Optimal Allocation of Electric Vehicle Subsidies: Consumers or Dealers (or Both)*

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Abstract

National, state, and local governments have implemented various subsidy programs to promote electric vehicle (EV) adoption by reducing upfront costs for consumers. Standard economic theory suggests that the effectiveness of such subsidies should not depend on whether they target consumers or dealers. Since dealers are an important intermediary in most vehicle purchase decisions, with the capacity to nudge consumers towards EVs, subsidies targeting dealers could accelerate adoption. This paper tests that assumption using a unique EV rebate program in Connecticut (CHEAPR), which provides both consumer and dealer rebates. We exploit cross-sectional and temporal variation in rebate levels to estimate the effects of consumer and dealer subsidies on EV prices and adoption. Our results show that while 73% of consumer subsidies are passed through to buyers, dealer subsidies have no statistically significant effect on prices or adoption. Using a structural model of automobile demand and supply, we further analyze the optimal allocation of subsidies to maximize EV adoption under a fixed budget. Policy counterfactuals reveal that reallocating subsidies to the consumer side can increase adoption, and in particular, focusing on battery electric vehicles (BEVs) and price-sensitive models significantly boosts adoption and environmental benefits. Additionally, targeting consumer subsidies to low-income buyers or vehicles with high North American value-added can enhance equity or domestic growth while increasing EV adoption and environmental benefits.

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1 Introduction

The pass-through of a subsidy or tax matters for understanding the distributional implications of that policy. Standard economic theory suggests that economic incidence (i.e., who benefits from the subsidy) is independent of statutory incidence (i.e., who receives the subsidy). That is, the equilibrium outcome is independent of who nominally pays the tax or receives the subsidy (Jenkin (1872)).

Contrary to the prediction of standard economic theory, some research shows that statutory incidence matters. For example, Chetty et al. (2009) suggest that the economic incidence of a tax depends on who pays the tax in the case of the alcohol market. An increase in excise tax (included in the posted price) reduces beer consumption more than a similar increase in sales tax (added at the register). In addition, Jiménez et al. (2020) show that statutory incidence matters in the mortgage market. Specifically, they find a reduction in pass-through rates due to a shift in mortgage tax from borrowers to lenders.

Subsidies and tax credits are widely used to incentivize the purchase of green products such as solar panels or alternative fuel vehicles. In the U.S., these subsidies are available from both the federal government and from a number of states that want to increase the take-up of these technologies. National and state governments in the U.S. spent nearly 22 billion dollars on electric vehicle (EV) subsidies in 2021 (Bennett and Isaac (2023)), and understanding who benefits from these policies and how effective they are at inducing purchases is a key part of assessing these policies. If economic incidence is independent of statutory incidence, no matter how policymakers distribute the subsidy between buyer and seller, the effects on equilibrium outcomes should be the same. However, if statutory incidence matters in the EV market, subsidizing one agent - buyer or seller – would lead to higher pass-through and, potentially, differential vehicle adoption rates.

This paper examines the incidence of electric vehicle subsidies and asks two questions: first, does the statutory incidence of subsidies affect the economic incidence, and if so, who benefits from the subsidies for electric vehicles? Second, we ask whether alternative subsidy design could change electric vehicle purchase patterns to achieve particular policy goals. To answer these questions, we study a unique EV rebate program in Connecticut (CHEAPR) that provides both consumer (up to $3,000) and dealer (up to $300) subsidies for each EV purchase. This unique program provides a novel quasi-experiment with temporal and cross-sectional variation to examine whether consumer and dealer incentives impact EV prices and adoption equally.

To test whether economic incidence is independent of statutory incidence and learn about pass-through rates, this paper employs a reduced-form model specification to evaluate the effects of consumer and dealer subsidies on equilibrium outcomes. Taking advantage of the cross-sectional and temporal variation, we examine the effects of these two subsidies on EV prices and adoption using a rich dataset of new vehicle registration data in Connecticut and nine other control states from 2018 to 2022. In addition, to further separate the effects of consumer and dealer subsidies, we employ an event-study approach to analyze only EV purchases that took place nine months before and after a reduction in either consumer or dealer subsidy.

The findings from the reduced-form model indicate that consumer and dealer subsidies influence electric vehicle prices and adoption in distinct ways. A substantial portion of consumer subsidies, approximately 73%, is passed through to consumers. In contrast, dealer subsidies do not significantly impact EV prices statistically. Utilizing an event-study approach, which focuses on EVs that experienced reductions in either consumer or dealer subsidies alone, we further validate that consumers benefit predominantly from consumer subsidies. At the same time, they receive no benefits from dealer subsidies.

