What Does an Electric Vehicle Replace?

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Abstract

The emissions reductions from the adoption of a new transportation technology depend on the emissions from the new technology relative to those from the displaced technology. We evaluate the emissions reductions from electric vehicles (EVs) by identifying which vehicles would have been purchased had EVs not been available. We do so by estimating a random coefficients discrete choice model of new vehicle demand and simulating counterfactual sales with EVs no longer subsidized or removed from the new vehicle market. Our results suggest that vehicles that EVs replace are relatively fuel-efficient: EVs replace gasoline vehicles with an average fuel economy of 4.2 mpg above the fleet-wide average and 12 percent of them replace hybrid vehicles. Federal income tax credits resulted in a 29 percent increase in EV sales, but 70 percent of the credits were obtained by households that would have bought an EV without the credits. By simulating alternative subsidy designs, we find that a subsidy designed to provide greater incentives to low-income households would have been more cost effective and less regressive.

Keywords: electric vehicles, substitution, demand estimation, second choice data

JEL classification: L91, Q48, Q51

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1 Introduction

The diffusion of electric vehicles (EVs), coupled with cleaner electricity generation, offers a promising pathway to reduce air pollution from on-road vehicles and to strengthen energy security. In contrast to conventional gasoline vehicles with internal combustion engines, EVs use electricity stored in rechargeable batteries to power the motor. When operated in all-electric mode, EVs consume no gasoline and produce zero tailpipe emissions. But the stored electricity is generated from other sources such as power plants, which produce air pollution. Therefore, the environmental impacts of EVs depend on two critical factors. First, the emissions created from operating EVs depend on the fuel source of electricity generation. Second, the emissions diverted from EVs depend on the difference in emissions intensity between EVs and the vehicles that EVs replace. While prior literature has focused on the first factor (Archsmith et al., 2015; Holland et al., 2016), few analyses explore the second factor. We fill this gap by examining what EV buyers would have purchased had EVs been unavailable. This counterfactual serves as the proper baseline to evaluate the emissions impacts of EV diffusion.

Since the introduction of the first mass-market models into the United States in late 2010, EVs sales have grown rapidly, as shown in Table 1. To encourage adoption, the federal government provides a federal income tax credit to new EV buyers based on each vehicle's battery capacity and the gross vehicle weight rating, with the amount ranging from \$2,500 to \$7,500. Several states have established additional state-level incentives to further promote EV adoption, including tax exemptions and rebates for EVs and non-monetary incentives such as high-occupancy vehicle (HOV) lane access, toll reduction, and free parking.[1]

A potential concern associated with subsidy policies is that they may create "non-additional" emissions reductions: some EV buyers would have purchased EVs even if there was no subsidy.[2] Since early adopters may place a higher value for new technology and the environment, it is likely that some buyers have received a windfall gain without changing their behavior.

Moreover, even if the tax credits increased EV sales, the emissions impact may be small if EVs replace vehicles with low emissions ratings. The effect that EVs have on emissions depends on how clean EVs are relative to the vehicles they are replacing. Many EV buyers could have bought a low-emission gasoline vehicle had EVs or EV incentives not been available. This could arise from consumer preference heterogeneity and sorting: consumers that value fuel efficiency or

[1]In addition, federal, state, and local governments also provide funding to support charging station deployment.

[2]Additionality is a key issue for many other subsidy policies such as carbon offset programs (Bento et al., 2015) and subsidy programs for alternative-fuel vehicles (Beresteanu and Li, 2011; Huse, 2014).

environmentally friendly vehicles buy vehicles that are fuel-efficient or deemed environmentally friendly, such as the Toyota Prius or the Toyota Prius Plug-In. For these buyers, opting to buy the EV yields small or even negative emissions benefits.

To understand these issues, we use a stylized model to derive a simple expression relating vehicle substitution patterns -represented by cross-price elasticities of demand- to emissions changes. Our model shows that the greater the substitution a non-EV has with an EV, the greater the impact the vehicle's emissions have on the emissions effect of the EV. We then estimate a random coefficient discrete choice model of vehicle demand by leveraging a rich household survey of US new vehicle buyers and market-level sales data from 2010 to 2014. The estimation takes advantage of the second-choice information from household survey data, which greatly improves the precision of the random coefficient estimates and the resulting substitution patterns. With the model, we simulate counterfactual market outcomes by removing the EVs from the market to examine how consumers substitute between EVs and non-EVs. We then conduct other counterfactual exercises to examine the cost-effectiveness of the income tax credits policy in terms of reducing on-road emissions and compare it with alternative policy designs.

Our approach builds on the methodology used by Holland et al. (2016) to estimate EV replacement vehicles. Their approach assigns a replacement vehicle based on stated preference second choice survey data.[3] Instead of using survey data solely to assign a substitute model for each EV, we estimate a vehicle demand model incorporating both aggregate sales data and second choice survey data. The estimated own- and cross-price elasticities can directly reflect the substitution patterns between EVs and vehicles of other fuel types. The recovered consumer preference parameters allow us to run simulations to quantify the difference in emissions between the observed EV sales and the simulated replaced vehicles, as well as the impact of the subsidy programs on increasing EV sales. Our structural approach also allows us to compute how much EV subsidies lead to additional EV purchases, which allows us to evaluate the cost-effectiveness of the subsidies.

With our estimated demand model, we run counterfactual simulations, which reveal three

[3] Holland et al. (2016) create a composite substitute gasoline vehicle for each EV by taking the weighted average of emissions of the top gasoline substitute vehicles reported in the survey. But they do not have substitute choice data for certain EV models including the Honda Fit EV, Fiat 500 EV, and BYD e6. In addition, the approach in Holland et al. (2016) assumes that sales of a specific EV model replace the same gasoline vehicle, which might be strong. For example, because of heterogeneous consumer preferences, some Nissan LEAFs replace a Toyota Prius, while other Nissan LEAFs might replace a Ford Fusion. We define theoretically the emissions of a composite vehicle that accurately represent the emissions of all vehicles that replace an EV. This definition is a weighted average of the emissions of all vehicles that are substitutes for an EV, where the weights are proportional to each vehicle's cross-price elasticity of demand with respect to the EV's effective price.

key findings. First, electric vehicles appear to be replacing relatively fuel- efficient vehicles, as households that generally prefer EVs also prefer conventional gasoline vehicles with better fuel economy. Second, the availability of and support for EVs has not led to a significant reduction in market share for hybrid vehicles. Hybrids had been supported by the federal government in the 2000s and have seen a decline in market share since 2014, a time when EVs had started to gain significant market share. But our results suggest that EVs have had a limited impact on hybrid sales. Instead, the elimination of the federal subsidy for hybrids has caused a significant reduction in hybrid sales. Third, the cost-effectiveness of the subsidy program is limited by the fact that about 70 percent of consumers would have purchased EVs without the subsidy. We find that this result is sensitive to the price elasticity of demand, where more elastic demand implies a greater number of additional EV purchases. By comparing the current uniform subsidy with an alternative policy design that removes the subsidy for high-income households and provides additional subsidies to low-income households, our analysis shows that better targeting could potentially increase the cost-effectiveness of the subsidy programs in terms of EV demand and environmental benefits. Our simulation results contribute to the literature on the diffusion of low-emission technologies and the cost-effectiveness of subsidy programs promoting these technologies (Allcott et al., 2015; Boomhower and Davis, 2014; Langer and Lemoine, 2018; Sallee, 2011).[4]

Our study adds to the literature on the demand for electric vehicles and the EV market. Li et al. (2017) employ data on EV sales and charging stations at the city level to quantify the interplay between the availability of charging infrastructure and the installed base of EVs. Our structural approach allows us to address several key issues surrounding EV demand that reduced-form methods are unable to quantify, including the identification of vehicles that are being replaced by EVs and the welfare effects of EV policies. Springel (2016) estimates a structural model of consumer vehicle choice and charging station entry in the Norwegian EV market and compares the effectiveness of direct purchasing price subsidies with charging station subsidies. Li (2016) examines the issues of compatibility in charging technology and finds that mandating compatibility in charging standards would increase the sales of EVs. Muehlegger and Rapson (2018) use the EV subsidy receipts data and vehicle transaction prices to estimate the pass-through rate of the EV incentive program in California and find that 100 percent of the subsidies were passed through to consumers and that a decrease of 10 percent in EV prices increases EV demand by 65 percent. In contrast to these papers, our study focuses on identifying the vehicles that EVs replace.

[4]See Appendix A for a detailed review of this literature.

We organize the rest of the paper as follows. Section 2 briefly describes the industry and policy background of the study and the data. In Section 3, we develop a simple analytical model to show emissions impacts of vehicle substitution depend on key vehicle demand parameters to help guide our empirical analysis. Section 4 presents the empirical model and estimation strategy. Section 5 presents the estimation results of the substitution. In Section 6, we present the counterfactual simulations to evaluate the environmental benefits of the introduction of EVs and the impact of the EV subsidy. We also conduct simulations to examine the impact of EVs on hybrid vehicle sales and whether an income-dependent subsidy design could improve the cost-effectiveness of the subsidy. Section 7 concludes.

2 Industry and Policy Background and Data

In this section, we first present industry background focusing on the recent development of the US EV market and discuss current government policies. We then present the data used in the empirical analysis.

2.1 Industry Background

There are currently two types of EVs for sale in the United States: battery electric vehicles (BEVs) which run exclusively on high-capacity batteries (e.g., Nissan LEAF), and plug-in hybrid vehicles (PHEVs) which use batteries to power an electric motor and use another fuel (gasoline) to power a combustion engine (e.g., Chevrolet Volt). The deployment of both types of EVs currently faces significant financial barriers: EVs are more expensive than their conventional gasoline vehicle counterparts. The manufacturer's suggested retail price (MSRP) for the 2014 Honda Accord Hybrid is $29,945, while the 2014 Honda Accord Plug-In Hybrid is listed at $40,570, which is over a $10,000 difference. A key reason behind the cost differential is the cost of the battery. Battery market analysts predict that as battery technology improves, the cost should come down.

Governments have recently provided generous monetary and non-monetary incentives for EVs.[5] The US federal government provides income tax credits for new qualified EVs in the range of $2,500 and $7,500 based on each vehicle's battery capacity and the gross vehicle weight rating. Several states add state-level incentives to further promote EV adoption. For example,

[5] Several cities in China such as Beijing implement a license restriction policy for the registration of new vehicles and some PEV models are exempt from this restriction.

through the California Clean Vehicle Rebate Project (CVRP), California residents can receive a rebate of $ 2,500 for purchasing or leasing a BEV and $1,500 for a PHEV, and the rebate amount increases to $4,500 and $3,500, respectively, for lower-income consumers.

There are at least two challenges that could undermine the effectiveness of the subsidy policy. First, the uniform subsidy to EV buyers may not always result in additional EV sales in the sense that many of the buyers who claim the subsidy may still purchase EVs even if there were no subsidy policy. Since early adopters of EVs are those who favor the newest technology, have the strongest environmental awareness, and usually have higher income, it is more likely that the effect of a uniform subsidy policy, such as the current federal EV income tax credit, on boosting additional EV sales is limited.[6]

The second challenge has to do with the type of vehicles that are replaced by electric vehicles. A potential efficiency loss could arise if the subsidy does not induce people to switch from a gas guzzler to an EV, but from another fuel-efficient gasoline vehicle, or another hybrid vehicle to an EV, making little net gain of environmental benefits. Holland et al. (2016) evaluate the heterogenous environmental benefits of EVs by comparing the externalities of EVs with their gasoline counterparts. However, the relative environmental benefits would be smaller if a higher fuel-efficient vehicle such as a hybrid vehicle is compared. At the national average fuel mix, BEVs and PHEVs do not have an advantage over hybrid vehicles in emissions reduction, and PHEVs even generate more emissions than hybrid vehicles (Appendix Table D.1). With the expiration of the tax credits for hybrid vehicles, the income tax credits for EVs are likely to encourage consumers who would otherwise purchase hybrid vehicles to purchase EVs. Table 1 shows that as the market share of EVs increases in most recent years, the market share of hybrids starts to decline. Chandra et al. (2010) find that the rebate programs in Canada primarily subsidize people who would have bought hybrid vehicles or fuel-efficient cars in any case and may not be the most effective way to encourage people to switch away from fuel-inefficient vehicles like large SUVs or luxury sport passenger cars, at least in the short or medium run.

One of the justifications for EV subsidies is to reduce the emissions from the transportation sector by replacing fuel-inefficient vehicles with EVs. When life-cycle emissions are accounted for, however, substantial heterogeneity in environmental benefits could exist. For example,

[6] The CVRP used to offer incentives of $1,500 for PHEVs and $2,500 for BEVs, but the majority of the rebates went to high-income households. To direct the rebates toward households that value the rebates most, CVRP has been redesigned such that lower-income households will be able to claim a larger rebate. Households with income less than 300 percent of the federal poverty level will be able to get $3,000 for PHEVs and $4,000 for BEVs, and households with gross annual income above certain thresholds -$250,000 for single filers, $340,000 for head-of-household filers, and $500,000 for joint filers- are no longer eligible for the rebates.

EVs may not have an advantage over conventional vehicles in locations where the electricity is generated through fossil fuels. Thus, even if the EV subsidy results in additional EV purchases, the reduction of overall emissions would be limited. By incorporating spatial heterogeneity of damages and pollution export across jurisdictions, Holland et al. (2016) find considerable heterogeneity in environmental benefits of EV adoption depending on the location and argue for regionally differentiated EV policy. They find that the environmental benefits of EVs are the largest in California because of large damages from gasoline vehicles and a relatively clean electric grid, but the benefits are negative in places such as North Dakota where the conditions are reversed.

