Technology Complementarities and Subsidy Policy: Evidence from Electric Vehicle and Solar Panel Adoption

Maria Garcia-Osipenko*

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Abstract

Government policies target air pollution and climate change by incentivizing adoption of electric vehicles (EVs) and/or residential solar panels (PVs). Knowledge of whether these goods are complements or substitutes can be used to design policies that target environmental externalities more efficiently. I use California household-level data to estimate a structural multi-product demand model. I find that consumers view PVs and EVs as complements, with the degree of complementarity varying with vehicle size and income. Counterfactual experiments reveal that complementarity significantly increases bundled EV-PV purchases. This complementarity can be leveraged to design policies that achieve emission targets at lower cost.

JEL: D12, Q42, Q48, Q51, Q54, Q58, R48.

Keywords: Solar Panels, Electric Vehicles, Complementarity, Multi-Product Demand Model, Environmental Policy, Renewable Energy.

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I Introduction

Climate change is a worldwide concern. Many countries have adopted programs aimed at reducing greenhouse gas emissions. In April 2022, President Biden set a goal for the United States to achieve a 50 percent reduction in net greenhouse gas emissions from 2005 levels by 2030. The transportation and electric power sectors are the main targets for accomplishing this objective as they generate 52% of American greenhouse gas (GHG) emissions (U.S. Environmental Protection Agency, 2022).For example, in August 2022, the Inflation Reduction Act (IRA) allocated approximately $369 billion toward energy security and climate change initiatives, including subsidies and incentives to promote the development and deployment of renewable energy sources. These subsidies target two key technologies—solar panels (PVs) and electric vehicles (EVs) — that have the potential to reduce carbon emissions and other air pollutants when adopted independently. Understanding how customers perceive the relationship between PVs and EVs offers the potential to leverage synergies between them to design subsidy schemes that lower the cost of achieving a given reduction in emissions.

In this paper, I estimate the extent to which solar panels and electric cars are substitutes or complements. The potential channels for complementarity include lower operating costs, driven by specific electricity rate structures, and environmental preferences, as the environmental benefits of driving an EV are amplified when the vehicle is charged with clean solar power. The products could, however, be substitutes. A potential mechanism for substitutability is that both goods satisfy the demand for environmentally-friendly technology or the desire to signal a "green" lifestyle. Moreover, both technologies enable long-term cost savings and can satisfy preferences for new technology. As a result, budget-constrained consumers may select only one technology to suit their preferences.

I focus on California, which is the state with the most solar energy production, EV sales, and public EV charging stations (Environment California Research and Policy Center, 2021). My primary data set is the California Vehicle Surveys in 2013, 2017, and 2019. Respondents report their vehicles' features, including size, fuel type, purchase year, car model year, and if they have solar panels or plan to install them in the next five years. I also observe each respondent's age, income bin, type of housing, household size, and education.

I use these data to estimate a static discrete-choice model of demand for solar panels and electric vehicles following Berry, Levinsohn and Pakes (1995) and Gentzkow (2007). The model allows consumers to purchase a car only, a solar panel system only, or both, without imposing any a priori assumption about whether EVs and PVs are substitutes or complements. I use a two-stage procedure to estimate the structural parameters following Berry, Levinsohn and Pakes (1995) and Bayer, Ferreira and McMillan (2007a). Consumer preferences for product characteristics are identified using an instrumental variables method. Specifically, I use the sums of characteristics of competing products in a market as instruments for prices. The instrument's design follows the logic of Berry, Levinsohn and Pakes (1995), which holds that a product's price will depend on its comparability to other goods in the market.

I find that the average household benefits from higher gas mileage, greater horsepower, and the adoption of solar systems, while experiencing disutility from higher purchase prices and increased operational driving costs. Additionally, the results suggest that solar panels and electric vehicles are complements, with the willingness to pay for this complementarity increasing with income. Further, owners of larger electric vehicles are willing to pay more for the synergy between EVs and solar panels. On average, a 1% decrease in the price of EVs results in a 0.23% increase in the demand for PV systems. On the other hand, a 1% decrease in the price of PV systems results in a 0.69% increase in the demand for EVs.

I use these results to (i) quantify the contribution of complementarity between PVs and EVs to the adoption of each technology at current prices; (ii) consider the consequences of ignoring complementarity when designing subsidies to incentivize their adoption with the goal of reducing carbon emissions; and (iii) investigate the most efficient way to allocate a fixed budget for subsidies between the two markets to achieve a given reduction in emissions.

I find that complementarity plays a substantial role in the joint take-up rate. In the absence of complementarity, purchases of EVs and PVs together would be 64% lower. Further, the marginal impact of subsidies for solar panels on reducing carbon dioxide (CO_2) and fine particulate matter ($PM_{2.5}$) emissions would be much more effective than subsidies for EVs. However, complementarity between solar panels and EVs generates an additional 38% reduction in CO_2 emissions from EV subsidies. For $PM_{2.5}$, 56% of the emission reductions attributed to EV subsidies are due to the complementary adoption of solar panels. Lastly, I show that the optimal allocation of a fixed subsidy budget to PV and EV markets will vary depending on the emissions target. Allocating the entire budget to PV subsidies is most cost-effective in reducing health damages from exposure to $PM_{2.5}$ while providing roughly equal shares of the subsidy budget to EVs and PVs reduces CO_2 emissions most efficiently.

Overall, the paper contributes to the growing literature on PV and EV adoption. Prior studies investigated how adoption of EVs is affected by policy incentives (Barwick, Kwon and Li, 2024; Muehlegger and Rapson, 2023, 2022; Armitage and Pinter, 2022; Remmy, 2023; Xing, Leard and Li, 2021; Jenn, Springel and Gopal, 2018; Sheldon, DeShazo and Carson, 2017), deployment of the public charging infrastructure (Dorsey, Langer and McRae, 2022; Springel, 2021; Li, 2019; Li et al., 2017), demographics heterogeneity and political ideology, (Davis, Li and Springel, 2023; Jacqz and Johnston, 2023; Archsmith, Muehlegger and Rapson, 2021; Linn, 2022; Sheldon and Dua, 2019), peer effects (Tebbe, 2023), and technology advancement (Forsythe et al., 2023). Previous studies of rooftop PV adoption examined the effects of financial incentives (Feger, Pavanini and Radulescu, 2022; Langer and Lemoine, 2022; Pless and van Benthem, 2019; De Groote and Verboven, 2019; Gillingham and Tsvetanov, 2019; Burr, 2016; Hughes and Podolefsky, 2015; Sarzynski, Larrieu and Shrimali, 2012), heterogeneity of adopters' socioeconomic characteristics (Dorsey and Wolfson, 2024; De Groote and Verboven, 2019; Crago and Chernyakhovskiy, 2017; De Groote, Pepermans and Verboven, 2016; Borenstein and Davis, 2016; Kwan, 2012), pro-environmental preferences (Crago and Chernyakhovskiy, 2017; Dastrup et al., 2012), and peer effects (Bollinger et al., 2022; Gillingham and Bollinger, 2021). Furthermore, Bollinger et al. (2023) consider complementarity between rooftop solar and energy storage technology adoption. Additionally, several studies investigate spatial variation in the environmental benefits of EV and PV adoption (Dauwalter and Harris, 2023; Graff Zivin, Kotchen and Mansur, 2014; Muehlegger and Rapson, 2020; Holland et al., 2016).

Although several studies examined PV adoption and EV adoption independently, the relationship between them has received relatively little attention. The most closely related studies provided some evidence of joint adoption (Delmas, Kahn and Locke, 2017; Cohen et al., 2019; Ferdousee, 2021; Lyu, 2023; Sharda et al., 2024). Although their findings show correlated adoption of technologies and provide suggestive evidence of complementarity, they do not identify cross-price elasticities within a demand system for differentiated goods. As a result, prior studies have been unable to quantify the extent to which price changes in one technology influence the adoption of the other, or to evaluate how counterfactual policies would affect adoption rates. Further, while Lyu (2023) provides causal evidence of complementarity, their analysis relies on aggregated data at the zip code tabulation area level. In contrast, my study leverages individual-level data, allowing for a more granular examination of household-level heterogeneity in adoption decisions. This approach enables a richer understanding of how different consumer segments— that differ by income, age, and education — respond to policy incentives.

My study is the first to develop a multi-prodcut discrete-choice model with complementarity to explore the interaction between the automotive and solar panel industries. This approach allows for a direct quantification of complementarity, distinguishing it from correlation in consumer preferences. More broadly, I provide the first application of a multi-market discrete-choice model to a setting where consumption in both markets generates common environmental externalities. This feature enables me to assess the comparative efficiency of various counterfactual policies aimed at promoting the adoption of EVs and PVs in terms of their ability to mitigate environmental externalities. My findings provide a new perspective on the extensive literature on designing efficient subsidies for EVs and PVs.

The next section provides background on California's solar and electric vehicle industries. Section 3 describes the data and presents reduced-form estimates of the relationship between solar panels and electric car demands. Section 4 specifies the demand model with complementarity for two technologies followed by identification arguments; section 5 specifies the estimation strategy. The results are described in section 6. Section 7 presents counterfactual policy evaluations. Section 8 concludes.

II Background

A Electric Vehicle Industry

Electric vehicles include battery-electric vehicles (BEV), which only run on electricity; plug-in hybrid electric vehicles (PHEV), which can use both an electric motor and an internal combustion engine as a backup; fuel cell electric (FCEV), which use an electric-only motor powered by hydrogen; and plug-in fuel cell electric vehicles (PFCEV), which combine features of BEVs and FCEVs. According to the California Energy Commission (2024), California sold 1,996,931 total EVs as of the second quarter of 2024, the most of the 50 states.[1] It accounted for roughly 39% of all new electric car sales between 2011 and 2024 in the United States.

Electric vehicle incentives in the United States have been in place for over ten years. The incentives come in the form of rebates on purchases, tax exemptions and credits, and other benefits, such as access to HOV lanes and fee waivers (charging, parking, tolls, etc.). The size of a car's battery or the range of an all-electric vehicle may affect the amount of financial incentives.

A federal income tax credit of up to $7,500 is available for BEV and PHEV vehicles acquired in 2010 or later. I take the federal subsidy into account when constructing the prices of electric vehicles in my analysis.

Moreover, there are various incentives provided by states and utility companies.[2] However, I do not account for these rebates in my analysis because I am unable to observe take-up of the rebates and whether individual households satisfy eligibility criteria which are linked to vehicle models, household income, and varied features of regional utility programs. This omission introduces a likely source of measurement error in vehicle prices, which I address through an instrumental variables approach.

[1] Figure A.1 shows the electric vehicle market has been steadily growing since its inception in late 2000 and is projected by industry analysts to expand more in the following years.

[2] For example, California's Clean Vehicle Rebate Project (CVRP), created in 2010, offered up to $2,500 for the purchase or lease of BEVs and $1,500 for the purchase or lease of PHEVs. Low-income households that meet the requirements could qualify for an extra subsidy of $2000 starting from 2016.

