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PUBLIC PURCHASING SUBSIDIES AND THE FEAR OF MISSING OUT: A FULL-SAMPLE ANALYSIS OF ELECTRIC VEHICLE ADOPTION IN GERMANY

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Public Purchasing Subsidies and the Fear of Missing Out:

A Full-Sample Analysis of Electric Vehicle Adoption in Germany

Abstract: This is the first study to employ a national full sample dataset for a socioeconomic analysis of the adoption of electric vehicles (EVs). We use the most recent vehicle registration dataset from the Federal Motor Transport Authority of Germany, which includes the entire underlying population of German vehicle owners. Combining web-scraped data covering all vehicles available in the German market with actual registration data allows a unique analysis of the individual decisions to purchase an EV. Our results suggest that financial incentives are the most relevant factor for EV adoption, with a €1,000 subsidy increase boosting EV choice probability by 1.2 percentage points. Given that EVs currently constitute 12% of newly registered private vehicles in Germany, our model calculates that, in the absence of subsidies, this share would be 1.2%. In contrast, a uniform maximum subsidy of €9,000 from 2011 to 2023 could have increased the adoption rate to 20%. These results underscore the importance of financial incentives in achieving policy targets for EV adoption and suggest that purchase subsidies exhibit increasing marginal returns.

Keywords: *Electric vehicles, Vehicle choice, Financial Incentives, Discrete choice*
JEL: *Q42, R41, H23, C35*

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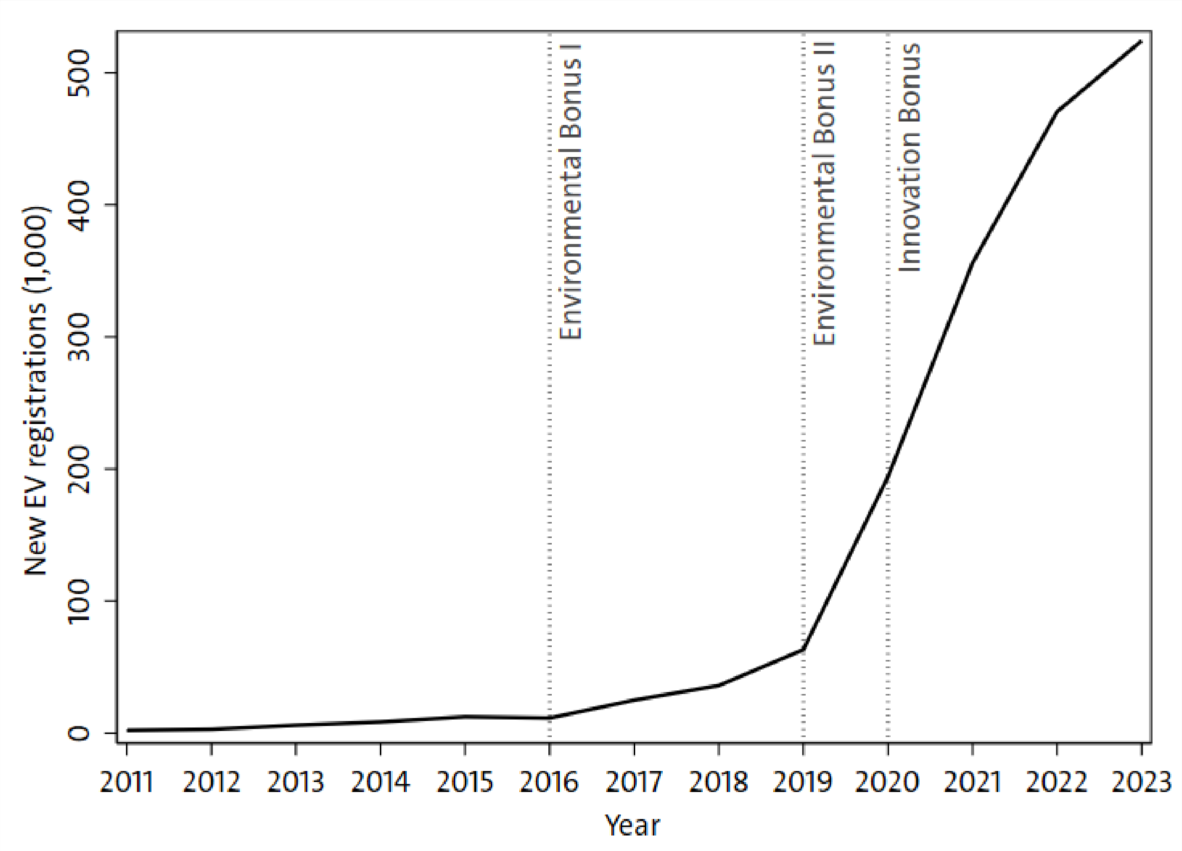
1 Introduction

In 2022, approximately 760 million tons of carbon dioxide were emitted in the EU from road transport fuel combustion, with Germany accounting for the largest share at 142 million tons (Eurostat, 2024). Passenger cars and motorcycles were identified as the primary source of emissions, representing 60% of the total (Destatis, 2024). As the impacts of climate change become increasingly pronounced, countries are seeking solutions to reduce greenhouse gas emissions and promote sustainable practices. In this context, many countries have recognized the pivotal role of electric vehicles (EVs) in mitigating carbon emissions from the transportation sector (see, e.g., Archsmith et al., 2015). Germany has set an ambitious target: 15 million EVs are to be registered by 2030 (German Government, 2021). To achieve this goal, production capacity has been expanded and public funding has been made available, positioning Germany as the second largest seller of EVs in the world after China (Liu et al., 2023) and among the top three countries in the field of EV research (Haghani et al., 2023).

To increase the number of registrations, the German government set up a framework of financial incentives designed to encourage the adoption of EVs among consumers. The purchase premium for EVs introduced by the German government in 2016 (German Government, 2020) was one of the highest ever launched in a country and was taken up by 1.4 million car buyers by the time it expired in late 2023 (ADAC, 2024). However, Germany, like most other countries, is far from achieving its stated registration target of 15 million EVs. Although the number of new EV registrations has exhibited an almost exponential growth trajectory in recent years (Figure 1), by the end of 2023, there were only 1.6 million registered EVs in Germany (German Federal Motor Transport Authority, 2024c).

Figure 1 Development of new EV registrations in our database



Note: This figure shows the absolute number of new electric vehicle (EV) registrations in Germany (2011–2023). The data are from the German Federal Motor Transport Authority (2024b). Launched by the German government in 2016, the Environmental Bonus I allowed EV buyers to receive a purchase premium of €4,000. The second stage of the Environmental Bonus started in 2019; EV buyers received a €6,000 purchase premium for EVs with a retail price below €40,000 and €5,000 for an EV in the price range of €40,000–€65,000. From 2020, the Innovation Bonus provided EV buyers access to €9,000 for EVs below €40,000 and €7,500 for EVs in the price range of €40,000–€65,000. Prior to 2016, there was no purchase premium for EVs.

This is the first study to use the most recent 2023 administrative German vehicle registration dataset, featuring actual vehicle registrations as well as owner-specific information of the whole underlying population of 69 million vehicles analyzing the technical, (infra)structural, and socioeconomic determinants of individual decisions for or against EVs. Because our administrative dataset encompasses persons' actual car registrations, we obtain postpurchase decision data at the individual level. In addition, we employ web-scraping techniques to gather comprehensive data on all vehicles available in the German automobile market between 2011 and 2023, thereby facilitating the identification of a potential purchase alternative for the cars in our vehicle registration dataset.