2.2 Data

We use three data sets to estimate the model of vehicle demand. The primary data source is household-level survey data from the US New Vehicle Customer Study by MaritzCX Research. It is a monthly survey of households that purchased or leased new vehicles. The data provide detailed information of demographic characteristics of households that purchased each vehicle, and the alternative vehicles they considered while making the purchase decisions. We use survey data for five model-years: model year (MY) 2010 through MY 2014, where each model year is defined as September of the previous calendar year to August of the current calendar year. (For example, MY 2011 is defined as September 2010-August 2011.) For computational purposes, we draw a sample of 11,628 transactions from the data after removing observations with missing observed consumer attributes or information on the purchased and seriously considered models, and end up having 1,509, 1,860, 2,287, 2,899, and 3,073 transactions for MY 2010-MY 2014, respectively. As the market share of EVs is tiny, so that would include enough EV observations to have sufficient variation in consumer demographic attributes for EV buyers to identify the preference for EVs among different demographics, we use non-random sampling by including all EV observations from the survey sample and randomly drawing observations for the other fuel types. To adjust for non-random sampling, we then follow Manski and Lerman (1977) to include a weighted exogenous sample maximum likelihood by re-weighting each observation in the likelihood. The weight is defined by the actual market share in the population divided by the within-sample market share.

Table 2 summarizes the demographic information for the households that made those purchase transactions. The average household income for the survey respondents in the sample is $140,448, which is higher than the average household income of $117,795 for married couples in the United

States[7]. This feature of the data is caused by oversampling consumers who purchased EVs and hybrid vehicles. The average household size is 2.66 people, and 63.9 percent of the heads of household have earned a college degree. Of the respondents, 66.1 percent of the respondents are from an urban or suburban area, with an average commuting of 25.6 minutes and average gasoline price of \$3.48 during the survey time. About 50 percent of the sampled households selected a light truck, and the average price of the vehicles that the sampled households purchased is \$33,451. The average fuel economy of the purchased vehicles is 34.8 mpg.[8] Appendix Table D.2 provides further descriptive statistics for new vehicle buyers by fuel type. EV buyers have a much higher income and a larger percentage of them graduated with a college degree.

The household survey data also include alternative vehicle choices that consumers considered while purchasing vehicles, providing a valuable source for identifying unobserved preference heterogeneity. Table 3 summarizes the top alternative vehicle choices reported by survey respondents for EV models. The data reflect that EV buyers have a strong preference for alternative fuel technologies, since most of them still consider PHEVs or hybrid vehicles as their second choices. This strong correlation of the fuel economy between the purchased vehicle and the alternative choices greatly facilitates estimating the random coefficients for vehicle fuel economy. For luxury EV models, such as Tesla Model S, customers might also consider luxury gasoline models such as Audi A7 as their alternative choices. The proximity in price, size, and some other observed vehicle attributes would help in identifying consumer heterogenous preference for those attributes.

Figure 1 summarizes consumers' second choices by fuel type based on the survey data and reflects the heterogeneous preference of fuel type among different groups of consumers. Among gasoline buyers, 96.9 percent would consider another gasoline vehicle as a second choice, 2.9% percent would consider a hybrid vehicle model as an alternative, and only about 0.2 percent would consider either BEVs or PHEVs as substitutes. Gasoline vehicle buyers, who are the majority of new vehicle purchasers, are generally less interested in the EV technology. Hybrid vehicle buyers demonstrate a stronger preference of fuel economy, and 39.7 percent of them would consider another hybrid vehicle as an alternative choice. However, only 3 percent would consider EVs as second choices. Those consumers who purchase hybrid vehicles enjoy vehicles that save fuel cost but do not favor the plug-in feature of EVs. Both PHEV and BEV buyers show a strong

[7]Data source: IRS Statistics of Income, 2014.

[8]This average is significantly higher than the average fuel economy of all purchased vehicles during the sample period because of the oversampling of EV and hybrid buyers.

interest into EVs: many of them are considering another EV as their second choices. However, 34.5 percent of PHEV buyers consider a hybrid vehicle as an alternative, and only 16.5 percent consider a BEV model. PHEV buyers are more willing to adopt the EV technology but are less interested in all-electric vehicles, probably because of the limited range of BEVs. BEV buyers are most into the EV technology, and 41.3 percent of them pick another BEV model as their second choice, 25.3 percent consider PHEVs, and only 18.6 percent consider another gasoline vehicle as substitute. BEV adopters are those who care most about the feature of electrification and those who are most into the newest technologies. The general pattern of this figure reveals the strong correlation between alternative choices and the purchased vehicles and reflects the critical role that the substitution pattern plays in reflecting the heterogenous preference of consumers.

We merge vehicle characteristics data from Wards Automotive, which provide detailed attributes of each vehicle model in each model year, including horsepower, size, curb weight, wheelbase, and fuel economy.[9] The data set is further complemented by aggregate vehicle sales data, which provide market-level information on vehicle demand, obtained from registration data compiled by IHS Automotive. The IHS data record the quarterly number of registrations for each vehicle model, broken down by fuel type, which are aggregated to model-year level to construct the market share for each vehicle model in each model year. All the above data sets are matched at the make-model-fuel type level, for example, Ford-Focus-gasoline, and the vehicle attributes are assigned using the base model. The total number of vehicle models that are defined in the model-year choice sets are 424, 404, 418, 441, and 459 for MY 2010- MY 2014, respectively. Table 2 summarizes the basic attributes of those vehicle choices and the composition of the choice sets by fuel type.

We assign average vehicle prices based on respondent-reported price information in the MaritzCX survey data. Respondents are asked to report the sales or lease prices of their vehicles, within a few months after purchase. These values reflect the price that households paid on average for each vehicle and may be different from the traditionally used MSRP because of negotiations or temporary promotions. These prices exclude any credits received from trade-ins and include sales taxes. We compute market by model by fuel type prices as the unweighted average transaction price for all purchases and leases in the raw survey data. We do not adjust these prices for tax credits or rebates because we do not observe whether households claimed these incentives. Since many of the household observations lease plug-in electric or fully electric vehicles, credits

[9]The Wards Automotive data have a fine level of vehicle identification detail. We merge base model year by make, model and fuel type to the MaritzCX survey data, where the base model is defined as the trim with the lowest MSRP among all trims by make, model, and fuel type identification within the same model year.

or rebates for these vehicles go to the leasing company, which then likely passes through the incentive as a lower purchase price.[10] We collect data of monthly average gasoline prices by region from the Energy Information Administration (EIA).[11] We convert all prices, including average transaction prices and fuel costs, to real 2014$ using the Bureau of Labor Statistics (BLS) Consumer Price Index.

We obtain detailed information on locations and open dates of all charging stations from the Department of Energy's Alternative Fuels Data Center (AFDC). By matching the zip code of each charging station with the zip codes reported in the survey data, we assign the total number of charging stations available in the city to each observed survey respondent.

3 Theory of Substitution

To motivate our empirical analysis, we lay out a stylized model of vehicle substitution to illustrate how substitution between vehicles from a policy or non-policy change affects emissions. Consider a new vehicle market where there are J unique models for sale, where each model is indexed by j. Model j has lifetime emissions equal to e_j and has aggregate demand $q_j = q_j(p_1, p_2, ..., p_J)$, where p_j represents the sales price net of subsidies for vehicle j. Total lifetime emissions of vehicles sold are

$$E = \sum_{j=1}^{J} e_j q_j(p_1, p_2, ..., p_J). \tag{1}$$

Without loss of generality, we assume that $j = 1$ is an EV and $j = 2, 3., ..., J$ are gasoline or hybrid models. We assume that the EV's price is subsidized by an amount s, so that the EV's price is $p_1 = p_1^0 - s$, where p_1^0 is the EV's price without a subsidy. Differentiating total lifetime emissions with respect to the EV subsidy yields

$$\frac{dE}{ds} = -e_1 \frac{dq_1}{dp_1} - \sum_{j=2}^{J} e_j \frac{dq_j}{dp_1}. \tag{2}$$

[10]Our treatment of the purchase price for plug-ins and electric vehicles adds measurement error to the price variable for households that are able to claim the monetary incentives. We address this concern with how we estimate the price sensitivity parameters. We estimate price elasticities based on all the models in the choice sets, where a large majority of models are conventional gasoline vehicles that do not have tax credits or rebates. Since plug-ins and electric vehicles comprise only a tiny share of the choice sets, mismeasuring their prices will have a minimal effect on our estimated price elasticities. Furthermore, we instrument for price in the demand estimation, which further reduces concerns about price measurement error.

[11]EIA reports monthly gasoline prices by region, defined by the Petroleum Administration for Defense Districts (PADDs). We assign gasoline prices to each sampled household based on its PADD region and the month of vehicle purchase.

Normalizing the change in the subsidy by the EV's price (so that $\frac{dE}{ds'} = \frac{dE}{ds}p_1$) and defining the own-price and cross-price elasticity of demand with respect to the EV price as $\epsilon_1 = \frac{dq_1}{dp_1}\frac{p_1}{q_1}$ and $\epsilon_j = \frac{dq_j}{dp_1}\frac{p_1}{q_j}$, respectively, we can express equation (2) as

$$\frac{dE}{ds'} = -e_1 q_1 \epsilon_1 - \sum_{j=2}^{J} e_j q_j \epsilon_j. \tag{3}$$

Equation (3) reveals that the effect of the subsidy on lifetime emissions is proportional to the own-price elasticity of demand for the EV and the cross-price elasticity of demands for all other vehicles. The cross-price elasticities ϵ_j represent the substitution pattern between the EV and the non-EV models. The larger the value of this derivative, the greater the substitution and the more of an impact the non-EV model has on the emissions impact of the subsidy. Consider the simple example where $\epsilon_j = 0$ for $j = 3, 4, ..., J$. Then equation (3) becomes

$$\frac{dE}{ds'} = -e_1 q_1 \epsilon_1 - e_2 q_2 \epsilon_2. \tag{4}$$

If the demand responses offset one another so that there is no change in total new vehicle sales, then the change in emissions depends on the relative difference between the lifetime emissions of the EV and the non-EV $j = 2$:

$$\frac{dE}{ds'} = (e_2 - e_1) q_1 \epsilon_1. \tag{5}$$

This simplified equation is conceptually the same approach taken by prior studies to quantify the emissions impacts of EVs.

3.1 Defining a Composite Substitute

This approach above is an accurate representation of the full impact if (1) the only substitution that takes place is between the EV and a single vehicle, (2) the single vehicle is the correct substitute, or (3) the $j = 2$ model's emissions accurately reflect the emissions of all the vehicles that are substitutes for the EV. In most cases, an EV will have more than one vehicle as a substitute. Here we derive a simple formula defining the emissions of a composite vehicle that satisfies the third condition when more than one vehicle substitute for the EV. We begin by assuming that a change in the subsidy does not change total vehicle sales: $-\frac{dq_1}{dp_1} = \sum_{j=2}^{J} \frac{dq_j}{dp_1}$. Denote the emissions of the composite vehicle by e_c. We want to find an e_c that solves $\frac{dE}{ds'} = (e_c - e_1) q_1 \epsilon_1$.

Substituting this expression into equation (3) yields

$$\frac{dE}{ds'} = -e_1 q_1 \epsilon_1 - \sum_{j=2}^{J} e_j q_j \epsilon_j = (e_c - e_1) q_1 \epsilon_1. \tag{6}$$

Making cancellations and isolating e_c yields

$$e_c = -\sum_{j=2}^{J} e_j \frac{q_j \epsilon_j}{q_1 \epsilon_1}. \tag{7}$$

Emissions for the composite vehicle equal to the product of emissions and the ratio of the cross-price elasticity of demand are scaled by sales of vehicle j, and the own-price elasticity of demand is scaled by sales of the EV. In our empirical demand model, we are able to identify composite vehicle emissions based on estimated own-price and cross-price demand elasticities. Equation (7) can be further simplified to

$$e_c = -\sum_{j=2}^{J} e_j \frac{dq_j}{dq_1}. \tag{8}$$

This general expression can be used to accurately evaluate hypothetical settings where electric vehicles are added or removed from the market. This expression suggests that evaluating the impact of EV subsidy on reducing emissions depends on the estimation of the substitution pattern between EVs and all the other vehicle models in the market.

3.2 Additionality

In this section, we derive an equation that shows how the non-additionality of a subsidy is affected by demand parameters. We define non-additionality as the proportion of EVs that would have been bought without the subsidy to the total EV sales with the subsidy. A higher ratio implies more non-additional purchases and more subsidy dollars going to households that would have bought an EV without the subsidy. The proportion is equal to

$$N = \frac{q_1(p_1^0)}{q_1(p_1)}. \tag{9}$$

Differentiating N with respect to s' and substituting the price elasticity of demand for the

EV yields

$$\frac{dN}{ds'} = \frac{q_1(p_1^0)}{q_1(p_1)}\epsilon_1 \tag{10}$$

Evaluating equation (10) at the price where the subsidy is equal to zero ($p_1^0 = p_1$) yields

$$\frac{dN}{ds'} = \epsilon_1 \tag{11}$$

This equation shows that non-additional purchases are proportional to the EV own-price elasticity of demand. More elastic demand (more negative ϵ_1) implies relatively fewer non-additional purchases and a greater number of purchases that are created by the subsidy. In contrast to the results we derived for the emissions impacts of the subsidy, the additionality of the subsidy depends on the own-price elasticity of demand only.

4 Empirical Model and Estimation

In this section, we discuss our empirical model and estimation strategy. We estimate vehicle demand preference parameters using a random coefficient discrete choice model in the spirit of Berry et al. (1995, 2004), Petrin (2002), and Train and Winston (2007). Our model most closely follows the structure of Train and Winston (2007), as we exploit household demographics and second choice data to identify the model parameters.

4.1 Vehicle Demand

The household survey data are not representative of the entire population since they include only buyers of new vehicles. Therefore, we model new vehicle preferences conditional on the decision of buying a new vehicle. Our approach will not be able to capture the substitution between the new vehicle models and the outside option: buying a used car, continuing using the household's old vehicle, or relying on public transportation. Instead, our model represents how consumers choose among new vehicles and how changes in new vehicle attributes or the selection of new vehicles available for purchase affects new vehicle sales. Two factors suggest that our model could reasonably capture the substitution that consumers make when deciding between an EV and another vehicle option. First, EVs represent a new segment of the light-duty vehicle market, where few used vehicle options represent plausible substitutes. Second, EVs are generally expensive options relative to most new or used vehicles. If consumers substitute among similarly priced vehicles, the EV substitutes are likely to be expensive new vehicles.