B Solar Photovoltaic (PV) Industry

California is an attractive place for property owners to install solar panels because of its pro-solar laws, abundant sunshine, and generous solar subsidies. California consistently ranks first in the nation for producing solar energy. It has the highest installed capacity out of all 50 states and ranks second in solar installations per capita, surpassed only by Hawaii. 25% of the state's electricity is generated from solar.[3]

Several incentive programs were in effect during my study period. One of the most important federal policies promoting the expansion of solar energy in the US is the 30% solar Investment Tax Credit (ITC) implemented in 2006 (Solar Energy Industries Association, 2022).

In addition to the federal ITC, California offers other solar incentive programs, depending on the location and utility provider. For example, the CSI Single-Family Affordable Solar Homes (SASH) Program has provided a capacity-based incentive of $3,000 for every kW of home solar installed to qualified low-income households since 2009 (California Public Utilities Commission, 2022a).

Another important policy is net energy metering (NEM). During the analyzed period, NEM 1.0 and NEM 2.0 were in effect. NEM allows customers of three utilities (PG&E, SCE, and SDG&E) to produce their own energy to serve their electricity needs directly on-site and obtain a credit toward their electric bills for any excess energy sent back to the grid. Customers that generated electricity for the grid received full retail rate credits (California Public Utilities Commission, 2022b).

C Substitutes or Complements?

In principle, solar panels and electric vehicles could be substitutes or complements. One potential mechanism for complementarity is decreasing operating costs when used together (p-complementarity). Many utilities provide electricity price plans that offer financial incentives for EV owners to charge their cars using their solar panels. Appendix D provides an example.

Another potential channel is the preference for being environmentally friendly (q-complementarity). In this case, PV adoption increases the utility experienced by owning an EV because owners derive utility from knowing that the environmental benefits of their EV ownership increase if the power is generated by solar.[4] fi On the other hand, there are at least three channels through

[3]The left panel of Figure A.2 shows California's mean installed price per watt from 2007 to 2020. Between 2007 and 2020, prices fell by around 50%. The right panel demonstrates the total solar capacity installed each year between 2008 and 2019.

[4]For example, Coffman, Bernstein and Wee (2017) find that given Hawaii's electricity fuel mix, the Nissan Leaf (EV) would produce 31 MTCO_2 and the Toyota Prius (hybrid electric vehicle) 27 MTCO_2 during their 150,000-mile lifetimes. However, using residential solar PV for weekend charging directly significantly decreases the GHG emissions of EVs compared to HEVs. In this case,the Nissan Leaf will produce almost 8 MTCO_2 less than the Toyota Prius over their lifetimes.

which EVs and PVs could be perceived as substitutes. First, both goods may satisfy the demand for "green" products. Due to the high costs of adopting these technologies, budget-constrained households may choose to adopt just one of the two technologies to reduce their carbon footprint. Similarly, both goods can serve to signal wealth and the owner's "green" lifestyle. Finally, both technologies enable long-term cost savings on energy bills despite high upfront costs. Hidrue et al. (2011) finds that savings are the primary motivation for most people to buy an EV. Finally, both goods may satisfy the demand for adopting cutting-edge technology. Again, budget-constrained households may choose to invest in only one technology.

The literature provides some evidence that EVs and PVs may act as complementary technologies. Delmas, Kahn and Locke (2017) provide descriptive evidence of increasing joint purchases of EVs and PVs in California. Ferdousee (2021) uses a bivariate probit regression model to show that education, income, and household type are associated with the probability of joint adoption in California. Lyu (2023) uses an instrumental variables regression to conclude that each existing PV leads to approximately 0.184 additional EV sales, while each EV purchase leads to about 0.26 additional PV installations. Cohen et al. (2019) find that having an EV in Austria increases the likelihood of owning a PV by 31%, and the probability of owning an EV increases by 7.1% for PV owners. This study adds to the literature by developing the first discrete-choice model of complementarity (or substitability) for electric vehicle and solar panel purchases. Importantly, my approach allows for flexible substitution patterns between the two sides of the market, which can be difficult to implement in a reduced-form analysis. Moreover, the model estimates allow me to assess the efficacy of counterfactual policies. I estimate the model using the California Vehicle Survey.

III Data

A Data Sources

My primary data source is the California Vehicle Survey (CVS) of household and commercial vehicle fleet owners conducted by the California Energy Commission in 2013, 2017, and 2019 (National Renewable Energy Laboratory, 2024). The data describe individual and household characteristics of respondents and their ownership of the technology. In particular, I observe whether a household has solar panels installed on the residence, whether they are planning on purchasing solar panels within the next five years, and characteristics of the respondent's car. I cut the sample to respondents who reside in single-family or mobile houses. The 2010–2012 California Household Travel Survey (CHTS) was used to get data on the 2013 CVS respondents' vehicles. Households that completed the CHTS and stated their intention to purchase a vehicle in the near future were included in CVS's household component. Both surveys used the same household ID numbers, enabling their responses to be linked.

The linked data overrepresents individuals who are highly educated and have higher incomes, while minority groups are underrepresented. Additionally, the survey slightly overrepresents those in the 35-64 age group, who make up 59% of respondents compared to 53% in the broader population. Participants are representative of the geographic distribution of households throughout California, and roughly representative of "1, 2, and 3 or more" household vehicle ownership categories as reported in the 2015 American Community Survey. In Section 7, I apply sampling weights to ensure that the simulation of counterfactual policies is representative of California's demographics.[5]

The second data source is the Distributed Solar Public Data from Lawrence Berkeley National Laboratory (2023) (LBNL). LBNL publishes non-confidential project-level data on residential photovoltaic systems. The data includes the total installed price for the system, the installation date, the system size, zip code, customer segment, and other system features. I used their data to construct prices of solar panels in different geographic areas and years.

To construct vehicle prices, I used several datasets. The vehicle MSRP prices were taken from AutoWeb (2022) website. California Auto Outlook reports published by California New Car Dealers Association (2022) provide annual top-selling models in each segment and their total registrations in California. I used these reports to construct average prices for gas and hybrid vehicles in each size segment each year. California Energy Commission provides statistics on annual new Zero Emission Vehicles sales in California (California Energy Commission, 2022). I used this dataset to construct average electric vehicle prices by different size categories for different years. In addition, I accounted for electric vehicle federal incentives of $7,500 in the product price.[6]

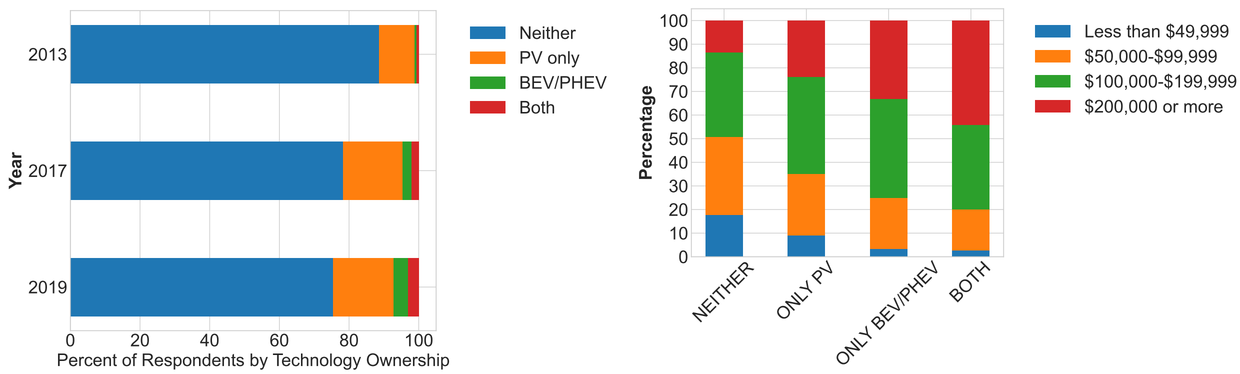
Global horizontal irradiation variables for California counties were retrieved from Global Solar Atlas (Solargis, 2022). The number of charging stations in each county for each of the analyzed years was taken from the Alternative Fuels Data Center by the U.S. Department of Energy (2022). The essential variables that this dataset contains are the addresses of all charging stations for electric vehicles, dates when they were opened, and whether they are publicly accessible. The number of high-occupancy vehicle lanes in different regions of California was drawn from the annual reports of the California Department of Transportation (2022).

[5]Table A.1 presents summary statistics from the combined three California Vehicle Surveys, along with comparative data from the population-representative Current Population Surveys (CPS) conducted in 2013, 2017, 2019 (IPUMS, 2024). The statistics in both surveys are presented for people who live in single-family or mobile houses.

[6]As noted earlier, I did not include state and utility company level incentives due to varying eligibility requirements and my inability to observe take-up. This introduces some measurement error in prices which I address using IVs explained in section 5.

B Descriptive Evidence

Figure 1a demonstrates the proportion of individuals who own each technology for each year the survey was implemented. Most respondents (approximately 81%) have neither electric vehicles nor solar panels. However, the percentage of respondents who own one or both technologies has been rising over time.



(a) Sample Structure by Technology

(b) Income Distribution by Category

Figure 1: Technology Ownership by Year and Income

The sample contains significantly more PV owners than EV owners. The cost difference between PVs and EVs could explain this. The average total cost of a PV installation was around $26,000, while the price for most electric vehicles ranged from $35,000 - $50,000 after accounting for rebates and tax credits.

Figure 1b shows how household income varies with technology adoption. As expected, mean household income increases as we move from non-ownership to those owning a PV only, to those owning EVs only, and finally to those owning both technologies.

According to the survey, 68% of EV owners have installed PV or intend to install it within the next five years, which is consistent with the hypothesis that these two technologies complement each other. In order to quantify the difference in probabilities of purchasing a PV for households with and without electric cars and vice versa, I estimate the following logit regression:

$$P(Y = 1 \mid X_1, X_2, \ldots, X_K) = \frac{1}{1 + e^{-(\beta_0 + \sum_{k=1}^{K} \beta_k X_k)}} \tag{1}$$

where Y is a dependent variable, and X_k ($k = 1, \ldots, K$) are the independent variables. For EV adoption, I estimate a binary logit regression in which the dependent variable equals 1 if the household owns an EV and 0 otherwise. For solar panel adoption, I use an ordered logit model, where the dependent variable takes three values: 0 if the household neither owns a PV system nor plans to install one within the next five years; 1 if the household plans to install a PV system within the next five years; and 2 if the household already has a PV system. Independent variables include ownership of an PV (or EV, depending on the regression), as well as controls for age and income groups, household size, county and year fixed effects.[7] I find that households with a PV system have 3.28 times higher odds of owning an EV compared to households without a PV system, all else constant. Similarly, households that own an EV have 3.14 times higher odds of having a PV system or planning to install one within the next five years, relative to households without an EV. Odds ratios for both EV and PV ownership are monotonically increasing with income. Additionally, larger households are more likely to invest in PV systems but less likely to purchase EVs.[8]

Rescaling these results as average marginal effects reveals that the probability of purchasing an EV is 5.7% higher if the household owns a PV, while EV ownership is associated with an increase in the probability of installing a PV by 19.8%. Interestingly, these results are similar to the evidence for Austria from Cohen et al. (2019), 7.1% and 31%, respectively. The findings of Lyu (2023) are also qualitatively similar but a direct comparison is complicated by differences in effect size measures and study populations.[9]

Thus, adoption of the two technologies is strongly positively correlated. A household that owns one of the technologies is, on average, more likely to own the other. In the absence of correlated preferences, that would mean that solar panels and electric vehicles are complements. However, another potential explanation for the high correlation is that people who get high utility from owning a solar panel (or EV) also tend to get high utility from purchasing an EV (or solar panel); in other words, correlated preferences. I develop a model to disentangle the relative importance of these two potential explanations.

