2017). For example, battery research conducted for EVs can be transferred to solar panels and wind farms to address energy storage challenges (Levin, 2021).

A robust electric vehicle market can strengthen a nation's international standing and soft power. Transitioning away from petroleum dependency can boost a nation's energy security by helping it become less dependent on the global oil prices set by OPEC, Saudi Arabia, and Russia, among others. And as a nation's electric vehicle market strengthens, so does international bargaining power concerning climate agreements. When a country invests in an EV program, it sends a signal that they are willing to take climate change seriously, which may, in turn, encourage other nations to take part and cooperate in other national security partnerships.

From a private industry standpoint, EV subsidies can offer the 'big push' funding necessary for growing the industry that private investors often consider too risky. Oil supplies are expected to become more difficult and costly to retrieve over time as existing offshore wells dry up (Ellyatt, 2020). Investors are typically short-term biased, meaning they may not be willing to offer the significant upfront capital necessary for long-term EV industry growth; governments can attempt to close this market failure with a large investment.[4] Economies

[3] Unfortunately, these job-creating intentions do not always play out if implemented without dedicated job training programs, as the coal/oil labor force is typically composed of blue-collar non-college-educated workers. In contrast, the EV market relies on highly trained engineers and EV technicians. Because of this, EV programs may prematurely crowd out these blue-collar jobs and force these workers onto unemployment benefits.

[4] Researchers have found consumer hesitancy regarding EVs' reliability, range, and perceived challenges associated with unfamiliar technology ownership and maintenance. Upfronting costs associated with EV ownership can stabilize these concerns (Thogersen and Ebsen 2019, Hidrue et al., 2011, Egbue and Long, 2012), and middle-aged, well-educated, high-income populations are the most responsive (He and Zan 2018, Jenn. et al 2018).

of scale predicts that electric vehicle manufacturing costs will decrease over time as the market expands and the average price of inputs decreases. Hence, governments justify incentives to accelerate market development and maintain globally competitive manufacturers (Gillespie, 2021).[5]

Because consumers do not naturally internalize these externalities, policymakers have designed a variety of mandates and incentives to encourage EV uptake. In the next section, I explain several types of electric vehicle incentive programs implemented and the basic econometric variation researchers have studied to assess the overall effectiveness of these programs. Section III derives the theoretical model and explains empirical specifications. Section IV presents the data and controls used for my analysis. Section V visualizes data, shows descriptive statistics, and lists regression outputs. Section VI interprets empirical results, and Section VII concludes while discussing the limitations and implications of my research.

[5] Not all inputs for electric vehicles have decreased over time. Scarcity among inputs, such as lithium-ion batteries or semiconductors, has dramatically increased the price of EVs in the last year.

II. Literature review

With a better understanding of the various reasons policymakers choose to promote EV markets, I will now cover a variety of direct and indirect incentives that policymakers use to encourage EV adoption. After reviewing the effectiveness of these programs, I derive my research question and review similar research on vehicle markets in Switzerland, my region of interest.

A. Electric Vehicle Incentives

Indirect incentives refer to market-level approaches that encourage a transition toward promoting EVs. These programs usually take the form of mandates or restrictions aimed at manufacturers, such as the European Union's *Automotive Fuel Economy Policy,* the U.S.'s *Average Fuel-economy Standard*, and Switzerland's *CO2 Act* (passed September 2020), all of which mandate that the fuel economy of every manufacturer's new fleet must meet a certain average emissions level that becomes progressively more environmentally friendly over time (Castiglioni & Schaller, 2021).[6] Other such programs are aimed at only certain geographical regions in an automobile market, such as the *zero-emission vehicle (ZEV) mandate*, a program started in California and since enacted in thirteen U.S. states, where larger automobile companies are required to sell a certain percentage of EVs as part of their fleet. This ZEV mandate is structured similarly to a flipped cap-and-trade policy – manufacturers that don't sell enough ZEVs can purchase credits from those who produce above the required level or pay a fee to the government at a high price (O'Kane, 2021).[7]

While policies that mandate average-emission levels have correlated with increasing fleet fuel efficiency, a variety of secondary market effects have limited the overall success of these programs. Consumers in non-participating ZEV states argue that they have limited potential for expansion in their own EV markets because

[6] Other notable features of the CO2 Act include a national climate fund for supporting charging infrastructure, gradual elimination of subsidies for mineral oils, and increased fuel importation costs.

[7] This policy alone has allowed Tesla, a manufacturer that produces only BEV (Battery Electric Vehicles), to maintain profits year after year by selling ZEV credits. Q2 of 2021 was the first quarter where Tesla made profits without accounting for ZEV credit revenues.

automakers tend to only market their EV fleet in participating states where they can receive and sell ZEV credits (Marbury & Gray, 2022).

This type of negative externality is described by Goulder et al. (2012) as a leakage effect, or an unintended negative consequence on a separate region or aspect of a market. Goulder et al. (2012) identify two leakage effects in the automobile market when fuel-efficiency manufacturer-based mandates are passed. On the new vehicle market, the researchers explain that emission-reduction mandates implemented in one region can free up a manufacturer to reduce the fuel economy of its fleet outside of the adopting region; an adaptable enough automaker would need to make no changes to the fuel efficiency of their vehicle fleet, as they can simply divert their fuel-efficient vehicles into participating regions.[8] Without an incentive to dynamically change the environmental friendliness of their fleet, automakers will not invest in eco-friendly technologies. This leakage effect causes environmental inequity on a global scale, as automakers concentrate fuel-efficient parts and vehicles in regions that are financially able to promote EV adoption while regions without the financial resources to incentivize fuel-efficient vehicles are stuck buying vehicles that are worse for the environment. The second leakage effect that Goulder et al. (2012) identify is in the used vehicle market, where they explain that when governments mandate that automakers produce more fuel-efficient vehicles, the price of new vehicles increases as automakers are forced to redesign manufacturing techniques to make their automobiles more eco-friendly; because of this, consumers often hold onto fuel-inefficient vehicles for longer before scrapping due to an increase in the price of new fuel-efficient vehicles.[9] These leakage effects that can occur with market-level mandates highlight the importance of testing for negative-side effects before declaring a policy successful; just

[8] Goulder et al. (2012) modeled the leakage resulting from *California's Greenhouse Gas Vehicle Emission Standards* (or the *Pavley Regulations*), which required large automobile manufacturers to reduce the per-mile GHG emissions starting in 2009. While this policy was never enacted, Goulder estimates that 74% of the pollution reduced in California would have 'leaked' or been transferred into other parts of the U.S. through fuel-inefficient vehicle sales.

[9] This retirement delay for used fuel-inefficient vehicles has been named the *Gruenspecht Effect* after Economist Howard Gruenspecht, who researched the topic extensively in the 1980s (Gruenspecht 1982, Gruenspecht 1988). The effect has since been studied by many economists (such as Jacobsen & van Benthem 2015). Some economists argue that fuel-economy standards (as opposed to gasoline taxes) fail to create strong incentives to scrap older fuel-inefficient vehicles (Davis & Knittle 2016).

because more electric vehicles are purchased due to an incentive program doesn't mean the policy is decreasing total emission levels.

Aside from market-level indirect mandates, governments have also used directed per-vehicle financial and non-financial incentive programs to increase EV adoption rates across emerging and established EV markets. Financial incentives are defined as direct monetary incentives that can influence both the supply and demand side of the marketplace (such as tax exemptions or manufacturer subsidies), which can be based on the battery capacity, range, or efficiency of an automobile.[10] Non-financial incentives refer to special perks offered to every EV owner, like free charging stations, bus & high-occupancy vehicle (HOV) lane access, or unique parking spots, all of which have been shown to sway consumers towards purchasing EVs (Habich-Sobiegalla et al., 2018; Hardman & Tal, 2016). Researchers have found a decreasing marginal effect of these non-financial policies over time as an EV market expands - when bus lanes are crowded with electric vehicles, the exclusivity of the perk loses its value (Jenn et al., 2020).[11]

When studying the impact of financial incentives at the consumer level, researchers have found that tax discounts, charging station subsidies, and purchase premiums (one-time discounts applied at the point of sale) have been shown to positively impact EV adoption rate (Singh et al., 2020; Zhang et al., 2016), and regions with the largest EV financial incentives are correlated with having the strongest electric vehicle markets (Lutsey, 2015). Tax decreases for fuel-efficient vehicles have been shown to be more than twice as effective at increasing fuel-efficient automobiles sales when compared to tax increases for fuel-inefficient vehicles (Ciccone & Soldani, 2021),[12] but consumers respond most strongly to discounts applied directly at the point of sale rather than as a tax rebate realized at the end of the fiscal year; up to a fourth of consumers may ignore EV

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[10] Battery-size and range-based incentive programs have been criticized for encouraging EV manufacturers to build batteries excessively large, to the point where they can become unsafe and highly combustible. California, for example, paused its battery-size incentive programs in 2019 because of the increased potential for fire risk. Additionally, the manufacturing process of a standard lithium-ion car battery emits about 17.5 tons of carbon dioxide, which increases with battery size. This poses serious policy concerns over what types of excess waste policymakers may be inadvertently incentivizing.

[11] While Jenn et al., (2020) find non-financial incentives have a decreasing marginal effect over time, Yao et al. (2020) find that tax waivers and mandates have a statistically significant positive relationship with EV sales.

[12] Ciccone & Soldani (2021) estimate elasticities of -1.99 for tax decreases and 0.77 for tax increases.

tax-rebate options on filed tax returns (DeShazo, 2016).[13] To sufficiently influence purchasing decisions, constituents must be aware of the policies available, which explains why discounts directly noticeable at the point of sale are more effective than tax rebates applied at the end of the fiscal year (Green et al., 2013).[14] Because incentive programs that offer direct discounts at the point of sale have been shown to be most effective, my research focuses on testing how effective direct monetary incentives are at influencing EV sales and market share. I focus my research on the Swiss vehicle market, an ideal region for my research, for reasons that will be discussed in the next section.

B. Eco-Friendly Vehicle Incentives in Switzerland

Switzerland provides ideal research conditions for analyzing the influence of electric vehicle incentives. At the national level, Switzerland's government has attempted to promote the EV market with average fuel economy standards, but all measures that use direct per-vehicle EV incentives fall under the jurisdiction of the 26 cantonal governments in Switzerland. Each canton has unique policies for determining annual vehicle taxes, and several cantons have purchase premium or charging station subsidy programs (Bundesamt fur Energie, 2021; Schaller, 2020). Researchers have exploited these canton-level differences in Switzerland to identify how consumers react to variations in the intensity of automobile incentives. This section will summarize the findings of three previous research projects and explain how my research expands on their methodologies and conclusions.

Examining the used vehicle market in Switzerland, Alberini et al. (2017) studied the bonus-malus incentive programs in three cantons to compare the time until a consumer retires their vehicle (a bonus refers to a

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[13] Unfortunately, survey data in the United States (Consumers Union, 2016) has found that consumers are typically not aware of how EVs work, how much they cost, or the EV policies available for them, which can limit the effectiveness of policies. Many tax rebates can only be applied for if someone files income taxes, which low income-households are not required to do in many countries that offer EV incentives, excluding these persons from the incentives offers (Jaiswal et al. 2021). Consumers who cash in on tax incentives are sometimes 'free riders' who would have purchased the EV anyways, as Chandra, et al. (2010) estimated that 74% of incentives realized in a Canadian hybrid-electric incentive program went to consumers that would have bought the vehicles anyways.

[14] Green et al. (2013) argues that EV policies are most efficient when focused on early adoption markets and that policymakers should focus EV incentives on emerging markets.

discounted tax on fuel-efficient vehicles while a malus refers to a higher tax on inefficient vehicles). Between 2005 and 2011, the canton of Obwalden had a malus program that applied to used and new vehicle registrations. In contrast, the cantons of Geneva and Ticino applied fees only to new vehicle registrations. This difference provides an opportunity to investigate how the incentive programs impacted vehicle retirement; as discussed earlier, the second leakage effect observed by Goulder (2012) suggests that consumers will hold onto used inefficient vehicles if the eco-friendly policies that increase the price of fuel-inefficient vehicles apply only to new vehicles. Using nine control cantons without either type of incentive program, the researchers found that Obwalden's bonus-malus that applied to both new and used vehicles reduced the lifetime of existing high emitters by 5.4%, whereas Geneva's program that only applied to new vehicles extended the lifetime of existing high emitters by about 3.5%, indicating that Swiss vehicle owners responded as expected by holding onto used vehicles for longer if fees did not apply to them.