We define household i's utility from purchasing vehicle model j as:

$$u_{ij} = \underbrace{\sum_{k=1}^{K} x_{jk}\bar{\beta}_k - \alpha_1 lnp_j + \xi_j}_{\delta_j} + \underbrace{\alpha_2 \frac{lnp_j}{Y_i} + \sum_{kr} x_{jk} z_{ir} \beta^o_{kr} + \sum_{k} x_{jk} v_{ik} \beta^u_k}_{\mu_{ij}} + \varepsilon_{ij}, \tag{12}$$

where δ_j is the mean utility of vehicle model j which is constant across consumers in the same market. x_{jk} stands for the k_{th} vehicle attribute for model j. We include horsepower, weight, gallons per mile, and some vehicle segment dummy variables as the observed vehicle attributes. Price p_j is the average transaction price observed from the survey data, which is constant for the same model by fuel type for all households buying a vehicle in the same market.

The second component, μ_{ij}, captures heterogeneous utility driven by both observed and unobserved consumer characteristics. Y_i is household i's income in the corresponding year, and we assume consumer price sensitivity to be inversely related to income. One would expect α_2 to be negative, as higher-income households would be less sensitive to a price increase because of the diminishing marginal utility of money. z_{ir} denotes consumer i's other demographic variables- including family size, education level, whether living in an urban area, the average gasoline price, and the number of charging stations in the area- which are interacted with certain vehicle attributes to capture variation in consumer preference due to observed heterogeneity.

The unobserved consumer taste v_{ik} is assumed to have a standard normal distribution. The coefficient β^u_k can be interpreted as the standard deviation in the unobserved preference for the vehicle attribute k conditional on the consumer's observed attributes. Let $\theta = \{\beta^o_{kr}, \beta^u_k\}$, denoting the "nonlinear" parameters, and it is understood that the vector $\delta = \{\delta_1, ..., \delta_j\}$ is estimated conditional on a given θ_1. The last component, ε_{ij}, is the idiosyncratic preference of household i for vehicle model j, and it is assumed to have an i.i.d. type one extreme value distribution.

A useful feature of the MaritzCX data is that they include vehicle models that consumers seriously considered other than the purchased model. This allows for a ranking of both the first and second vehicle choices.[12] We exploit the second choice data as a source of variation to identify unobserved heterogeneous preferences conditional on observed household characteristics.

[12] We use survey response data from multiple questions to assign a second choice. The first question is "When shopping for your new vehicle, did you consider any other cars or trucks?" Respondents answering yes to this question were then asked to provide make, model, model year, fuel type, and other vehicle information for the model that they most seriously considered but did not purchase.

For example, if the second choices of an EV model include only EV models, this would suggest that EV buyers have a very strong preference for this particular fuel type. If, on the other hand, the second choices include many non-EV counterparts of the EV models within the same make, this would suggest a less strong preference for EV type, but preference for the same make is an important factor. Similarly, the comparison between the chosen model and the second choice in other dimensions of vehicle attributes such as vehicle size or fuel economy can also inform us about consumer preference heterogeneity for these vehicle attributes.

To use the second choice information, we form the likelihood function based on the joint probability of household i choosing j as the first choice and considering h as the second choice:

$$P_{ijh} = \int \frac{exp[\delta_j(\theta) + \mu_{ij}(\theta)]}{1 + \sum\limits_{g} exp[\delta_g(\theta) + \mu_{ig}(\theta)]} \cdot \frac{exp[\delta_h(\theta) + \mu_{ih}(\theta)]}{\sum\limits_{g \neq j} exp[\delta_g(\theta) + \mu_{ig}(\theta)]} f(v)dv. \tag{13}$$

The probability of observing household i choosing model j is conditional on the household's v_i vector, and the probability is calculated by integrating over the distribution of v. Instead of constructing moments exploiting the exogeneity assumption that unobserved product attributes are uncorrelated with observed attributes, we use the maximum likelihood estimation (MLE) method with a nested contraction mapping to estimate θ and δ (Train and Winston, 2007; Langer, 2012; Goolsbee and Petrin, 2004; Whitefoot et al., 2013; Murry and Zhou, 2017). Let $lnR_i = lnP_{ijh}$, denoting the individual log-likelihood of household i choosing the observed purchased model j and considering the observed alternative choice h. The log-likelihood function of the entire sample for a single market is therefore:

$$lnL = \sum_{i=1}^{N} lnR_i. \tag{14}$$

The nonlinear parameters θ are estimated by maximizing the likelihood function.[13] Given the larger number of mean utilities δ, we follow the two-step procedure in Berry et al. (1995), which shows that under certain regularity conditions, for each θ, there exists a unique δ that matches the predicted market shares with observed ones. The market demand is the sum of individual consumers' demand, and the predicted market share is calculated by calculating P_{ij} with parameters $\theta = \{\beta^o_{kr}, \beta^u_k\}$ and $\delta = \delta_1, ..., \delta_j$ and averaging over the N consumers in the

[13]In Appendix B, we lay out more details of the likelihood function and the gradient for estimation.

survey sample. Following this strategy, we back out the mean utility vector δ for any given θ using the contraction mapping technique:

$$\delta_j^t(\theta, S) = \delta_j^{t-1}(\theta, S) + ln(S_j) - ln(\hat{S}_j(\theta, \delta^{t-1}(\theta, S))). \tag{15}$$

Once θ and δ are estimated using the MLE method, we then recover the parameters in mean utility:

$$\delta_j = -\alpha_1 lnp_j + \sum_{k=1}^{K} x_{jk}\bar{\beta}_k + \xi_j,$$

where ξ_j denotes the unobserved vehicle attributes of model j. To control for the correlation of price with the unobserved product attributes, following Train and Winston (2007), we use BLP-style instruments that measure the sum of distance and squared distance in attribute space between own product and other products in the same firm and from other firms.

4.2 Identification

Consumer utility is composed of three parts: mean utility, observed heterogeneity, and unobserved heterogeneity. The linear parameters in the mean utility $\bar{\beta}$ and α_1 are identified through the variation in market shares corresponding to variation in price and other observed vehicle attributes. Because of the potential correlation between price and the unobserved vehicle attributes ξ_j, functions of attributes of other competing products that capture the intensity of competition are used as instruments to provide exogenous variation in prices. The maintained exogeneity assumption is that unobserved product attributes are not correlated with observed product attributes.

The nonlinear parameters β_{kr}^o and α_2 in the observed individual heterogeneity component are identified from the correlation between household demographics and vehicle attributes. For example, if we observe that households with a high level of education disproportionately purchased more electric vehicles, we would expect a positive coefficient for the interaction between household education level and the EV dummy. If higher-income groups tend to be less sensitive to vehicle prices and disproportionately buy more expensive vehicle models, we would expect a negative sign for α_2, which captures the impact of income on consumers' price sensitivity.

The unobserved consumer heterogeneity parameters β_k^u are primarily identified by the correlation between first and second choice vehicle attributes. For example, if consumers who purchase high fuel-economy vehicles tend to state that they would have purchased a high fuel-economy vehicle if their first choice was not available, we would expect a large coefficient for the parameter associated with fuel costs (i.e., the standard deviation of the preference for the fuel cost). Berry et al. (2004) note that having micro-level second-choice data helps the estimation of random coefficients when they have observations for only one market year, and Train and Winston (2007) also mention that including alternative choice data significantly improves the precision of the random coefficient estimates. In contrast to these studies, however, the unobserved heterogeneity parameters in our model are also identified by changes in choice sets over time. We leverage the feature of our sample, which includes periods where no electric vehicles were available (2010 and 2011), followed by periods of availability (2012-2014) and an expansion of available options (see Table 1). The variation in the choice sets over time provides an additional source of identification for the random coefficients.

5 Estimation Results

We first report parameter estimates for the random-coefficient model and then use the estimates to calculate price elasticities to show implied substitution patterns.

5.1 Parameter Estimates

Table 4 reports the estimation results of the demand model. The mean utility δ represents the average preference consumers have for each vehicle model and is estimated by equating the predicted market shares to the observed market shares. The mean preference coefficients for price and each observed vehicle attribute are recovered from instrumental variables (IV) estimation with the instruments accounting for the endogeneity of price. Both ordinary least squares (0LS) and IV results are reported in panel (a) of Table 4 and reflect the preferences for vehicle attributes that are generally expected. Consumers have a negative preference for price and the price coefficient in the IV specification is more negative, suggesting OLS underestimates the price sensitivity. Consumers have a positive preference for acceleration, measured by the ratio of horsepower to weight, and also prefer heavier vehicles. The coefficient for gallons/mile is positive but statistically insignificant. Consumers in general dislike AFVs and EVs, probably because of range anxiety concerns. Conditional on other vehicle attributes, consumers do not have a significantly different preference for pickup trucks relative to passenger cars. The positive signs for MY 2011-MY 2014 dummies suggest that consumers prefer vehicles in later model years relative to MY 2010, controlling for other vehicle attributes. This is consistent with broad sales patterns during this time period, when total sales had been recovering from the recession.

Turning to the consumer heterogeneity parameters, with the aid from the individual transaction data, the interaction terms of consumer demographics with vehicle attributes are estimated precisely with intuitive signs. The coefficient of log(price) divided by income captures the extent to which a consumer's price sensitivity varies with income. The negative sign of the estimate suggests that households with lower income react more negatively to a vehicle's price than households with higher income. The elasticities implied from the price preference are further discussed below. Households of a larger family size prefer larger vehicles that are heavier. Compared with households that live in suburban and rural areas, households that live in urban areas are less likely to adopt pickups, probably because of less towing utility and limited parking space, but are more interested in EVs because of both more frequent city driving needs and better refueling infrastructure provided in urban areas. The interaction of the household-specific gasoline price with gallons/mile, which measures the operating cost per mile of the vehicle, has a negative sign, suggesting that consumers have a negative preference for fuel costs. The estimation results also suggest that consumers who have more education and live in cities with more charging stations are more likely to adopt EVs.

We include four random coefficients, which represent unobserved consumer preferences for fuel economy (gallons/mile), acceleration (horsepower/weight), light trucks, and AFVs. Based on the standard normal distribution of the random taste variable v_{ik}, the coefficient β_k^u can be interpreted as the standard deviation in the unobserved preference for the vehicle attribute k. To reduce simulation noise and bias, following Train and Winston (2007), we use 150 Halton draws to approximate the distribution for the unobserved consumer taste v.[14] All four coefficients are statistically significant, indicating that consumers have heterogenous preferences for those vehicle attributes conditional on the observed consumer characteristics. Those precisely estimated random coefficient parameters help alleviate the well-known problem of independence of irrelevant alternatives experienced in traditional logit models and play a critical role in defining the substitution patterns.

To illustrate the importance of estimating the model parameters with the second-choice data, we re-estimate the first-stage parameters (the observed and unobserved interaction terms) without these data. Recall that we estimate the model parameters with five years of data where

[14] Halton draws are a type of low-discrepancy sequence. The demand results are similar when the number of Halton draws is increased to 200.

for each household observation we observe a second choice. The unobserved heterogeneity is identified from both changes in choice sets and vehicle attributes over time and the correlation between first- and second-choice vehicle attributes. Therefore, removing the second-choice data allows us to test the importance of including these data relative to exploiting panel variation that is traditionally used to identify unobserved heterogeneity (Berry et al., 1995). Our model also has household demographics interacted with vehicle characteristics, and we include these as well to isolate the impact of leveraging the second choice data. Petrin (2002) finds that including household demographic by vehicle characteristics interactions is crucial for obtaining precise estimates of the unobserved heterogeneity terms. Therefore, we keep them in the model for each set of estimates.

The first-stage parameter estimates without the second-choice data are shown in panel (b) of Table 4 under "(2) No 2nd Choice." Overall, the signs and magnitudes of the observed heterogeneity terms are consistent with the estimated parameters with the second-choice data included. These terms also maintain a high level of statistical significance, suggesting that incorporating the second-choice data is not necessary for precise estimation of observed heterogeneity. This is intuitive because the observed heterogeneity terms are identified from correlations between observed household demographics and vehicle characteristics, which are not dependent on the second-choice data.

Comparing the estimates of the standard deviations of preference parameters reveals striking differences between the two models. Without the second-choice data, all but one of the standard deviations becomes insignificant, and the magnitudes are much different from the parameters estimated with the second-choice data. This reveals that we are unable to obtain precise measures of unobserved heterogeneity without including the second-choice data, even with panel variation from five years of rapidly changing vehicle attributes and choice sets. To the best of our knowledge, this is the first illustration of the value of exploiting repeated choice data to identify unobserved heterogeneity parameters relative to the value of using panel variation to identify these parameters. The lesson from this comparison is clear: the second-choice data greatly improve the statistical precision of the unobserved heterogeneity parameters relative to a model estimated using the standard panel variation approach.

5.2 Elasticities and Substitution Patterns

The demand system implies sensible price elasticities. All of the implied own-price elasticities are greater than one, ranging from -3.97 to -2.37 with the average being -2.67 and the standard deviation being 0.21. The sales-weighted average elasticity among all 2,146 products in five model years is -2.75. The magnitude of the own-price elasticities is close to the one obtained by Durrmeyer and Samano (2017) and slightly smaller than those obtained by Berry et al. (1995), Petrin (2002), Beresteanu and Li (2011), and Li (2012), since our demand estimation is based on consumers who purchase new vehicles (excluding outside option). Our estimate is close to that of Train and Winston (2007), who also estimate the demand focusing on new vehicle buyers and find an average own-price elasticity of -2.32. Appendix Figure D.1 plots the own-price elasticities against price and demonstrates that more expensive models tend to have less elastic demand.

Table 5 shows the cross-price elasticities for a selected group of models. One obvious pattern is that the demand for less expensive models tends to be more price sensitive. More expensive models such as Tesla Model S have lower own-price elasticities in magnitude. Compared with other conventional gasoline vehicles, electric vehicles such as the Nissan LEAF and the Chevrolet Volt have larger cross-price elasticities with hybrid vehicles such as Toyota Prius. Battery electric vehicles such as the Nissan LEAF and the Tesla Model S do not have large cross-price elasticities with plug-in hybrid vehicles such as the Chevrolet Volt. BEVs can only run on electricity and many of them have limited range. PHEVs, on the other hand, rely on gasoline mode to boost the range, since the electric range is only around 30-40 miles. These two different kinds of plug-in vehicles are likely to attract consumers with different driving needs as consumers with more frequent long-distance travels are more likely to adopt PHEVs. Therefore, it makes sense that no strong substitution exists between PHEVs and BEVs, especially when there were only a few models during the early deployment stage. Ford F-150, the only pickup truck in the selected sample, does not have much substitution with the other small and mid-size sedans, and it has almost zero substitution with EV models. The substitution pattern indicates that consumers who purchase EVs generally favor mid-size sedans that are relatively fuel-efficient rather than large vehicles.