IV Model and Identification

A The Model

I develop a discrete choice model to of a residential photovoltaic system and electric vehicle adoption following Berry, Levinsohn and Pakes (1995) and Gentzkow (2007).

Each household $i = 1, .., N$ in market $t = 1, .., T$ maximizes utility by choosing an individual product j or a bundle of two products $\mathbf{b}$. I focus on bundles comprising two product categories indexed by C (car) and S (solar panel). Let J_t^C denote the set of available car products in market t, and let J_t^S denote the set of solar panel choices in market t, where $J_t^S = \{0, 1\}$ represents the decision to either not purchase (0) or purchase (1) a PV system.

[7] As more control variables are included, the coefficient on technology ownership decreases but continues to indicate a large and precisely estimated positive association.

[8] Full regression results are reported in Tables B.2 and B.3.

[9] Average marginal effects and standard errors are reported in Table B.4.

Assume that the bundles are ordered so that $\mathbf{b} = 0$ is the outside option, which consists of purchasing neither product (or choosing another product outside these categories). The indirect utility of household i in market t from choosing a singleton product j (i.e., a product from either J_t^C or a PV system) is given by:

$$u_{itj} = \delta_{tj} + \mu_{itj} + \varepsilon_{itj} \tag{2}$$

$$u_{it0} = \varepsilon_{it0} \tag{3}$$

where δ_{tj} is the market t-specific average utility of product j, μ_{itj} is an individual-specific utility deviation from δ_{tj}, and ε_{itj} and ε_{it0} are error terms. The mean utility of singleton j can be further decomposed into observable and unobservable components as:

$$\delta_{tj} = \mathbf{x}_{tj}\boldsymbol{\beta} + \alpha p_{tj} + \xi_{tj} \tag{4}$$

where $\mathbf{x}_{tj}$ is a vector of observed product characteristics, $\boldsymbol{\beta}$ is the corresponding vector of coefficients, p_{tj} is the price of product j in market t, and ξ_{tj} captures unobserved product characteristics (which are observed by consumers and firms, but not by the researcher). The individual-specific deviation from mean utility is defined by an interaction between observable consumer demographics and product characteristics as follows:

$$\mu_{itj} = \mathbf{X}'_{tj}\Phi\mathbf{D}_{it} \tag{5}$$

where $\mathbf{X}_{tj}$ is a vector of product characteristics (including price), $\mathbf{D}_{it}$ is a vector of observed household characteristics, such as age of household head, income, number of household members, the level of education, and Φ is a matrix of interaction coefficients.

To simplify exposition, I will refer to the products that bundle $\mathbf{b}$ contains as $j \in \mathbf{b}$. Following Gentzkow (2007), the indirect utility of individual i in market t from purchasing bundle $\mathbf{b}$ is:

$$\begin{aligned} U_{it\mathbf{b}} &= \sum_{j\in\mathbf{b}} u_{itj} + \Gamma_{t\mathbf{b}} + \varepsilon_{it\mathbf{b}} \\ &= \sum_{j\in\mathbf{b}} \left(\delta_{tj} + \mu_{itj}\right) + \Gamma_{t\mathbf{b}} + \varepsilon_{it\mathbf{b}} \\ &= \sum_{j\in\mathbf{b}} \delta_{tj} + \Gamma_{t\mathbf{b}} + \sum_{j\in\mathbf{b}} \mu_{itj} + \varepsilon_{it\mathbf{b}} \\ &= \delta_{t\mathbf{b}} + \mu_{it\mathbf{b}} + \varepsilon_{it\mathbf{b}} \end{aligned} \tag{6}$$

$\Gamma_{t\mathbf{b}}$ is an average interaction between the products in a bundle $\mathbf{b}$ in market t that determines whether individuals, on average, obtain higher or lower utility from joint consumption. $\Gamma_{t\mathbf{b}}$ is set to 0 for singleton bundles. $\delta_{t\mathbf{b}} = \sum_{j\in\mathbf{b}} \delta_{tj} + \Gamma_{t\mathbf{b}}$ is the market t-specific average utility for bundle $\mathbf{b}$, $\mu_{it\mathbf{b}}$ is an individual-specific deviation from $\delta_{t\mathbf{b}}$, and $\varepsilon_{it\mathbf{b}}$ is an idiosyncratic taste shock, i.i.d. across (i, t, b) and assumed to be drawn from a type-1 extreme value distribution.[10]

B Identification

The parameters that have to be identified are the vector of mean product utilities ($\boldsymbol{\delta}$), coefficients on interactions between observable demographics and product characteristics Φ, coefficients on product characteristics $\boldsymbol{\beta}$, the α-price coefficient, and the vector of interaction terms $\boldsymbol{\Gamma}$.

1 Mean Utility and Consumer Preferences

All mean product utilities (δ's) are identified by within-market variation in product shares. That is, conditional on Φ, $\boldsymbol{\beta}$, α, and $\boldsymbol{\Gamma}$, the δ's can be uniquely chosen so that model-predicted average choice probabilities match observed market shares.

Similarly, the coefficients on interactions between observable demographics and product characteristics, Φ, are identified by the observed covariances between the demographic characteristics of consumers that chose product j and the product's characteristics.[11] In other words, Φ sets the model's prediction for the covariance between each demographic variable and a product characteristic equal to its population counterpart. Finally, coefficients on product characteristics ($\boldsymbol{\beta}$) are identified by matching predicted and observed levels of product characteristics within and across markets.

2 Marginal Utility of Income

Instruments are generally required to identify α. This is because prices and ξ_{tj} will be correlated if unobserved product characteristics that increase consumer utility are capitalized into market prices.

[10] To address potential concerns about high upfront costs of the technologies, the model incorporates heterogeneity in budget constraints by interacting price with household income, ensuring that consumers with different income levels exhibit varying price sensitivities. This specification mirrors the approach used in Berry, Levinsohn and Pakes (1995) to account for budget constraints in differentiated product demand models. Additionally, similar to Bayer, Ferreira and McMillan (2007b) and Bayer et al. (2016), who model housing demand, this approach acknowledges that lower-income consumers face greater financial constraints, making them less likely to buy expensive products. This method is commonly used in structural demand estimation, particularly in contexts where upfront costs and budget constraints significantly influence consumer choices.

[11] Using the first-order conditions with respect to Φ, one can show that the maximum likelihood estimates of Φ are the ones that equate the observed and predicted covariance between the product's attributes and the demographic factors of the customers who selected that product. In the limit, as the number of consumers approaches infinity, Φ is identified as the solution to the system of the $L(K+1)$ equations, where L is the number of demographic variables and K is the number of product characteristics:

$$E_{\text{Population}}\left[x^k D^l\right] = E_{\text{Model}}\left[x^k D^l; \Phi\right]$$

I do not observe all of the product attributes that may affect price. For example, for cars, I do not observe direct measures of comfort, design, ride smoothness, predicted resale value, prestige, etc.[12]

To deal with endogenous prices, I use BLP-style instruments based on the sum of observable characteristics of rival products within each market. The product characteristics included in the instrument set are: horsepower, miles per gallon, fuel type indicators (gasoline, hybrid, or electric vehicle). These instruments are relevant because the distance between products in characteristics space affects the prices that firms can charge. The instruments are also commonly judged to reasonably satisfy the exclusion restriction under an assumption that the other product characteristics arise as part of an exogenous development process. Other studies that have used versions of these instruments to identify the marginal utility of income in models of the demand for EVs include Li (2019), Beresteanu and Li (2011), Xing, Leard and Li (2021), Li et al. (2021), Springel (2021).

3 The Interaction Term

The challenge with identifying Γ is distinguishing complementarity from unobserved preferences. In principle, there could be unobserved sources of heterogeneity not present in my model that could be conflated with complementarity. Therefore, I need a source of variation in the data that would reflect complementarity. Similar to Gentzkow (2007) I obtain this variation, in part, from between-market variation in "control variables" that affect the utility of one good but not of the other. The utility of EVs, but not PVs, will be impacted by factors like average fuel economy, horsepower, the number of EV charging stations, and the number of HOV lanes in a county where the household is located.[13] Similarly, the county-level global horizontal irradiation rate is a factor that affects the utility of PVs but not EVs. Additionally, price variation also helps to identify complementarity terms.

Stepping back, Gentzkow (2007) shows that the sign of Γ_b determines whether the two products are substitutes or complements.[14] If $\Gamma_b > 0$, products in the bundle are Hicksian complements with negative cross-price derivatives.[15] If $\Gamma_b < 0$, they are substitutes. If $\Gamma_b = 0$, the demand for

[12]Moreover, prices might be linked to marketing initiatives. For example, a product may be promoted via advertising and special offers. The price will then be negatively correlated with advertising, with higher advertising accompanied by lower prices. As an alternative, businesses might charge more for their goods to cover the cost of advertising, which leads to a positive correlation. In either scenario, the product's pricing is no longer independent of the unobserved variables influencing consumers' purchasing decisions.

[13]The instrument assumes that public EV charging infrastructure influences EV adoption but does not directly affect the utility of solar adoption. While it may indirectly raise electricity demand, it does not independently alter the appeal of rooftop solar. Moreover, EV owners are generally assumed to prefer home charging due to its cost advantages, making it unlikely that public charging availability substantially displaces residential electricity demand.

[14]See the discussion of Figure 1 in Gentzkow (2007) for an intuitive visualization

[15]Drawing on the lemma from Schlee and Khan (2022), when the nonnegativity constraint on the numeraire good is non-binding — meaning that consumer expenditures on goods like solar panels and electric vehicles do not fully exhaust their budget — Marshallian and Hicksian demands coincide, even with discrete goods. Consequently, the goods in question can be regarded as either Marshallian or Hicksian complements.

one product is independent of the prices of another product in a different category.