Our study innovates by transforming and combining vehicle purchase alternative (choice) data with information on consumers' postpurchase behavior to estimate the adoption probabilities of EVs using a multinomial choice model after McFadden (1974). We introduce a novel model framework that allows for the identification of determinants at both the technical and socioeconomic levels. Thus, our study not only adds to studies based on survey data but also adds to the few studies using real-world data, which are typically constrained by smaller samples. We thus mitigate potential survey and small sample biases while isolating determinants of personal EV adoption for an underlying national population.

Consistent with previous research, our findings confirm that financial incentives, vehicle range, charging infrastructure, income level, and environmental concern significantly increase the likelihood of EV adoption; higher fuel costs of EVs compared to combustion engine cars and an increase in the buyer's age are associated with a decreased likelihood of acquiring an EV. In particular, financial incentives emerge as the most influential factor, with a €1,000 increase in subsidies increasing the likelihood of choosing an EV by 1.2 percentage points. Our model predicts that without subsidies, EVs would constitute only 1.2% of the private German car fleet, excluding used cars. If all EVs had received the initial €4,000 environmental bonus, the share would be approximately 5%, whereas a uniform €9,000 subsidy could have driven adoption up to 20%. Thus, we note an increasing marginal effect of observed financial incentives.

The remainder of the paper proceeds as follows: In Section 2, we review the literature on EV adoption and embed our central contribution. In Section 3, we elaborate on our database. In Section 4, we outline our modeling approach and identification strategy, explaining how we integrate real-world postpurchase data with purchase alternatives to estimate EV adoption determinants. In Section 5, the results are presented. In Section 6, potential policy implications and concluding remarks are discussed.

2 Literature Review

During the last one and a half decades, the literature on the determinants of EV adoption has converged to a largely agreed-upon set of most influential factors, including retail price, driving range, and charging infrastructure as well as socioeconomic characteristics (e.g., age, sex, income, and environmental awareness); more recent studies have also considered the role of EV subsidization. Table A1 in the Appendix (Section A) provides a tabular overview of publications on EV adoption, highlighting the consensus findings.

Early findings point to environmental consciousness as a significant driver of EV adoption (Caperello & Kurani, 2012). However, socioeconomic factors introduce additional complexity, as adoption behavior varies across demographic dimensions such as age and sex (Egbue & Long, 2012). In addition, financial constraints, particularly high initial purchase prices, were mentioned as barriers to adoption (Graham-Rowe et al., 2012). Furthermore, concerns regarding the driving range play a decisive role in consumer decision-making, influencing the relative attractiveness of EVs compared with internal combustion engine vehicles (Lieven et al., 2011; Skippon & Garwood, 2011).

Moons & De Pelsmacker (2012), who focused on subjective norms such as the environmental concerns of Belgian citizens, were among the first to use regression analysis to examine EV uptake. Their results suggested that EV adoption depends on people's socioeconomic characteristics by providing evidence that early adopters of EVs tend to have a higher social status and a higher education level, which was corroborated by subsequent studies (e.g., Carley et al., 2013; Javid & Nejat, 2017; Jia & Chen, 2021).

In the context of EV adoption, Jensen et al. (2013) were among the first to use discrete choice analysis in the tradition of McFadden (1974). They used a two-wave stated preference experiment where data were collected before and after respondents experienced an EV for three months in Denmark. The study employed a hybrid choice model that incorporated latent variables to measure individual attitudes and allowed the coefficients to vary between the two waves to test whether real-life experience changes preferences for EV characteristics and attitudes. The findings indicated that real-life experience with EVs significantly alters consumer preferences, particularly increasing the importance of technological factors, e.g., driving range and charging infrastructure.

Since then, choice analysis has provided a methodological foundation for empirical research in the field of EV adoption, facilitating a deeper understanding of consumer decision-making and policy implications. For example, Axsen et al. (2015) analyzed consumer preferences for EVs using survey data from 1,754 new vehicle-buying households in Canada. Their findings suggested that consumer preferences vary significantly, with segments driven by environmental concern, technological enthusiasm, or fuel cost savings. Similarly, Javid & Nejat (2017) considered a range of factors, such as demographics, travel habits, socioeconomic status, infrastructure, and regional specifics, via multiple logistic regression analysis of data from the 2012 California Household Travel Survey. They found that household income, education level, and regional gas prices significantly affect peoples' adoption of vehicles with an electric engine. More recently, Rotaris et al. (2021) collected data on 996 Italian and 938 Slovenian respondents between October and December 2018 and analyzed a stated preference survey with 12 hypothetical choice scenarios comparing EVs and internal combustion engine vehicles. Using a hybrid mixed logit model, they found that the purchase price and driving range are the most important factors influencing consumers' choices, whereas charging time is not a significant factor.

In addition to the literature on overall EV adoption, a branch of literature has emerged that identifies financial incentives as having a key impact on the uptake of EV technology. Hardman et al. (2017) reviewed the literature on the role of financial incentives in the context of EV adoption and identified two strands: (i) papers analyzing postpurchase behavior on the basis of surveys of EV buyers and (ii) papers analyzing hypothetical EV purchases on the basis of choice experiments. In the first strand, Bjerkan et al. (2016) surveyed 3,400 targeted EV owners, ensuring responses from individuals directly affected by Norway's extensive EV incentive programs. Their survey included questions on purchasing motivation, the perceived effectiveness of incentives and long-term satisfaction with EV ownership. The results indicated that upfront monetary incentives significantly influence purchasing decisions but have a diminishing effect on long-term satisfaction and retention. In addition, Tal & Nicholas (2016) investigated the impact of U.S. federal tax credits on plug-in vehicle sales through a large-scale sample of nearly 3,000 EV owners. Their estimates suggested that 30% to 49% of purchases were influenced by the federal tax credit. While postpurchase surveys, which collect data from consumers who have already bought (or will) buy an EV, provide insights into real-world behavior, these studies may suffer from selection bias; they include only people who have already chosen to buy an EV, excluding those who considered but ultimately rejected the option of an EV. In contrast, data obtained from choice experiments can be used to define the (quasi)experimental setting in such a way as to obtain a more representative sample including nonadopters.

Larson et al. (2014) presented an early example of a paper in the second strand, which analyzed hypothetical EV purchases on the basis of choice experiments. Based on a survey in Manitoba, the authors focused on Canadian consumer attitudes toward EV pricing and policy incentives. The stated choice experiment assessed acceptable price ranges and willingness to pay premiums for EVs, emphasizing the role of financial incentives in individuals' decision-making. Similarly, Langbroek et al. (2016) relied on a choice experiment in which respondents selected between conventional EVs and EVs with varying attributes, including financial incentives, range, and charging infrastructure in Stockholm. Interestingly, the results suggested that individuals who are already inclined toward EV adoption are less influenced by financial incentives. More recently, DeShazo et al. (2017) surveyed 1,261 prospective new car buyers in California and collected responses through an online platform. The experiment introduced varying levels of rebates and policy designs to estimate consumer willingness to adopt EVs under different financial conditions. The study highlighted that income-targeted rebates could improve cost-effectiveness and equity.

While choice experiments enable inference based on a representative sample, including individuals who do not yet own an EV, they are limited to hypothetical choices, meaning that the results may not fully translate into actual purchasing and market behavior (Jensen et al., 2013; Jia & Chen, 2021; Lane & Potter, 2007). As a result, the selection of the study design is ultimately a trade-off: On the one hand, postpurchase survey data provide information on actual EV adopters but suffer from potential survey biases, e.g., because nonadopters are not represented. On the other hand, (quasi) experiential settings can feature a representative sample. However, the results obtained from hypothetical decisions may not translate into real purchasing decisions. In any case, both designs undoubtedly suffer from small sample bias, as the number of participants rarely allows conclusions to be drawn about an entire population.