Continuing this research, Alberini and Bareit (2019) separately studied the impact of these bonus-malus taxes on new vehicle sales in Switzerland. Using the same registration data between 2005 and 2011, the researchers paneled all new vehicle registrations at the model-trim and canton-year level and then calculated the annual registration tax of each vehicle model-trim based on the canton-level tax law in place that year.[15] Controlling for vehicle class and model, canton-level fuel prices, vehicle-specific transportation costs, as well as a variety of other vehicle characteristics and fixed effects, the researchers estimated that a one percent decrease in registration fees corresponds to a 0.08% increase in the number of sales of a particular vehicle class.[16] When calculating the cost-benefit of such a program, the researchers find that the malus program is

[15] The researchers studied only diesel and gasoline vehicle registrations with up to nine seats and classified all vehicles into separate categories by their CO_2 grams emitted/km traveled (<100, 101-130, 131-150, 151-200, 201- 250, and 250+).

[16] Note 1: Vehicle characteristics include weight, engine size, horsepower, body type, transmission, and fuel type.

Note 2: The researchers assumed that sales respond symmetrically to bonuses and maluses, which Ciccone and Soldani (2021) show is not the case in Norway.

Note 3: Alberini & Bareit (2019) found no significant time-delayed or pre-emptive anticipation response among consumers when a policy change was enacted.

excessively costly for consumers at 7x the social cost of carbon (abatement cost) estimated by the Swiss government (Office for Spatial Development, 2021).

The researchers then estimated how the bonus-malus programs impacted the number of vehicles sold. Because registration taxes are calculated separately by canton, the researchers focused specifically on Geneva's tax-incentive registration program, which offers a bonus if a vehicle's CO_2/km ≤120g (a 50% decrease in registration tax applied to 12% of the most fuel-efficient vehicles) and malus if CO_2/km >200g (50% increase in registration tax applied to the top 21% of polluting vehicles). They estimated that if the same Geneva-style program were applied to the 14 cantons without a malus program in place in 2011, 735 fewer high-emitting cars (<120g CO_2 /km) would have been sold and, due to substitution, 47 more low-emitting cars would have been sold. When studying the bonus program, the researchers estimated that if Geneva's bonus was applied (again, only in 2011 to these 14 cantons without a policy in place), the number of cars below 120g CO_2/km would increase by 1,556 units, while that of vehicles with 121g CO_2/km or more would decrease by only 95. While having more eco-friendly cars on the road would reduce average vehicle emissions, total emissions would increase by 2,193 tons of CO_2 per year.[17] This represents slightly less than 1% of road-transportation emissions from these 14 cantons, but it is still alarming that a decrease in the cost of low-emission vehicles increases the total number of vehicles and consequently the total emissions from road transportation due to more cars being on the road. This indicates that some consumers who would not have chosen to purchase a vehicle without the incentive program would choose a fuel-inefficient vehicle because the incentive decreased the price of the vehicle.

This unintended side effect was previously observed in France, where D'Haultfoeuille et al. (2014), using a discrete-continuous choice model, found that overly generous French incentive programs offered for low-emission vehicles in 2008 decreased the average emissions but increased the total emissions from vehicles on

[17] This assumes that every canton responds to the policy in the same manner, which researchers have shown is not the case as green party share, education level, income, etc. influence responsiveness to EV policies.

the road. The researchers identify two key leakage effects that cause this unintended consequence in the automobile market: a manufacturing-scale effect due to the increased emissions resulting from the construction process of new vehicles, and a fleet-size effect, as a larger percentage of the population decides to purchase and use fuel-efficient vehicles due to the decreased price of ownership.[18] While a policy may appear productive, testing whether leakage effects occur in the larger automobile market is important for analyzing the overall effectiveness of a program. Instead of adapting a game theory model to assess for leakage effects, my research project will employ a simple modeling adjustment to test whether these manufacturing & fleet-size effects (and resulting effects on total CO_2 emissions) occur when implementing policies that encourage EV adoption. But before testing for leakage effects in the market due to eco-friendly vehicle incentives, I first adapt modeling techniques to evaluate whether purchase premium policies have influenced the sale and market share of electric vehicles.

Schaller (2020) offers the most recent research on the EV market in Switzerland to examine how EV market share is influenced by EV incentives. During the period of his research (2010-2019), each of the 26 cantons has relatively time-invariant tax-rebate programs that incentivize fuel-efficient vehicles. Only three cantons (as of 2019) had introduced purchase premium incentive policies ranging from a 3500 CHF to 5000 CHF credit towards electric vehicle purchases.[19] Using canton-level registration taxes, charging station subsidies, as well as other control variables such as income, population density, and education level, he finds that, at a statistically significant level, purchase premiums are shown to have the greatest effect out of all EV incentive programs at influencing the market share of EVs registered: a 1000 CHF[20] increase in purchase premiums corresponds to a 0.3 percentage point increase in battery electric vehicle market share - the largest

[18] The authors also noted a third leakage effect resulting from a consumer-driven rebound effect: consumers who own more fuel-efficient vehicles choose to drive longer distances because the price of transportation, in fuel or electricity, decreases.

[19] In 2019, the cantons of Ticino, Thurgau, and Basel-Stadt introduced purchase premiums.

[20] 1.00 CHF (Swiss Franc) is approximately 1.10 USD.

benefit per unit cost when compared to other canton-level price incentives such as charging-station subsidies or annual vehicle tax rebates offered to EV owners.[21]

For Schaller's research, only 11 months of data were available following the implementation of any purchase premium policy. To more accurately test the effect of purchase premiums on EV market sales and share, my research uses an additional two years of data and includes newly implemented purchase premium policies. Additionally, my analysis more clearly classifies what types of subsidies are included.[22] I use an adaptation of Alberini & Bareit's theoretical modeling techniques for my primary analysis and build my empirical specification model using similar techniques as Schaller. I then test for possible fleet-size effects and impact on average emissions with an adapted empirical specification model. Before these models can be derived, I must first build the theoretical model used for my research.

[21] Schaller found that a 1000 CHF increase in charging station subsidies (subsidies offered to EV owners to build a charging station at home) corresponded to a 0.15 percentage point increase in EV sales, although this estimator is not statistically significant.

[22] Note 1: my research uses purchase premium policies from three cantons that implemented or modified canton-wide premium policies following the conclusion of Schaller's period of analysis.

Note 2: A couple questionable modeling techniques were used in Schaller's research that my research aims to avoid:

- Including purchase premiums offered only to companies, such as the incentive in the canton of Basel-Stadt.
- Using several control variables, such as green-party share, that are excessively extrapolated and interpolated for at least 95% of missing data points.

III. Theoretical Model and Empirical Specification

A discrete choice random utility model (forming a linear mixed logit model) can be used to distinguish the effect that specific in-group characteristics have on predicting consumer choice compared to an out-group choice set. This model is ideal for research scenarios where there is a limited amount of within-market information (i.e., consumer characteristics) but readily available market outcome data (i.e., number of goods consumed).

A. Deriving the Theoretical Model

Following Berry (1994), the utility of individual (n) when choosing some alternative out-of-market good (i) can be assumed to be some choice against alternative options in set (J):

$$Choice_n \in \{J, i\} \quad J = (1, \dots, \dots, j)$$

$$n \; chooses \; i \; \Leftrightarrow \; (U_{ni} > U_{nj} \; \forall J)$$

For this model, the set (j) will represent all possible passenger vehicle options that a consumer can choose. Variable (i) represents the out-of-market choice, which in this case is represented by individual (n) choosing not to purchase a passenger vehicle. The utility that each consumer gets from the out-of-market choice (i) can be decomposed into two components, assuming additive and linearly separable utility functions:

$$U_{ni} = V_{ni} + \varepsilon_{ni}$$

Where V_{ni} represents observable and ε_{ni} represents random unobservable individual-specific factors of valuation, or the "love of variety" taste term.[23] This random variable allows modeling the probability that the consumer (n) chooses option (i) over other items in set (j):

$$P_{ni} = \Pr(U_{ni} > U_{nj})$$

[23] Term 'love of variety' was coined by Petrin (2002).

$$P_{ni} = \Pr(V_{ni} + \varepsilon_{ni} > V_{nj} + \varepsilon_{nj} \ \forall J)$$

$$P_{ni} = \Pr(\varepsilon_{ni} - V_{nj} + V_{ni} > \varepsilon_{nj} \ \forall J)$$

The logit model assumes that every draw of random utility is an i.i.d. type I extreme value distribution (UCB, 2002).[24] The CDF of this random variable is shown by:

$$F(\varepsilon_x) = e^{-e^{-\varepsilon x}}$$

This random variable distribution can be adjusted for the observable characteristics of the in-market choices and out-of-market choice to find the probability of consumer (n) choosing (i) over all alternatives.

$$P_{ni}|\varepsilon_{ni} = \prod_{j \in J} e^{-e^{-(\varepsilon_{ni} - V_{nj} + V_{ni})}}$$

Because ε_{ni} appears unknown and is assumed randomly distributed for an outside researcher, the function is integrated over the distribution of possible values of ε_{ni}.

$$P_{ni} = \int_{\varepsilon_{ni}=-\infty}^{\infty} \left(\prod_{j \in J} e^{-e^{-(\varepsilon_{ni} - V_{nj} + V_{ni})}} \right) e^{-\varepsilon_{ni}} e^{-e^{-\varepsilon_{ni}}} \, d\varepsilon_{ni}$$

And because $V_{ni} - V_{ni} = 0$, the CDF can be substituted into the probability product, and the exponent rule of summation can be applied.

$$P_{ni} = \int_{\varepsilon_{ni}=-\infty}^{\infty} \left(\prod_{j \in \{J,i\}} e^{-e^{-(\varepsilon_{ni} - V_{nj} + V_{ni})}} \right) e^{-\varepsilon_{ni}} d\varepsilon_{ni}$$

[24] A type I extreme value distribution, or Gumbel distribution, assumes that $\mathrm{Var}(\varepsilon_{ni}) = \frac{\pi^2}{6}$. This assumption also ensures that the scale of observed utility value measurements is implicitly normalized.

$$\mathrm{P}_{ni} = \int_{\varepsilon_{ni}=-\infty}^{\infty} e^{\left(-\sum_{j\in\{J,i\}} e^{-\left(\varepsilon_{ni} - \mathrm{V}_{nj} + \mathrm{V}_{ni}\right)}\right)} e^{-\varepsilon_{ni}} d\varepsilon_{ni}$$

$$\mathrm{P}_{ni} = \int_{\varepsilon_{ni}=-\infty}^{\infty} e^{\left(-e^{-\varepsilon_{ni}} * \sum_{j\in\{J,i\}} e^{-\left(\mathrm{V}_{ni} - \mathrm{V}_{nj}\right)}\right)} e^{-\varepsilon_{ni}} d\varepsilon_{ni}$$

Defining $e^{-\varepsilon_{ni}}$ as t, with the understanding that $\lim_{\varepsilon_{ni}\to\infty} -t = 0$ and $-e^{-\varepsilon_{ni}} d\varepsilon_{ni} = dt$

$$\mathrm{P}_{ni} = \int_{t=\infty}^{0} e^{\left(-t * \sum_{j\in\{J,i\}} e^{-\left(\mathrm{V}_{ni} - \mathrm{V}_{nj}\right)}\right)} (-dt)$$

$$\mathrm{P}_{ni} = \int_{t=0}^{\infty} e^{\left(-t * \sum_{j\in\{J,i\}} e^{-\left(\mathrm{V}_{ni} - \mathrm{V}_{nj}\right)}\right)} dt$$

$$\mathrm{P}_{ni} = \frac{e^{\left(-t * \sum_{j\in\{J,i\}} e^{-\left(\mathrm{V}_{ni} - \mathrm{V}_{nj}\right)}\right)}}{-\sum_{j\in\{J,i\}} e^{-\left(\mathrm{V}_{ni} - \mathrm{V}_{nj}\right)}} \Bigg|_0^{\infty}$$

$$\mathrm{P}_{ni} = \frac{1}{\sum_{j\in\{J,i\}} e^{-\left(\mathrm{V}_{ni} - \mathrm{V}_{nj}\right)}} = \frac{e^{\mathrm{V}_{ni}}}{\sum_{j\in\{J,i\}} e^{\mathrm{V}_{nj}}} = \frac{e^{\mathrm{V}_{ni}}}{e^{\mathrm{V}_{ni}} + \sum_{j\in J} e^{\mathrm{V}_{nj}}}$$