To illustrate this, consider a simple model with two goods, A and B, and homogeneous consumers. Normalizing the outside option to zero, assume that the utility of purchasing the goods is:

$$u_{0t} = 0, \tag{7}$$

$$u_{At} = \delta_{At} - \alpha p_{At} + \epsilon_{At}, \tag{8}$$

$$u_{Bt} = \delta_{Bt} - \alpha p_{Bt} + \epsilon_{Bt}, \tag{9}$$

$$u_{ABt} = u_{At} + u_{Bt} + \Gamma + \epsilon_{ABt}, \tag{10}$$

where δ_{At} and δ_{Bt} represent mean utilities in market t, and ϵ_{At}, ϵ_{Bt} and ϵ_{ABt} are error terms.

Let P_A, P_B, P_{AB} denote probabilities of purchasing products A, B and bundle of A and B, respectively. The total demand per consumer for good A is $Q_A = P_A + P_{AB}$, and for good B is $Q_B = P_B + P_{AB}$. Using the assumed parametric form for utility, the change in demand for good A with a one unit change in the price of good B can be expressed as follows:

$$\begin{aligned} \frac{dQ_{At}}{dp_{Bt}} = \alpha\, (&\exp(\delta_{At} + \delta_{Bt} - \alpha p_{Bt} - \alpha p_{At}) - \\ &- \exp(\delta_{At} + \delta_{Bt} - \alpha p_{Bt} - \alpha p_{At} + \Gamma_{ABt}))/ \\ &(1 + \exp(\delta_{At} - \alpha p_{At}) + \exp(\delta_{Bt} - \alpha p_{Bt}) + \\ &+ \exp(\delta_{At} + \delta_{Bt} - \alpha p_{Bt} - \alpha p_{At} + \Gamma_{ABt}))^2 \end{aligned} \tag{11}$$

In equation 11, we can see that when $\Gamma_{ABt} > 0$, the goods are complements, when $\Gamma_{ABt} < 0$, the goods are substitutes, and when $\Gamma_{ABt} = 0$, the goods are independent.

Now, to see how the interaction term, Γ, is identified consider a simple example. Suppose a variable affects only the utility of product A. If $\Gamma > 0$, an increase in this variable will lead marginal consumers to switch from consuming neither product to consuming both products. If $\Gamma = 0$, changing the utility of only one product will not affect the likelihood of purchasing the other product. However, if a variable affects the utilities of both products simultaneously, disentangling the synergy term becomes challenging. An increase in this variable would raise the utility of both products, potentially leading consumers to switch from buying neither product to buying both, even if the goods are independent. To isolate the effect of Γ, it is crucial to observe conditions where consumers opt for both products solely due to the complementarity effect.

Assume that Z_{Bt} is a control variable that affects the utility of product B, but not A. Equation

12 shows the partial derivative of product A's probability with respect to control variable Z:

$$\begin{aligned}\frac{dQ_{At}}{dZ_{Bt}} = \theta(&\exp(\delta_{At} + \delta_{Bt} - \alpha p_{Bt} - \alpha p_{At} + \theta Z_{Bt} - \\ &- \exp(\delta_{At} + \delta_{Bt} - \alpha p_{Bt} - \alpha p_{At} + \Gamma_{ABt} + \theta Z_{Bt})/ \\ &(1 + \exp(\delta_{At} - \alpha p_{At}) + \exp(\delta_{Bt} - \alpha p_{Bt} + \theta Z_{Bt}) + \\ &+ \exp(\delta_{At} + \delta_{Bt} - \alpha p_{Bt} - \alpha p_{At} + \theta Z_{Bt} + \Gamma_{ABt}))^2\end{aligned} \tag{12}$$

The interaction term Γ_{ABt} is identified through between-market variation in prices and control variables. This identification is possible because Γ_{ABt} is an implicit function of both $\frac{dQ_{At}}{dp_{Bt}}$ and $\frac{dQ_{At}}{dZ_{Bt}}$, which can be observed across different markets where prices and other control variables vary. The additional within-market variation in Z_{Bt} provides further identifying variation, helping to precisely determine the effect of Γ_{ABt}.

C Implications of Product Interactions for Taxing Externalities

This paper applies the multi-product model in a novel setting with externalities. I emphasize the importance of accounting for the synergy term Γ when implementing policies aimed at incentivizing the adoption of environmentally friendly technologies such as solar panels and electric vehicles. The degree of complementarity or substitutability is crucial when assessing how a policy will affect environmental externalities.

The model makes it possible to obtain not just the externalities associated with individual markets but also the total externalities related to tax and subsidy programs. For instance, if we were to examine the EV and PV markets independently, subsidies for electric cars would not impact the purchase of solar panels. However, if we consider how the public views these two technologies as complements (substitutes), then supporting the electric vehicle industry will also lead to a rise (fall) in solar system purchases. Therefore, compared to a scenario where the products are assumed to be independent, the specific aim of reducing carbon emissions may be achieved with fewer resources.

To illustrate the implications of these interactions, consider the stylized supply and demand diagrams presented in Figure 2. They demonstrate how the effect of a subsidy for the positive externalities of EVs on the PV market varies depending on whether two products are independent, substitutes, or complements. This visualization bridges the conceptual model with its policy implications.

Both EVs and PVs produce positive externalities by reducing CO_2 and $PM_{2.5}$ emissions. Let $Qsoc$ denote the socially optimal quantity for EVs and PVs in their respective markets. Panel (a) illustrates independent goods. Here, a subsidy for EVs decreases the consumer's price from $P1$ to $P2$, resulting in an increase in the quantity of EVs demanded from $Q1$ to the socially optimal level

($Qsoc$). $P2'$ here reflects the new total (pre-subsidy) price of the product. Importantly, the demand for PVs remains unaffected as these products are independent. The government cost to achieve this result is indicated by the shaded blue area.

In the case of substitutes, panel (b) shows that as the price of EVs decreases due to a subsidy, the demand for PVs shifts leftward from $D1$ to $D2$. This substitution effect diminishes the overall effectiveness of carbon reduction policies by reducing solar installations and, therefore, weakens the intended externality reduction. Consequently, the government must increase subsidies for both products to maintain the socially optimal adoption levels of each.

Finally, panel (c) illustrates the complementarity scenario, where EV subsidies not only increase EV adoption, but also increase demand for photovoltaics, shown by a rightward shift from $D1$ to $D2$ in the PV market. Therefore, now the government has to spend less resources to achieve a socially optimal level of PV adoption. The complementarity effect reinforces the subsidy's impact, suggesting that well-coordinated policies can exploit this relationship to maximize reductions in emissions. Thus, understanding the extent of the complementarity shift is crucial for setting the appropriate optimal subsidy level.

V Estimation

A Choice Set

The choice set consists of buying nothing, a good from one set only, from another set only, or a bundle. The options in the car set include a gasoline car, a hybrid car, an EV, or none of the above. The household can choose among five sizes for gas cars (compact, midsize, SUV, pick-up, van), and three sizes for hybrids (compact, midsize, SUV), two sizes for EVs (compact and midsize or bigger). I consolidated the midsize EV and SUV EV categories to minimize the number of products with zero observed market share, given the limited availability of SUV options in 2013.[16] The solar panel set consists of either installing a solar panel or not. Thus, there are 22 possible alternatives, including the outside option. The outside option is choosing not to purchase either a car or a solar panel.

The dataset is structured at the individual level, with some individuals associated with more than one vehicle, which could introduce some double counting. In cases where the primary driver of a vehicle is not explicitly identified, the vehicle is assigned to the household head. Notably, only 8% of individuals in the sample are associated with driving more than one vehicle. Finally, I exclude sports cars, diesel, hydrogen, plug-in hydrogen, gasoline-ethanol flex fuel, and compressed natural gas vehicles from the sample. This exclusion is due to the limited number of observations

[16] According to U.S. Department of Energy, in 2013, there was just one model of SUV electric car available (Toyota Rav4).

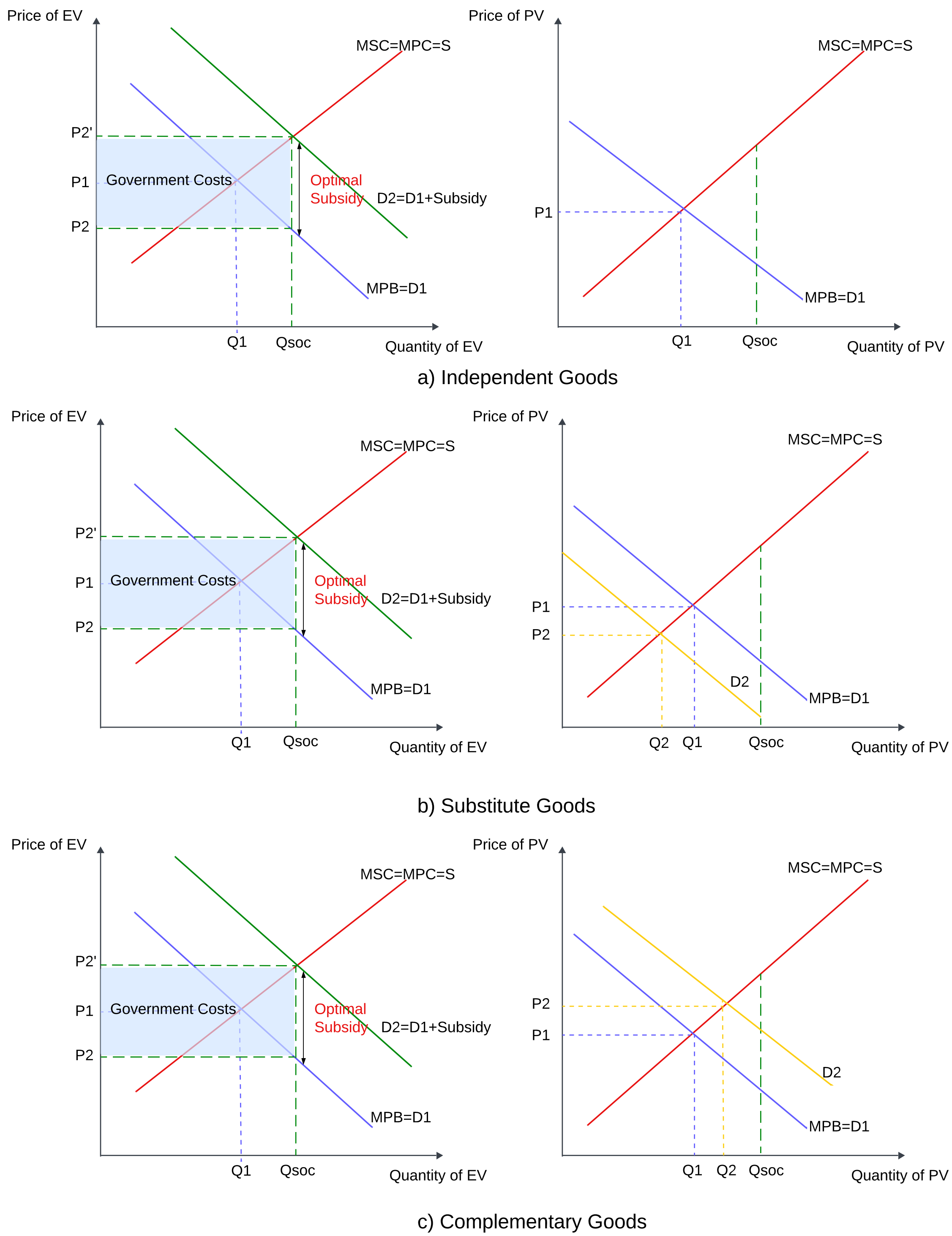


Figure 2: Optimal Subsidies in Interdependent Markets

Note: These figures show the optimal subsidies across three different scenarios: goods are a) independent, b) substitutes, or c) complements. The optimal subsidies are highest in the case of substitutes, as an increase in the demand for one good results in a decline in the demand for the other. Conversely, when goods are complements, the optimal subsidy is smallest, since the complementary relationship amplifies the subsidy's effect, reducing the need for larger subsidies.

for these cars and their substantial differences from the main categories, making it impractical to categorize them appropriately. In total, there are 19,859 individual-car level observations.