This study is the first to bridge this gap by integrating the strengths of both choice experiments and postpurchase survey data. We innovate by transforming and combining vehicle purchase alternative (choice) data with information on consumers' postpurchase behavior from an entire underlying population. This approach allows us to capture both hypothetical preferences and real-world purchasing behavior, mitigating the limitations inherent in each of the two methods when used in isolation.

3 Data

We use the German Federal Motor Transport Authority's vehicle registration dataset featuring all registered vehicles in Germany as of December 31, 2023 (German Federal Motor Transport Authority, 2024a). The German Federal Motor Transport Authority collects data for administrative purposes; it contains information necessary for car registrations, such as the owner's age, sex, and residence (county-level), as well as the vehicle's manufacturer and type. The dataset therefore consists of pooled cross sections, with single observations being identified at the owner level (via a unique person ID) and the car level (via the car's model, registration year, and county). We do not analyze repeated observations; each car appears in our data only once—in the year of its registration. However, this does not result in a loss of information, as a specific purchase decision is made only once. For example, if person 1 registers a new car in 2018, this car will (only) appear under his specific person ID in 2018. However, we do not need information about person 1 or the car in the years after 2018 to determine the factors influencing his purchase decision.

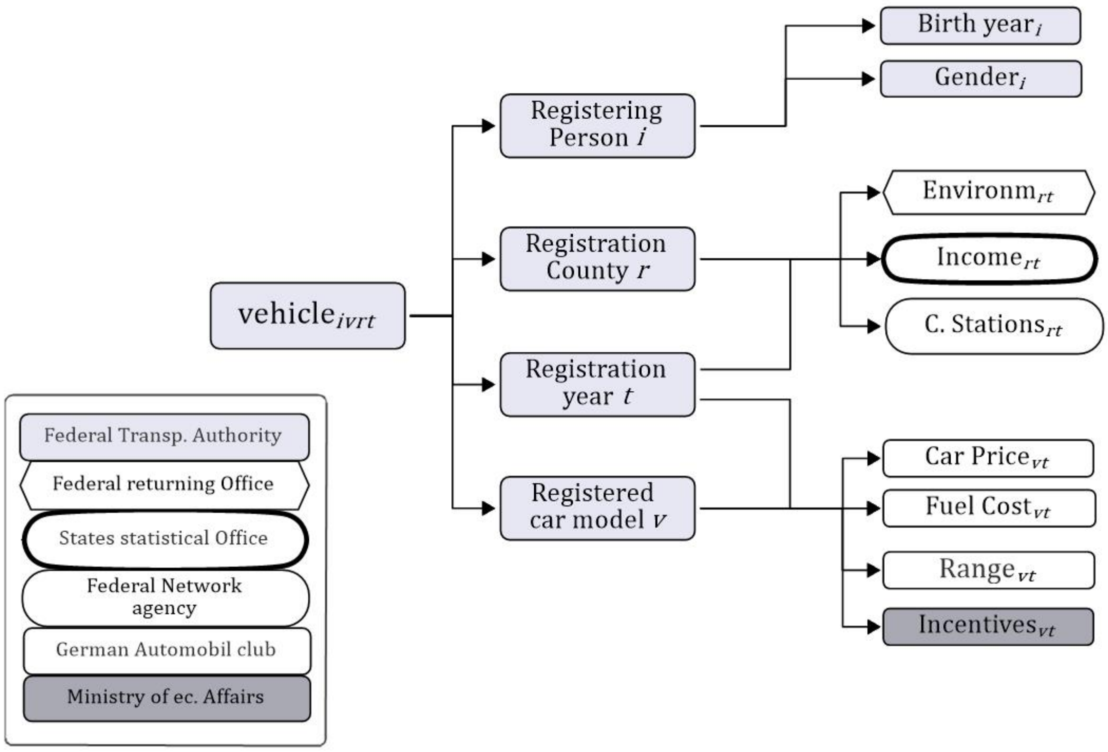
However, the vehicle registration dataset lacks important technical and socioeconomic information at both the owner and vehicle levels, which is necessary for a comprehensive analysis of the determinants of EV adoption. For example, it does not consider vehicle prices, fuel consumption, or the general charging infrastructure for EVs. In addition, the data do not include owners' income, attitudes toward environmentalism or information on granted financial incentives in the registration year.

We thus gather data from different external sources. Vehicle-related technical characteristics are drawn from the General German Automobile Club (ADAC). As the ADAC does not provide a publicly available database, we develop and implement a targeted web scraping algorithm to retrieve information on vehicles' retail prices, production period, range (for EVs), and fuel consumption from their website (www.adac.de). We obtain county-level data on the official charging infrastructure in Germany from the Federal Network Agency. The data include the number of charging stations and the date of installation. We use year-specific electricity and gas prices from the Federal Network Agency and www.en2x.de. The *Statistische Ämter der Länder* (States' Statistical offices) provide county-level data on per capita yearly primary income. We proxy peoples' attitudes toward environmentalism via the share of second votes obtained by the Green party in the German federal elections from 2009–2021 at the county level. The data are obtained from the *Bundeswahlleiterin* (Federal Returning Officer).[1] Finally, information on purchase incentives is drawn from the official websites of the German Federal Gov-

[1] As the German election cycle is four year, we approximate general environmentalism: the 2009 election results are used for registration years 2009–2011, the 2013 election results are used for the years 2012–2015, the 2017 election results are used for the year 2016–2019, and the 2021 election results are used for the years 2020–2024.

ernment and Federal Ministry for Economic Affairs. Figure 2 shows how the socioeconomic and technical determinants of EV adoption were assigned to a single vehicle in the vehicle registration dataset.

Figure 2 Assigning determinants of EV adoption to the vehicle registration dataset



Note: A single observation (vehicle) in the vehicle registration dataset provided by (German Federal Motor Transport Authority, 2024a) is identified at four different levels: its registering person (*i*), the county of registration (*r*), the year of registration (*t*), and the car model (*v*). First, we assign the owner's birth year and sex to each vehicle using the registering person identifier (*i*). Second, environmentalism, income, and the number of charging stations are ascribed to a vehicle using its registration county (*r*) and year (*t*). Finally, we assign the retail price, average fuel cost and range, and potential purchase premium received to the vehicle using information on the car's model (*v*).

After adding targeted information on both the vehicle and its owner to the administrative dataset, we clean the data to ensure a valid analysis. The original vehicle registration dataset contains 69,120,484 observations identified at the vehicle owner level, reflecting all registered vehicles currently registered in Germany. First, we discard nonpassenger cars, e.g., trucks and tractors (N=20,021,799), and vehicles where information on the vehicle type is missing (N=1,238,682). Next, we exclude hybrid vehicles, as they cannot be clearly identified as EVs or combustion engine vehicles (N=3,271,963). Owing to the low number of EV registrations prior to 2011, we discard the 15,239,162 car registrations prior to 12/2010. Since there is no deep market for second-hand EVs yet and we do not wish to compare a new EV with a second-hand combustion engine vehicles, 20,435,081 second-hand passenger cars are excluded. As vehicles registered by a corporate entity do not feature socioeconomic characteristics, we do not include such vehicles in our analysis (N=2,556,545). Finally, in consultation with the German Federal Motor Transport Authority, any observations suspected of having been recorded incorrectly are eliminated (N=560,255). The final dataset features 5,796,617 cars that are registered to persons who are 17 years or older.