Dividing the numerator and denominator by $e^{\mathrm{V}_{ni}}$ yields:

$$\mathrm{P}_{ni} = \frac{1}{1 + \sum_{j\in J} e^{\mathrm{V}_{nj} - \mathrm{V}_{ni}}}$$

And the chance of choosing an in-market good (j) is $(1 - \mathrm{P}_{ni})$, or:

$$\mathrm{P}_{nj} = \frac{\sum_{j\in J} e^{\mathrm{V}_{nj} - \mathrm{V}_{ni}}}{1 + \sum_{j\in J} e^{\mathrm{V}_{nj} - \mathrm{V}_{ni}}}$$

Thus, the chance of choosing any vehicle, such as *j = 1*, is:

$$\mathrm{P}_{nj}|(j = 1) = \frac{e^{V_{nj=1} - V_{ni}}}{1 + \sum_{j \in J} e^{V_{nj} - V_{ni}}}$$

On taking logs:

$$ln(P_{nj=1}) + ln(C) = V_{nj=1} - V_{ni}$$

The left-hand side term $ln(C)$ now remains constant, regardless of changes in choice type *j*. Because the variable choice made by consumer (n) is made by all consumers across the entire market of interest, the terms can be aggregated across all consumers, and the (n) subscripts are dropped. This aggregates the probabilities across all consumers, so the in-market choice *j=1* logarithmic term can be interpreted as a proportion of the number of sales of vehicle *j=1* in the whole market, or the market share of choice *j=1*:

$$ln(Market\ Share_{j=1}) = C^{*} + B_1 * V_{j=1} \tag{1}$$

Furthermore, the denominator within the left-side logarithmic expressions can be readjusted to the right-hand side of the model. The logarithmic term thus represents total market sales of the in-market group choice *j=1*.

$$ln(Market\ Sales_{j=1}) = C^{**} + B_1 * V_{j=1}$$

$$ln(Market\ Sales_{tj=1}) = C_t^{**} + B_1 * V_{tj=1} \tag{2}$$

Because the random distribution of the i.i.d. sample terms is time-invariant, the expression can include period (t) subscripts.[25] This model tells us that the natural log of market sales of the in-market choice in each

[25] This is a flawed assumption considering the likelihood of heteroscedasticity occurring in many panel datasets. This erroneous assumption is adjusted for with clustered standard errors in the OLS regression model.

period (t) is equal to a choice set-specific time-varying constant plus a vector of the observable characteristics of the in-market choice.[26]

In this model, the log-transformed terms are readily interpreted as elasticities, which is especially valuable when attempting to analyze the effect of some observable explanatory variable on the change in market sales or market share of a specific choice (j) of the in-market group. This theoretical model can thus be transformed into an OLS regression, with a set of variables proxying for the control variable ${C_t}^{**}$, which represents the baseline vector of observable characteristics in the out-of-market group (V_{it}) as well as other constant values representing differences in observable characteristics of the in- and out-of-market groups. As will be seen in the next section, specific variables can proxy for these terms based on data availability regarding market and consumer-level data.[27] For my model, I adapt proxies based on expected observable price difference characteristics and available data regarding baseline differences.[28]

[26] For this specific project, t is represented by the given quarter that the vehicle is purchased. This same modeling decision is made in other research utilizing mixed logit models such as from Klier & Linn (2015) and D'Haultfoeuille, Givord, & Boulin (2014).

[27] Alberini and Bareit (2019) use the following FE to account for the ln (Market Sales) of the out of market choice: make-model, canton-by-year, class-by-year, class-by-canton, and make-by-canton fixed effects. Researchers (Li 2017; Haaf et al. 2014) used a further evolved model to separate terms used additive and linearly separable functional format. Petrin (2002) uses an exciting modeling technique by dividing consumers into tertial income groups with separate estimator coefficients for utility relative to price.

[28] Similar controls are used in my analysis as previous researchers (Alberini & Bareit, 2019; Schaller, 2020) studying the Swiss vehicle market due to the availability and reliability of federal-level demographic data.

B. Empirical Specification

The empirical specification uses several terms to proxy for the vector of observable characteristics of the in-market choice $(B_1 * V_{j=1})$. Time-varying social and fixed effect controls and a time-constant geographic-specific control can proxy for the time-varying constant term $({C_t}^{**})$, which depends on relative observable differences between the in and out of market choice. Model (1) estimates this relationship, where $EV\ Sales_{it}$ represents the market share of newly registered electric vehicles in each canton (i) in each quarter (t). Three regressors are chosen to represent the characteristics that are observable to the consumer when deciding to purchase an EV over a non-EV $(\beta_1, \beta_2, \beta_3)$, where remaining $(\beta_0, \beta_4, \beta_5, \beta_6)$ refer to baseline differences that influence vehicle sales:

Model 1 (Electric Vehicle Sales)

$$ln(EV\ Sales_{it}) = \beta_0 + \beta_1 PP_{it} + \beta_2 CS_{it} + \beta_3 TR_{it} + \beta_4 Z_{it} + \beta_5 FE_t + \beta_6 FE_i + e_{it}$$

Model (1) sets the in-market choice (j) to all fully electric vehicles. The outcome variable in this model is $ln(EV\ Sales_{it})$, which comes from equation (2). The variable of interest PP_{it} represents the direct discount purchase premium available for a consumer in the given canton (i) for a given quarter (t). Two terms also control for the vector of observable characteristics and CS_{it} represents canton-level funding for a standard charging station in each quarter. TR_{it} represents the percentage higher paid in annual vehicle taxes for a standard electric vehicle compared to a comparable gas/diesel vehicle in the specific canton-quarter measurement. Z_{it} is comprised of a vector of social controls, including tertiary education level, and population density for those over the age of 25. FE_t represents yearly fixed effects and FE_i canton-level fixed effects.

Model 2 (Electric Vehicle Market Share)

$$ln(EV\ Market\ Share_{it}) = \beta_0 + \beta_1 PP_{it} + \beta_2 CS_{it} + \beta_3 TR_{it} + \beta_4 Z_{it} + \beta_5 FE_t + \beta_6 FE_i + e_{it}$$

In model (2), the in-market choice (j) is again set to all fully electric vehicles. The denominator of the regressand can be reverted to equation (1) so that the term instead represents the market share of electric vehicles. The only difference in the constant term $(C_t{}^*)$ is a constant representing differences in observable characteristics, so the same variables $(Z_{it} + FE_t + FE_i)$ can proxy.

Model 3 (All Vehicles Sales)

$$ln(Total\ Market\ Sales_{it}) = \beta_0 + \beta_1 PP_{it} + \beta_2 CS_{it} + \beta_3 TR_{it} + \beta_4 Z_{it} + \beta_5 FE_t + \beta_6 FE_i + e_{it}$$

Model (3) tests whether the implementation of a purchase premium influences the registration of the total number of vehicles, so the in-market choice (j) is changed to reflect all possible vehicle choices. A positive regressor (β_1) would indicate a fleet-size effect occurring. The same constant is present in model (3) as in model (1), so the same proxies are used to control for the time-varying baseline difference.

Model 4 (Average CO_2 Emissions)

$$ln\ (Avg\ CO_2\ emissions_{it}) = \beta_0 + \beta_1 PP_{it} + \beta_2 CS_{it} + \beta_3 TR_{it} + \beta_4 Z_{it} + \beta_5 FE_t + \beta_6 FE_i + e_{it}$$

Model (4) tests whether purchasing premiums influence the average CO_2 emissions of vehicles on the road. To provide consistency with comparisons to models (1-3), model (4) forgoes the random utility model assumptions by using the same proxies to control for the effect of purchase premium policies. This modeling decision is permittable because average CO_2 emissions are expected to be tightly negatively correlated with EV market share, so CO_2 emissions can substitute for electric vehicle market share while showing the true impact of purchase premiums on the overall market emission level.

IV. Data

This research project aggregates data from several sources. The primary dataset on new vehicle registrations was purchased directly from the Swiss Government with gracious funding from Davidson College's Whitton Mentoring Fund.[29] Information on all vehicle incentives was collected from cantonal government websites or surveys by non-profit organizations based in Switzerland. The remaining variables controls were imported from open data offered by Switzerland's Federal Statistical Office (ASTRA, 2022). The following section will introduce the datasets used for this research and explain data cleaning and organizing procedures.[30]

A. All New Vehicle Registrations (2016-2021)

The Swiss Government's Federal Roads Office (ASTRA) records a significant amount of information on vehicle registrations and ownership. The dataset I use offers information on all new vehicle registrations in Switzerland from Jan. 2016 to Dec. 2021. No personal data except for the canton of residence and ZIP code information of the vehicle's owner is stored, but extensive vehicle information is recorded: fuel type (electric, hybrid, gasoline, diesel, hydrogen, etc.), number of seats, engine power, CO_2 emission level, as well as nearly 50 other vehicle classifications and characteristics (ASTRA, 2019).

The vehicle category (Fahrzeugart) is an important vehicle classification that allows for control over the type of vehicles studied by filtering out the registrations of vehicles ineligible for purchase premium programs.[31] Vehicles are only kept if they are four-wheeled powered vehicles with between two and nine seats that can reach speeds of 45km/hr. (28 mph); this narrows the selection down to passenger vehicles

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[29] Davidson College's Robert C. Whitton (1966) Mentoring Fund supports projects that promise cooperation and collaboration between students and faculty or staff members.

[30] Visit HTML file here to see data processing pipeline.

[31] Such as ATVs, busses, agricultural equipment, trailers, etc.

(Personenwagen), heavy passenger vehicles (Schwerer Personenwagen),[32] and light motor vehicles (Leichter Motorwagen).[33] After cleaning the data, 1,732,720 new registrations between 2016 and 2021 remain.[34]

For each canton and each quarter of the year between 2016-2021, three explanatory variables of interest are tallied: the total number of fully electric vehicles registered, the total number of all vehicles, and the market share of electric vehicles, calculated by dividing this first variable term from the second and multiplying by 100.[35] EV market share data for two cantons is shown in the next section (figure 3) and indicates that EV market shares have generally increased exponentially across cantons. The actual number of vehicles registered, however, follows a different trend.

Figure (1) in Section V. shows all vehicle registrations, electric vehicle registrations, and non-electric vehicle registrations. If the trajectory in EV market sales continues, every month of 2022 would be expected to have as many electric vehicles registered as the entire year of 2016. While variation between Q1-2016 to Q4-2019 can be explained by seasonal factors, Q1-2020 and onwards highlights a progressively decreasing number of total vehicles registered. This could be for various demand-side, supply-side, and vehicle-related reasons (EY Switzerland, 2021). Trends that impact the entire vehicle market in Switzerland are controlled with social and dummy variables.[36]

While these figures describe the number of electric and non-electric vehicles purchased over time, they do little to clarify whether vehicle emission levels have decreased. Schaller (2020) argues that a recent uptick

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[32] Schwerer Personenwagen are passenger vehicles heavier than 3.5 tons (Bundesamt fur Strassen, 2016).

[33] 70.3% of new registrations are passenger vehicles, 1.2% are light motor vehicles, and 0.01% are heavy passenger vehicles. The largest three vehicle classes filtered out of the population are motorbikes (Motorrad), delivery trucks (Lieferwagen), and goods transport vehicles (Sachentransportanhanger), which account for 11.1%, 7.8%, and 2.8% of new registrations, respectively.

[34] The original datasets contained 2,425,320 registrations. After filtering by car class, I remove all new vehicle registrations with missing/mislabeling registration year, month, canton, and fuel type, those registered outside of Switzerland, and those vehicles with more than nine or less than two seats.