Additionally, the reduced-form model estimates that for every $1,000 increase in consumer subsidies, per capita EV sales rise by about 4.5%. In contrast, dealer subsidies show no statistically significant effect on EV sales. Our event-study analysis reinforces this conclusion, demonstrating that a decrease in consumer subsidies leads to a decline in EV adoption. In contrast, reducing dealer subsidies has no noticeable impact on EV sales. These findings highlight the importance of exploring targeted subsidy design to maximize EV adoption and environmental benefits.

To fully understand how subsidy design affects outcomes, this paper estimates a model of demand and supply for new cars, in which heterogeneous consumers choose vehicles to maximize utility and dealers simultaneously choose vehicle prices to maximize profits, given a set of subsidies. While the reduced-form results highlight the effectiveness of the consumer subsidy in decreasing the upfront purchasing cost and increasing EV sales, the estimated demand and supply model allows us to examine how policymakers can reallocate EV subsidies to achieve particular goals, such as maximizing EV adoption and environmental benefits, keeping the level of state government spending fixed. The structural model allows for more realistic substitution patterns and accounts for the equilibrium effect on the supply side that a linear reduced-form model cannot fully explain.

The structural model results are consistent with the reduced form findings, showing that dealers respond much more strongly to consumer incentives than to incentives that go directly to the dealer. For every $1,000 increase in consumer incentives, dealer reactions are equivalent to a 3% marginal cost reduction for a cost pass-through rate of 100%. However, dealer incentives do not significantly influence dealer behavior, suggesting that their magnitude (or salience to consumers) may be insufficient to prompt dealerships to alter pricing strategies or nudge them towards selling EVs instead of traditional internal combustion engine vehicles. Overall, these results suggest that targeted consumer subsidies are more effective in enhancing EV adoption than dealer incentives, highlighting the need for policymakers to optimize subsidy designs for maximum impact.

We utilize estimated demand and supply models to explore various policy counterfactuals aimed at optimizing the allocation of subsidies for EVs under the CHEAPR program. The analysis indicates that consumer incentives are critical in boosting EV adoption and mitigating environmental impacts. Specifically, removing consumer subsidies results in a 7.11% decline in EV sales due to a price increase of $394, highlighting the high price sensitivity of the EV market. Removing the incentives also leads to increased CO_2 damages, underscoring the importance of subsidies in promoting cleaner vehicle choices.

Moreover, we evaluate different distributions of consumer incentives and their impact on market outcomes, identifying the most cost-effective subsidy designs that promote higher EV adoption and environmental sustainability. We can achieve significantly greater environmental benefits and adoption by reallocating subsidies to focus exclusively on BEVs. Specifically, targeting subsidies to BEVs rather than PHEVs leads to more substantial reductions in emissions and damages. Furthermore, reallocating incentives to price-sensitive EV models generates even greater improvements in EV adoption and environmental outcomes. Beyond adoption and environmental benefits, targeting those with high North American value-added[1] can support domestic manufacturing. Finally, target-

[1] the percentage of U.S./Canadian equipment (parts) content. Data from the National Highway Traffic Safety

ing low-income households proves to be an effective strategy for enhancing equity in EV adoption while simultaneously delivering substantial environmental benefits. Overall, our analysis underscores the potential for refining EV consumer subsidy designs to achieve a more sustainable and efficient market, offering crucial insights for policymakers aiming to balance economic growth with environmental objectives.

This paper contributes to several strands of the literature. First, our paper contributes to the literature on the incidence of durable goods incentives, which has been particularly focused on incentives for efficient vehicles. Several studies have documented high pass-through rates for consumer incentives. In vehicle buyback settings, Kaul et al. (2016) report a pass-through rate above 100% for the high-end car segment, and Busse et al. (2012) also find that dealers pass 100% of the Cash for Clunkers rebate to consumers. Similarly, Sallee (2011) finds that consumers captured virtually all of the state and federal hybrid vehicle incentives, while Muehlegger and Rapson (2022) report that the pass-through rate of EV subsidies in California is indistinguishable from 100 percent. More recently, Barwick et al. (2023) found high pass-through of electric vehicle incentives on a global scale, and Allcott et al. (2024) also find that this holds for the incentives in the Inflation Reduction Act. For a related technology, solar panels, Pless and van Benthem (2019) find high pass-through rates for both owned and leased solar installations, despite differences in whether the household or solar company receives the subsidy. This paper adds further support for the pattern of high pass through of incentives for efficient durable goods, while also providing the first evidence that this outcome depends on statutory incidence in the vehicles context.