Table 1 provides the definitions and comprehensive summary statistics of all the model variables. Panel A, which represents the entire database, shows that approximately 11% of new first-time registered EVs are located on German roads. Car owners' fuel costs are approximately 8.5 Euro per 100 km on average. A fully fueled car in our dataset drives an average of 828 km before requiring a refill. Governmental incentives, i.e., purchase grants, range from zero (for combustion engine cars) to 9,000 Euro over the time period of our analysis. On average, persons in Germany are 53 years old when they register a car, and close to 40% are females. Germans, on average, pay a total of approximately 31,000 Euro for a new car. On average, each county features a total of 53 charging stations one year prior to the individual decision to purchase a car. A comparison of the summary statistics in Panel A with those in Panel B, which presents information on a subsample featuring EV owners only, reveals that men acquire EVs more frequently than women do, with only 28% of EVs registered to female owners. In addition, Panel B shows that an EV received a mean purchase premium of €7,720. Furthermore, EV registrations are concentrated in wealthier counties and those with greater environmental awareness; on average, EV owners reside in counties with a mean income of €31,000 and a Green Party voter share of 15%, both well above the overall sample average (Panel A). In addition, one year prior to EV acquisition, the average number of charging stations in an owner's county is 128, which is more than twice the overall sample average.

Table 1 Summary statistics

Panel A: Overall summary statistics (*N*= 5,796,617)					
Variable	Definition	Mean	St. Dv.	Min	Max
EV	0 = combustor; 1 = EV	0.11	-	0	1.00
Fuel cost	(Fuel consump./100 km)∗Fuel price	8.48	2.59	3.41	41.23
Range	Range (km)	827.57	162.60	89	883
Incentives	Financial incentives (1000 Euro)	0.85	2.50	0	9
Age	Age of owner (years)	52.87	13.23	17	78
Gender	1 = female; 0 = male	0.38	-	0	1
Income	Primary income (1,000 Euro)	27.99	5.63	14.36	51.96
Environmentalism	Green party sec. votes (%), Fed. elections 2009-2021	10.84	5.42	0	35.96
Charging Stations	No. of charging stations	52.6	13.77	0	1,599

Panel B: Summary statistics for EVs (*N*= 636,966)					
Variable	Definition	Mean	St. Dv.	Min	Max
Fuel cost	(Fuel consump./100 km)∗Fuel price	6.15	1.17	3.41	12.70
Range	Range (km)	378.6	118.94	89.0	883
Incentives	Financial incentives (1000 Euro)	7.72	1.99	0.00	9
Age	Age of owner (years)	51.05	12.07	17.00	78
Gender	1 = female; 0 = male	0.28	0.45	0.00	1
Income	Primary income (1,000 Euro)	30.70	5.08	15.46	51.96
Environmentalism	Green party sec. votes (%), Fed. elections 2009-2021	14.57	5.58	0.00	35.96
Charging Stations	No. of charging stations	128.3	207.8	0.00	1,599

Note: The data include 5,796,617 (new) private cars registered after 12/2010 (Panel A). Panel B shows the summary statistics, with the dataset restricted to all 636,966 electric vehicles (EVs).

4 Identification and empirical framework

Figure 2 shows that only technical determinants can be assigned to the car type itself (i.e., EV or combustion engine vehicle), whereas other variables are individual-specific (age, sex, income, and environmentalism). Using two levels of identification, a conventional logit model cannot be applied directly to estimate adoption probabilities based on car type. This approach would require grouped data, wherein each observation within a group may represent a distinct individual, yet all individuals in the group share a common characteristic (McFadden, 1974). More specifically, an identification problem arises because key explanatory variables, such as the vehicle range or financial incentives, are exclusively defined for EVs. This induces perfect collinearity between the exogenous variables and the car type (dependent variable).

Multinomial choice models in the tradition of McFadden offer a solution by allowing for the simultaneous identification of vehicle-specific and individual-level covariates, given that the outcome variable represents the consumer's purchase decision between EVs and conventional vehicles. However, as such models typically rely on choice experiment data, our vehicle registration dataset—extended with all relevant determinants of EV adoption—must be transformed into a choice-based format to enable valid estimation.

The transformation follows a two-step procedure to construct a synthetic alternative for each registered EV or conventional vehicle, representing the counterfactual choice available to the buyer but ultimately not selected.[2] First, we classify all registered vehicles in our administrative dataset into price segments of €10,000 intervals. Moreover, we derive the mean values of our technical attributes (fuel costs and range) for all available EVs and combustion engine vehicles in Germany within each price category at the time of registration (t).[3] In a second step, we assign the hypothetical alternative within the same price segment—incorporating both vehicle-specific and individual-specific characteristics—to the observed choice in the corresponding year t via the unique person ID.[4]

By constructing synthetic alternatives to observed purchase decisions, this approach allows for the estimation of adoption probabilities based on both technical and socioeconomic determinants while leveraging real-world data of an underlying population. We

[2] During the data cleaning process, we exclude all vehicles for which there was no suitable counterpart (N=380).

[3] By aggregating vehicle attributes, we avoid issues arising from an excessive number of alternatives while maintaining the relevant variation in observed market conditions.

[4] Our price-based segmentation is necessary to ensure the validity of model comparisons. However, it also precludes the explicit inclusion of vehicle price in the econometric model in Equation (1). Consequently, while the model implicitly controls for price effects by limiting comparisons within the same price category, any direct estimation of price effects on adoption probabilities would be severely downward biased.

illustrate the transformation process by presenting two exemplary cases from our dataset (see Figure B1 in the Appendix, Section B).

Our econometric model includes every variable that has been identified to be of significance in earlier studies (see Table A1 in the Appendix, Section A) and is written as follows:

$$choice_{i,v,r,t} = \beta_0 + \beta_1 \overrightarrow{socio}_{i,r,t} + \beta_2 stations_{r,t-1} + \beta_3 \overrightarrow{tech}_{v,t} + \beta_4 incentives_{v,t} + \varepsilon_{i,v,r,t} \tag{1}$$

where

$$choice_{i,v,r,t} = \begin{cases} 1 & \text{individual } i \text{ chooses alternative } j \text{ (EV or combustion engine vehicle)} \\ 0 & \text{otherwise} \end{cases}$$

$$charging\ stations_{r,t-1} = \text{lagged number of charging poles}$$

$$\overrightarrow{socio}_{i,r,t} = individuals\ age_{i,t}, gender_i, income_{r,t}, \text{and } environmentalism_{r,t}$$

$$\overrightarrow{tech}_{v,t} = range_{v,t} \text{ and } fuel\ cost_{v,t}$$

$$incentives_{v,t} = \text{recieved financial incentives}$$

All socioeconomic variables as well as charging infrastructure in our model (Equation 1) are identified at the individual level *i* (with differences in in-variable variation) and pooled into a k_1 -dimensional vector $x_i = x_{i1}, \ldots, x_{ik1}$ of individual characteristics with the corresponding parameter vector $\beta_j = \beta_{j1}, \ldots, \beta_{jk1}$. All the technical determinants and financial incentives available at car model class *v* are assigned to one of two categories *j* (EV or combustion engine vehicles) and pooled into a k_2-dimensional vector $z_{ij} = z_{ij1}, \ldots, z_{ijk2}$ of alternative specific attributes with the corresponding parameter vector $\gamma = \gamma_1, \ldots, \gamma_{k2}$. The resulting error term ε_{ij} is then independently and identically standard extreme value distributed over all categories $j = [0,1]$ and all individuals $i =$