[35] The electric vehicles that are considered electric vehicles are tallied. All vehicles with a fuel category (Treibstoff) of Electric (Elektrish), Fuel-cell (Wasserstoff / Elektrisch), and fully electric range-extended vehicles (only those with an engine displacement *Hubraum* category of 0) are included.

[36] On the supply-side, global shortages have limited the ability of manufacturers to source the parts necessary for constructing vehicles. With fewer vehicles available to purchase, the price for new vehicles has increased, and consumers are more likely to substitute for used vehicles or other cheaper forms of transportation.

in SUV purchases in Switzerland may mean that CO_2 emissions aren't changing in Switzerland even though more electric vehicles are being purchased. Perhaps some auxiliary effects occur when the purchase premium policies are implemented, where some consumers choose to purchase an electric vehicle to complement a fuel-inefficient vehicle rather than substitute for it.

To find whether vehicles on the road are decreasing emissions, I calculate the mean CO_2 g/km emissions for all vehicles registered within each canton in each year-quarter.[37] As Schaller (2020) found, the average CO_2 emissions of vehicles on the road are generally increasing from 2016 to 2019, but CO_2 emissions levels have appeared to decrease rapidly from 2020 onwards (figure 2). Unsurprisingly, with the introduction of more electric vehicles, the average CO_2 level of newly registered vehicles is also decreasing.

Table 6 shows summary statistics for these regressands of interest. A total of 24 year-quarterly data points between 2016 and 2021 are available for each of the twenty-six cantons, yielding 624 aggregated canton-year-quarter data points. Because the dataset begins in 2016 when fully electric vehicles were not common across Switzerland, more than half of canton-quarter data points contain less than 50 electric vehicle registrations, and only two cantons (the cantons of Aargau, Zurich, and Vaud - three of the four largest cantons) ever have more than one thousand electric vehicle registrations in a single quarter, all of which occur in the years of 2020 or 2021.[38] A total of 33 canton-quarter-year new vehicle registration cross-sections have average fleet tailpipe CO_2 emission levels of less than 100 g/km, all of which occur in the last two quarters of 2021.

[37] I assume that mislabeled values are randomly distributed across canton and time for data cleaning procedures. I remove the 353 non-electric vehicles listed as having incorrectly low (less than 10 CO_2 g/km) carbon emissions and filter out the 174 vehicles listed with inaccurately high CO_2 emissions (more than 500 CO_2 g/km). The range-extended electric fuel-type vehicles (REX) contain both fully-electric and hybrid vehicles, so I sort this fuel type category into non-electric vs. electric vehicle categories depending on whether they are listed as having an engine displacement/size (Hubraum) larger than 0. 156, or 18% of REX models, are non-fully electric vehicles. All Electric Vehicles with non-zero CO_2 emissions are replaced with 0 for CO_2 g/km (1257, or %1.6 of the 77,890 electric vehicles listed incorrectly high CO_2 emissions).

[38] Two canton-year-quarters (Appenzell Rh.-Ext and Glarus in year-quarter 2016-Q2 and 2016-Q4) contained no electric vehicle purchases. Because the natural log of 0 cannot be calculated, these canton-quarters are removed from the regression in model (1) and (2).

B. Purchase Premiums

To determine whether a canton's purchase premium should be included in the study, I choose to only include policies that offer canton-wide direct discounts to all cantonal residents. Out of the 26 cantons in Switzerland, eight have offered some form of a purchase premium sometime between 2016 and 2021, but only four cantons meet the criteria decided upon.[39] The other four cantons with some form of a purchase premium policy that is not included in the analysis are removed because the premium policies are only offered to a select proportion of the canton's population – whether by being offered only to a certain city, municipality, or registered companies within the canton.[40] Tables (1) and (2) show this distinction.

From previous research, it is expected that purchase premiums will increase the sales of electric vehicles. Assuming this is true across all cantons, the modeling decision to include only certain purchase premiums does provide some room for downward bias in the explanatory regressor (β_1), as consumers may be influenced to purchase an electric vehicle by a purchase premium policy that is not being reflected in the explanatory variable (PP_{it}); regardless, the bias resulting from this modeling decision is limited, as in all cases the proportion of eligible participants in each of the four unincluded purchase premium policy make up less than 15% of the canton's total population.[41]

Important to note is that when all cantons introduced premiums for fully electric vehicles, most also introduced smaller premiums for hybrid electric vehicles. This has the potential to create bias in the (PP_{it}) estimator in models (1) and (2), as consumers could be choosing to opt into hybrid vehicles (which are listed in the out-of-market category) instead of fully-electric vehicles. If more hybrids are purchased because of hybrid electric vehicle subsidies implemented simultaneously with fully electric vehicle subsidies, the effect of purchase premiums on the calculated market share of electric vehicles would be expected to be systematically underestimated.[42] While a control could be introduced for a hybrid vehicle premium, these premiums are

[39] Purchase Premium Policies: Thurgau 2019, 2020, & 2021; Ticino 2019 (2); Valais 2020; Schaffhausen 2021
[40] Unincluded Purchase Premiums: Basel-Stadt; Chavornay; St. Gallen; Gland; Hochdorf; Ville de Nyon; Ville de Prilly
[41] Calculated by finding the proportion of the population eligible for the purchase premium policy within the canton
[42] Hybrid vehicles would be counted as non-EV and thus included in the denominator of the EV market share term

significantly more challenging to compare across canton policy; in most cantons, a smaller proportion of the vehicle price is reimbursed for hybrid electric vehicles as opposed to a standard purchase premium offered to fully electric vehicles.

C. Charging Station Subsidies

Several cantons offer charging station subsidies to support the building of electric vehicle charging infrastructure. The same methodology as with purchase premium policies is used to determine whether the charging station subsidy is included in the model, as the incentive program is only included in this study if they offer canton-wide direct discounts for standard customers.[43] Nine different cantons have some form of a charging station subsidy policy, but only four meet the necessary criteria (table 3).[44]

D. Annual Motor Vehicle Tax

The second control for time-varying canton-specific preference for electric vehicles is the annual motor vehicle tax (Motorfahrzeugsteuer), an annually recurring tax paid by all owners of vehicles permitted to drive on public roads. Every canton has time-varying tax calculation formula based on one or multiple vehicle characteristics (such as horsepower, weight, and engine size). The fewer tailpipe emissions a vehicle produces, the cheaper this annually recurring tax will generally be, but several cantons have higher taxes for electric vehicles than their gasoline/diesel-burning counterparts. When deciding whether to purchase an electric vehicle, consumers are expected to be influenced by how much more they can save on this annual tax compared to a non-electric vehicle. The tax ratio (TR_{it}) variable is introduced to control for the relative cost of an electric vehicle's internal-combustion counterpart. I calculate this ratio using the Touring Club Suisse annual

[43] Charging Station Subsidies: Geneva 2019; Ticino 2019; Valais 2020; Vaud 2021

[44] Four of the five cantons with charging station subsidies are not included because they contain charging station subsidies unavailable to the standard purchasers of the electric vehicles but instead to owners of apartment building complexes. In one of these cantons, an electric vehicle owner would need to be an employee or resident of one of these charging stations beneficiaries to be able to use the charging station, so a separate control for charging stations offered to apartment owners & businesses is not included due to low inclusivity of these policies towards all EV owners.

reports, which list the expected annual motor vehicle tax a consumer would pay on their vehicle.[45] This ratio is not uniform across every electric vehicle and respective gas/diesel counterparts within each canton, so I proxy for this term by calculating the percentage higher paid on taxes for the leading Tesla Model S compared to a BMW X5 xDrive 40d.[46] Descriptive statistics are shown in table (6), where the ratio across canton-years is between -1.00 (representing an EV annual tax of 0$) and 1.92 (an electric vehicle tax 3x the cost of a non-electric vehicle).[47]

E. Social Control Trends and Remaining Fixed Effects

Data for the two social controls included come from annual releases from the Federal Statistical Office of Switzerland. The first of these controls is population density for citizens over the age of 25, which is intended to control for changes in the size and degree of urbanity of the consumer base (ASTRA, 2021). As a canton increases in size and density, its consumers are expected to become more favorable toward electric vehicle adoption; areas that are more densely populated and built to serve more people typically have better infrastructure to support the travel and charging of electric vehicles.[48] I choose to include population density measurements of those over the age of 25 as opposed to all residents because Swiss citizens below the age of 25 have been shown to be unlikely to register new vehicles (ASTRA, 2021).[49] In all models, the natural log is

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[45] This represents the vehicle tax paid only during the first year of ownership in each canton. Many cantons (such as Zurich) have zero Annual Vehicle Taxes only for the first three years of EV ownership. The increase after this period is not reflected in the tax ratio. Every quarterly period is assigned the canton-year tax ratio measurement.

[46] This includes the Tesla Model S 75 D for years 2016-2019 and Long Range model for years 2020-2021. These two vehicles are similar in price, horsepower, and weight, except that the Tesla is fully electric and has the highest level-A emissions rating, whereas the diesel-combustion BMW has a poor emissions rating of E on a scale from A-G.

[47] Only seven cantons have had some form of tax ratio policy change during the years studied. For example, between the years 2017 to 2018, the canton of Basel-Stadt changed this annual tax from being calculated by curb weight and CO_2 emissions to cubic capacity and horsepower (TCS Schweiz, 2018). This decreased the annual motor vehicle tax on a Tesla Model S from 1780 CHF to 141 CHF, changing the tax ratio paid on a tesla from 191.80% (almost three times) more to 73.09% less than a BMW.

[48] There are many more reasons why urban dwellers are more likely to purchase electric vehicles. For example:
1.) Fewer technicians are available to repair highly complex vehicles in rural areas.
2.) Longer travel distances are typical in rural areas, increasing the range anxiety associated with EV ownership.
3.) Urban areas have more areas available for electric vehicle parking.
4.) Urban dwellers are more responsive to new social trends.

[49] ASTRA records owner demographic information on all new vehicle registrations but this information is not included in the ASTRA dataset used for this analysis.
See (ASTRA Personenwagenbestand Altersverteilung der Halter, 2021) for more details.

taken on the population density to control for outliers and provide consistency with comparisons across regressands.[50]

The third social control is the tertiary education percentage for those over 25. This measures the percentage of a canton's population that has graduated from a university or other higher education institution. A well-educated consumer base is a strong indicator of many factors that influence the sale of electric vehicles, such as more awareness regarding ecological problems and more willingness to adopt newer trends. Additionally, tertiary education percentage is a strong indicator for GDP, which has been shown to influence electric vehicle adoption, as wealthier families are often more likely to be able to afford the more expensive electric vehicles on the market.[51] I include canton-fixed effects to control for time-invariant differences uncaptured by the time-varying social and vehicle price controls. These dummy variables control for the canton-specific factors unexpected to change over the 5-year period, such as geographical location and features, as well as market and social factors uncaptured by the time-varying social controls such as public perception.[52]

I include fixed time (quarter-year) effects to control for changes in the nationwide EV market. This primarily focuses on EV price and accessibility, which have shifted to make electric vehicles significantly more practical and attainable for purchase over time.[53] Because the responsiveness of a specific canton may vary over time, standard errors are clustered at the canton level to ensure heteroskedastic robustness.

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[50] Percentage increases in market sales are controlled for with percentage increases in population density.

[51] Canton-level GDP data was not included as a social control because it is not available for the years 2020 & 2021 See (ASTRA, Bruttoinlandsprodukt (BIP) nach Grossregion und Kanton) for more details.

[52] Geography example: a consumer in a highly mountainous canton would be less inclined to purchase an electric vehicle than consumers in flatland areas, given the maneuverability and suitability of most electric vehicles.
Market factor example: it is more difficult for dealers in rural areas to source and import electric vehicles.
Social factor example: canton-specific public perception towards purchasing EVs is expected to be mostly time-invariant.

[53] These time-fixed effects also control for supply chain disruptions that may have decreased the availability of electric vehicles across Switzerland in 2020 and 2021.