Table 6 summarizes the elasticity estimates by fuel type. Across different fuel types, the sale-weighted own-price elasticities are similar since all fuel types include vehicle models with a large price range. Each cell in the matrix represents the average sales change of a vehicle model in that fuel type from a price change of a vehicle model of other fuel types. For example, a 10 percent increase in the price of hybrid vehicle model will increase the sales of a BEV model by 0.37 percent on average, and a 10 percent increase in the price of another BEV model will increase the sales of a BEV model by 0.13 percent. Both BEVs and PHEVs have a larger cross-price elasticity with respect to hybrid vehicle models relative to the cross-price elasticity with respect to gasoline, diesel, and flexible-fuel vehicle (FFV) models, suggesting that EV buyers prefer vehicles with better fuel economy. Because of the large selection of model choices, gasoline vehicles are a major substitute for vehicles of all fuel types. Since our data mostly cover the first few years after the introduction of EVs, the within-segment substitution for BEVs and PHEVs is relatively small, considering that we do not have enough between-segment variation to identify a strong substitution between EV models.

6 Counterfactual Analysis

In this section, we conduct simulations to examine the counterfactual vehicle fleet where we remove all EV models from the choice sets and where the EV subsidy were removed. The magnitude of the resulting sales changes of the other fuel types could suggest what types of vehicles were replaced by EVs. The estimated substitution patterns are then translated into emissions reductions to assess the environmental benefits of EVs and EV subsidies.

6.1 The Environmental Benefits of EVs

The introduction of EVs could lead consumers who would originally choose gasoline or hybrid vehicles to purchase EVs, and the substitution pattern critically determines the environmental benefits of promoting EVs. To examine the substitution pattern of EVs with other fuel types, we conduct a counterfactual exercise where all EVs are removed from the choice set. The resulting changes in sales of other fuel types will reveal what types of vehicles EVs replace. Since we do not allow consumers to choose an outside option, as the demand estimation is conditional on buying a new vehicle, consumers who purchased EVs would switch to another non-EV model. In 2014, 109,449 EVs were sold in the US vehicle market. The simulation results suggest that 78.7 percent of EVs replaced conventional gasoline vehicles, 12 percent of EVs replaced hybrid vehicles, 2.4 percent replaced diesel vehicles, and the remaining 6.9 percent replaced FFVs (Table 7). The average fuel economy of the vehicles that were replaced by EVs is 28.9 mpg. This number can be interpreted as the fuel economy level of the composite substitute of EVs, as defined in Section 3. Among gasoline vehicles replaced by EVs, 74 percent of them have fuel economy above 25 mpg. The vehicle models that were replaced by EVs most are: Honda Accord, Toyota Prius, Toyota Camry, Honda Civic, Toyota Corolla, Nissan Altima, and Chevrolet Cruze. This substitution pattern suggests that EVs mainly attracted consumers who were originally choosing mid-size and fuel-efficient gasoline or hybrid vehicles, rather than gas-guzzlers such as large SUVs or trucks.

To evaluate the environmental impact of the introduction of EVs, we evaluate the total gasoline saved and CO_2 emissions reductions from EVs by comparing the gasoline consumption of the actual vehicle fleet with the counterfactual fleet without EVs. The existence of EVs helps save lifetime gasoline consumption of 0.51 billion gallons, resulting in a CO_2 emissions reduction up to 9.94 millions pounds, assuming the lifetime VMT for all vehicle is 195,264.[15] If we do not estimate the substitution pattern but assume each EV replaces a conventional gasoline vehicle with fuel economy of 23 mpg, the total lifetime gasoline saved would become 0.65 billion gallons, with an emissions reduction of 12.8 billion pounds of CO_2. Simply assuming EVs replace a gasoline vehicle of an average mpg would overestimate the environmental benefits of EVs by 27 percent. The overestimated portion would be larger if EVs replace a greater number of fuel-efficient vehicles such as hybrid vehicles.

If EVs were removed from the market, consumers who value the EV technology will suffer from a welfare loss. We find that the removal of EVs from the choice set leads to a total consumer welfare loss of $670.3 million in 2014.[16] Panel (b) of Table 7 summaries the impact of the removal of EVs on consumer surplus by income quintile. The results reveal a greater impact on wealthier households, since they are more interested in the EV technology and thus benefit more from the introduction of EVs.

6.2 Impacts of Income Tax Credits

The federal government has adopted several policies to support the EV industry including providing federal income tax credits for EV purchases, R& D support for battery development, and funding for expanding charging infrastructure. Congressional Budget Office (CBO) estimates that the total budgetary cost for those policies will be about $7.5 billion through 2017. The tax credits for EV buyers account for about one-fourth of the budgetary cost and are likely to have the greatest impact on vehicle sales. Under the tax credits policy, EVs purchased in or after 2010 are eligible for a federal income tax credit up to $7,500. Most popular EV models on the market are eligible for the full amount. The credit will expire once 200,000 qualified EVs have been sold by each manufacturer. In 2014, the federal government spent $725.7 million on income tax credits for EV buyers. To examine the effectiveness of the income tax credit policy

[15] In reality, EVs might have a larger VMT than gasoline cars because of lower fuel cost or a lower VMT because of limited range and inconvenience of charging.

[16] The average welfare loss per household is estimated as the change in consumer surplus as shown by Small and Rosen (1981). Total welfare loss is calculated as average consumer surplus loss multiplied by the market size of new vehicles.

in terms of stimulating EV sales, we use our parameter estimates to simulate the counterfactual sales of EVs that would arise in the absence of the tax credits to EV buyers in 2014. The counterfactual sales could help us identify the percentage of "non-additional" EV sales and also evaluate the environmental benefits of the policy. The resulting sales increase in gasoline and hybrid vehicles could help us evaluate the environmental benefits of the "additional" EV sales. The short-run benefits could be small if the additional sales simply come from people who were considering buying other fuel-efficient vehicles.

The simulation results of the federal EV subsidy are summarized in Table 8. Our estimates imply that removing the federal income tax credits reduces EV sales by 28.8 percent in 2014, with BEVs experiencing a sales reduction of 32.6 percent and PHEV sales falling by 24.5 percent. The results suggest that about 70 percent of the EV buyers would still purchase EVs without income tax credits. Since the EV subsidy lowers the effective price of purchasing EVs, consumers would enjoy a welfare increase due to the subsidy, especially for those who purchase EVs. Our estimation results suggest that the EV subsidy program leads to a total increase in consumer surplus of \$165.2 million. The average increase of consumer surplus per household due to policy may not be large, since most households do not purchase EVs. Panel (b) of Table 8 summarizes the incidence of the federal EV subsidy. The distribution impacts imply that the EV subsidy program is regressive, as higher-income households benefit more from the subsidy because they are more likely to purchase EVs and thus claim the subsidy.

If there were no federal-level EV subsidy, 78.9 percent of the "additional" EV buyers would switch to gasoline vehicles with an average fuel economy of 27.2 mpg, and 11.8 percent would switch to hybrid vehicles with an average fuel economy of 45 mpg, with the remaining switching to diesel and flex-fuel vehicles. Using the miles per gallon gasoline equivalent (MPGe) introduced by the US Environmental Protection Agency (EPA) [17], we can then translate those substitution patterns to energy consumption reduction from the increased sales of EVs. By inducing consumers to switch to more fuel-efficient EVs, the income tax credit policy leads to a lifetime gasoline consumption of 0.15 billion gallons and CO_2 emissions reduction of 2.91 billion pounds, which is equivalent to reducing 1,750 gasoline vehicles of an average fuel economy of 23 mpg. If we assume each EV replaced an conventional gasoline vehicle with a fuel economy of 23 mpg, the gasoline consumption saved would become 0.19 billion gallons and the CO_2 emissions would become 3.74 billion pounds, equivalent to removing 2,250 gasoline cars from the road. Not

[17] The MPGe metric was introduced in November 2010 by EPA. The ratings are based on EPA's formula, in which 33.7 kilowatt-hour of electricity is equivalent to 1 gallon of gasoline.

taking account of the actual substitution pattern would overestimate the environmental benefits by 27 percent (Table 9).

Appendix Table D.3 summarizes the environmental benefits of EV income tax credits by evaluating the external cost savings from emissions reduction of various pollutants. In 2014, the EV subsidy results in total environmental benefits of \$73.8 million from a more fuel-efficient vehicle fleet, by taking account of the reduction of CO_2, VOC, NO_x, $PM_{2.5}$, and SO_2.

The environmental benefits and increase in consumer welfare are much lower than the total spending of \$725.7 million, since the majority of the subsidies are non-additional and the additional portion mainly induces consumers who would purchase fuel-efficient vehicles anyway to switch. The current subsidy policy offers equal tax credit amounts to all buyers of the same electric model. Alternatively, more credits could be given to lower-income households, with no tax credits given to the highest-income households. This policy design would mimic the policy reform of California's CVRP, which intends to direct the incentives toward households that are likely to value the rebates the most. The subsidy could also target first-time buyers, who may not have a good sense of vehicle fuel consumption but are more sensitive to upfront costs.

A discussion of a number of caveats regarding our environmental analysis is in order. First, the estimates of the environmental benefits are relatively crude, as they do not incorporate spatial heterogeneity of the upstream emissions from electricity generation. As Holland et al. (2016) show, great spatial heterogeneity exists regarding the environmental benefits promoting EVs, and in some locations where electricity generation relies much on fossil fuels, EVs should be taxed rather than being subsidized. The focus of our study is to demonstrate that the substitution pattern is also an important factor in determining the environmental benefits, which matters even if we focus on a specific location where the grid fuel mix is fixed. Nevertheless, different markets might reflect different substitution patterns, which leads to different environmental benefits of promoting EVs. Therefore, incorporating spatial heterogeneity and estimating location-specific substitution patterns would help us determine the location-specific environmental benefits of EVs, but it would require more detailed and representative location-specific sales and consumer survey data. However, our analysis provides empirical evidence of EV substitution at the national level and will provide guidance for the federal government to evaluate the effectiveness of federal EV subsidies. The findings of the paper would be policy-relevant since most markets worldwide subsidize EVs at the national level.

Second, when estimating the environmental benefits of replacing gasoline vehicles with EVs, we assume that VMT is fixed and is the same for both EVs and gasoline vehicles. However, consumer mileage heterogeneity plays a critical role in evaluating the effectiveness of tax and subsidy policies (Grigolon et al., 2018). In addition, when consumers switch to fuel-efficient vehicles with a lower marginal cost of driving, they might drive more, resulting in a rebound effect that undermines some environmental benefits of EVs. Nevertheless, when consumers switch to smaller and lower-performance vehicles, the marginal benefits of driving per mile could be reduced. Thus, the rebound effect could be weakened by shrinking vehicle size and the net response of miles could be zero or negative (Anderson and Sallee, 2016; West et al., 2017). Moreover, because of the limited range of EVs and the inconvenience of charging in some locations, it is less likely that consumers would increase miles traveled once adopting EVs. Assuming that EVs and gasoline vehicles have the same VMT would mostly likely provide a lower-bound estimate of the environmental benefits of EVs in the section above.

Third, our demand estimation is conditional on consumers choosing a new vehicle without considering the outside option, which includes used car markets or public transportation. Therefore, when we estimate the benefits of the EV subsidies, we exclude the possibility that the subsidy could induce households that were considering public transportation or used cars to purchases new EVs. To fully evaluate the benefits of EVs, incorporating the outside options would require us to model consumer demand of public transportation and used cars, which is beyond the scope of the paper. However, considering that EV adopters favor the newest technologies and have a disproportionately high leasing rate (44 percent, Appendix Table D.2) and most of the EV survey respondents report another new vehicle models as their alternative choices, we believe that it is reasonable to assume that they would still choose a new vehicle even when the subsidy was removed. Thus, ignoring the outside option unlikely produce large bias in our analysis.

6.3 The Effect of Electric Vehicles on Hybrid Sales

One possible concern with promoting electric vehicles is that the policy may have reduced demand for alternative clean vehicles such as hybrids. Before the introduction of electric vehicles, hybrid technology was anticipated to provide a pathway to dramatically reducing emissions from light duty vehicles. Since we have shown that hybrids are relatively close substitutes for electric vehicles, the introduction of electric vehicles has reduced hybrid market share and may explain why the market share of hybrids has not continued to grow as it did during the 2000s.

To quantify the impact of electric vehicles on hybrid sales, we conduct several counterfactual exercises. In scenario 1, we remove all the EV models from the choice sets, and then predict the counterfactual market shares of the remaining fuel types for MY 2010-MY 2014. In scenario 2, we remove the federal income tax credits for EVs, which vary across EV models, and then predict the market shares of all fuel types. In panel (a) of Figure 2, we plot the observed and simulated market shares of hybrid vehicles. The dashed lines represent out-of-sample shares that we obtained from Wards Automotive. The observed market share of hybrids grew substantially from 2000 to 2010, then eventually leveled off by 2015, around the time that EVs began to gain a non-trivial market share. As shown in the figure, the simulated market share for hybrids within our sample shows little difference from the observed hybrid market share. We conclude, therefore, that the introduction of EVs has had only a small impact on the sales of hybrids during our sample period.

The federal government provided income tax credits of up to $3,400 for hybrid vehicles purchased after December 31, 2005. All the hybrid vehicles purchased after December 31, 2010, were not eligible for this credit. The termination of federal support for hybrid vehicles could have discouraged the sales of hybrid vehicles. To investigate this impact, we conduct simulations to estimate the counterfactual sales of hybrids if the federal government had continued subsidizing hybrid vehicles.