The vector of product characteristics $\mathbf{x_{tj}}$ includes miles per gallon, horsepower, the vehicle's length multiplied by its width and by its height, dollars per mile (the cost of driving a car), and ownership of PV. The vector of observable household characteristics, D_{it}, includes dummy variables for income groups and for the age of the household head, the number of household members, and an indicator for whether the individual has a bachelor degree or higher level of education. I divide households into 4 annual income groups: 1) below \$50,000; 2) between \$50,000 and \$100,000; 3) between \$100,000 and \$200,000; 4) above \$200,000. Finally, control variables such as the number of HOV lanes in the region, the number of charging stations in the household county, and irradiation rate in the county enter the utility of the products that contain electric vehicles, while the global horizontal irradiation rate in the county enters the utility of products with solar panels.[17]

A limitation of my data is that the specific EV and PV attributes that households select, such as the model of the car are not present in the survey data. This is why I group cars into broad categories based on size and fuel type. In principle, one could learn more by designing a novel survey to collect additional microdata on more granular characteristics of EVs and PVs among adopters. This could be an interesting direction for future research.

B Estimation strategy

I use a two-stage method related to that developed by Berry, Levinsohn and Pakes (1995) and Bayer, Ferreira and McMillan (2007a) to estimate model parameters. In the first stage, I estimate the heterogeneous parameters (Φ), using maximum likelihood, and I recover the mean utilities (δ) using a contraction mapping procedure.[18]

The Type 1 extreme value distribution assumption on ε_{itj} implies that for a guess of Φ and δ_{tj}, the probability that household i in market t chooses bundle b is:

$$P_{itb} = \frac{\exp\{\delta_{tb} + (\mathbf{x_{tb}}, p_{tb}) \cdot (\Phi D_{it}) + \Gamma_{tb}\}}{1 + \sum_{k=1}^{J} \exp(\delta_{tk} + (x_{tk}, p_{tk}) \cdot (\Phi D_{it}) + \Gamma_{tb})} \tag{13}$$

[17] I exclude HOV lanes from the final specification due to their statistical insignificance, as their inclusion did not impact the rest of estimated coefficients.

[18] The maximum likelihood estimator maximizes the probability that the model correctly predicts each household's product choice based on the observed product characteristics. Due to a small sample when estimating mean utilities, I deal with zero observed shares by assuming that one person in the market bought the product with zero market share. This way I can use the contraction mapping algorithm.

The log-likelihood function is:

$$\text{LL}(\Phi, \delta) = \frac{1}{N \times T} \sum_{t=1}^{T} \sum_{i=1}^{N} \ln P_{it}(\Phi, \delta) \tag{14}$$

where $P_{it}(\Phi, \delta)$ is the probability of the observed outcome for decision maker i in market t. The goal of the first step is to find the heterogeneous parameters and a vector of mean utilities that maximize $\text{LL}(\Phi, \delta)$.

In the second stage, I decompose mean utilities obtained in the first step into observed and unobserved characteristics according to equation 4. Because prices are correlated with unobserved product characteristics ξ_{tj}, I estimate equation 4 using the instrumental variables method.

To correct for the endogeneity of prices, I follow the logic of Berry, Levinsohn and Pakes (1995) that the price of product j will depend on the characteristics of other products in the market. Specifically, the sums of characteristics of the other products in the market $\sum_{j' \neq j, j' \in \mathcal{J}_t} \mathbf{x}_{tj'}$ will serve as instruments for price. I estimate standard errors of all parameters by bootstrapping over both stages of estimation with 1,000 repetitions.

VI Results

A Parameter Estimates

Table 1 presents the model estimates.[19] The left side displays the estimated coefficients for product characteristics. Most coefficients are precisely estimated. The average household has a positive valuation of vehicle horsepower, miles per gallon, solar panels, and synergy between EVs and PVs. I evaluate the utility of mileage per gallon separately, conditional on purchasing an EV and the other types of cars. We can see that for gas and hybrid cars, the coefficient on mileage per gallon is positive. This implies that consumers get positive utility from higher fuel efficiency. However, the negative coefficient on miles per gallon equivalent (MPGe) for electric vehicles might be picking up some unobserved characteristics that correlate with MPGe, such as luxury features and performance packages that drain the battery. Moreover, households experience a decrease in utility on average due to higher prices and bigger sizes of cars.

The right side of Table 1 displays the estimates of the coefficients on interactions of observable demographic characteristics with product characteristics. Most coefficients have the expected signs. Higher-income households exhibit lower sensitivity to vehicle prices. Furthermore, these households place greater value on the reduced operational costs associated with driving the vehicle.

[19]Table B.5 in the appendix shows the quality of model fit. I estimate model-predicted shares for the whole population and then product shares within different income group households. The table shows that the model does a good job of matching the observed shares in the data.

Table 1: Parameter Estimates of Mean Utility and First Stage Parameters

Mean Utility		**First Stage Parameters**	
Constant	-0.160	Income (50-100k) × prices	0.222
	(0.041)		(0.023)
MPG_{EV}	-2.022	Income (50-100k) × $ per mile	-1.561
	(0.173)		(0.576)
MPGgas/hybrid	1.097	Income (100-200k) × prices	0.369
	(0.211)		(0.022)
Horsepower	2.981	Income (100-200k) × $ per mile	-2.954
	(0.071)		(0.580)
Car size	-0.408	Income (200k or more) × prices	0.519
	(0.022)		(0.024)
Solar	1.001	Income (200k or more) × $ per mile	-5.425
	(0.501)		(0.665)
Γ	1.368	HH members × Car size	-0.043
	(0.100)		(0.003)
Prices	-1.637	College degree × mpg	2.207
	(0.046)		(0.133)
		College degree × PV	0.042
			(0.043)
		GHI × PV	1.837
			(0.910)
		Stations × EV	0.201
			(0.162)
		Age (35-64) × PV	-0.082
			(0.068)
		Age (35-64) × EV	0.203
			(0.133)
		Age (65 or older) × PV	0.292
			(0.073)
		Age (65 or older) × EV	-0.039
			(0.143)
Observations	396		19,859

Note: Bootstrapped standard errors reported in parentheses.

This finding is intuitive as wealthier households have a greater capacity to make upfront investments that lead to long-term cost savings. Essentially, higher-income households are more likely to prioritize and invest in vehicles with lower running costs, reflecting their ability to absorb higher initial expenditures for future financial benefits. Larger families tend to place less value on larger vehicles, likely because they opt for multiple smaller, more affordable cars rather than a single, more expensive large vehicle. In addition, we can see that higher educated consumers value fuel efficiency and solar system more than people with lower levels of education. In addition, the estimates indicate that older individuals place a higher value on solar panels. This may be attributable to their higher accumulated wealth, which provides them with the financial flexibility to invest in solar panel installations. Conversely, older people appear to value EVs less. This may be due to a potential aversion to adopting new technologies, which is often observed in older demographics. Lastly, households residing in counties with higher numbers of EV charging stations get higher utility from EVs, whereas households living in places with higher global horizontal irradiation rates value solar panels more.

B Results Interpretation

Table 2 presents estimates of marginal willingness to pay (WTP) to help interpret parameter differences between income groups. The results show that higher-income households are willing to pay more for additional fuel-efficiency and horsepower. For example, households with an annual income above \$200,000 are willing to pay \$267 for an additional horsepower. In comparison, households with less than \$50,000 per year are willing to pay \$182 for an extra horsepower. The willingness to pay for PV also increases with income, ranging from \$6,118 for lower-income households to \$8,957 for the highest-income households.

The WTP estimates for the synergy between EVs and PVs range from \$8,977 to \$13,666, increasing with household income and car size. The WTP for the complementarity between bigger-size EVs and solar panels is slightly higher compared to compact EVs and solar panels. Bigger cars need more electricity to charge, therefore increasing the potential savings from charging with solar. On average, a 1% decrease in the price of EVs results in a 0.23% increase in the demand for PV systems. Similarly, a 1% decrease in the price of PVs leads to 0.69% increase of EV demand. The asymmetry of elasticities is likely due to the substitution patterns. If the price of PV system increases, consumers might substitute towards other types of vehicles (like traditional gas cars, hybrids) that do not include PV but still satisfy the basic need for transportation. This suggests a higher elasticity for EVs because there are multiple alternatives that fulfill the same basic transportation need. When the price of EVs increases, the substitution effect for PV might be less pronounced. This is because the needs that PVs satisfy (e.g., renewable energy usage, reduced utility costs) are less directly related to mere transportation and may involve broader environmental and economic considerations. Thus, if consumers are committed to these broader needs, they have fewer substitute options that satisfy the same criteria, making their demand for PVs more inelastic.

Table 2: Willingness to Pay Estimates, US dollars

Income	(I) ≤ 50 k	(II) 50-100 k	(III) 100-200 k	(IV) ≥ 200 k
MPG	67	78	87	98
Horsepower	182	211	235	267
Car Size	-25	-29	-32	-37
PV	6,118	7,081	7,902	8,957
EV compact+PV Interaction	8,977	10,390	11,595	13,142
EV midsize+PV Interaction	9,335	10,803	12,056	13,666

C Complementarity Decomposition

I decompose complementarity into two primary channels: electricity cost savings and consumer preferences. A portion of this complementarity arises from the potential cost savings associated with the combined use of EVs and PVs. The remaining portion is attributed to consumers' willingness to adopt environmentally friendly practices. Households may benefit from the combined ownership of PV systems and EVs, as installing solar panels can reduce electricity costs by shifting increased consumption from EVs to lower price tiers. In addition, EV time-of-use (TOU) rates that require having an EV allow households to sell excess solar energy at higher rates during peak generation hours.