V. Visualizations, Descriptive Stats, Regressions

Figure 1

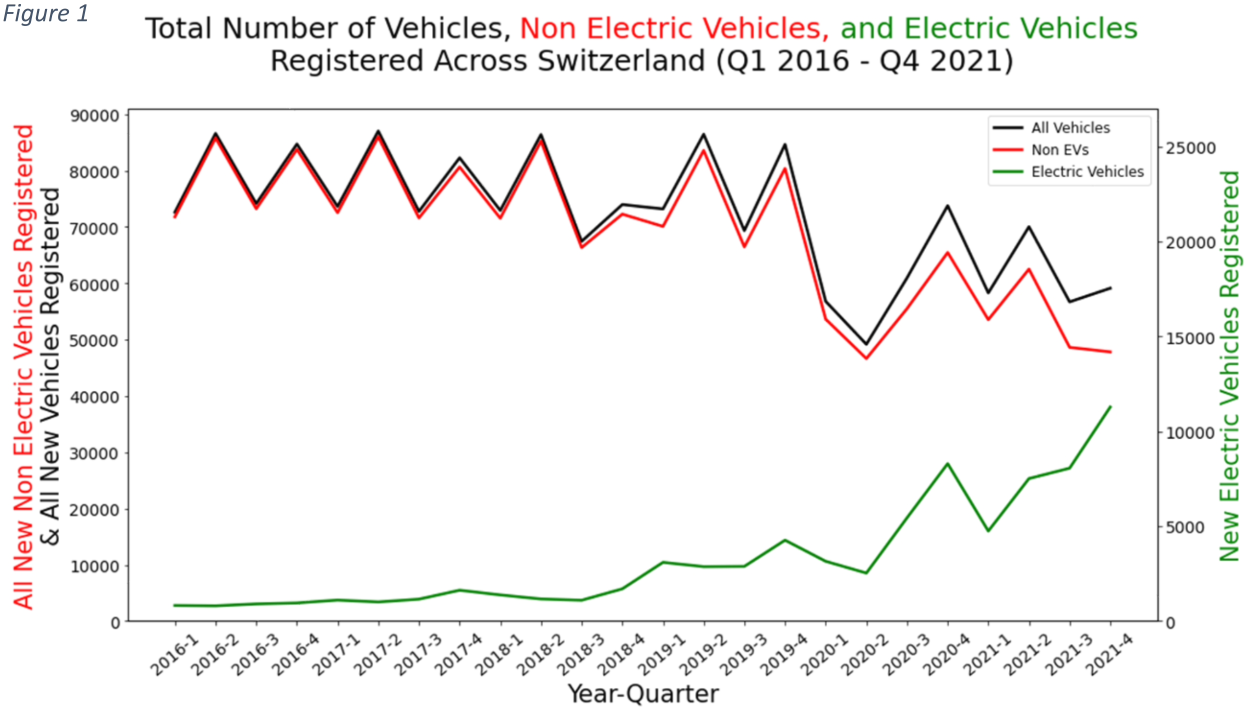
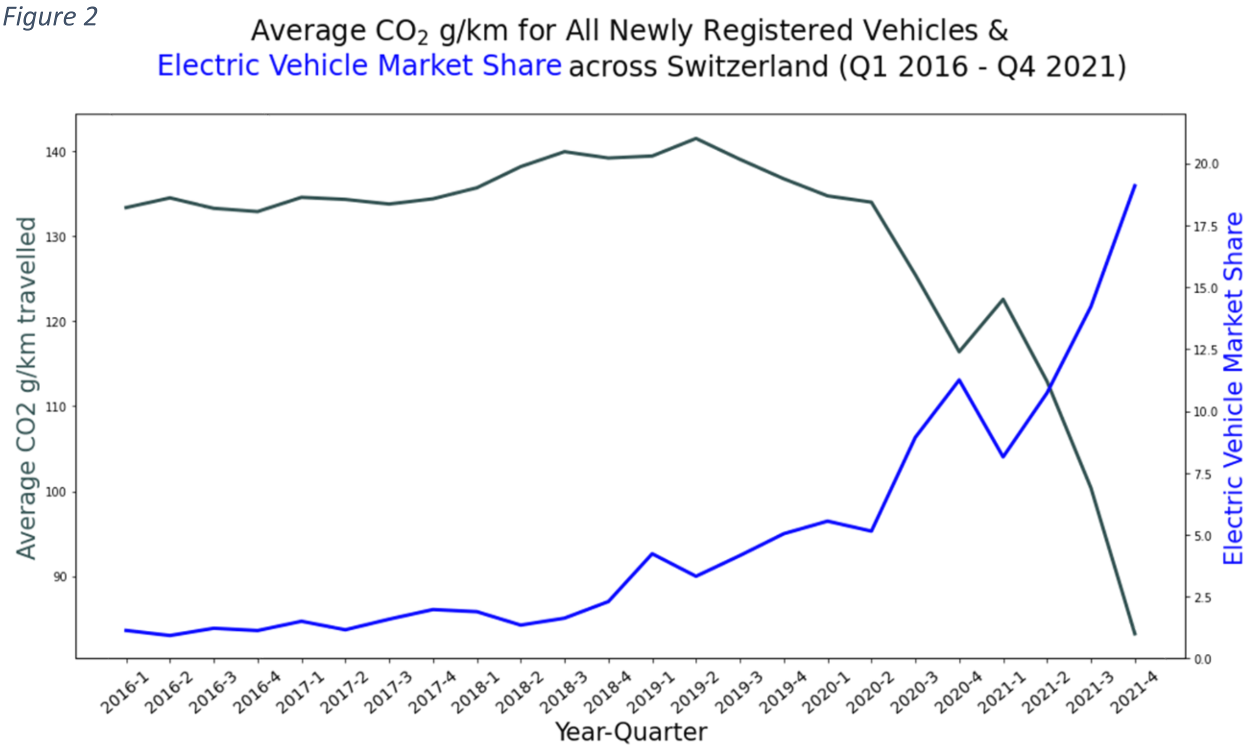


Figure 2



EV market sales, all vehicle sales, and EV market ratio in the large canton of Zurich (left) and the small canton of Uri (right). Charts on the next page show EV market share and sales for all cantons with purchase premium policies.

Figure 3 – Market Sales/Share in Zurich and Uri

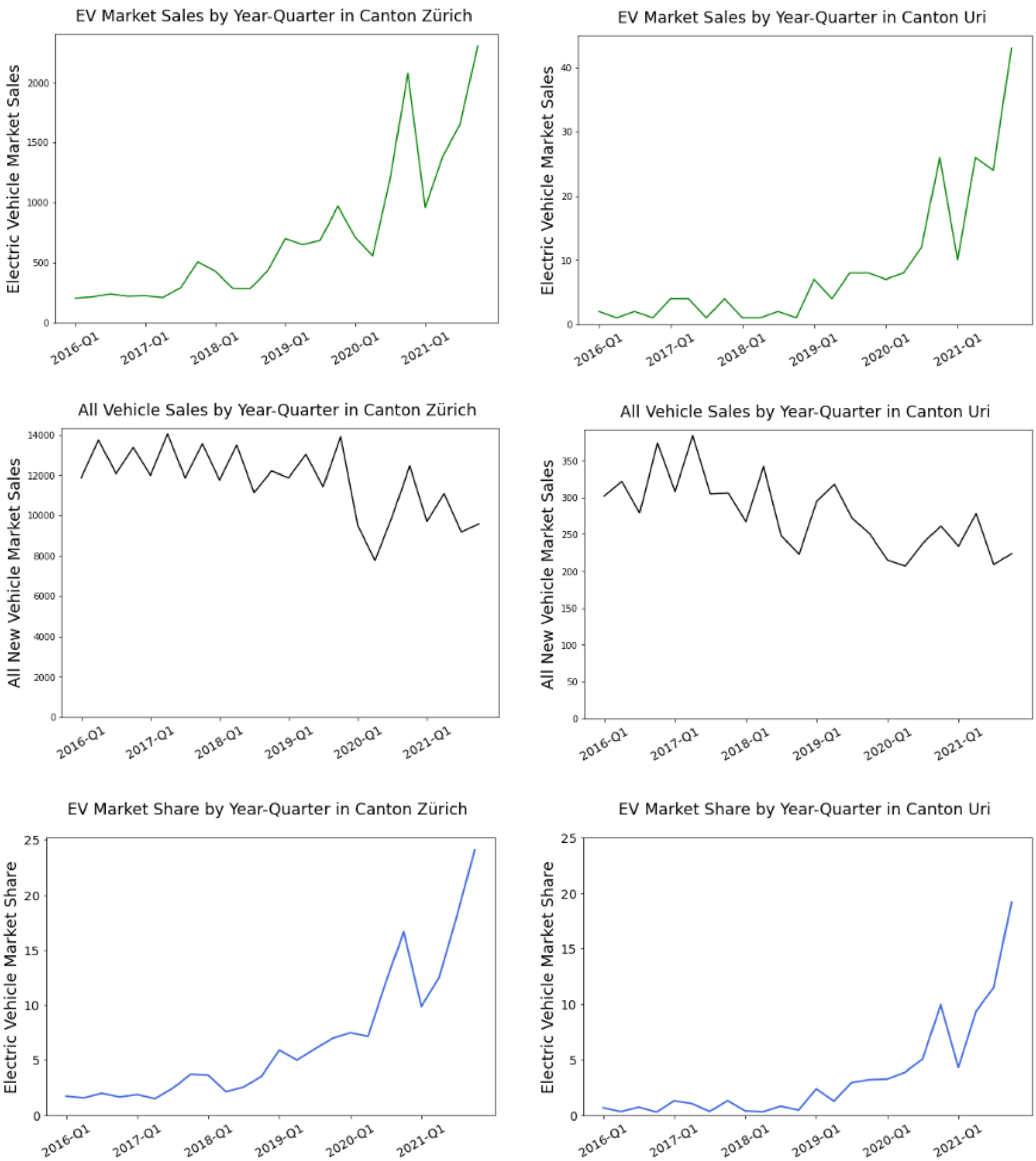


Figure 4 – Sales Data in Cantons with Purchase Premium

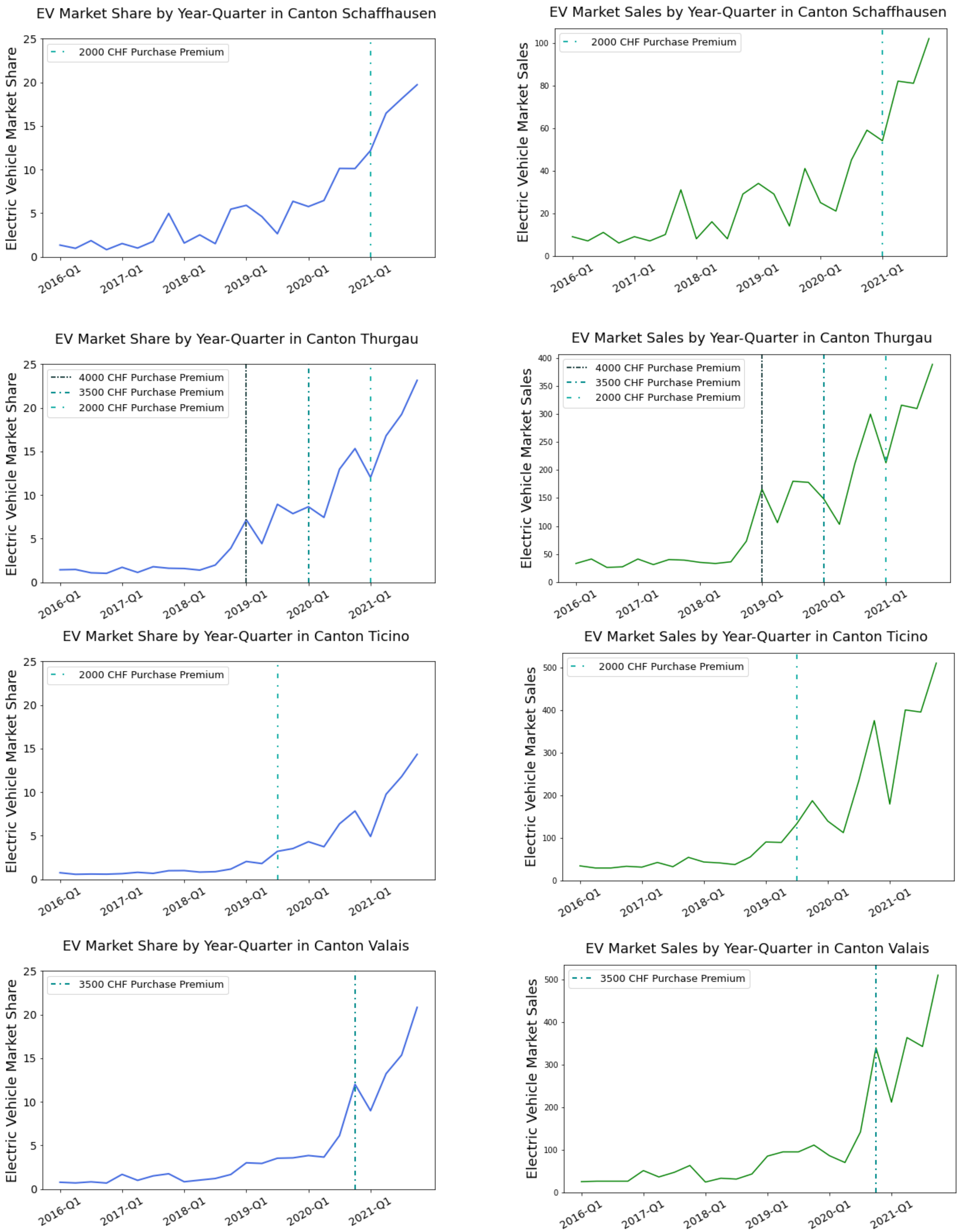


Table 1

Included Purchase Premiums

Canton	Premium (CHF)	Time Period	Notes
Thurgau	4000 3500 2000	Q1 2019-Q4 2019 Q1 2020 - Q4 2020 Q1 2021 - Present	Decreased every year
Ticino	2000	Q3 2019 - Q4 2021	Ended by Q1 2022
Valais	3500	Q3 2020 - Present	Began Nov. 1, 2020 Ending Q4 2022
Schaffhausen	2000	Q1 2021 - Present	