We assume that all the hybrid vehicle models that were once subsidized by the government continue being subsidized with the original subsidy amounts. We run three counterfactual scenarios (panel (b) of Figure 2). In scenario 1, we assume the government continues subsidizing hybrid vehicles during MY 2010-MY 2014 while also maintaining its subsidy for EVs. In scenario 2, the government continues subsidizing hybrids during MY 2010-MY 2014 but does not provide any subsidy for EVs. In scenario 3, the government continues subsidizing hybrids, but EVs were removed from the market. As implied by the results, the removal of the subsidy for hybrids played a larger role in reducing the sales of hybrid vehicles, than did the competition from EVs. Beresteanu and Li (2011) find that the federal income tax credit program for hybrids contributes to 20 percent of the total sales of hybrid vehicles. This suggests that although the introduction of EVs has slightly reduced the market share of hybrids, the elimination of the income tax credit is the major factor in the decline of hybrid vehicle sales in recent years.

6.4 Alternative Subsidy Designs

As with other energy subsidy programs, the cost-effectiveness of EV incentives could be undermined if the subsidies are poorly-targeted and are mainly taken up by wealthier consumers who would buy EVs without subsidies. To further investigate the "additionality" of the current federal income tax credits for EVs and whether better targeting could improve the effectiveness of the program in terms of boosting EV demand, we conduct two policy simulations to compare the current uniform subsidy with alternative subsidy designs that incorporate an income-dependent structure.

Through CVRP program, California has been providing state-level subsidies to EV buyers since 2010. The standard rebate amounts are $2,500 for BEVs and $1,500 for PHEVs. On March 29, 2016, CVRP started to implement income eligibility requirements such that households with income levels above certain thresholds are no longer eligible for the EV rebate, while lower-income households can claim an additional rebate of $2,000 on top of the standard rate. The income caps for high-income households are set at $150,000 for single filers and $300,000 for joint filers. The households whose income levels are less than or equal to 300 percent of the federal poverty level are categorized as the lower-income consumers. The motivation for switching from a uniform subsidy to an income-dependent subsidy is to make EVs more accessible to a larger number of drivers, especially those in lower-income households and communities that are more affected by air pollution. Since higher-income households are less sensitive to prices and have a stronger preference for newest technologies, they are more likely to adopt EVs without the subsidy. Therefore, providing more generous subsidies to lower-income households that are more price-sensitive could potentially reduce the policy cost of increasing EV sales.

The current federal-level EV subsidy is not designed to favor low-income households. To investigate whether an income-dependent structure could be more effective in terms of inducing additional EV sales, we conduct two counterfactual exercises that compare the current federal EV subsidy with alternative subsidy policies that mimic the design of CVRP. We remove the subsidy for households with income levels above the defined thresholds in both alternative policies, and we provide lower-income households with an additional subsidy of $2,000 in alternative policy 1 and $4,000 in alternative policy 2. The income cap and low-income groups are defined the same way as in the CVRP.[18]

The simulation results are summarized in Table 10. Under the current uniform subsidy, the government spent $0.73 billion in 2014 in subsidizing EVs, and a total number of 109,850 EVs were sold in the market, leading to an average spending of $6,630 per EV. With the removal of the subsidy to the high-income group and increased subsidy of $2,000 to low-income

[18]The income cap is $150,000 for single filers and $300,000 for joint filers. Low-income households are defined as those with income less than or equal to 300 percent of the 2018 federal poverty level. For households with one to eight persons, the combined household income must be less than $36,420, $49,380. $62,340, $75,300, $88,260, $101,220, $114,180, and $127,140 respectively (https://cleanvehiclerebate.org/eng/income-eligibility).

households, EV sales would decrease by 701, a 0.6 percent decrease. However, the total subsidy spending decreases from \$0.73 billion to \$0.64 billion, a 12.3 percent decrease. As a result, the income-dependent subsidy reduces the average spending per EV from \$6,630 to \$5,870, which is equivalent to a saving of \$760 (11.4 percent) per EV. When high-income households are no longer eligible for the federal subsidy with the amount up to \$7,500, the total reduction of EV sales is modest since the majority of wealthy consumers would still purchase EVs because of their low price sensitivity. The increased EV sales from low-income consumers due to the increased rebate of \$2,000 also compensates part of the sales loss from high-income groups. Since the alternative subsidy eliminates the spending on the "non-additional" portion of EV sales from high-income households, the average spending of subsidizing each EV is reduced.

In the second alternative policy design, an additional subsidy of \$4,000 is provided to low-income households, and high-income groups whose incomes are above the thresholds are still not eligible for the subsidy. The total EV sales under alternative policy 2 increase by 1,232 (1.12 percent) compared with the existing policy. Even though an additional subsidy of \$4,000 is given to low-income households, the total spending is \$0.66 billion, which is 9.6 percent lower than the total spending of the current subsidy. The average spending per EV is \$5,970 for alternative 2, leading to a saving of \$660 (10 percent) per subsidized EV. The savings are still mainly from the removal of the subsidies given to households with higher income, which would purchase EVs in the absence of the subsidy. By inducing additional EV sales, all the subsidy designs result in a reduction of CO_2 emissions by replacing vehicles that are less fuel-efficient with EVs.

The current subsidy policy reduces the total CO_2 emissions from the new vehicle fleet by 1.32 metric tons, and alternative policies 1 and 2 achieve a total CO_2 emissions reduction of 1.29 and 1.37, respectively. The average cost of CO_2 reduction is then estimated to be \$552, \$489, and \$484, respectively. Both of the alternative policies are less costly than the existing policy in terms of reducing emissions. Although alternative policy 2 has a higher average subsidy cost per EV than alternative 1, it achieves a lower cost per CO_2 reduction by inducing more sales of BEVs, which are more fuel-efficient. By providing more generous subsidies to low-income households, small and mid-size BEVs become more affordable to those consumers who prefer smaller vehicles. The BEV models that experience the highest sales increases in alternative 2 are Nissan LEAF, Smart ForTwo EV, and Fiat 500e. Beresteanu and Li (2011) estimate the cost of CO_2 reduction to be \$177 per ton from the income tax credits for hybrid vehicles. Our estimates of the cost of CO_2 reduction of EV subsides are larger, since the federal subsidy for EVs is more than twice the amount of the hybrid subsidy. Our estimates also suggest that subsidizing EVs is a relatively costly way to achieve the emissions reduction goals.

Panel (b) of Table 10 compares the distributional impacts of the three subsidy designs. The current uniform subsidy is regressive, since it benefits higher-income households more, as they are more likely to purchase EVs and claim the subsidy. Both alternative policies are less regressive than the existing policy, since they eliminate the subsidy for households whose income levels are above the threshold. Alternative policy 2 benefits the bottom income group the most, as it gives the most generous subsidy to low-income households. In summary, compared with the current uniform subsidy, the income-dependent subsidy designs are more effective in stimulating EV demand and reducing emissions, and they could also be better justified on distributional grounds.

7 Conclusions

Promoting electric vehicles is considered an effective way to increase fleet fuel economy and reduce emissions from on-road transportation. The environmental benefits of subsidizing EVs critically hinge on the fuel efficiency of the substitute vehicles. Encouraging consumers who would otherwise purchase another fuel-efficient vehicle to switch to EVs would not lead to significant emissions reductions.

The paper provides a theoretical and empirical analysis on how substitution patterns between vehicles of different fuel types affect the emissions impacts of electric vehicle policies. The styled theoretical model shows that the emissions impacts crucially depend on own-price and cross-price elasticities of demand, where the emissions of non-EVs with a larger cross-price elasticity have a bigger impact on the emissions impacts of EVs. To characterize the price elasticities and the substitution pattern, we estimate a flexible discrete choice model of new vehicle demand that incorporate rich consumer heterogeneity. A key differentiating feature of our demand model is that we identify random preference heterogeneity by leveraging the second-choice information from household survey data, which greatly improve the precision of estimated preference heterogeneity and implied substitution patterns. Our simulation results suggest that 79 percent of EVs replace gasoline vehicles with an average fuel economy of 27.2 mpg, and 12 percent of EVs replace hybrid vehicles with an average fuel economy of 45 mpg. If we had simply assumed that each EV replaces an average gasoline vehicle of 23 mpg, we would have overestimated the environmental benefits of EVs by 27 percent.

Our estimates imply that in 2014, the federal income tax credit for EVs led to a 28.8%

increase in EV sales, the majority of which replaced vehicles that are relatively fuel-efficient. The increased EV sales translate to \$73.8 million of environmental benefits due to reduced emissions of major air pollutants. The cost-effectiveness of the policy is hindered by the fact that about 70 percent of consumers would purchase EVs in the absence of the subsidy, and the subsidy mainly attracted consumers who would otherwise have purchased fuel-efficient gasoline or hybrid vehicles. By comparing the current uniform subsidy with alternative policy designs that limit eligibility and provide additional subsidies to low-income households, we find the income-dependent subsidies could potentially increase the cost-effectiveness of the subsidy program and are less regressive. Policies intended to promote EV technology and reduce emissions would be more effective by better targeting marginal buyers and encouraging consumers who would otherwise purchase gas-guzzlers such as large SUVs to adopt EVs.

Table 1: Sales Shares and Available Models of Hybrids and EVs, 2000-2017

Years	Hybrid Share	EV Share	Hybrid and EV Share	No. of hybrid Models Offered	No. of EV models offered
2000	0.05	0.00	0.05	2	0
2001	0.12	0.00	0.12	2	0
2002	0.21	0.00	0.21	3	0
2003	0.29	0.00	0.29	3	0
2004	0.49	0.00	0.49	4	0
2005	1.23	0.00	1.23	8	0
2006	1.52	0.00	1.52	10	0
2007	2.15	0.00	2.15	15	0
2008	2.37	0.00	2.37	17	0
2009	2.77	0.00	2.77	21	0
2010	2.37	0.00	2.38	30	2
2011	2.09	0.14	2.23	33	4
2012	3.01	0.37	3.38	44	11
2013	3.19	0.63	3.82	50	17
2014	2.75	0.72	3.47	50	22
2015	2.21	0.66	2.87	51	28
2016	1.99	0.90	2.89	52	33
2017	2.13	1.14	3.27	45	41

Notes: The statistics presented are derived from Wards Automotive new vehicle sales data, which provide annual estimates of sales by make, model, and fuel type. Shares are defined as annual sales of the vehicle type divided by total annual sales. To compute statistics for EVs, we define EV models that are identified in the Wards data as either plug-in electric or battery electric vehicles.

Table 2: Household and Vehicle Summary Statistics

	2010		2011		2012		2013		2014		All Years	
Variables	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Household income (1,000$)	146.78	107.92	160.10	134.60	130.65	104.49	136.78	115.16	136.21	107.96	140.45	114.16
Household size	2.62	1.21	2.67	1.20	2.71	1.23	2.66	1.21	2.65	1.21	2.66	1.21
With a college degree	0.62	0.49	0.62	0.49	0.63	0.48	0.65	0.48	0.65	0.48	0.64	0.48
Living in an urban area	0.65	0.48	0.64	0.48	0.66	0.47	0.66	0.47	0.68	0.47	0.66	0.47
Average commuting time (min.)	25.78	5.81	25.57	5.84	25.48	5.78	25.72	5.75	25.52	5.67	25.60	5.76
Average gasoline price ($)	2.75	0.16	3.42	0.42	3.65	0.27	3.67	0.22	3.57	0.23	3.48	0.40
Average vehicle price (1,000$)	31.17	11.39	32.00	11.49	33.16	11.28	34.19	12.84	34.98	14.00	33.46	12.54
Average mpg of the vehicle	23.38	5.57	28.51	18.65	36.80	27.87	39.78	27.05	38.06	25.56	34.81	24.50
Purchasing a light truck	0.49	0.50	0.49	0.50	0.41	0.49	0.36	0.48	0.41	0.49	0.42	0.49
Household observations	1,509		1,860		2,287		2,899		3,073		11,628	
Horsepower/weight (hp/lb)	0.06	0.02	0.06	0.02	0.06	0.02	0.07	0.02	0.06	0.02	0.42	0.49
Wheelbase*width (in^2)	8,399	1,165	8,339	1,173	8,313	1,193	8,289	1,167	8,314	1,172	8,330	1,173
% of ICE models	92.92		91.58		89.71		88.44		88.24		90.12	
% of hybrid models	7.08		7.67		8.85		8.62		8.28		8.11	
% of EV models	0.00		0.74		1.43		2.95		3.49		1.77	
Vehicle choice set size	424		404		418		441		459		2146	

Notes: The household-level data represent a sample (11,628 observations) drawn from the MaritzCX household survey data. Data of vehicle attributes are obtained from Wards Automotive. Household income is converted to 2014 $ using the BLS calculator. Household size is the number of individuals living in the respondent's household. Gasoline prices are quarterly average national prices from the EIA. Average mpg of the vehicle represents the average miles per gallon of the vehicles bought by the household sample. Horsepower/weight measures a vehicle's acceleration, and wheelbase*width measures a vehicle's footprint. ICE (internal combustion engine) models include gasoline, diesel, and FFV models.

Table 3: Summary of second choices for EV buyers

Make	Model	Fuel type	Top 1 second choice	Top 2 second choice
Honda	Accord Plug In Hybrid	PHEV	Tesla Model S	Toyota Prius
Ford	C-Max Energi	PHEV	Toyota Prius	Chevrolet Volt
Ford	Fusion Plug In Hybrid	PHEV	Chevrolet Volt	Toyota Prius Plug In
Toyota	Prius Plug-in	PHEV	Chevrolet Volt	Nissan LEAF
Chevrolet	Volt	PHEV	Toyota Prius	Nissan LEAF
Fiat	500 Electric	BEV	Nissan LEAF	Mini Cooper
Mercedes-Benz	B Class Electric	BEV	Nissan LEAF	Ford Fusion Hybrid
Ford	Focus Electric	BEV	Nissan LEAF	Chevrolet Volt
Nissan	LEAF	BEV	Chevrolet Volt	Toyota Prius
Tesla	Model S	BEV	Nissan LEAF	Audi A7
Toyota	RAV4 EV	BEV	Nissan LEAF	Tesla Model S
Chevrolet	Spark Electric	BEV	Nissan LEAF	Chevrolet Volt
Smart	fortwo electric	BEV	Nissan LEAF	Chevrolet Volt
Mitsubishi	i-MiEV	BEV	Nissan LEAF	Ford Focus Electric
BMW	i3	BEV	Nissan LEAF	Tesla Model S

Notes: The data summary is based on the sample of 2018 EV buyers from the MaritzCX household survey data. The table summarizes the most popular alternative vehicle choices for the households that purchased different EV models. Top 1 second choice indicates the most frequently reported alternative choices among the buyers of a specific EV model. Top 2 second choice reports the second most reported alternative choices for each EV model.