Second, this paper contributes to a growing body of research on the effect of subsidies and tax incentives on energy-efficient vehicle adoption. Beresteanu and Li (2011), Chandra et al. (2010), and Gallagher and Muehlegger (2011) found that federal and provincial incentives were influential in increasing hybrid vehicle uptake. Clinton and Steinberg (2019) showed that in the early years of the electric vehicle market, incentives increased adoption, albeit without improving overall welfare. Jacqz and Johnston (2024), Linn (2022), Xing et al. (2021), Liu (2022), and Allcott et al. (2024) have examined tradeoffs in subsidy targeting. Lohawala (2023) found that one feature of federal subsidies – the dynamic phaseouts – can have major implications for total EV sales. Separately, Wang and Xing (2023), Barwick et al. (2024), Remmy (2023), and Sinyashin (2021) have documented how subsidy design can affect the attributes of product offerings, while Springel (2021) and Li et al. (2017) compare the effects of vehicle subsidies to charging station subsidies and Armitage and Pinter (2022) compare subsidies on the consumer side to supply-side policies. We add evidence about the benefits of redesigning subsidies to target particular environmental or distributional objectives, and unlike prior papers, we also document how the subsidy's statutory incidence can affect overall sales. Unlike the papers that consider supply-side policies that target manufacturer choices, we focus on policies that affect dealer behavior rather than manufacturer behavior.

Our paper's findings have important policy implications. EV incentive programs of various types are increasingly implemented in the U.S. and other countries. In addition, the lessons about targeting have broader policy implications for other green technology incentive programs nationally and internationally.

The rest of the paper is organized as follows. Section 2 describes the institutional background of the U.S. EV market and, specifically, the CHEAPR program. Section 3 presents the data used

Administration's Part 583 American Automobile Labeling Act Reports.

for reduced form and structural model analyses. Section 4 investigates whether statutory incidence matters by estimating the effect of consumer and dealer subsidies on EV prices and adoption. Sections 5, 6, and 7 introduce a demand and supply model for new cars and examine the effect of two subsidies on dealer behavior. Section 8 determines the most cost-effective way for policymakers to maximize EV adoption and achieve environmental goals under the current level of state government spending using structural model estimates and counterfactual analyses. Section 9 concludes.

2 Institutional Background

Since national and state governments widely use subsidies to promote electric vehicle adoption, the answer to whether subsidies should go to buyers or sellers has important implications for optimal tax dollar use in the U.S. electric vehicle market. Specifically, we study a unique rebate program in Connecticut (CHEAPR) that provides both consumer and dealer subsidies for each EV purchase. This program allows us to answer whether giving the same dollar to consumers or dealers leads to higher EV take-up.

2.1 U.S. Electric Vehicle Market

Electrification of transportation is widely seen as a crucial part of the solution to climate change and energy security. As a result, countries worldwide have set ambitious goals to promote electric vehicles and phase out gas-fueled cars entirely. For example, the U.S. government plans to have half of all new vehicles electric in 2030 (The White House (2021)). The European Union also aims to have at least 30 million zero-emission vehicles by 2030 and effectively ban new non-electric cars starting from 2035 (European Commission (2022)).

Since the high upfront cost remains one of the main barriers to EV adoption for consumers, national and state governments have employed a range of generous financial incentives to spur adoption. According to Kelley Blue Book (2021), the average transaction price for an electric vehicle is \$57,346. This is roughly \$17,000 higher than the average price of \$39,571 for all cars in the industry. To alleviate this high purchasing price, the U.S. government has spent billions of dollars on federal tax credits for EVs targeted explicitly toward consumers. State governments have also spent millions on various EV financial incentive programs. For example, according to Muehlegger and Rapson (2022), by 2020, California has spent roughly \$900 million on EV subsidies.

Thanks to these financial incentives, the EV market has grown exponentially and is expected to expand in the next decade. The number of EVs on the road jumped from about 22,000 to a little over 2 million over the 2011–2021 decade (BLS (2023)). EV market share has expanded from 0.17% in 2011 to 4.6% in 2021 (BLS (2023)). Furthermore, with increased consumer interest, battery technology advancement, and automakers' commitments to EVs, many forecasts expect a strong acceleration in the years to come. For example, S&P Global Mobility forecasts that EVs can account for 40 percent of total car sales by 2030 (BLS (2023)).