Table 2

Unincluded Purchase Premiums

Canton	Premium (CHF)	Reason Excluded
Basel-Stadt	5000	Only offered to qualifying companies
Lucerne	500	Only offered in municipality of Hochdorf (composes 10% of Lucerne population)
St. Gallen	5000	Only offered in capital city (composes 15% of St. Gallen population)
Vaud	750-2000	Five municipalities offer incentives (compose 10% of Vaud population)

Table 3

Included Charging Station Subsidies

Canton	Charging Station Subsidy (CHF)	Time	Notes
Geneva	1000	Q1 2019 - Present	Began Janurary 1, 2019
Ticino	500	Q3 2019 - Present	Began June 19, 2019 Finished by Q1 2022
Valais	1500	Q4 2020 - Present	Began November 1, 2019 For one 11kW-22kW station
Vaud	2000	Q1 2021 - Present	Began December 4, 2020

Table 4

Unincluded Charging Station Subsidies

Canton	Charging Station Subsidy (CHF)	Reason Excluded:
Bern	60,000	Offered for large charging station complexes in apartment buildings
Lucerne	500	Offered only to apartment buildings
St. Gallen	500	Offered only to apartment buildings in cities of Wil and Steinach
Thurgau	1000	Offered only to apartment buildings
Zurich	2000	Only for residents in the municipality of Horgen

Table 5

Regressands
Descriptive Statistics

Model:	EV Registrations (*# vehicles*) (1)	EV Market Share (*0-100*) (2)	Total Registrations (*# vehicles*) (3)	Avg. Vehicle Emissions (*CO_2 g/km*) (4)
Count	624	624	624	624
Mean	124.82	4.77	2776.79	130.82
St. Dev.	222.57	4.93	2753.87	14.17
Min	0.00	0.00	176.00	73.17
25%	19.00	1.22	655.25	128.94
50%	47.00	2.60	1939.50	134.18
75%	133.00	6.68	3649.50	139.07
Max	2305.00	24.07	14052.00	153.22

Table 6

Vehicle Price and Social Controls
Descriptive Statistics

	Tax Ratio (*-1+*)	Pct Tertiary (*0-100*)	Pop. Density (25+) *persons/km^2*	Pop. (25+) *persons*
Count	156	156	156	156
Mean	-0.53	32.54	359.86	237,078
St. Dev.	0.60	6.66	756.40	250,704
Min	-1.00	19.24	20.61	11,034
25%	-1.00	27.99	65.30	52,261
50%	-0.68	31.42	159.07	171,715
75%	-0.42	35.93	253.37	292,486
Max	1.92	52.01	3,967.51	1,143,880

Model 1: Number of Electric Vehicles Registered, Logarithmic

	Model: (1.1) Purchase Premiums	Model: (1.2) Vehicle Price Controls	Model: (1.3) Social Controls	Model: (1.4) Canton FE	Model: (1.5) Time FEs w/out Canton FEs	Model: (1.6) Time FEs & Canton FEs
PP / 1000	0.527***	0.346***	0.493***	0.186**	0.285***	0.086***
	(0.111)	(0.099)	(0.082)	(0.092)	(0.094)	(0.016)
CS / 1000		1.214***	0.559**	0.335***	0.308	0.038
		(0.231)	(0.275)	(0.124)	(0.330)	(0.051)
Tax Ratio		−0.274	−0.307	−0.281**	−0.305	−0.103
		(0.319)	(0.287)	(0.133)	(0.269)	(0.063)
Pct Tertiary			0.119***	0.093***	0.064	0.005
			(0.034)	(0.025)	(0.043)	(0.018)
ln(Pop. Den. 25+)			−0.018	27.502***	0.217	−4.800
			(0.242)	(4.142)	(0.297)	(4.012)
R^2	0.047	0.101	0.361	0.862	0.514	0.950
R^2 Adj.	0.046	0.097	0.356	0.855	0.491	0.945
Sample Size	622	622	622	622	622	622
Time FE	No	No	No	No	Yes	Yes
Canton FE	No	No	No	Yes	No	Yes

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$, Robust standard errors clustered at Canton level

Model 2: Market Share of Electric Vehicles, Logarithmic

	Model: (2.1) Purchase Premiums	Model: (2.2) Vehicle Price Controls	Model: (2.3) Social Controls	Model: (2.4) Canton FE	Model: (2.5) Time FEs w/out Canton FEs	Model: (2.6) Time FEs & Canton FEs
PP / 1000	0.450***	0.360***	0.455***	0.202*	0.164***	0.099***
	(0.053)	(0.057)	(0.043)	(0.106)	(0.056)	(0.029)
CS / 1000		0.612***	0.169	0.386**	−0.195*	0.107
		(0.145)	(0.172)	(0.158)	(0.104)	(0.106)
Tax Ratio		−0.121	−0.068	−0.298**	−0.073	−0.101*
		(0.127)	(0.154)	(0.126)	(0.118)	(0.055)
Pct Tertiary			0.106***	0.113***	0.022	0.029
			(0.021)	(0.035)	(0.016)	(0.034)
ln(Pop. Den. 25+)			−0.287***	29.928***	0.077	−5.519
			(0.090)	(6.821)	(0.069)	(4.386)
R^2	0.061	0.084	0.284	0.701	0.749	0.865
R^2 Adj.	0.060	0.080	0.278	0.686	0.737	0.852
Sample Size	622	622	622	622	622	622
Time FE	No	No	No	No	Yes	Yes
Canton FE	No	No	No	Yes	No	Yes

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$, Robust standard errors clustered at Canton level

Model 3: All Vehicles Sales, Logarithmic

	Model: (3.1) Purchase Premiums	Model: (3.2) Vehicle Price Controls	Model: (3.3) Social Controls	Model: (3.4) Canton FE	Model: (3.5) Time FEs w/out Canton FEs	Model: (3.6) Time FEs & Canton FEs
PP / 1000	0.078	-0.013	0.040	-0.016	0.121	-0.013
	(0.094)	(0.086)	(0.091)	(0.020)	(0.102)	(0.019)
CS / 1000		0.606^{***}	0.390	-0.049	0.503^{*}	-0.068
		(0.174)	(0.264)	(0.051)	(0.262)	(0.070)
Tax Ratio		-0.150	-0.236	0.014	-0.228	-0.003
		(0.268)	(0.229)	(0.019)	(0.239)	(0.043)
Pct Tertiary			0.013	-0.020^{*}	0.043	-0.024
			(0.026)	(0.011)	(0.040)	(0.019)
ln(Pop. Den. 25+)			0.268	-2.496	0.140	0.766
			(0.230)	(3.194)	(0.263)	(1.274)
R^2	0.002	0.029	0.143	0.947	0.193	0.960
R^2 Adj.	0.000	0.024	0.136	0.945	0.155	0.956
Sample Size	624	624	624	624	624	624
Time FE	No	No	No	No	Yes	Yes
Canton FE	No	No	No	Yes	No	Yes

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$, Robust standard errors clustered at Canton level

Model 4: Average CO_2 emissions of Vehicles Registered, Logarithmic

	Model: (4.1) Purchase Premiums	Model: (4.2) Vehicle Price Controls	Model: (4.3) Social Controls	Model: (4.4) Canton FE	Model: (4.5) Time FEs w/out Canton FEs	Model: (4.6) Time FEs & Canton FEs
PP / 1000	-0.042^{***}	-0.030^{***}	-0.035^{***}	-0.017^{***}	-0.008^{**}	-0.008^{**}
	(0.013)	(0.011)	(0.009)	(0.006)	(0.004)	(0.003)
CS / 1000		-0.084^{***}	-0.057^{*}	-0.100^{***}	-0.003	-0.002
		(0.025)	(0.032)	(0.011)	(0.013)	(0.005)
Tax Ratio		0.009	0.004	-0.009	0.016^{**}	0.013^{***}
		(0.011)	(0.015)	(0.006)	(0.007)	(0.004)
Pct Tertiary			-0.007^{**}	-0.027^{***}	0.005^{***}	0.000
			(0.003)	(0.003)	(0.002)	(0.001)
ln(Pop. Den. 25+)			0.025^{*}	0.076	-0.029^{***}	-1.261^{***}
			(0.014)	(0.408)	(0.008)	(0.432)
R^2	0.044	0.074	0.141	0.519	0.905	0.951
R^2 Adj.	0.042	0.070	0.134	0.494	0.901	0.946
Sample Size	624	624	624	624	624	624
Time FE	No	No	No	No	Yes	Yes
Canton FE	No	No	No	Yes	No	Yes

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$, Robust standard errors clustered at Canton level

VI. Empirical Interpretations:

To understand how well the purchase premium subsidy and controls explain variation in the response variable of interest, I use six different specifications on each of the four models:

0.1) Include just the purchase premium variable

0.2) Introduce vehicle price controls (charging station subsidy, tax ratio)

0.3) Introduce social controls (population, population density, tertiary education percent)

0.4) Introduce canton-fixed effects

0.5) Introduce time-fixed effects without canton-fixed effects

0.6) Include all vehicle price, social, canton, and time-fixed effects

A. Model 1 (Electric Vehicle Sales) Interpretations

Without controlling for any confounding variables, model (1.1) indicates that a 1000 CHF increase in an electric vehicle purchase premium correlates with an approximate 52.7% increase in electric vehicle sales. The decrease in this coefficient on the second specification (1.2) indicates that the purchase premium regressor in model (1.1) is biased upwards without the inclusion of vehicle price estimators.[54] The tax ratio coefficient in model (1.2) indicates that a one-percentage-point increase in the annual vehicle tax of an electric vehicle relative to its non-electric vehicle counterpart decreases the number of electric vehicles purchased by 0.27%; while statistically insignificant, the sign of the coefficient is expected as more expensive annual taxes likely

[54] Two of the four cantons with purchase premium policies also have charging station subsidy policies, and several cantons that introduced purchase premiums also had favorable annual tax incentives. As a result, severe endogeneity in model (1.1) inflates the effect of purchase premiums on electric vehicle sales.

discourage consumers from buying electric vehicles.[55] Social controls in model (1.3) appear to predict electric vehicle variation well, with the R-squared value increasing more than three-fold from the previous model. For interpreting tertiary education percentage: a one percentage point increase in the tertiary education of a canton increases the electric vehicle market share by 11.9%. With the introduction of canton-level fixed effects in model (1.4), the effect of population density appears to increase dramatically, suggesting that a one percent increase in population increases electric vehicle market share by 27.5%. When fixed-canton-level variation is controlled for, the strong positive correlation between population density and time results in an upward bias in this estimate, which is empirically shown by the decrease and loss of statistical significance for the social control estimators in model (1.5). When both time-fixed effects and canton-fixed effects are included in model (1.6), only the purchase premium policy and fixed effects are statistically significant. This indicates that much of the variation in the vehicle price and social controls comes from cross-canton and cross-year variation. Unexpectedly, the sign on the population density estimator flips negative when base-cantonal and time effects are controlled for in the model.[56] The estimate on purchase premiums in the final model (1.6) indicates that a 1000 CHF increase in purchase premiums increases the sales of electric vehicles by 8.6%. This is both statistically significant at the 1% level and large in magnitude; the canton of Valais, which introduced a 3500 CHF purchase premium in Q3 of 2020, would be expected to witness a 30.1% increase in electric vehicle purchases following the implementation of this policy.[57]

[55] In the year 2017, the leading Tesla Model S in the canton of Schaffhausen (which used horsepower to calculate taxes) cost *984 CHF* in annual registration taxes, whereas the leading BMW X5 xDrive cost *384 CHF* in annual registration taxes. The next year, Schaffhausen decreased the annual motor vehicle tax for this same Tesla to *336 CHF* while holding the BMW's tax the same. This amounted to a 1.68-point decrease in annual motor vehicle taxes of the Tesla relative to the BMW, which when ignoring social, time, and canton controls in model (1.2), would predict a 52% increase in electric vehicle sales with policy change.