I use information on residential location to link individuals to their utility companies, including Southern California Edison (SCE), San Diego Gas & Electric (SDG&E), and Pacific Gas and Electric Company (PG&E).[20] Then, I use utility-specific information on rate plans to calculate the average savings that consumers may realize by comparing electric bills under different rate plans and discounting the results at 3% annually over ten years. Additional details on these calculations are provided in Appendix E.[21]

On average, the discounted complementarity savings over ten years amount to approximately $1,775 for customers on the block rate plan, and $2,081 for those who choose the cost-minimizing plan. The model-predicted WTP for complementarity varies significantly across markets, with the highest values observed in 2013, followed by a marked decline in most markets by 2017 and 2019. This pattern likely reflects the early adopters' strong preference for environmentally friendly goods. The mean model-predicted WTP across all markets is $10,690, but when excluding 2013, this value

[20] Additionally, the dataset includes a small percentage of individuals serviced by Sacramento Municipal Utility District, Pacific Power, Liberty Utilities, Lassen Municipal Utility District, and Imperial Irrigation District. Due to their minimal representation, I exclude these companies from the calculation of the average savings for each region.

[21] Table C.6 presents the cost savings due to complementarity if a customer is on the block rate plan and if they are on the cost-minimizing plan, which could either be the block rate plan or one of the time-of-use plans offered by utility companies, based on the assumed consumption profile. Although the TOU plan may provide greater savings, most customers continue to use the block rate plan. The table also presents the model's predicted willingness to pay (WTP) for complementarity across markets.

drops to \$8,072, indicating that around 30% of the WTP for complementarity can be explained by financial savings, while the remainder reflects consumers' valuation of additional benefits, such as their preference for environmentally friendly choices.

VII Counterfactual and Policy Experiments

I perform several counterfactual experiments using the estimated model. Specifically, I consider (i) the importance of complementarity in the adoption of technologies; (ii) the magnitude of the subsidy effects on the adoption of technology with and without accounting for complementarity between goods; and (iii) the cost-minimizing design of subsidies between the two markets.

A Quantifying the Complementarity Effect

In the first column of table 3, we can see the predicted shares of each product (which, by construction, perfectly match the observed shares) in the model that allows for flexible substitution patterns among the goods. The second column presents the shares that would be observed if EVs and PVs were restricted to be independent, given current market prices and subsidies. The results imply that the share of bundles that include solar panels and electric vehicles would fall by 64%, and in total consumers would buy fewer EVs and PVs.

Table 3: Product shares, %

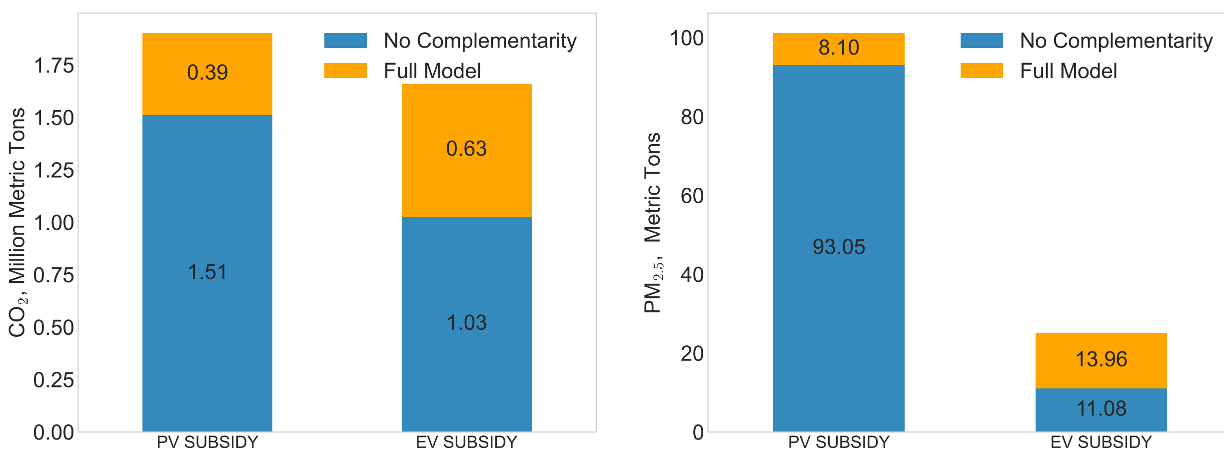
Product	*Model predictions*		
	w/ complementarity	Independent goods	% Change
All Solar	14.49	13.97	-3.62
All EV	2.36	1.73	-26.59
PV & EV bundle	1.03	0.37	-64.04
Only PV	13.47	13.6	0.99
Only EV	1.33	1.36	2.35

B Complementarity Role in Subsidy Effects

The model also enables me to conduct back-of-the-envelope calculations of the effects of subsidies on carbon emissions and particulate matter ($PM_{2.5}$) reductions. For the analysis, I rely on data from several government sources and research reports to make assumptions. Key assumptions include California's potential market size of 20.6 million people and a typical residential solar system generating 9,000 kWh per year. Additionally, electricity generation emissions are estimated to be 457.5 lb/MWh for CO_2 and 0.028 lb lb/MWh for $PM_{2.5}$. Vehicle CO_2 emissions vary by fuel type, with gasoline cars emitting 12,594 lbs CO_2 annually. For $PM_{2.5}$, I assume that gas cars emit at the current emission standard of 0.003 grams per mile. Finally, the average annual vehicle miles traveled (VMT) is 14,489 miles. Supporting details are provided in Appendix F.

Next, I assume that the California government has $2 billion dollars to spend on EV and PV subsidies. This amount has been selected as it approximates the current expenditure by California on the promotion of these technologies.[22] Given the specific assumptions and my model estimates, I compute the predicted reductions of CO_2 emissions when a subsidy is provided only for solar panels and then only for EVs. According to Figure 3a, when EVs and PVs are considered independently, subsidizing PVs is more effective, resulting in a reduction of 1.52 million metric tons of CO_2 per year. However, when the complementary effect between EVs and PVs is taken into account, the impact of the subsidies increases. The solar subsidy then contributes an additional 0.39 million metric tons of CO_2 reductions, while the EV subsidy adds 0.63 million metric tons of CO_2 reductions. This complementarity reduces the difference in effectiveness between the two types of subsidies. Policymakers can achieve a specific target of greenhouse gas emissions by spending fewer budget resources by accounting for the interdependency between solar panels and electric vehicles.

The effects of government spending on $PM_{2.5}$ emissions are presented in figure 3b. We can observe that subsidizing PVs is far more efficient in reducing $PM_{2.5}$ emissions. Nevertheless, we can see the importance of accounting for complementarity as almost 56% of the $PM_{2.5}$ reductions from EV subsidies are due to the complementarity channel.



(a) CO_2

(b) $PM_{2.5}$

Figure 3: Emission reductions per year from EV and PV adoption

[22]For example, in 2022, the Governor's budget included $922.4 million over two years for the Equitable Building Decarbonization program, which supports residential electrification and includes PV systems installation (Legislative Analyst's Office, 2022b) In addition, the state proposed $6.1 billion over five years for various zero-emission vehicle (ZEV) initiatives, which translates to over $1.2 billion annually (Legislative Analyst's Office, 2022a)

C Optimal Subsidy Allocation

Next, I analyze different ways to allocate subsidies between PVs and EVs to incentivize their adoption. I vary the share of the budget allocated to each technology, from full support for PVs, to full support for EVs, to a combination of both. Additionally, I consider subsidies for purchasing both technologies as a bundle, or for one if the household already owns the other. The results can advance our understanding of the most cost-effective ways to reduce air pollutants.

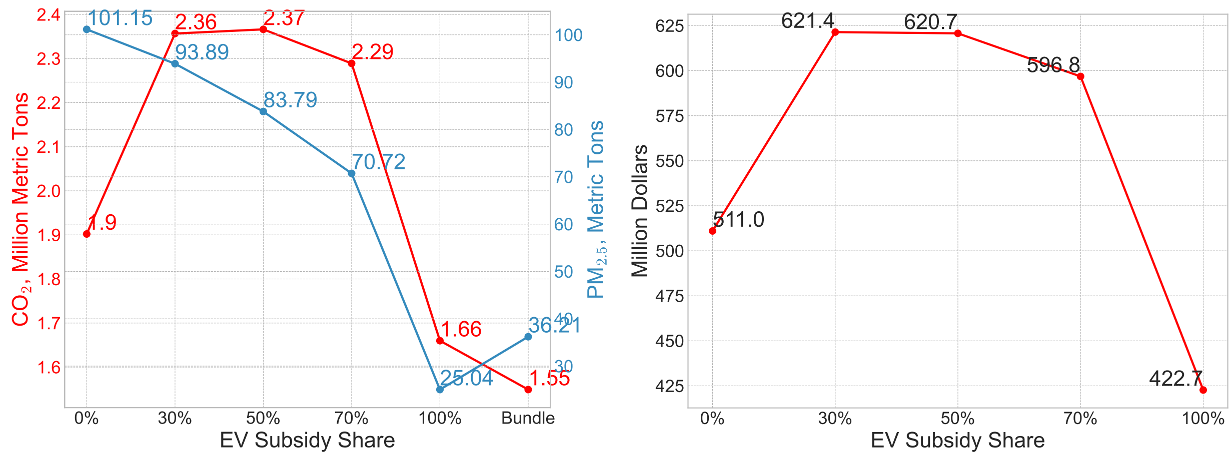
Figure 4a demonstrates the effects of subsidies on annual carbon dioxide and particulate matter emissions. The results of the full model imply that the most effective way to reduce CO_2 emissions is to invest half of the resources in subsidies for electric vehicles and half for PVs. In contrast, the most significant decreases in $PM_{2.5}$ come from subsidies for solar systems with a gradual decline as we move towards giving more subsidies to EVs. Therefore, choosing which emission target that should be prioritized will determine the most effective way to provide subsidies.

Moreover, I calculate the total annual monetary benefits in order to see which allocation is optimal in terms of investment returns. I apply the EPA's Social Cost of Carbon (SCC) for the emission year 2024, valued at $245 per metric ton in 2024 dollars (U.S. Environmental Protection Agency, 2023).[23] The half-half allocation of budget resources leads to approximately $580 million in annual returns from reductions of CO_2 alone. For $PM_{2.5}$, I use the EPA's CO-Benefits Risk Assessment Health Impacts Screening and Mapping Tool (COBRA), which provides region-specific estimates of the economic value of health benefits from emission reductions in targeted sectors. To reflect the timing of health impacts—such as delayed changes in mortality and non-fatal heart attacks—COBRA applies a 2% discount rate, as recommended by the EPA. The results are presented in figure 4b. The results show that the optimal allocation of subsidies is to spend approximately 70% of resources on PV and 30% on EV in both cases. The payback period of the investment is about 3 years and 8 months at the discount rate of 7% and 3 years and 5 months at 3%.