Table 4: Demand Estimation Results

Panel (a): Mean Utility Parameters

	(1) OLS		(2) IV	
	Coefficient	S.E.	Coefficient	S.E.
constant	-2.4560	0.1028	-2.4728	0.1113
log(price)	-1.3497	0.2572	-1.7375	0.8164
horsepower/weight	1.9525	0.3211	2.2664	0.6870
weight	1.3393	0.2505	1.2943	0.2606
gallons/mile	0.1805	0.1283	0.1327	0.1529
AFV dummy	-3.6229	0.5823	-3.6632	0.5942
EV dummy	-2.9321	0.2652	-2.8913	0.2791
pickup dummy	0.4192	0.2863	0.7285	0.6828
model year 11 dummy	0.2743	0.1143	0.2763	0.1144
model year 12 dummy	0.3127	0.1075	0.3321	0.1153
model year 13 dummy	0.0559	0.1063	0.0687	0.1098
model year 14 dummy	0.1741	0.0920	0.1768	0.0929

Panel (b): Heterogeneous Utility Parameters

	(1) 2^{nd} Choice		(2) No 2^{nd} choice	
	Coefficient	S.E.	Coefficient	S.E.
Observed Heterogeneity				
log(price)/income	-9.0659	0.4839	-15.9223	0.8972
family size*vehicle weight	0.0892	0.0207	0.2207	0.0315
urban*pickups	-0.6678	0.0561	-0.7232	0.0705
urban*EV	0.2305	0.0482	0.3636	0.0583
gasoline price*gallons/mile	-0.3078	0.0234	-0.6481	0.0410
education*EV	0.8309	0.0808	1.1437	0.0939
stations*EV	0.6728	0.1022	0.7164	0.1190
Random coefficients				
gallons/mile	1.9291	0.0565	1.5953	0.9018
horsepower/weight	1.0865	0.0396	0.1136	0.2129
light trucks	0.2823	0.0254	0.7164	0.1099
AFVs	0.9493	0.0886	0.4692	0.3074
Average own-price Elasticity	-2.67			

Notes: The number of households is 11,628. The value of the simulated log-likelihood at convergence is -144,129.4 based on 150 Halton draws per household. The instrumental variables used to estimate the linear parameters are the difference and squared difference in characteristics (fuel economy, horsepower, and weight) with other vehicles sold by the same manufacturer and the squared difference in characteristics of vehicles sold by other manufacturers. Specification (1) includes consumers' second choices in the likelihood function while specification (2) only incorporates consumers' purchased choices in constructing the likelihood.

Table 5: A sample of own- and cross-price elasticities

Products	Nissan Sentra	Chevrolet Cruze	Honda Civic	Ford Focus	Nissan Leaf	Tesla Model S	Chevrolet Volt	Toyota Prius	Honda Accord	Ford F-150	Price in 2014
Nissan Sentra (gas)	-3.01	0.06	0.06	0.06	0.05	0.03	0.04	0.05	0.05	0.02	13,351
Chevrolet Cruze (gas)	0.07	-2.95	0.07	0.07	0.06	0.04	0.05	0.06	0.06	0.02	19,243
Honda Civic (gas)	0.12	0.11	-2.91	0.11	0.10	0.07	0.08	0.09	0.09	0.03	20,106
Ford Focus (gas)	0.07	0.06	0.06	-2.97	0.05	0.04	0.05	0.05	0.05	0.02	20,026
Nissan LEAF (BEV)	0.01	0.01	0.01	0.01	-2.83	0.02	0.03	0.03	0.01	0.00	29,799
Tesla Model S (BEV)	0.00	0.00	0.00	0.00	0.01	-2.37	0.01	0.01	0.00	0.00	74,935
Chevrolet Volt (PHEV)	0.01	0.01	0.01	0.00	0.02	0.01	-2.66	0.01	0.00	0.00	35,203
Toyota Prius (HEV)	0.04	0.04	0.03	0.03	0.10	0.07	0.09	-2.68	0.03	0.01	24,027
Honda Accord (HEV)	0.12	0.12	0.12	0.12	0.10	0.09	0.10	0.10	-2.67	0.04	24,436
Ford F-150 (gas)	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	-2.53	29,806

Notes: The table reports a sample of own- and cross-price elasticities which are calculated based on the parameter estimates reported in Table 4 with the IV specification of the mean utility parameters and second choice specification of the heterogeneous utility parameters. The elasticity estimates are calculated with the same individual weights and Halton draws used in the demand estimation. More details are provided in Appendix C. The last column in the table gives the average transaction price in 2014 for those selected vehicle models. The sales-weighted average elasticity among all 2,146 products in five model years is -2.75.

Table 6: Own and Cross-Price Elasticity of Demand Estimates by Fuel Type

	BEV	PHEV	Hybrid	Gasoline	Diesel	FFV
BEV	0.013	0.018	0.015	0.004	0.003	0.002
PHEV	0.012	0.011	0.009	0.002	0.002	0.002
Hybrid	0.037	0.036	0.029	0.009	0.007	0.006
Gasoline	0.028	0.027	0.028	0.029	0.026	0.027
Diesel	0.003	0.004	0.004	0.006	0.007	0.007
FFV	0.012	0.012	0.013	0.021	0.024	0.024
Own Price Elasticity	-2.751	-2.649	-2.705	-2.761	-2.606	-2.680

Notes: The table summarizes the sales-weighted average own- and cross-price elasticity estimates by fuel type. The elasticity estimates are based on the parameter estimates reported in Table 4. BEV stands for battery electric vehicle, which represents vehicles that operate only with electricity, including a Tesla Model S. PHEV stands for plug-in hybrid vehicle, which represents vehicles that are able to operate with either electricity or gasoline, including a Honda Accord plug-in hybrid. FFV stands for flex-fuel vehicle, which represents vehicles that are able to operate on E85 fuel. On average, a 1 percent increase in a BEV model will increase the sales of other BEV models by 0.013 percent.

Table 7: Sales and Incidence Impacts of Removing EVs

Panel (a): Sales Impact

Fuel types	Sales change	Percentage	Average MPG
Gasoline	86114	78.7%	27.2
Hybrid	13167	12.0%	45.1
Diesel	2594	2.4%	27.4
FFV	7574	6.9%	22
All non-EVs	109449	100%	28.9

Among gasoline vehicles	Sales change	Percentage
low mpg (<19)	1,972	2.3%
medium mpg ($\geqslant$19 & $<$ 25)	20,409	23.7%
high mpg ($\geqslant$ 25)	63,733	74.0%

Panel (b): Welfare Impact

	Income quintile				
	(1)	(2)	(3)	(4)	(5)
Average welfare loss per household ($)	-33.41	-42.38	-50.35	-58.8	-73.51
Total welfare loss (million $)			-670.3		

Notes: The table summarizes the sales impact of removing all EVs from the choice set in MY 2014 on other vehicles of different fuel types and its welfare impact on consumers. The percentage column in panel (a) reports the percentage of the total sales increase from non-EV models that each fuel type contributes to. Average mpg represents the average miles per gallon of the vehicles that experience sales increases as a result of the removal of EVs. In panel (b), the average welfare loss per household is calculated as the change in consumer surplus as shown by Small and Rosen (1981). Total welfare loss is calculated as average consumer surplus loss multiplied by the market size of new vehicles.

Table 8: Sales and Incidence Impacts of Removing EV Subsidies

Panel (a): Sales Impact

Fuel types	Sales change	Percentage change		
EV	-31501	-28.8%		
BEV	-18861	-32.6%		
PHEV	-12640	-24.5%		
Other fuel types	Sales change	Percentage Change	Percentage of EV sales reduction	Average MPG
Gasoline	24867	0.23%	78.9%	27.2
Hybrid	3728	0.92%	11.8%	45
Diesel	741	0.17%	2.4%	27.5
FFV	2165	0.15%	6.9%	22
All non-EVs	31501	0.24%	100%	28.9

Panel (b): Welfare Impact

	Income quintile				
	(1)	(2)	(3)	(4)	(5)
Average welfare loss per household ($)	-9.38	-10.81	-12.30	-13.93	-16.75
Total welfare loss (million $)			-165.2		

Notes: The table summarizes the market and consumer welfare impact of removing the federal-level income tax credit for EVs in the year of 2014. In panel (a), the percentage of EV sales reduction represents the percentage of the original EV purchasers that switch to a specific non-EV fuel type if the federal subsidy were removed. Average mpg represents the average miles per gallon of the vehicles that experience sales increase due to the removal of federal EV subsidy. In panel (b), the average welfare loss per household is calculated as the change in consumer surplus as shown by Small and Rosen (1981). Total welfare loss is calculated as average consumer surplus loss multiplied by the market size of new vehicles.

Table 9: Environmental Benefits and Substitution

Actual benefits	
Gasoline consumption saved (billion gal.)	0.15
CO_2 emissions saved (billion lb.)	2.91
Equivalent reduction of gasoline cars	1,750
Counterfactual benefits if replacing a 23-mpg gasoline car	
Gasoline consumption saved (billion gal.)	0.19
CO_2 emissions saved (billion lb.)	3.74
Equivalent reduction of gasoline cars	2,250

Notes: The table reports the estimated lifetime emissions reduction achieved by the federal-level income tax credit for EVs in 2014, by comparing the actual fleet with the counterfactual fleet when the federal subsidy is removed. The estimation of the energy reduction from the increased EVs due to subsidy is based on the miles per gallon gasoline equivalent (MPGe) provided by EPA. Equivalent reduction of gasoline cars represents the equivalent number of gasoline cars with a fuel economy of 23 mpg (2014 average level) that can be reduced by the increased EVs due to subsidy, in terms of emissions.

Table 10: Comparison of Current Subsidy with Alternative Designs

Panel (a): Sales and Environmental Impact

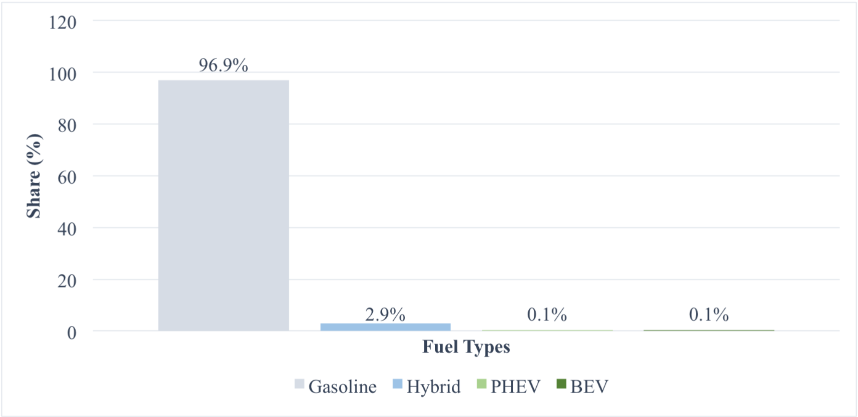
	Current subsidy	Alternative 1	Alternative 2
Total spending (billion $)	0.73	0.64	0.66
Total EV sales	109,853	109,152	111,085
Total BEV sales	57,791	57,554	58,900
Total PHEV sales	52,062	51,598	52,185
Average spending per EV ($)	6,630	5,870	5,970
Total CO_2 reduction (mil. metric tons)	1.32	1.29	1.37
Cost of CO_2 reduction ($/metric ton)	552	498	484

Panel (b): Welfare Impact

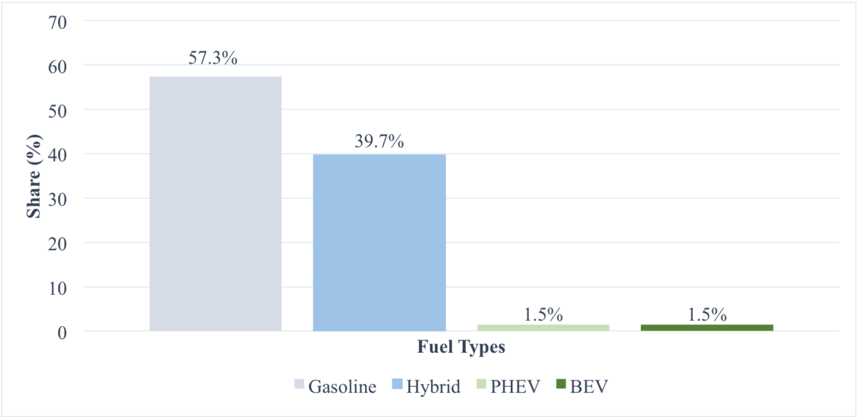
	Welfare change per household ($)		
Income Quintile	Current subsidy	Alternative subsidy 1	Alternative subsidy 2
1	9.38	11.73	14.73
2	10.81	11.07	11.40
3	12.30	12.30	12.30
4	13.93	13.29	13.29
5	16.75	8.99	8.99
Total welfare change	165.2 million	154.4 million	163.9 million

Notes: The current subsidy policy provides uniform tax credits to all EV buyers. Both alternatives 1 and 2 set an income cap such that the highest income group is not eligible to claim the subsidy. Further, Alternatives 1 and 2 provide an additional $2,000 and $4,000, respectively, to lower-income households, compared with the current policy. In panel (b), the income groups are defined the same way as for the income eligibility implemented in the CVRP in California. The welfare change per household is calculated as the change in consumer surplus as shown by Small and Rosen (1981). Total welfare change is calculated as average consumer surplus change multiplied by the market size of new vehicles.