[56] This may occur because cantons with small populations in the year 2016 experienced more significant percent changes in population density over the five-year study period, and since smaller cantons may be less adaptive to electric vehicle policies over time, this variable is picking up on variation in a canton's population's systematically lower adaptiveness to electric vehicle market growth.

[57] Actual electric vehicle sales in the canton of Valais increased from 70 vehicles in Q2-2020 to 142 vehicles in Q3-2020. About a third of this increase in electric vehicle registrations can be explained by the purchase premium policy.

B. Model 2 (Electric Vehicle Market Share) Interpretations

Because the only difference between models (1) and (2) is the introduction of a relatively constant denominator (total number of vehicles sold) into the explained variable, similar results are expected in model (2) as in model (1). This proves true as regression coefficients are relatively similar in magnitude and significance for the first two models. R-squared values in model (2) appear to show slightly less correlation when compared to model (1). Unsurprisingly, time-fixed effects introduced in model (2.5) appear to be better indicators of electric vehicle market share than the electric vehicle market sales, seen by lower R-squared values in model (1.5).[58] When vehicle price controls, social controls, time-fixed effects, and canton-fixed effects are controlled for, model (2.6) indicates that a 1000 CHF increase in purchase premiums increases the market share of electric vehicles by 9.9%, significant at the 1% level. The magnitude for this is large; when a 4000 CHF purchase premium came into play in the canton of Thurgau in Q1 of 2019, the canton witnessed an 83.6% increase in electric vehicles market share compared to the previous quarter. Approximately 40% of this market share increase can be explained by the implementation of the premium policy.

C. Model 3 (All Vehicles Sales) Interpretations

Few non-fixed effect controls show statistical significance throughout specifications in model (3), and evident by the R-squared values, canton-fixed effects appearing in models (3.4) and (3.6) control for much of the variation in total vehicle registrations.[59] Importantly, the regressor on purchase premiums is negative and not statistically significant in the final model (3.6), so no statistical inference can be drawn on how purchase premiums influence the sale of all vehicles. There is thus no statistically noticeable fleet-size or manufacturing-size effect occurring from vehicle incentives, which is contrary to what previous researchers such as D'Haultfoeuille et al. (2014) have found in the French vehicle market. This is excellent news for policymakers

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[58] EV market share is expected to depend more on market conditions and availability, which vary more with time. EV market sales are more dependent on baseline-cantonal differences in consumer size and interest.

[59] For each canton, vehicle sales appear to decrease at a relatively constant rate with time. With the introduction of canton controls in model (3.4), the high correlation between population density and time for each canton can control for the general decline in vehicle sales over time, reflected by the negative sign on the coefficient.

interested in encouraging EV sales as it indicates that consumers are substituting into electric vehicle purchases with the implementation of a purchase premium program instead of deciding to purchase additional vehicles because of the premium policy.

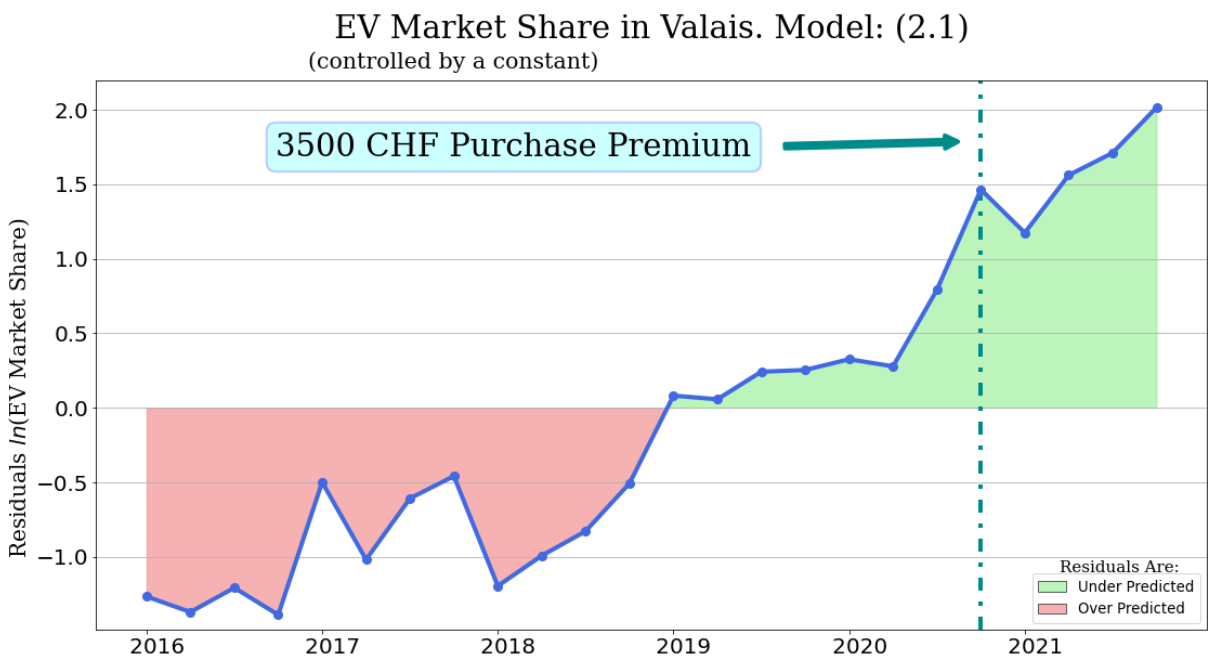
D. Model 4 (Average CO_2 Emissions) Interpretations

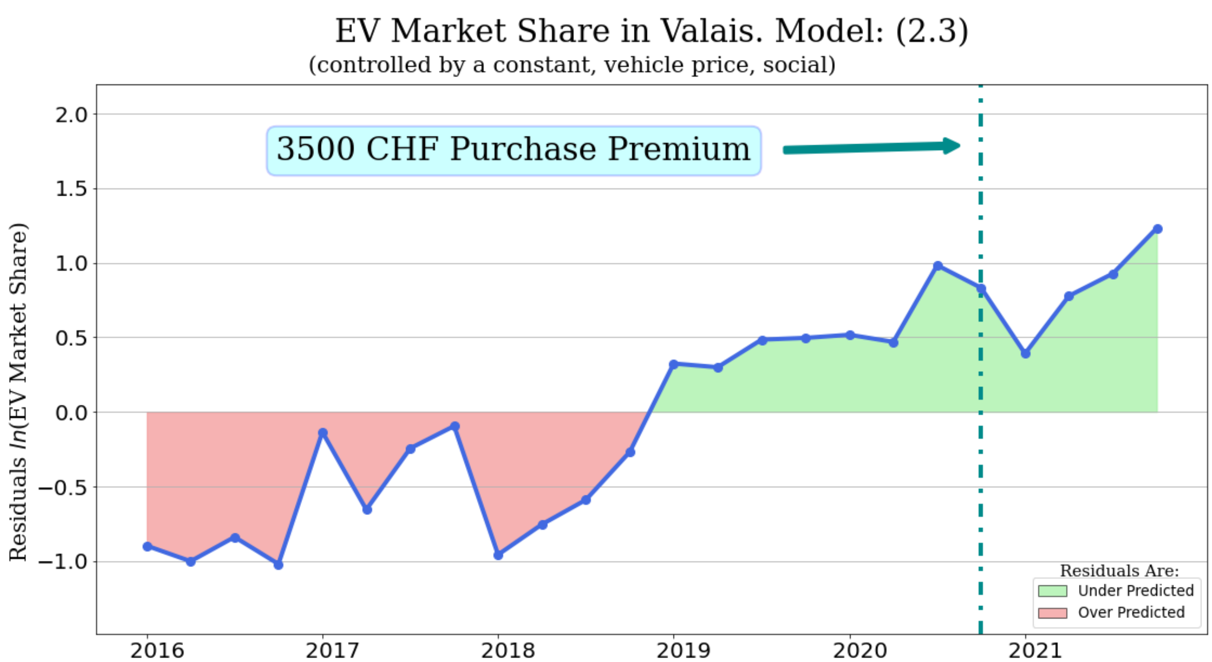
Model (4) tests whether electric vehicles purchased because of premium policies were able to decrease the average tailpipe emissions of vehicles on the road. Results in the final model (4.6) are significant at the 5% level and indicate that a 1000 CHF increase in purchase premium policy would be expected to decrease the average tailpipe CO_2 emissions of newly registered vehicles by 0.8%. The significance of this coefficient can be better interpreted with the following example: when Ticino implemented a 2000 CHF purchase premium policy in Q3 of 2019, average tailpipe emissions for newly registered vehicles decreased in this canton from 139.4 (Q2-2019) to 135.6 CO_2/km (Q3-2019); approximately 1.6% of this 2.7% decline in emissions is predicted by the purchase premium policy coefficient. Because new registrations make up about 9.2% of all registered vehicles in Switzerland, it would likely take time for this policy to impact overall emissions for all vehicles on the road (Statista, 2019). Assuming the policy had the same effect in all cantons, if the same Ticino-style premium had been implemented across Switzerland starting in Q3 of 2019, the average tailpipe emissions for vehicles on the road would be expected to decrease by about 0.4% CO_2 g/km after 2.5 years in play.[60]

[60] Assumes that new vehicle registrations replace approximately 9.2% of currently registered vehicles every year and that the same percentage of all vehicles are retired each year over the 2.5-year period (Q3 2019 – Q4 2021)

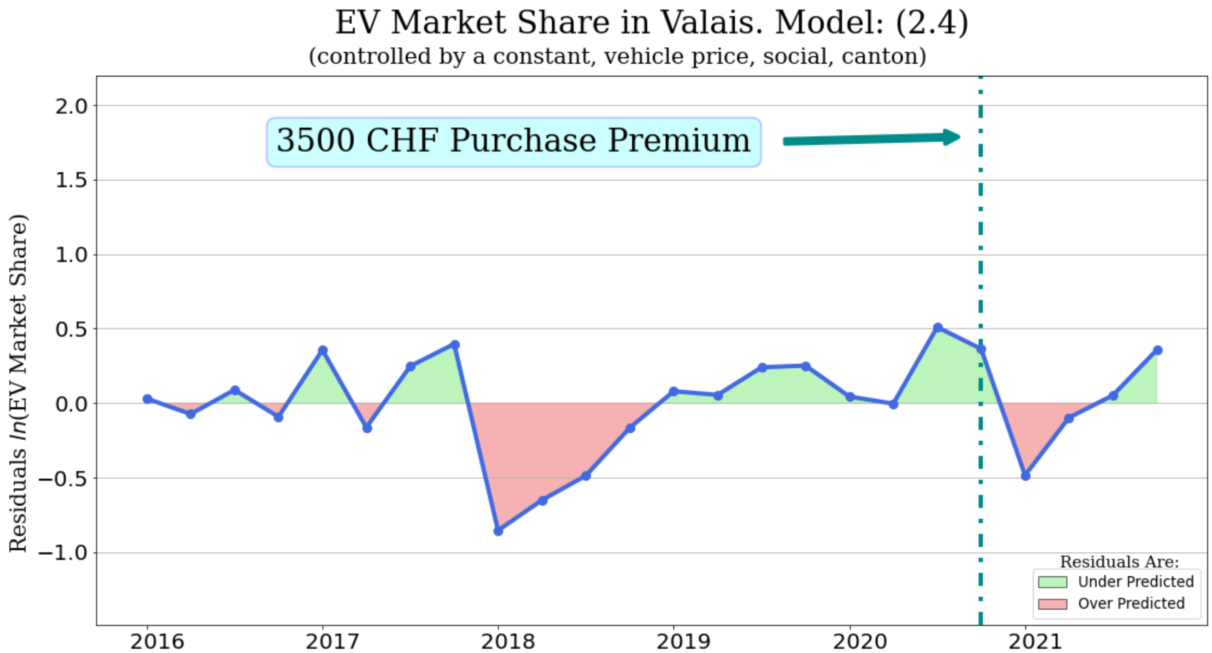
Residuals for the canton of Valais are graphed below for models (2.1), (2.3), (2.4), and (2.6) with the explanatory variable excluded. The residuals can help visualize the estimated effect of the purchase premium policy for each specification.