VIII Conclusion

This study contributes to the ongoing global discussion on green technology investment policy by providing a theoretically motivated analysis of the spillover effects between two industries, solar panels and electric vehicles. I presented descriptive evidence that the odds of installing a solar panel are about three times as large as the odds for a person without an EV, and vice versa. There are two competing explanations for this result. First, households with high utility from adopting solar panels also get high utility from purchasing an EV. Another reason is that the two goods complement each other.

[23] I adjust for inflation the value of 204$ in 2020 dollars for the emission year 2024 using the consumer price index.



(a) Annual Emissions Reductions

(b) Annual Total Monetary Value

Figure 4: Comparison of Annual Reductions and Benefits

I used a two-stage estimation procedure to recover structural parameters of the joint demand for solar systems and electric vehicles. These are the first estimates for substitution/complementarity patterns in demand system for solar panels and electric vehicles. This is also the first application of a multi-product demand model to consider externalities. The results suggest that the two technologies are complements. The potential channels for complementarity are decreased costs and higher environmental benefits.

I implemented several counterfactual policy experiments. They show that complementarity between solar panels and electric vehicles plays a significant role in how subsidizing consumer purchases in either market affects air pollution. In addition, I analyzed the range of potential allocations of fixed government budget resources on EV and PV subsidies and showed how this would reduce CO_2 and $PM_{2.5}$ emissions. The optimal allocation based on back-of-the-envelope calculations using conventional assumptions for monetizing damages from global warming and health effects of air pollution is to invest 30% of the resources into EV subsidies and 70% into PV subsidies.

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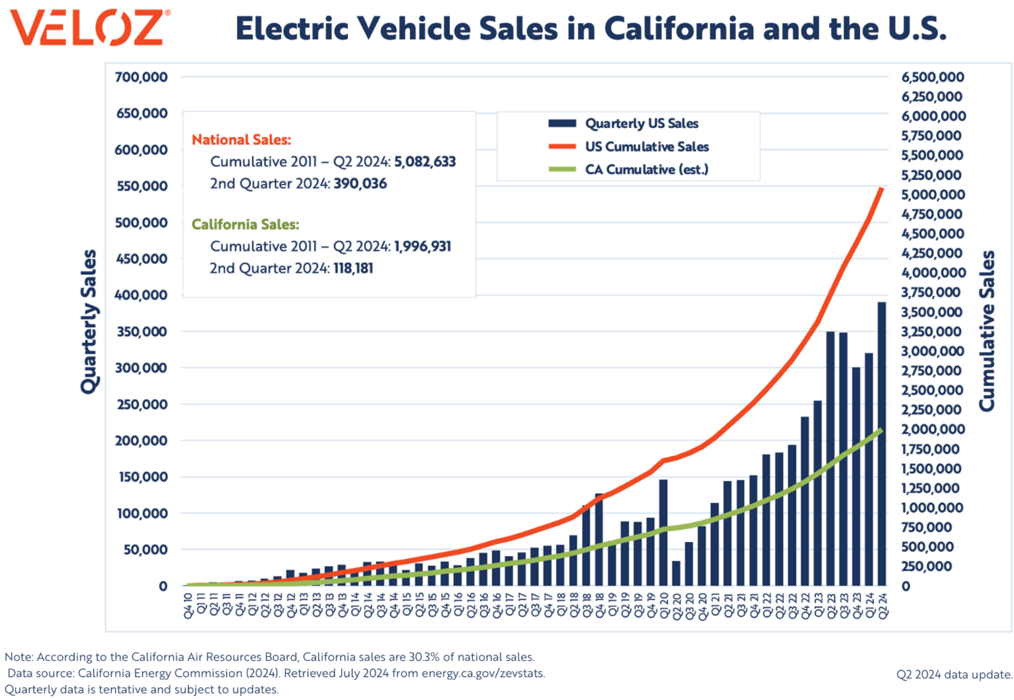
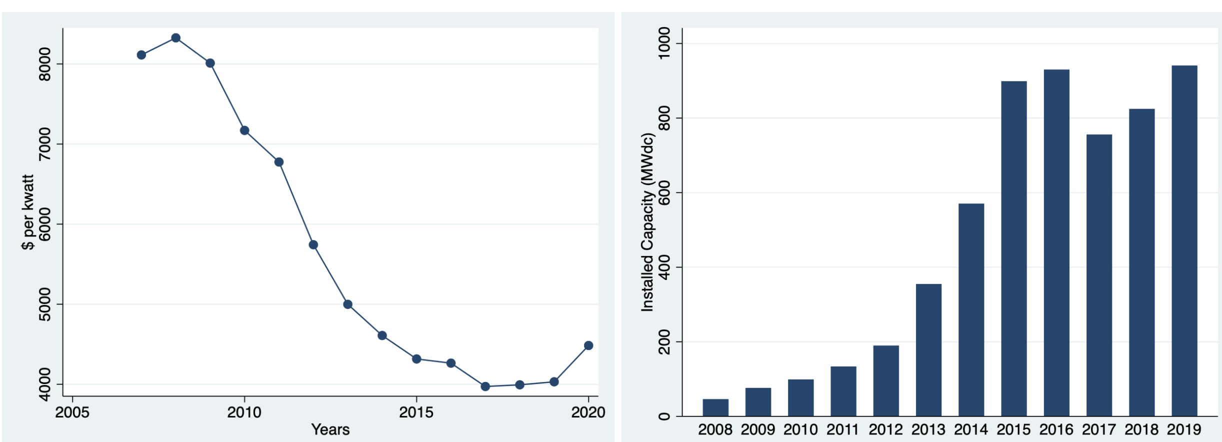
A Supplementary Figures

Figure A.1: Electric Vehicle Sales in California and the U.S.



Source:Veloz (2024)

Figure A.2: California Solar PV Pricing Trends & Deployment Growth



Source: Lawrence Berkeley National Laboratory (2023)

Table A.1: Summary Statistics

	California Vehicle Survey	California CPS
N of people	19,859	39,392
N of households	9,096	8,172
< \$50,000	16%	28%
\$50,000 - 99,999	32%	29%
\$100,000 - 199,999	37%	29%
> \$200,000	16%	13%
Black or African American	3%	5%
Hispanic	13%	33%
Female	49%	51%
Highest schooling:		
< High school	5%	14%
High school/GED	11%	24%
Associate's degree	12%	9%
Some College	16%	21%
College (4 year)	30%	21%
Post-graduate	27%	11%
Age group:		
18-34 years old	21%	28%
35-64 years old	59%	53%
65 or older	20%	20%

B Logistic Regression Results and Model Fit

Table B.2: Logistic Regression Results for EV Ownership

	(1)	(2)	(3)	(4)	(5)
Own PV	4.52	3.62	3.57	3.22	3.28
	(0.329)	(0.270)	(0.268)	(0.252)	(0.257)
Income (25k-34k)		0.60	0.59	0.50	0.53
		(0.380)	(0.374)	(0.318)	(0.334)
Income (35k-49k)		1.16	1.12	0.96	1.02
		(0.538)	(0.520)	(0.451)	(0.480)
Income (50k-74k)		2.42	2.34	2.11	2.25
		(0.971)	(0.941)	(0.852)	(0.912)
Income (75k-99k)		3.46	3.32	3.07	3.27
		(1.362)	(1.306)	(1.217)	(1.297)
Income (100k-149k)		4.28	4.08	3.66	3.93
		(1.659)	(1.582)	(1.429)	(1.537)
Income (150k-199k)		5.58	5.28	4.85	5.24
		(2.181)	(2.066)	(1.915)	(2.073)
Income (200k-249k)		8.60	8.25	6.27	6.82
		(3.377)	(3.243)	(2.489)	(2.712)
Income (250k+)		11.01	10.45	8.38	9.18
		(4.279)	(4.065)	(3.304)	(3.628)
Age (35-64)			1.62	1.59	1.52
			(0.185)	(0.190)	(0.182)
Age (65+)			1.83	1.28	1.10
			(0.238)	(0.174)	(0.156)
HH size					0.88
					(0.029)
County FE				✓	✓
Year FE				✓	✓
Observations	19,859	19,859	19,745	19,311	19,311

Note: Exponentiated coefficients. Standard errors are in parentheses.

Table B.3: Ordered logistic regression results for PV

	(1)	(2)	(3)	(4)	(5)
PV					
Own EV	4.36	3.54	3.54	3.08	3.14
	(0.293)	(0.242)	(0.242)	(0.214)	(0.219)
Income(25,000-34,999)		1.01	1.01	0.97	0.93
		(0.120)	(0.121)	(0.117)	(0.112)
Income (35,000-49,999)		1.64	1.66	1.63	1.53
		(0.163)	(0.166)	(0.165)	(0.156)
Income(50,000-74,999)		1.54	1.54	1.59	1.52
		(0.140)	(0.141)	(0.148)	(0.142)
Income(75,000-99,999)		1.88	1.90	1.98	1.90
		(0.168)	(0.170)	(0.181)	(0.174)
Income(100,000-149,999)		2.08	2.12	2.32	2.20
		(0.181)	(0.185)	(0.207)	(0.197)
Income(150,000-199,999)		2.53	2.62	2.98	2.82
		(0.230)	(0.239)	(0.279)	(0.265)
Income(200,000-249,999)		2.80	2.91	3.17	3.02
		(0.271)	(0.283)	(0.316)	(0.303)
Income(250,000+)		4.18	4.35	5.06	4.75
		(0.392)	(0.410)	(0.493)	(0.465)
Age(35-64)			0.86	0.88	0.95
			(0.033)	(0.035)	(0.038)
Age(65+)			0.99	0.92	1.09
			(0.046)	(0.045)	(0.056)
HH_size					1.13
					(0.013)
County FE				✓	✓
Year FE				✓	✓
Observations	19,859	19,859	19,745	19,745	19,745

Note: Exponentiated coefficients. Standard errors in parentheses.

Table B.4: Logit model results predicting PV and EV ownership.