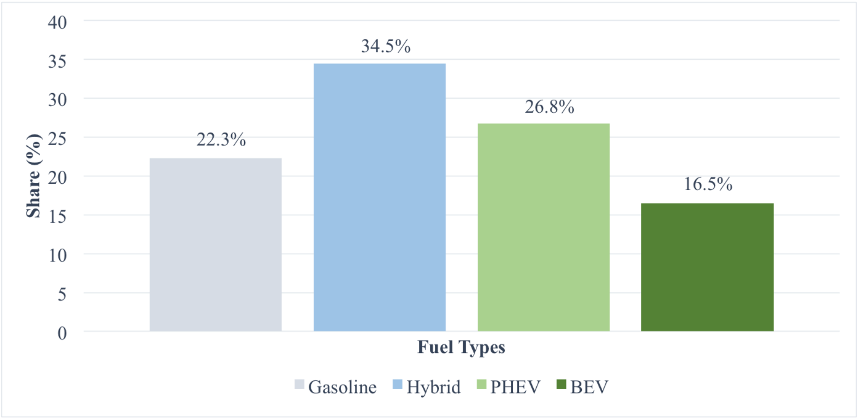
Figure 1: Consumer Second Choices by Fuel Type



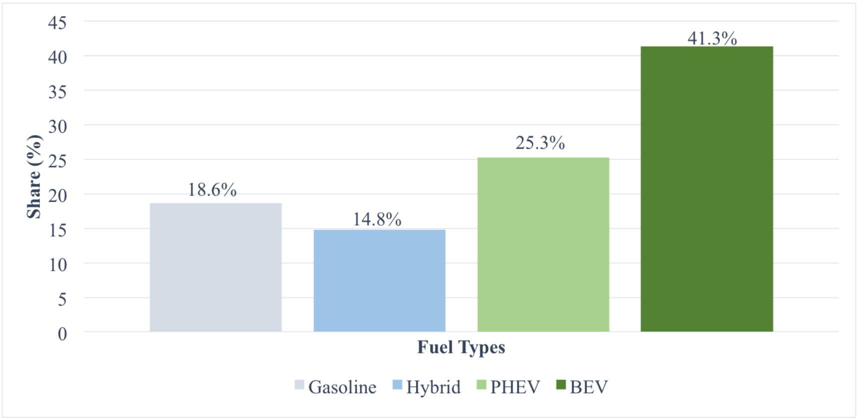
(a) Gasoline vehicle buyers



(b) Hybrid vehicle buyers



(c) PHEV buyers

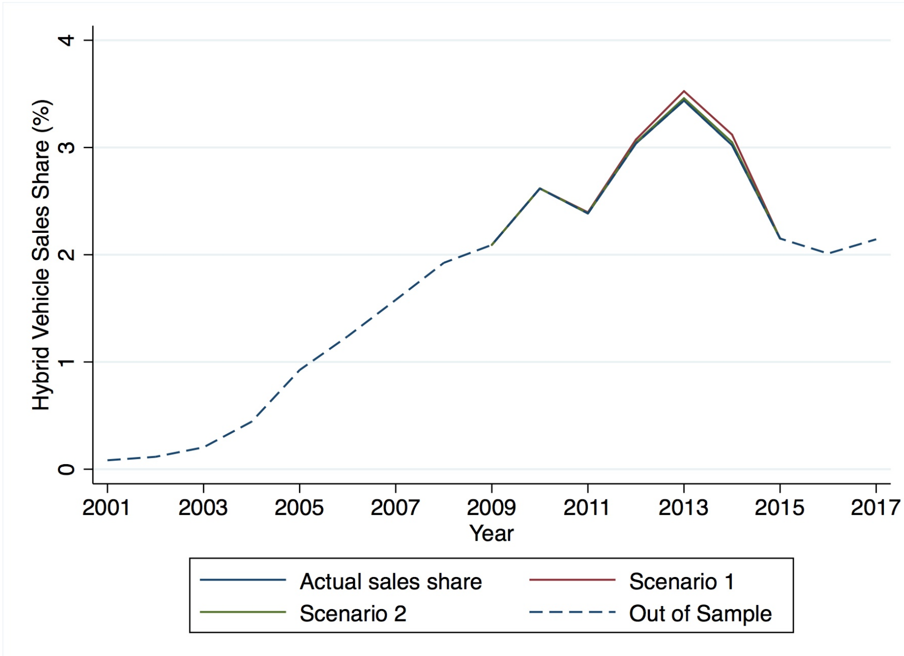


(d) BEV buyers

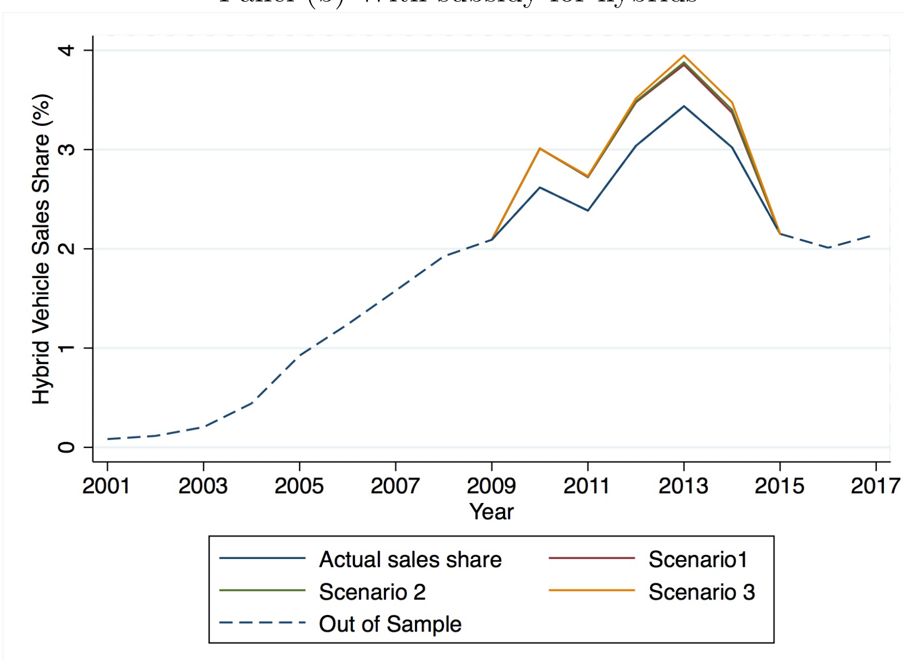
Notes: The figure plots the frequency of alternative vehicle choices by fuel type for different groups of consumers based on the survey responses of the 11,628 households in the sample. The number of observations for the buyers of gasoline vehicles, hybrid vehicles, PHEVs and BEVs is 9,295, 315, 1,246, and 772, respectively.

Figure 2: The Effect of Electric Vehicles on Hybrid Sales

Panel (a) No subsidy for hybrids



Panel (b) With subsidy for hybrids



Notes: the figure plots the impact of the introduction of EVs and EV subsidy on the market shares of hybrid vehicles. The dashed lines represent out-of-sample shares obtained from Wards Automotive. In Panel (a), Scenario 1 removes EV models from the market. Scenario 2 removes the federal income tax credits for EVs. In Panel (b), we assume that the government continues subsidizing hybrid vehicles between 2010-14 with their original subsidy amount in all the three scenarios. Scenario 1 keeps the current EV subsidy. Scenario 2 removes EV subsidy and Scenario 3 removes EVs from the market.

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Appendices

A Additional Literature Review

Our analysis contributes to the literature on the diffusion of vehicles with advanced fuel technologies (e.g., hybrid vehicles) and alternative fuels (e.g., FFVs). Kahn (2007), Kahn and Vaughn (2009), and Sexton and Sexton (2014) examine the role of consumer environmental awareness and signaling in the market for conventional hybrid vehicles. Heutel and Muehlegger (2015) study the effect of consumer learning in hybrid vehicle adoption, focusing on different diffusion paths of Honda Insight and Toyota Prius. Several recent studies have examined the impacts of government programs at both the federal and state levels in promoting the adoption of hybrid vehicles, including Diamond (2009), Beresteanu and Li (2011), Gallagher and Muehlegger (2007), and Sallee (2011). These studies consistently find that better environmental awareness, higher gasoline prices, and more generous incentives are associated with higher adoption of "green" vehicles. We add to this literature by estimating substitution patterns among gasoline-powered vehicles, hybrids, and EVs. To the best of our knowledge, our results are the first to provide cross-price elasticities among these vehicle types, which will allow researchers and policy-makers to determine how subsidy designs alter the sales mix of different power types.

Our analysis relates to the literature that studies the cost-effectiveness of energy subsidy programs. Allcott et al. (2015) find that some energy efficiency subsidies are poorly-targeted and are primarily taken up by consumers who are wealthier and more informed about energy costs. They conclude that restricting subsidy eligibility could increase the welfare gains from those subsidies. Boomhower and Davis (2014) find that half of all participants would have adopted the energy-efficient technology even with no subsidy. Ito (2015) shows that most of the treatment effects of incentives come from consumers who are closer to the target level of consumption, and the treatment effect is not significantly different from zero for consumers who are far from the target level. Fowlie et al. (2015) find evidence that high non-monetary costs contribute to the low participation of energy efficiency investment for households and there are demographic differences between households that chose to participate on their own and those that were encouraged to participate in the program by encouragement intervention. Langer and Lemoine (2018) investigate the efficient subsidy schedule for durable goods in a dynamic setting and show that an efficient subsidy often increases over time and that consumers' rational expectations of future subsidies and technological progress could substantially increase public spending. By empirically estimating a national vehicle demand model in a static setting and obtaining consumer preference parameters, we are able to run counterfactual simulations to examine the cost-effectiveness of the current EV subsidy design and compare it with other possible designs.

B Defining the Simulated Log-Likelihood and Gradient

The utility of household i purchasing vehicle model j is defined as:

$$u_{ij} = \underbrace{\sum_{k=1}^{K} x_{jk}\bar{\beta}_k - \alpha_1 lnP_j + \xi_j}_{\delta_j} + \underbrace{\alpha_2 \frac{lnP_j}{Y_i} + \sum_{kr} x_{jk} z_{ir} \beta^o_{kr} + \sum_{k} x_{jk} v_{ik} \beta^u_k}_{\mu_{ij}} + \varepsilon_{ij},$$

where δ_j is the mean utility of vehicle model j, which is constant across consumers, and μ_{ij} is the individual-specific utility component related to observed and unobserved consumer demographics. Let $\theta = \{\beta^o_{kr}, \beta^u_k\}$ be the non-linear parameters that are estimated from the first stage. The last component, ε_{ij}, is the idiosyncratic preference of household i for vehicle model j and is assumed to have an i.i.d. type 1 extreme value distribution. The probability of household i purchasing j and considering h as the second choice is:

$$P_{ijh} = \int \frac{exp[\delta_j(\theta) + \mu_{ij}(\theta)]}{1 + \sum_g exp[\delta_g(\theta) + \mu_{ig}(\theta)]} \cdot \frac{exp[\delta_h(\theta) + \mu_{ih}(\theta)]}{\sum_{g \neq j} exp[\delta_g(\theta) + \mu_{ig}(\theta)]} f(v)dv.$$

Note that the choice set of the second choice excludes the purchased product j. Since the random taste v_{ik} is not observed, the probability above is calculated by integrating over the distribution of the unobserved taste v. This high-dimensional integration is estimated via simulation where R denotes the number of simulation draws and the subscript r denotes a specific random draw r:

$$\begin{aligned} P_{ijh} &= \frac{1}{R} \sum_{1}^{R} \frac{exp[\delta_j(\theta) + \mu_{ijr}(\theta)]}{1 + \sum_g exp[\delta_g(\theta) + \mu_{igr}(\theta)]} \cdot \frac{exp[\delta_h(\theta) + \mu_{ihr}(\theta)]}{\sum_{g \neq j} exp[\delta_g(\theta) + \mu_{igr}(\theta)]} \\ &= \frac{1}{R} \sum_{1}^{R} \frac{A_{jr}}{B_r} \cdot \frac{A_{hr}}{B_r^{-j}} \\ &= \frac{1}{R} \sum_{1}^{R} P_{ijr} \cdot P_{ihr}^{-j}, \end{aligned}$$

where $B_r^{-j} = B_r - exp[\delta_j(\theta) + \mu_{ijr}(\theta)]$, which denotes the choice set for the second choice conditional on choosing j as the first good, and P_{ihr}^{-j} is the probability of choosing h from a choice set that excludes j conditional on a set of random draws r.