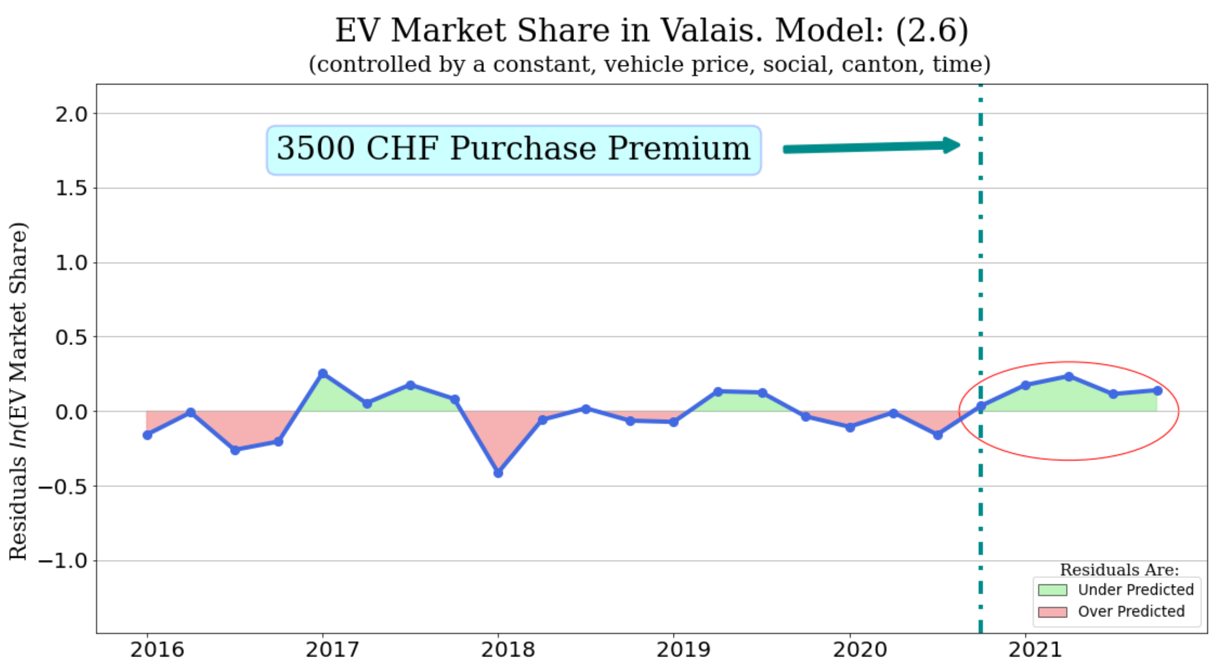
Figure 5 – Model Specifications





In the final specification of model (2.6), there appears to be a visible increase in the market share of electric vehicles after controlling for vehicle price, social, canton-fixed effects, and time-fixed effects. The remaining variation shown in the final specification below (model 2.6) can be attributed to the effect of the purchase premium or random variation.





VII. Conclusion:

Mitigating climate change is often considered the most pressing challenge of humanity today. Electric vehicles can help close this market failure, as a significant portion of greenhouse gas emissions in developed countries come from the road-transportation sector. While governments have used a variety of incentive programs to encourage consumers to adopt eco-friendly vehicles, discounts offered directly at point-of-sale have shown to be most effective at influencing consumer behavior. I further this research by using the most recent Swiss registration data between 2016 and 2021 to study the effect of discounting incentives on Switzerland's vehicle market. I find that purchase premium policies do influence consumers to purchase electric vehicles to a statistically significant degree, and I find no evidence of emissions-related negative externalities when testing effects on fleet-size and average CO_2 emissions. The following section will discuss how my research compares to previous studies on vehicle incentives, explain limitations in my study methodology, and draw conclusions regarding EV policy implications.

A. Comparisons to Previous Research

Results are somewhat similar to previous researchers who have studied eco-friendly incentives in the vehicle market. An estimate by Schaller (2020) can be inferred to represent that a 1000 CHF increase in purchase premiums will increase EV market share by about 7.0%, while I find that purchase premium policies correspond with an 8.6% increase in EV market share.[61] When testing the average emission level of newly registered vehicles, my results reach a similar conclusion as that of Alberini & Bareit (2019): incentives for eco-friendly vehicles can decrease the average emission level for all registered vehicles but unfortunately would account for just a fraction of a percent decrease in overall average transportation sector emission levels. When I test for the impact of purchase premiums on all vehicle sales, my results reach different conclusions than

[61] Schaller (2020) found that a 1000 CHF increase in purchase premiums corresponds influences a 0.3 percentage points increase in EV market share, which can be calculated to be an approximately 7.0% increase considering all policies in his study were introduced in 2019 and the mean EV market share in that year across all cantons was 4.0 percentage points.

previous researchers (D'Haultfoeuille et al., 2014; Goulder, 2012), as I find no evidence of an increase in total vehicle sales (or fleet-size effect) due to these purchase premium policies. While my results indicate that direct discount policies can increase EV sales & market share while decreasing average and total emission levels, these conclusions are drawn from the many modeling decisions made throughout this project, so I will now discuss limitations in assessing these results and offer recommendations for those interested in furthering this research.

B. Limitations & Areas for Future Research

Modeling decisions are expected to have biased results. The primary concern comes from how I interpreted purchase premiums, the variable of interest. The models used in this research only include policies for fully electric vehicles that are offered to all cantonal constituents, which likely introduces downward bias into the purchase premium estimator in models (1) & (2).[62] And while my model treats each purchase premium policy throughout Switzerland as equal (differing only in magnitude and period of implementation), there are some differences between how they are applied: the canton of Schaffhausen, for example, requires consumers benefiting from the premiums to have their home electricity run on 100% renewable energy (Energieforderung, 2021), and consumers in the canton of Ticino must wait to apply for the bonus after registering their vehicle before being able to apply for the premium.[63] These differences in technicalities mean that the effect of one policy is only assumed to be able to be compared identically across all cantons.[64]

Control variables also likely introduced bias. Like with purchase premiums, charging station subsidies were excluded if they were offered only to a subsection of the population in a particular canton, meaning policies were excluded that could have had some influence on EV sales. The second vehicle price control could

[62] Policies offered for hybrid vehicles that were implemented at the same time as those for fully electric vehicles are expected to systematically downward bias the number and market share of fully electric sales; similarly, the positive effect of policies offered in smaller cities and municipalities are uncaptured by the purchase premium estimator, likely biasing this estimator further. Future work could attempt to control for these hybrid & city-level premiums.

[63] The Ticino government indicates that 10% of consumers who applied for an EV premium in Ticino were rejected, meaning that salience issues exist among consumers regarding the types of vehicles eligible for the subsidy.

[64] Also assumed to be linear in effect.

also be a poor reflection of the variable it is intended to represent, as all that is being reflected is the tax on a Tesla Model S relative to a BMW X5; this doesn't account for possible tax changes on lower-end electric vehicles.[65] And for social controls, the decision to use population density for those over the age of 25 doesn't account for purchasing decisions made because of changes in the population size for those under 25.[66] These limitations in control variables indicate uncaptured variation and potential misspecification bias.

Problems may have arisen because regression results are based on canton-year-quarter paneled data. This allows for measurement error on the variable of interest, as the implementation date for purchase premiums was assigned to the closest quarter start.[67] Registration data (available at the monthly level) was aggregated to corresponding quarters, while social and vehicle price controls (available at the yearly level) were held constant across quarter measurements within a year. All controls (except for population density) are assumed additive and linearly separable based on previous research using mixed-logit models (Alberini & Bareit, 2019; Petrin, 2002; Haaf et al., 2014; Li, 2017), but this could easily not be the case.[68] And when testing for fleet-size effects, model (3) studies whether vehicle sales increase with purchase premium policies, but this doesn't test for whether consumers are holding onto and driving older fuel-inefficient vehicles or whether consumers choose to drive longer distances with fuel-efficient vehicles that are cheaper to travel with (a rebound effect). These limitations indicate that results cannot be directly assessed at face value without understanding the nuance abundantly present.

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[65] Additionally, the TCS tax ratio couldn't be calculated for the year of 2016 due to missing data, meaning the years of 2017 was used to supplement. However, the annual motor vehicle tax is highly time-invariant across Switzerland, so this likely introduced little bias.

[66] A boom in the population of those under 25 would not be reflected in this statistic, which may influence misspecification bias as new vehicles might be purchased due to the addition of new children into the household.

[67] Due to cross-sectional data point aggregation, vehicles registered in Valais in October 2019 were unfortunately forced to be labeled as being purchased during a period of purchase premiums. Fifty fewer EVs were registered in October 2019 than in November 2019, indicating that the estimator is likely biased downward by this specific monthly difference in registrations.

[68] The potential for a decreasing marginal effect of purchase premium policies is not accounted for in this research. For example, the effect of a 2000 CHF purchase premium could be only 25% more influential when compared to a 1000CHF incentive.

A repeated analysis of purchase premium policies in Switzerland would offer many opportunities for analysis improvement. Future analysis could use methods similar to Alberini & Bareit (2019) to group panel data by vehicle sales at the make-model level with more vehicle characteristic controls. Additionally, a mixed logit model and derived functional form like the one in this research could test the effect of purchase premiums on hybrid vehicle sales and market share. Finally, a more mature market would be expected to show longer-term responsiveness to purchase premium policies.[69]

C. Policy Implications

If policymakers wanted to enact a purchase premium, many of the conclusions drawn in the literature review section are valuable to keep in mind, namely:

1.) Subsidies are most effective if they are offered soon after registration.

2.) The effect of EV incentives does not impact all consumers equally. Middle-aged, wealthy, highly educated persons respond most to increases & decreases in premium policies.

3.) Policies should be targeted specifically in emerging markets and then phased out.

Fortunately, there is evidence that all these factors are accounted for in premium policies throughout Switzerland. In three out of four cantons with canton-wide premium policies, consumers can apply for the subsidy immediately after registration. Multiple wealthy cities and towns in Switzerland have independent premium policies to influence their constituents. And in Thurgau, the premiums have decreased in magnitude every year since implementation. Well-designed purchase premium policies throughout Switzerland can serve as models for future policymakers interested in incentivizing the EV market.

[69] An interesting test would be discovering whether the effect of purchase premium policies is expected to decrease with time as a market matures, as Jenn et al., (2020) would predict.

However, because of the nature of this research, policy recommendations are limited in scale. Results show that direct discounts at the point of sale can influence the sale of EVs to a statistically significant degree without negative externalities arising from fleet-size effects; if a policymaker intends to increase EV sales and decrease emission levels, this research suggests that direct discounts do work. It would, however, be overly costly and take many years for any significant impact on total CO_2 tailpipe emissions should these purchase premiums be implemented on a larger scale. The conclusions drawn from this research would need to be first placed into a larger analysis of the cost-benefit of all types of eco-friendly programs before any policy recommendations can be drawn.

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