$1, \dots, n$. With this assumption, a single difference of two ε_{ij} has a standard logistic distribution. In the next step, we set the vector for alternative 1 (combustion engine vehicle) to zero, i.e., $\beta_1 = 0$ or $\beta_j = 0$. On the basis of this normalization $\beta_j = 0$, 'combustion engine vehicle' is the base category (or baseline) and provides the reference point for all effects estimated. The choice probabilities in our binary discrete choice (logit) model (Equation 1) for $i = 1, \dots, n;\ J = 1, \dots, J$ are then given as follows:

$$p_{i,j}(x_i, \beta, \gamma) = P(y_{i,j} = 1 | (x_i, \beta, \gamma) = \frac{e^{\beta'_j x_i + \gamma'(z_{ij} + z_{iJ})}}{1 + \sum_{m=1}^{J} e^{\beta'_m x_i + \gamma'(z_{im} + z_{iJ})}} \tag{2}$$

for $j = 1, \dots, J - 1$

5 Results

5.1 Baseline results

To examine the specific parameters of our model, Table 2 (Column I) reports the baseline estimation results for Equation (1) as average marginal partial effects (AMPEs).[5] In line with previous research, we find significant positive effects of financial incentives, vehicle range, charging infrastructure, buyer income, and environmental concern on the likelihood of choosing an EV over a conventional vehicle; fuel costs and buyer age exhibit significant negative effects. More specifically, when all explanatory variables are held at their mean values and only EVs and conventional vehicles of similar price categories are compared, the results suggest that increasing the average fuel cost per 100 km of an EV relative to a conventional vehicle in the same price category (6.15€/100 km) by €1 results in an estimated 0.07 percentage point decrease in the probability of choosing an EV. Our

[5] To derive an AMPE for a single parameter, the model sets all variables to their means. Hence, when interpreting the results of Table 2, we implicitly assume that (i) the acquired EV has an average range of 379 km and benefits from a €7,720 purchase incentive, (ii) the vehicle owner is 51 years old, and (iii) the vehicle is registered in a county with an annual income of €31,000, a Green Party vote share of 14.6% in the most recent national election, and 128 available charging stations (Table 1, Panel B).

model further estimates that increasing the average range of EVs (379 km) by 1 km increases the probability of EV adoption by 0.03 percentage points, whereas the construction of 10 additional charging stations in a given county corresponds to a 0.004 percentage point increase in the likelihood of selecting an EV. Turning to socioeconomic determinants, we observe that increasing the average share of Green Party votes by 1 percentage point or the average income in the registrant's county of residence by €1,000 results in increases in the probability of adopting an EV by 0.07 and 0.05 percentage points, respectively. If the average age of car owners in our sample increases by one year, the model predicts a decrease of 0.01 percentage points in the likelihood of choosing an electric car over a conventional one.

Our findings indicate that financial incentives serve as the key determinant of EV adoption among the German population. Increasing the average financial incentive of €7,720 by €1,000 results in a considerable 1.2 percentage point increase in the probability of choosing an EV over a conventional vehicle in the same price category, holding all other variables constant.

To validate our model set up in Equation (1), we use the determinants of EV adoption from Table 2 to calculate the predicted probability of choosing an EV for every single person in our database using their actual age, income, etc., and then average those probabilities. We predict an overall probability of 12.3% that a German citizen will opt for an EV rather than a conventional vehicle, which is statistically significant at the 0.1% level. This estimate is only slightly higher than the observed share of newly registered EVs in our dataset (11%) (Table 1, Panel A), suggesting that our modeling framework effectively captures real-world adoption behavior. Moreover, the predicted probabilities of EV adoption provide a good approximation of the potential composition of the (private) vehicle fleet.

To ensure the robustness of our baseline specification, we estimated Equation (1) on a subsample that excludes small cars with a retail price below €10,000 (Table 2, Column II) and on a further restricted sample that additionally excludes luxury cars with a retail price above €150,000 (Table 2, Column III). The exclusion of small cars ensures that the model compares only vehicles that are meaningfully similar, as EVs priced below €10,000 may differ significantly from combustion engine vehicles in the same price range, especially in earlier years. Luxury cars were excluded from the analysis, as the decision-making process for purchasing such high-end vehicles may differ from that for purchasing a vehicle primarily intended for everyday use.

Table 2 Overall effects on EV adoption probabilities (AMPEs) in different samples

Variables	(I) Full sample	(II) > €10,000	(III) €10,000 to €150,000
Incentives	1.202***	1.2267***	1.2207***
	(0.0029)	(0.0029)	(0.0029)
Fuel cost	-0.0665***	-0.0688***	-0.0674***
	(0.0022)	(0.0022)	(0.0022)
Range	0.0343***	0.035***	0.0348***
	(9.3e-04)	(9.5e-04)	(9.5e-04)
Stations	0.0043***	0.0044***	0.0044***
	(2.7e-03)	(2.7e-03)	(2.7e-03)
Income	0.0506***	0.0517***	0.0514***
	(9.8e-03)	(0.001)	(1.0e-02)
Environmentalism	0.0709***	0.0724***	0.0716***
	(0.001)	(0.001)	(0.001)
Age	-0.0115***	-0.0118***	-0.0117***
	(3.6e-03)	(3.6e-03)	(3.6e-03)
Gender	0.0048	0.0049	0.0084
	(0.0102)	(0.0104)	(0.0103)
Observations	10,370,618	10,295,314	10,287,124
No. of cases	5,185,309	5,147,657	5,143,562

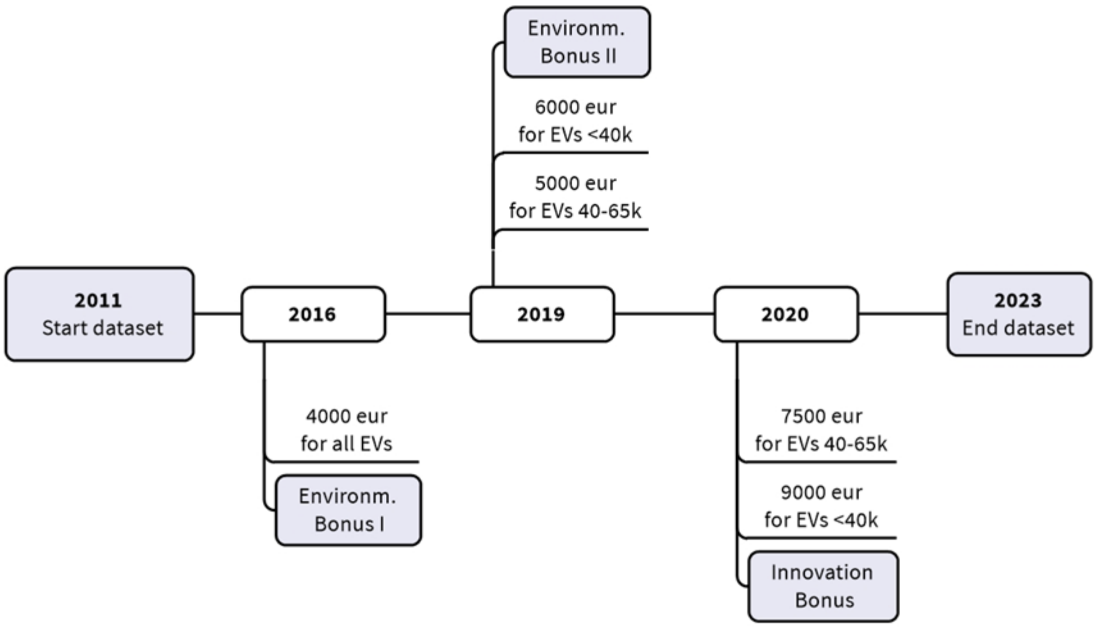
Note: The dependent variable is the binary variable choice (=1 if individual *i* chooses alternative *j*: electric vehicle (EV) or combustion engine vehicle). The estimates correspond to the binary choice model (Equation 1) and show the adoption probability of choosing an EV in percentage points. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

5.2 Changes in financial incentive policies

EV purchase subsidies in Germany have evolved over time and vary by vehicle type. As illustrated in Figure 3, the initial “Environmental Bonus I” (2016) provided a uniform

€4,000 subsidy per EV. In 2019, the government introduced a tiered system ("Environmental Bonus II"), granting €6,000 for vehicles under €40,000 and €5,000 for those priced between €40,000 and €65,000. In 2020, the "Innovation Bonus" further increased incentives to €9,000 for small cars and €7,500 for mid-range vehicles.