	Dependent variable is EV ownership		Dependent variable is PV ownership	
	Marginal Effect	Standard Error	Marginal Effect	Standard Error
PV ownership	.057	.005		
EV ownership			.198	.0148

Table B.5: Model Fit

Product	All observations		$50,000-$100,000		$100,000-$200,000		≥ $200,000	
	Data	Model	Data	Model	Data	Model	Data	Model
none	0.107	0.107	0.119	0.116	0.079	0.081	0.049	0.059
solar	0.019	0.019	0.018	0.019	0.019	0.018	0.022	0.019
gas compact	0.123	0.123	0.131	0.132	0.111	0.114	0.100	0.097
gas midsize	0.229	0.229	0.245	0.235	0.233	0.235	0.191	0.211
gas suv	0.183	0.183	0.182	0.190	0.198	0.187	0.187	0.171
gas van	0.042	0.042	0.044	0.042	0.042	0.044	0.040	0.041
gas pickup	0.077	0.077	0.088	0.085	0.071	0.075	0.043	0.057
hyb compact	0.016	0.016	0.015	0.015	0.016	0.016	0.021	0.017
hyb midsize	0.027	0.027	0.024	0.025	0.032	0.029	0.037	0.033
hyb suv	0.008	0.008	0.005	0.007	0.009	0.008	0.014	0.011
ev compact	0.012	0.012	0.008	0.010	0.013	0.013	0.024	0.019
ev big	0.011	0.011	0.008	0.005	0.013	0.012	0.023	0.031
gas comp+sol	0.020	0.020	0.017	0.019	0.022	0.022	0.029	0.024
gas mid+sol	0.034	0.034	0.030	0.029	0.036	0.040	0.050	0.049
gas suv+sol	0.034	0.034	0.025	0.029	0.042	0.039	0.056	0.050
gas van+sol	0.007	0.007	0.006	0.006	0.008	0.009	0.014	0.012
gas pickup+sol	0.014	0.014	0.014	0.013	0.015	0.016	0.015	0.017
hyb comp+sol	0.006	0.006	0.004	0.005	0.008	0.007	0.010	0.009
hyb mid+sol	0.009	0.009	0.006	0.006	0.010	0.010	0.017	0.016
hyb suv+sol	0.003	0.003	0.002	0.002	0.003	0.003	0.006	0.005
ev comp+sol	0.009	0.009	0.005	0.006	0.010	0.011	0.024	0.021
ev big+sol	0.010	0.010	0.005	0.003	0.009	0.010	0.027	0.032
observations	19,859		6,279		7,256		3,187	

C Complementarity Willingness To Pay

Table C.6: Summary of savings, cost-minimizing plans, and predicted WTP across various regions and years.

Year	Region	Utility	Block rate savings	Cost-minimizing plan	Cost-minimizing plan savings	Model-predicted WTP for complementarity
2013	Sacramento	PG&E	2,688	EV rate	1,487	18,628
2013	San Francisco	PG&E	2,688	EV rate	673	11,942
2013	Central Valley	PG&E	2,688	EV rate	1,890	13,821
2013	Rest of State	PG&E	2,688	EV rate	1,352	20,029
2013	Los Angeles	SCE	2,272	EV rate	2,948	17,053
2013	San Diego	SDG&E	2,395	EV-TOU-2	429	14,091
2017	Sacramento	PG&E	1,316	EV rate	2,217	10,093
2017	San Francisco	PG&E	1,316	EV rate	2,644	7,322
2017	Central Valley	PG&E	1,316	EV rate	1,978	12,595
2017	Rest of State	PG&E	1,316	EV rate	2,397	11,488
2017	Los Angeles	SCE	1,248	EV rate	1,014	2,290
2017	San Diego	SDG&E	3,051	Block rate	3,051	7,112
2019	Sacramento	PG&E	878	EV rate	2,613	1,068
2019	San Francisco	PG&E	878	EV rate	2,378	4,498
2019	Central Valley	PG&E	878	EV rate	2,738	9,261
2019	Rest of State	PG&E	878	EV rate	2,523	13,818
2019	Los Angeles	SCE	783	EV rate	3,550	6,520
2019	San Diego	SDG&E	2,667	EV-TOU-5	1,577	10,793
Average Across Markets			1,775		2,081	

D Complementarity Mechanism

Many utilities offer plans with a baseline allowance for monthly electricity usage. The baseline allowance is the maximum monthly energy use allowed at the lowest tier rate. Customers will advance to the higher tier price and beyond if they consume more than the allotted amount throughout the billing cycle. Customers who are on a Standard or Time-of-Use plan are affected by this. However, many utility companies offer electricity plans specifically for households with electric cars, and these plans usually do not have a baseline allowance.

In table D.7, I provide two different electricity plans' rates: for EV customers only (EV-TOU-2) and for all customers (TOU-DR1). If we compare rates, we can see that TOU-DR1 has lower prices per kWh during all hours if the household uses below 130% of the baseline allowance compared to the rates in the EV plan. Therefore, installing a solar panel will help deal with the increased energy consumption from the electric car and stay at tier 1, which provides the lowest rates possible. I give the example of three possible scenarios of household electricity usage in figure D.3. In the first instance, before and after purchasing an electric vehicle, the household consumes less than 130% of the baseline allotment. Therefore, such households lack the motivation to purchase solar to maintain their lower rate tier. Meanwhile, types 2 and 3 will benefit from installing solar panels to stay below 130% of the baseline. For type 2 households, the objective is to cut solely the extra power used for EV charging, whereas, for type 3 households, the goal is to reduce both the extra electricity used for EV charging and the initial excess demand in consumption.

Another way to get the additional savings from complementarity is to take advantage of EV-specific time-of-use (TOU) rate structures. These EV TOU rates, available only to households with an EV, enable households to sell excess solar energy back to the grid at higher rates during peak solar generation hours. They can then use energy at a lower cost during off-peak hours, such as at night when they charge their EVs. This setup allows customers with both EVs and PV systems to generate extra income by optimizing their energy generation and consumption patterns.

E Supporting Details for Complementarity Savings Calculations

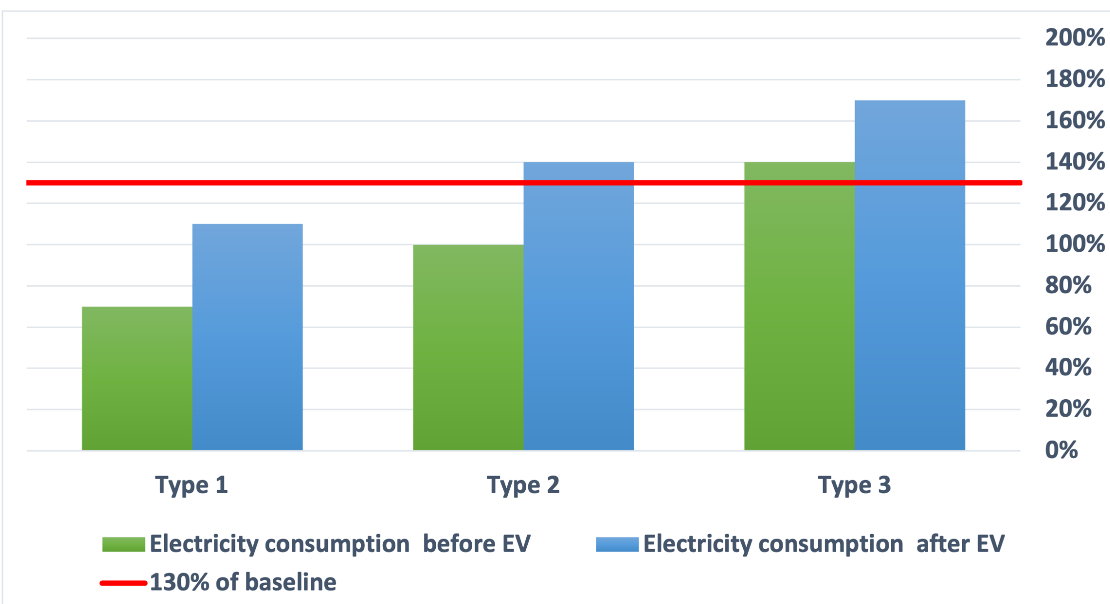
To compute savings from the complementarity channel in different regions of California, I use several data sources. I begin with the 2014 average daily load shape for California residential customers reported by California Energy Commission (2019). Additionally, data from the 2020 Residential Energy Consumption Survey (RECS) by U.S. Energy Information Administration (2020) indicate that single-family homes with solar panels and electric vehicles in California consume an average of 8,972 kWh annually, or 24.58 kWh per day. Of this, 1,749 kWh per year (4.79 kWh/day) is attributed to EV charging.

Table D.7: Example of Electricity Rates in SDG&E (Summer 2022)

On-Peak	**Super Off-Peak**	**Off-Peak**
4:00 pm - 9:00 p.m.	Midnight $-6:00$ a.m. Midnight - 2:00 p.m. (Weekends & Holidays)	All other hours
EV-TOU-2		
66.7¢	23.8¢	41.9¢
TOU-DR1		
Tier 1(Up to 130% baseline)		
58.5¢	23.4¢	35.6¢
Tier 2(> 130% baseline)		
69¢	33.6¢	45.8¢

Source: San Diego Gas & Electric Company (2022)

Figure D.3: Electricity consumption for different types of households



To estimate hourly electricity consumption, I subtract EV charging demand from the total daily consumption and distribute the remaining load according to the average daily load shape. EV charging is assumed to occur during off-peak hours (11:00 PM to 6:00 AM) in line with typical EV-TOU rate structure that offer lower prices during these hours, supported by Burlig et al. (2021).

For average daily solar generation, I calculate the median system size (in kW_DC) for each region and year using data from Lawrence Berkeley National Laboratory (2023). I adjust for regional differences in global horizontal irradiation rates using Solargis (2022) and apply system performance adjustments based on derating factors and inverter efficiencies as documented by Franklin (2019). Solar generation is assumed to occur between 10:00 AM and 5:00 PM, consistent with net load reduction periods identified by California Independent System Operator (2016).

Finally, I estimate the approximate electric bill for the average customer with these characteristics under various regional rate plans.

F Assumptions Used for Calculations

- Adult population (18 years and older) of California is 30,827,105 (U.S. Census Bureau, 2021). About 67% of this population live in one unit houses or mobile homes according to IPUMS (2024). Therefore, the potential market size is about 20,654,160 people.

- According to Lawrence Berkeley National Laboratory (2024), the median solar system size installed in California is 6.6 kW, which will generate approximately 9,000 kWh of electricity per year.

- California's electricity generation CO_2 equivalent emissions are 457.5 lb/MWh (U.S. Environmental Protection Agency, 2024b).

- The average annual emissions for a gasoline vehicle in California, including both upstream and tailpipe emissions, are 12,594 lbs of CO_2e. Hybrid car's annual emissions are 6,898 lbs of CO_2e. For battery electric vehicles, annual emissions are 1,385 lbs of CO_2e, while for plug-in hybrid electric vehicles (PHEVs), total emissions are 3,866 lbs of CO_2e (U.S. Department of Energy, 2024). Since in my estimation, I treat both PHEV and BEV as electric vehicles, I will assume that average EV emissions charged from the grid are 2,626 lbs (1,191 kg) per year.

- If EV is charged by PV, I will assume that BEV emits zero CO_2e and PHEV emits 2,939 lbs of CO_2e per year coming from gasoline (U.S. Department of Energy, 2024).

- Annual $PM_{2.5}$ emissions from electricity generation in California are 0.0281 lb/MWh accorfing to U.S. Environmental Protection Agency (2023), thus a PV system reduces emissions on average by 0.2529 lbs (0.115 kg) per year.

- The average annual vehicle miles of travel (VMT) is 14,489 (U.S. Department of Transportation, 2022).
- $PM_{2.5}$ emissions from cars are 0.003 grams per mile or 0.043 kg per year given the average mileage (U.S. Environmental Protection Agency, 2024a).

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