Let $lnR_i = lnP_{ijh} = lnP_{ij} + lnP_{ih}^{-j} = ln(\frac{1}{R}\sum_1^R P_{ijr}) + ln(\frac{1}{R}\sum_1^R P_{ihr}^{-j})$, the individual log-likelihood of household i choosing the observed purchased model j and considering the observed second choice h. The log-likelihood function of the entire sample for a single market is therefore:

$$lnL = \sum_{i=1}^{N} lnR_i.$$

The derivative of the individual log-likelihood function with respect to θ_k is

$$\begin{aligned}
\frac{\partial lnP_{ijh}}{\partial\theta_k} &= \frac{1}{P_{ijh}}\cdot\frac{1}{R}\sum_{r=1}^{R}\left[\frac{A_{jr}}{B_r}\left(\frac{A_{hr}}{C_r^{-j}}\right)' + \left(\frac{A_{jr}}{B_r}\right)'\left(\frac{A_{hr}}{C_r^{-j}}\right)\right] \\
&= \frac{1}{P_{ijh}}\cdot\frac{1}{R}\sum_{r=1}^{R}\left\{\frac{A_{jr}}{B_r}\frac{A_{hr}\left[\frac{\partial\delta_h(\theta)}{\partial\theta_k} + \frac{\partial\mu_{ihr}(\theta)}{\partial\theta_k}\right]C_r^{-j} - A_{hr}\sum_{g\neq j}A_{gr}\left[\frac{\partial\delta_g(\theta)}{\partial\theta_k} + \frac{\partial\mu_{igr}(\theta)}{\partial\theta_k}\right]}{\left(C_r^{-j}\right)^2}\right. \\
&+ \left.\frac{A_{jr}\left[\frac{\partial\delta_j(\theta)}{\partial\theta_k} + \frac{\partial\mu_{ijr}(\theta)}{\partial\theta_k}\right]B_r - A_{jr}\sum_g A_{gr}\left[\frac{\partial\delta_g(\theta)}{\partial\theta_k} + \frac{\partial\mu_{igr}(\theta)}{\partial\theta_k}\right]}{\left(B_r\right)^2}\frac{A_{hr}}{C_r^{-j}}\right\} \\
&= \frac{1}{P_{ijh}}\cdot\frac{1}{R}\sum_{1}^{R}\left\{\frac{A_{jr}}{B_r}\frac{A_{hr}}{C_r^{-j}}\left[\frac{\partial\delta_h(\theta)}{\partial\theta_k} + \frac{\partial\mu_{ihr}(\theta)}{\partial\theta_k}\right] - \frac{A_{jr}}{B_r}\frac{A_{hr}}{C_r^{-j}}\sum_{g\neq j}\frac{A_{gr}}{C_r^{-j}}\left[\frac{\partial\delta_g(\theta)}{\partial\theta_k} + \frac{\partial\mu_{igr}(\theta)}{\partial\theta_k}\right]\right. \\
&+ \left.\frac{A_{jr}}{B_r}\frac{A_{hr}}{C_r^{-j}}\left[\frac{\partial\delta_j(\theta)}{\partial\theta_k} + \frac{\partial\mu_{ijr}(\theta)}{\partial\theta_k}\right] - \frac{A_{jr}}{B_r}\frac{A_{hr}}{C_r^{-j}}\sum_{g}\frac{A_{gr}}{B_r}\left[\frac{\partial\delta_g(\theta)}{\partial\theta_k} + \frac{\partial\mu_{igr}(\theta)}{\partial\theta_k}\right]\right\} \\
&= \frac{1}{P_{ijh}}\cdot\frac{1}{R}\sum_{1}^{R}\left\{P_{ijhr}\left[\frac{\partial\delta_h(\theta)}{\partial\theta_k} + \frac{\partial\mu_{ihr}(\theta)}{\partial\theta_k} - \sum_{g\neq j}P_{igr}^{-j}\frac{\partial\delta_g(\theta)}{\partial\theta_k} - \sum_{g\neq j}P_{igr}^{-j}\frac{\partial\mu_{igr}(\theta)}{\partial\theta_k}\right]\right. \\
&+ \left.P_{ijhr}\left[\frac{\partial\delta_j(\theta)}{\partial\theta_k} + \frac{\partial\mu_{ijr}(\theta)}{\partial\theta_k} - \sum_{g}P_{igr}\frac{\partial\delta_g(\theta)}{\partial\theta_k} - \sum_{g}P_{igr}\frac{\partial\mu_{igr}(\theta)}{\partial\theta_k}\right]\right\},
\end{aligned}$$

where $P_{igr} = \frac{A_{gr}}{B_r}$, which is the probability of i choosing g as first choice conditional on a random draw r. $P_{igr}^{-j} = \frac{A_{gr}}{B_r^{-j}}$, which is the probability of i choosing g as a second choice from the choice set that excludes the first choice j conditional on a random draw r. $\delta_j(\theta)$ is estimated via contraction mapping and does not have an analytical solution. To estimate $\frac{\partial\delta_j(\theta)}{\partial\theta_k}$, we use implicit function theorem:

$$\frac{\partial\delta_j(\theta)}{\partial\theta_k} = -(\frac{\partial\hat{S}_j}{\partial\delta_j})^{-1}\frac{\partial\hat{S}_j}{\partial\theta_k},$$

where $\hat{S}_j$ is the predicted market share for model j, and

$$\frac{\partial\hat{S}_j}{\partial\delta_j} = \frac{1}{N}\sum_{i=1}^{N}\frac{\partial P_{ij}}{\partial\delta_j} = \frac{1}{N}\sum_{i=1}^{N}P_{ij}(1-P_{ij}) = \frac{1}{N}\sum_{i=1}^{N}P_{ij} - \frac{1}{N}\sum_{i=1}^{N}P_{ij}^2$$

$$\frac{\partial\hat{S}_j}{\partial\theta_k} = \frac{1}{N}\sum_{i=1}^{N}\frac{\partial P_{ij}}{\partial\theta_k} = \frac{1}{N}\sum_{i=1}^{N}P_{ij}\frac{\partial u_{ij}}{\partial\theta_k} - \frac{1}{N}\sum_{i=1}^{N}P_{ij}\sum_{g}P_{ig}\frac{\partial u_{ig}}{\partial\theta_k}.$$

$\frac{\partial\delta_h(\theta)}{\partial\theta_k}$ is estimated by the same method. The score matrix is then:

$$\frac{\partial lnR}{\partial\theta} = \underbrace{\begin{bmatrix} \frac{\partial lnP_{1jh}}{\partial\theta_1} & \frac{\partial lnP_{1jh}}{\partial\theta_2} & \dots & \frac{\partial lnP_{1jh}}{\partial\theta_k} \\ \frac{\partial lnP_{2jh}}{\partial\theta_1} & \frac{\partial lnP_{2jh}}{\partial\theta_2} & \dots & \frac{\partial lnP_{2jh}}{\partial\theta_k} \\ \dots & \dots & \dots & \dots \\ \frac{\partial lnP_{Njh}}{\partial\theta_1} & \frac{\partial lnP_{Njh}}{\partial\theta_2} & \dots & \frac{\partial lnP_{Njh}}{\partial\theta_k} \end{bmatrix}}_{N\times k}.$$

Then, averaging the above matrix across households using the sample weight for each household gives the gradient of the likelihood function, which is the average of the scores across individuals:

$$\frac{\partial lnL}{\partial\theta} = \underbrace{\begin{bmatrix} \sum_{i=1}^{N} w_i\cdot\frac{\partial lnP_{ijh}}{\partial\theta_1} & \sum_{i=1}^{N} w_i\cdot\frac{\partial lnP_{ijh}}{\partial\theta_2} & \dots & \sum_{i=1}^{N} w_i\cdot\frac{\partial lnP_{ijh}}{\partial\theta_k} \end{bmatrix}}_{1\times k},$$

where w_i is the sample weight for household i.

C Derivation of Own- and Cross-Price Elasticities of Demand

The predicted market share for model j is the average of individual probabilities of purchasing vehicle model j:

$$s_j = \frac{1}{N}\sum_{i=1}^{N}P_{ij} = \frac{1}{N}\sum_{i=1}^{N}\frac{exp(u_{ij})}{1+\sum_g exp(u_{ij})}.$$

The partial derivative of individual probability of purchasing j with respect to the price of j is:

$$\begin{aligned}\frac{\partial P_{ij}}{\partial p_j} &= \frac{exp(u_{ij})\frac{\partial u_{ij}}{\partial p_j}(1+\sum_g exp(u_{ij})) - exp(u_{ij})exp(u_{ij})\frac{\partial u_{ij}}{\partial p_j}}{(1+\sum_g exp(u_{ij}))^2} \\ &= \frac{exp(u_{ij})}{1+\sum_{j=1}^J exp(u_{ij})}\frac{\partial u_{ij}}{\partial p_j} - \left(\frac{exp(u_{ij})}{1+\sum_{j=1}^J exp(u_{ij})}\right)^2 \frac{\partial u_{ij}}{\partial p_j} \\ &= (P_{ij} - P_{ij}^2)\frac{\partial u_{ij}}{\partial p_j}.\end{aligned}$$

The own-price elasticity of product j is:

$$\frac{\partial lns_j}{\partial p_j} = \frac{p_j}{s_j} \cdot \frac{1}{N}\sum_{i=1}^N (P_{ij} - P_{ij}^2)\frac{\partial u_{ij}}{\partial p_j}.$$

The partial derivative of individual probability of purchasing j with respect to the price of model k is:

$$\begin{aligned}\frac{\partial P_{ij}}{\partial p_k} &= \frac{0 - exp(u_{ij})exp(u_{ik})\frac{\partial u_{ik}}{\partial p_k}}{(1+\sum_{j=1}^J exp(u_{ij}))^2} \\ &= -P_{ij}P_{ik}\frac{\partial u_{ik}}{\partial p_k}.\end{aligned}$$

The cross-price elasticity of product j with respect to price of product k is thus:

$$\frac{\partial lns_j}{\partial p_k} = \frac{p_k}{s_j} \cdot \frac{1}{N}\sum_{i=1}^N -P_{ij}P_{ik}\frac{\partial u_{ik}}{\partial p_k}.$$

D Additional Tables and Figures

Table D.1: Vehicle emissions per 100 miles (National average grid mix)

Vehicle Fuel Type	GHG Emissions
Gasoline	87 lb. CO_2
Hybrid Electric	57 lb. CO_2
Plug-in Hybrid Electric	62 lb. CO_2
All electric	54 lb. CO_2

Notes: The data are from the AFDC, https://www.afdc.energy.gov/vehicles/electric_emissions_sources.html (accessed on October 15, 2018). The emissions from electric vehicles are calculated based on the national average fuel sources used in electricity generation in the United States.

Table D.2: Summary Statistics of Household Data by Fuel Type

	EV Buyers		Non-EV Buyers	
	Mean	S.D.	Mean	S.D.
Household income (1,000$)	180.98	134.73	131.94	107.44
With a college degree	0.81	0.40	0.60	0.49
Charging stations	0.87	1.76	0.29	0.93
Living in an urban area	0.78	0.41	0.64	0.48
Average gasoline price ($)	3.73	0.25	3.43	0.40
Average vehicle price (1,000$)	32.58	13.28	32.37	12.03
Leasing the vehicle	0.44	0.50	0.15	0.36
Observations	2,018		9,610	

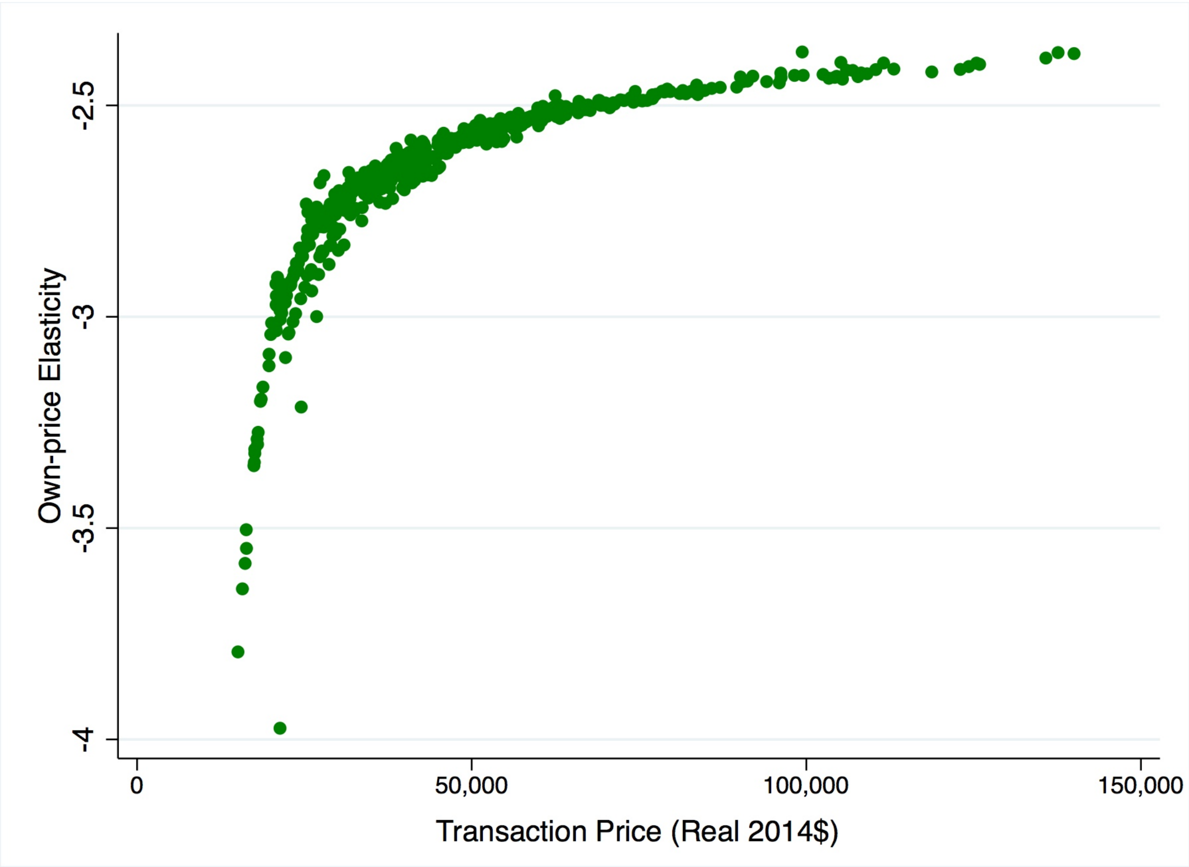
Notes: The data represent the 11,628 observations drawn from the MaritzCX household survey data. Household income is converted to 2014 $ using the BLS calculator. With a college degree indicates whether the purchaser of the vehicle has obtained a college degree. The number of charging stations is the cumulative sum of the charging stations that have been built in the survey respondent's neighborhood (zip code) by the purchase date of the vehicle. The charging stations data are collected from the AFDC. Gasoline prices are monthly average regional prices from the EIA. Average vehicle price is the average transaction price in year when the vehicle was purchased.

Table D.3: Environmental Benefits of EV Subsidy

Pollutants	Reduction (tons)	Damage ($/ton)	Damage reduction (million $)
CO_2	1,321,767.1	36.0	47.6
VOC	3,695.2	1,482.0	5.5
NO_x	2,478.3	6,042.0	15.0
$PM_{2.5}$	14.8	330,600.0	4.9
SO_2	25.2	35,340.0	0.9
All			73.8

Notes: The table summarizes the environmental benefits of the federal-level income tax credit for EVs, with a total spending of $725.7 million in 2014. The environmental estimates are based on the external cost savings from emissions reduction of various pollutants due to less petroleum consumption. The emissions rates and associated damage values are obtained from EPA (2008).

Figure D.1: Own-price Elasticity Estimates



Notes: The figure plots each vehicle model's own-price elasticity against its average transaction price in 2014. The elasticity estimates are calculated based on the parameter estimates reported in Table 6, and are calculated with the same individual weights and Halton draws used in the demand estimation.