Figure 3 Timeline of financial incentives for EVs in Germany



Note: Launched by the German government in 2016, the Environmental Bonus I allowed EV buyers to receive a purchase premium of €4,000. The second stage of the Environmental Bonus started in 2019; EV buyers received a €6,000 purchase premium for EVs with a retail price below €40,000 and €5,000 for an EV in the price range of €40,000–€65,000. From 2020, the Innovation Bonus provided EV buyers access to €9,000 for EVs below €40,000 and €7,500 for EVs in the price range of €40,000–€65,000. Prior to 2016, there was no purchase premium for EVs.

To account for variations in the magnitude of financial incentives, we follow the aforementioned procedure and predict expected EV shares within the total vehicle fleet, disaggregated by the specific financial incentive received. The model calculates the predicted probability of choosing an EV for each person, using their actual data on socioeconomic and technical determinants, but setting any potential incentive received to a value between zero (minimum incentive received before 2016) and €9,000 (maximum incentive received after 2016 for EVs with a purchase price up to €40,000). These probabilities are then averaged over all individuals in our dataset.[6] The results are presented in Table 3.

Our model suggests that without any subsidies, EVs would have comprised only 1.2 percent of the overall fleet. Moreover, if the German government had paid the original environmental bonus of €4,000 across the whole time period, the EV share would be approximately 5% today. If all vehicles had received the maximum subsidy of €9,000, our model predicts that one in five new cars on German roads would now be fully electric. Notably, these predictions indicate an exponential relationship between purchase subsidies and adoption probabilities, suggesting an increasing marginal effect of financial incentives (see Figure C1 in the Appendix, Section C). The first €4,000 in purchase subsidies led to an increase in adoption probability of approximately 4 percentage points, whereas the final €1,500 before reaching the €9,000 maximum resulted in a significantly larger increase of 6 percentage points.[7]

[6] While predictions provide valuable insights into the potential composition of the vehicle fleet, they impose restrictive assumptions on the underlying data generating process. These assumptions are generally valid in the context of financial incentives, as the government could theoretically have provided any observed incentive at any point between 2011 and 2023. However, for other variables, these assumptions may lead to unrealistic scenarios. In particular, for technical determinants, the model would assume uniform fuel consumption and range across all vehicles, irrespective of car model, engine type, or year of manufacture. Similarly, for socioeconomic variables, the model would impose rigid classifications, such as assigning all German car owners a fixed age, sex, or income level.

[7] Financial incentives may not only differ in their magnitude but also over the specific bonus program and vehicle price classes (Figure 3). To assess how the single programs and targeted vehicle classes may influence adoption probabilities, we compute the AMPEs for each incentive wave and vehicle category separately (see Tables C1 and C2 in the Appendix, Section C). We find evidence that the pronounced overall effects of incentives are primarily driven by the third wave (Innovation Bonus) and by middle-class vehicles within the €40,000–€65,000 price range.

Table 3 Predictions for overall EV adoption probabilities across incentives

Incentive	(1) Predictive Margin	(2) Standard Error
0 Euro	1.224***	(0.008)
4,000 Euro	5.169***	(0.014)
5,000 Euro	7.087***	(0.014)
6,000 Euro	9.53***	(0.014)
7,500 Euro	14.325***	(0.014)
9,000 Euro	20.616***	(0.023)

Note: The predictive margins correspond to the estimation results in Table 2 (Column I). The estimates are shown in percentage points. Number of observations: 10,370,618; Number of cases: 5,185,309. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Complementing our analysis, the marginal effect of incentives may also differ across socioeconomic classes. Table 4 shows the AMPEs of financial incentives on the probability of purchasing an EV for classes of significant socioeconomic determinants in Table 2. Our analysis reveals substantial heterogeneity in the demand for government subsidies for EV adoption across income levels, environmental attitudes, and age groups. The AMPEs of financial incentives across income strata suggest a pattern of opportunistic adoption: while controlling for wealth effects, the subsidy's impact on EV adoption nearly doubles from 0.96 percentage points in the lowest income group to 1.73 percentage points in the highest income group. This finding indicates that higher-income individuals, who are already more likely to be able to afford an EV, derive greater benefits from financial incentives. A similar pattern emerges across environmental preferences. In counties with the lowest share of Green Party voters, the estimated marginal effect of financial incentives is 1.04 percentage points, whereas it is 2.1 percentage points in counties with the highest levels of environmental awareness. This suggests that individuals already predisposed to purchasing an EV—due to environmental concerns—respond more strongly to subsidies. Finally, age seems to play a certain role in subsidy responsiveness: younger consumers are significantly more responsive to financial incentives, with the marginal effect of a €1,000 increase in subsidies declining by approximately 20% between ages 17 and 78.

Table 4 Conditioned effects of incentives on EV adoption probabilities (AMPEs)

Socio economic determinant	AMPE of incentive	Std. error
Environmentalism		
5%	1.04***	(0.004)
10%	1.172***	(0.003)
15%	1.32***	(0.003)
20%	1.486***	(0.005)
25%	1.671***	(0.008)
30%	1.876***	(0.011)
35%	2.103***	(0.016)
Income		
15,000 Euro	0.956***	(0.005)
20,000 Euro	1.042***	(0.004)
25,000 Euro	1.136***	(0.003)
30,000 Euro	1.237***	(0.003)
35,000 Euro	1.346***	(0.004)
40,000 Euro	1.465***	(0.006)
45,000 Euro	1.593***	(0.009)
50,000 Euro	1.731***	(0.013)
Age		
17 years	1.381***	(0.007)
25 years	1.339***	(0.005)
40 years	1.264***	(0.004)
65 years	1.147***	(0.003)
78 years	1.09***	(0.004)

Note: The dependent variable is the binary variable choice (=1 if individual *i* chooses alternative *j*: electric vehicle (EV) or combustion engine vehicle). The estimates correspond to the binary choice model (Equation 1) and show the adoption probability of choosing an EV in percentage points, holding the values of the explanatory variables constant. Number of observations: 10,370,618; Number of cases: 5,185,309. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

6 Discussion and conclusion

This study examines the determinants of EV adoption with a special focus on financial incentives at the personal level. We present a first analysis using an administrative dataset, which consists of the whole underlying population of (German) car owners. By combining a quasiexperimental setup with information on postpurchase behavior, we isolate the underlying factors influencing the adoption of EVs for an entire country's population at the smallest possible level.

Our results confirm the significant impact of key socioeconomic and technical determinants on the adoption of EVs. In line with previous studies (Jia & Chen, 2021, 2023), we provide evidence that financial incentives play a pivotal role in influencing the decision to purchase an EV. Our analysis reveals that an additional investment of 1,000 euros in financial incentives increases the probability of purchasing an EV by 1.2 percentage points, a substantial effect, given that the overall adoption probability is approximately 12%. When we let our model predict the share of EVs in the total (private) fleet, our results suggest that if the German government had paid the original environmental bonus of €4,000 across the board, the share of (new private) EVs would be approximately 5% today. Conversely, if all EVs had received the maximum €9,000 subsidy, we calculate that one in five cars on German roads would now be fully electric, suggesting an increasing marginal product of financial incentives within our sample.

This strong effect of financial incentives—as already suggested by Figure 1, which shows the evolution of new EV registrations—may be rooted in two major causes. First, it is widely acknowledged that consumers respond more positively to incentives presented as coupons rather than standard (price) rebates. Research suggests that coupons create a stronger psychological sense of added value, enhancing the appeal of a purchase (Folkes & Wheat, 1995; Grewal et al., 1998). The concept of receiving an additional item or benefit in the form of a coupon not only generates excitement but also fosters a sense of financial savings, leading to increased overall satisfaction with the transaction. In the context of EV purchases, this perception is especially pronounced: Hardman et al. (2017) concluded that although incentives have been implemented to reduce the purchase price of EVs, their impact on purchasing decisions is not driven primarily by consumers' economic considerations. Second, individuals may experience a phenomenon known as the “fear of missing out”. De Groote & Verboven (2019) reported that Belgian households demonstrated a notable discounting of the prospective advantages associated with novel technologies, e.g., solar photovoltaic systems, amounting to a multiple of the actual interest rate. The authors posited that a potential explanation for this observed behavior among households is a lack of trust in the government’s ability to honor its commitment to maintain the provision of subsidies in the future. In the case of EVs, this could manifest as concern that the current generous subsidies may be reduced or eliminated in the future. This effect adds to the coupon effect and is thought to be particularly pronounced in the later stages of subsidization.

Our results suggest that government funds aimed at increasing the EV fleet are best spent on financial incentives. However, even if the government would have maintained the highest value of state subsidies received (€9,000) throughout our observation period, our model predicts that approximately 2.5 million EVs would have been registered by the end of 2023. Notably, this figure still falls significantly short of the target value of 15 million for 2030.

Changing the composition of incentives may help to further increase their effectiveness. With German subsidies being restricted to vehicles with a maximum price of €65,000, the government has already tried to avoid the impression that wealthy people are funded with public money to buy expensive cars. However, our results indicate that individuals in high-income groups are still considerably more likely to exploit financial incentives than those in low-income groups are and that our strong incentive effects seem to be carried particularly by cars within the higher price segments. More targeted support programs could therefore help to reach poorer households. Opening up this group as potential buyers of electric cars is key to transportation transition (Gupta & Anand, 2025; Romero-Lankao et al., 2022). Policies could be designed to ensure that low-income households receive a larger portion of the subsidies or exclusive access to certain incentive programs. This could be achieved through the use of means-tested subsidies, where eligibility is based on income levels or other socioeconomic indicators. For example, the state of California restricted the access of high-income households to EV subsidies and increased the bonus for low-income households by 80% in 2016 (Hardman et al., 2017).

The scope of our study is inherently limited by its regional focus on German consumers. Although Germany represents a significant and influential market for EVs, the extent to which our findings can be generalized to other countries remains uncertain. Cultural, economic, and regulatory differences across nations can result in disparate consumer behavior and, most importantly, the diminished efficacy of incentive schemes. Nevertheless, our study offers valuable insights into the dynamics of EV adoption. By employing a dataset of the underlying population of actual individual car purchases, we utilize real-world information, thereby enhancing the validity of our findings. This circumvents the common pitfalls of sample selection biases that are typically encountered in studies that rely on survey data or limited samples. As a result, we provide a robust foundation for understanding consumer behavior in EV markets.

Future research could adopt a comparable methodological framework using extensive administrative data in other pivotal EV markets. Assuming broad data availability, as in our case, comparative studies in diverse international settings, such as the United States, China, or Norway, could help to gain a more nuanced understanding of global EV adoption trends and the varying influences of financial incentives.

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Public Purchasing Subsidies and the Fear of Missing Out:

A Full-Sample Analysis of Electric Vehicle Adoption in Germany

Appendix

A Determinants of EV adoption

Table A1 Literature review on the determinants of EV adoption

Study	Incentive	Technical determinants				Socio-economic determinants			
		Price	Charg. Infr.	Range	Fuel cost	Gender	Age	Income	Envirom.
Moons & De Pelsmacker (2012)		$-^{***}$		+		$+^{***}$	$-^{*}$	$+^{***}$	$+^{***}$
Carley et al. (2013)		$-^{***}$	$+^{***}$	$+^{***}$	–	$-^{***}$	$-^{***}$	+	$+^{***}$
Schuitema et al. (2013)		$-^{***}$		$-^{***}$					$+^{***}$
Jensen et al. (2013)		$-^{***}$	$+^{***}$	$+^{***}$	$-^{***}$	$-^{***}$	$+^{*}$		$+^{***}$
Noppers et al. (2014)		$-^{*}$		$-^{*}$					$+^{***}$
Peters & Dütschke (2014)		$-^{***}$	$+^{***}$	$+^{***}$	$-^{***}$				$+^{**}$
Axsen et al. (2015)		$-^{***}$	$+^{***}$	$+^{***}$	$-^{***}$			+	$+^{***}$
Tal & Nicholas (2016)	$+^{***}$					$+^{***}$	$+^{***}$		
Javid & Nejat (2017)			$+^{***}$		$-^{***}$	+	–	$+^{***}$	
Rotaris et al. (2021)		$-^{***}$	+	$+^{***}$	$-^{***}$	+	+	+	$+^{***}$
Jia & Chen (2021)	$+^{***}$	$-^{***}$	$+^{**}$		$-^{***}$	$-^{***}$	$-^{***}$	$+^{**}$	
Qian et al. (2023)	$+^{***}$	$-^{***}$	$+^{***}$	$+^{***}$		$+^{**}$	$-^{***}$		
Jia & Chen (2023)	$+^{***}$	$-^{***}$	$+^{***}$	$+^{***}$	$-^{***}$	–	$-^{**}$	$+^{**}$	

Note: */**/*** represent significance at the 10%/5%/1% confidence levels, respectively. + indicates a positive relationship, and – indicates a negative relationship.

B Data transformation example

This section provides an example of how the extended vehicle registration dataset was transformed into choice data. Figure B1 presents two exemplary cases from our dataset. The original vehicle registration data may include P1, a 50-year-old male residing in County 1 with an average income of €50,000. The county features a Green Party voter share of 10% and provides access to 45 charging stations in 2018. In addition, the dataset may contain P2, a 30-year-old female living in County 2 with an average income of €30,000. County 2 is characterized by a Green Party voter share of 30% and provides 15 charging stations in 2016. P1 purchased an EV (Model M1) in 2018 for €40,000, benefiting from a €4,000 government subsidy. The EV has a maximum range of 400 km, as specified by the manufacturer, and an average energy cost of €6 per 100 km. P2, by contrast, acquired a combustion engine vehicle (Model M2) for €30,000 in 2016, which incurs an average fuel cost of €8 per 100 km. To account for the natural range advantage of conventional vehicles, all combustion engine cars in our dataset are assigned a standardized range of 883 km, reflecting the maximum driving range of an EV in our dataset.

Figure B1 Transforming the (extended) vehicle registration dataset into choice data (example)

Vehicle Registration Dataset

Identification variables					Socio-Econ. determinants				Techn. determinants				
Person ID	Type	Model	Reg Year	County	Age	Sex	Income	Environm.	Price	Range	Fuel	C. Stations	Incentives
P1	EV	M1	2018	C1	50	M	50k	0.1	40k	400	6	45	4k
P2	Comb.	M2	2016	C2	30	F	30k	0.3	30k	883	8	15	0
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮

↓

Choice Dataset

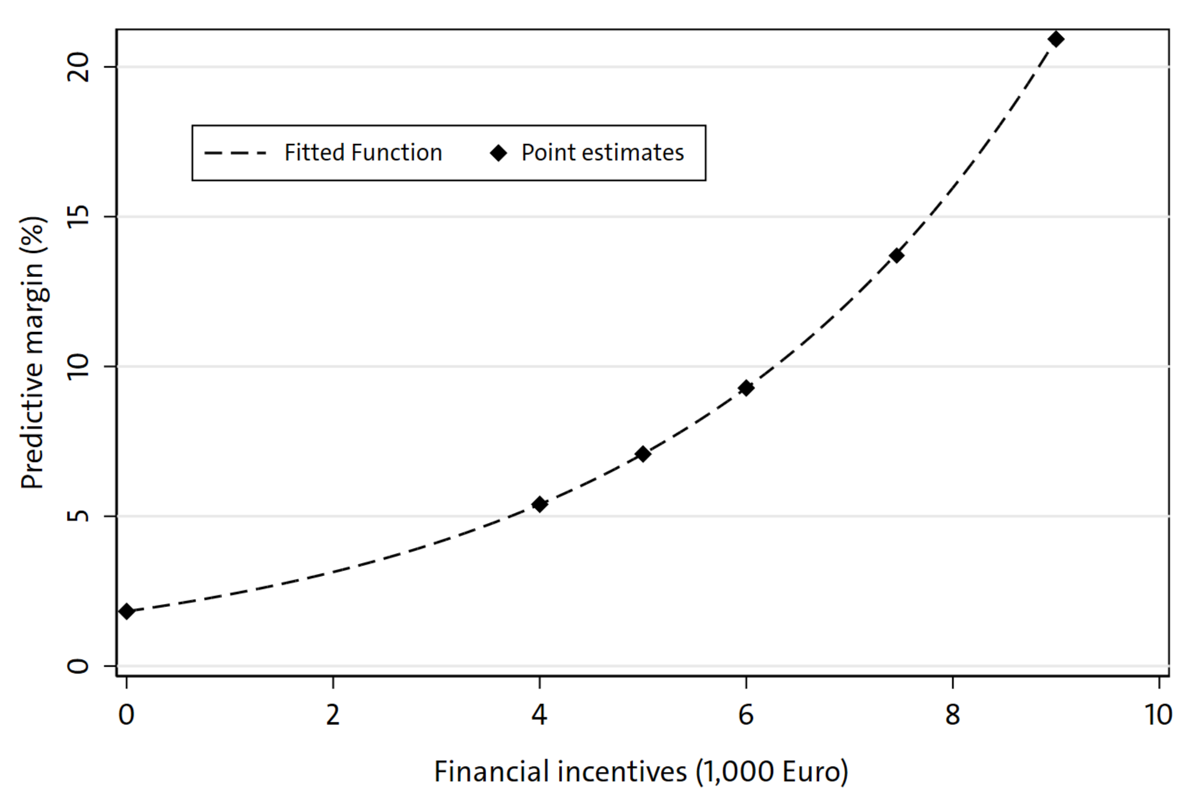
	Identification variables					Socio-Econ. determinants				Techn. determinants				
Choice	Person ID	Type	Model	Reg year	County	Age	Sex	Income	Environm.	Price	Range	Fuel	C. Stations	Incentives
1	P1	EV	M1	2018	C1	50	M	50k	0.1	40k	400	6	45	4k
0	P1	Comb.	**synt**	2018	C1	50	M	50k	0.1	**35-45k**	**883**	**7.5**	45	0
0	P2	EV	**synt**	2016	C2	30	F	30k	0.3	**25-35k**	**447**	**6.5**	15	4k
1	P2	Comb.	M2	2016	C2	30	F	30k	0.3	30k	800	8	15	0
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮

Note: This figure shows registration data examples for two individuals, P1 and P2, which capture their demographic details, income, county characteristics, and vehicle choices. P1 purchased an electric vehicle (EV) in 2018, whereas P2 acquired a combustion engine vehicle in 2016, with associated costs and performance metrics. To enable counterfactual comparisons, each individual is assigned a synthetic alternative vehicle that reflects market conditions while keeping their static attributes, e.g., socioeconomic determinants, unchanged.

To create meaningful counterfactual comparisons, we generate synthetic alternatives for each observed choice. For P1, a hypothetical combustion engine vehicle is assigned from the €35,000–€45,000 price range, with a standardized range of 883 km and an average fuel cost of €7.5 per 100 km, which is consistent with the average characteristics of combustion vehicles available in Germany in 2018 within this price category. For P2, a synthetic EV alternative is selected from the €25,000–€35,000 price range, incorporating a €4,000 purchase incentive, a maximum range of 447 km, and an average energy cost of €6.5 per 100 km, reflecting the average characteristics of EVs available in Germany in 2016 within this price segment. These counterfactual choices are linked to the original individuals through their person IDs, ensuring that all static attributes, such as the car owners' age and sex as well as the registration county's average income, environmentalism and charging infrastructure, remain consistent across the observed and synthetic vehicle choices.

C Additional results

Figure C1 Fitted values: EV adoption probabilities across incentives



Note: Point estimates correspond to the estimated predictive margins for the incentives reported in Table 3 in the main text.

Table C1 Overall effects on EV adoption probabilities, incentive waves

Variables	(1) 2011-2015	(2) 2016-2018	(3) 2019	(4) 2020-2023
Incentives	-	-	0.3153***	3.792***
			(0.0092)	(0.0176)
Fuel economy	-0.0199***	-0.0365***	0.0637***	0.4799***
	(0.0011)	(0.0021)	(0.0028)	(0.0137)
Range	0.000786***	0.0037***	0.0083***	0.1804***
	(2.8e-04)	(4.4e-04)	(1.2e-03)	(2.8e-03)
Stations	0.0012	0.0017	-0.0013*	-0.0335***
	(0.0041)	(0.0014)	(7.8e-03)	(0.0016)
Income	0.0072***	0.0214***	0.0099***	0.409***
	(5.6e-03)	(9.9e-03)	(0.0011)	(0.0062)
Environmentalism	0.001	0.0081***	0.0127***	0.0851***
	(9.8e-03)	(0.0016)	(0.0017)	(0.006)
Age	-0.002***	-0.0025***	-0.0034***	-0.0621***
	(2.0e-03)	(3.6e-03)	(3.9e-03)	(0.0022)
Gender	-0.0624***	-0.1177***	-0.0398***	0.1754***
	(0.0065)	(0.0107)	(0.0114)	(0.0631)
Observations	1,814,900	2,836,940	1,193,522	4,525,256
No. of cases	907,450	1,418,470	596,761	2,262,628

Note: The dependent variable is the binary variable choice (=1 if individual *i* chooses alternative *j*: electric vehicle (EV) or combustion engine vehicle). The estimates correspond to the binary choice model (Equation (1)) in the main text and show the adoption probability of choosing an EV in percentage points. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table C2 Overall effects on EV adoption probabilities, car price categories

Variables	(1) < €40,000 Euro	(2) €40 - €65,000	(3) > €65,000
Incentives	0.5838***	1.7213***	-2.8625***
	(0.0027)	(0.00588)	(0.1141)
Fuel economy	0.1124***	-0.7391***	-0.4962***
	(0.0013)	(0.0223)	(0.000308)
Range	0.0109***	0.299***	0.0725***
	(7.6e-04)	(0.0013)	(0.0012)
Stations	-0.0033***	-0.018***	0.0147***
	(0.0013)	(0.0025)	(0.0045)
Income	0.0312***	0.2572***	0.0248
	(0.0046)	(0.0103)	(0.0191)
Environmentalism	0.0086***	0.0839***	0.1058***
	(0.0044)	(0.0102)	(0.0203)
Age	-0.0071***	0.0643***	-0.1441***
	(0.0016)	(0.0037)	(0.0084)
Gender	-0.0711***	2.4611***	-3.4878***
	(0.0042)	(0.1137)	(0.2805)
Observations	8,386,348	1,677,610	306,660
No. of cases	4,193,174	838,805	153,330

Note: The dependent variable is the binary variable choice (=1 if individual *i* chooses alternative *j*: electric vehicle (EV) or combustion engine vehicle). The estimates correspond to the binary choice model (Equation (1)) in the main text and show the adoption probability of choosing an EV in percentage points. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

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