Despite the rapid growth in the last decade, the EV market has not reached maturity, and thus, subsidies have a key role in accelerating EV adoption. As battery technology improves and production costs become cheaper, the gap between EVs and gas-fueled cars is expected to shrink. For example, Bloomberg NEF (2021) optimistically forecasts that EVs will be cheaper to purchase, on average, within the next six years than conventional cars. However, until the market becomes more mature, it is essential that consumers can offset this price gap between EVs and conventional gas-fueled cars through financial incentives such as subsidies. Therefore, the answer to which side of the market (and how much) to subsidize can inform policymakers of a more effective way to maximize adoption under a budget constraint.

2.2 CHEAPR Program

The Connecticut Hydrogen and Electric Automobile Purchase Rebate (CHEAPR)[2] is the only EV incentive program in the U.S. that targets both buyers and sellers to accelerate adoption. In 2015, the Connecticut Department of Energy and Environmental Protection (DEEP) launched the CHEAPR pilot program to close the upfront price gap between EVs and conventional cars. Along with federal tax incentives, CHEAPR subsidies can reduce the cost of an EV by up to $9,000 (CHEAPR (2023)). After the launch of CHEAPR, annual sales of light-duty EVs in Connecticut increased from 616 units in 2012 to 2,304 units in 2017. The market share of EVs in Connecticut went from 0.69% in 2013 to 2.02% in 2018, in part with the help of CHEAPR (Alliance for Automotive Innovation (2021)).

Starting from May 19, 2015, consumers and dealers receive CHEAPR rebates for every purchase or lease of a new EV. Individual applicants are qualified to receive only one CHEAPR rebate (up to $3,000). The consumer can either choose to have the rebate applied to reduce the cost of the vehicle, or they may opt to retain the rebate, for example, to offset the cost of installing at-home charging equipment[3]. Dealerships receive up to $300 for each eligible vehicle sold or leased that received a CHEAPR incentive. Dealerships or manufacturer-owned or operated distribution locations that only sell BEVs (e.g., Tesla) do not qualify for a dealer incentive (CHEAPR (2023)).

To successfully reserve the funds for consumer and dealer subsidies, dealers must meet two deadlines. First, dealers are responsible for submitting CHEAPR applications on behalf of consumers no later than ten calendar days after the date of purchase or lease. Additionally, dealers must upload all supporting documents no later than 45 calendar days after the date of purchase or lease. If these deadlines are not met, the application will be canceled, and the rebate amount will be returned to the available program funds. Within ten calendar days from application approval, rebates will be issued to the dealership, leaser, or purchaser on a first-come, first-served basis based on receipt of complete applications (CHEAPR (2024)).

This unique program provides a novel quasi-experiment with temporal and cross-sectional variation to test if statutory incidence implies economic incidence. Since 2015, the program has undergone five reductions to consumer subsidies and three reductions to dealer subsidies. In addition, consumer subsidies vary across EV type and battery capacity: a car in the same EV type with higher battery capacity receives higher consumer subsidies. Dealer subsidies vary across brand groups ($0 for Tesla and positive for non-Tesla), EV type, and battery capacity (for parts of the program). Figure 3 illustrates the cross-sectional and temporal variation in consumer subsidies using examples of representative models. Figure 4 illustrates the cross-sectional and temporal variation in dealer

[2] portal.ct.gov/cheapr

[3] In the pilot program between May 2015 and May 2021, consumers are qualified to receive the rebate directly or transfer the rebate to the dealership. The majority of consumers (81%) assigned the rebate to the dealership (Johnson et al. (2016)). For many brands, the percentage of rebates assigned to dealerships reaches nearly 100% (Figure A3). Starting from June 2021, consumers are only qualified to transfer the rebate to the dealership who will deduct from the transaction price of the EV purchase.

subsidies using examples of representative models. The program eligibility and incentive amounts are summarized in Figure 2.

The state legislation passed in 2019 allocates \$3 million annually through the end of 2025 toward the CHEAPR program (Connecticut DEEP (2016)). This paper can offer CHEAPR program guidance on which side of the market and how much to subsidize going forward to maximize EV adoption, subject to this annual budget constraint. In addition, green-product incentive programs of various types are increasingly implemented in the U.S. and other countries. The effectiveness of the CHEAPR subsidy design has broader implications for optimal policy for other green products nationally and internationally.

Figure 1: Treated and Control States in this study

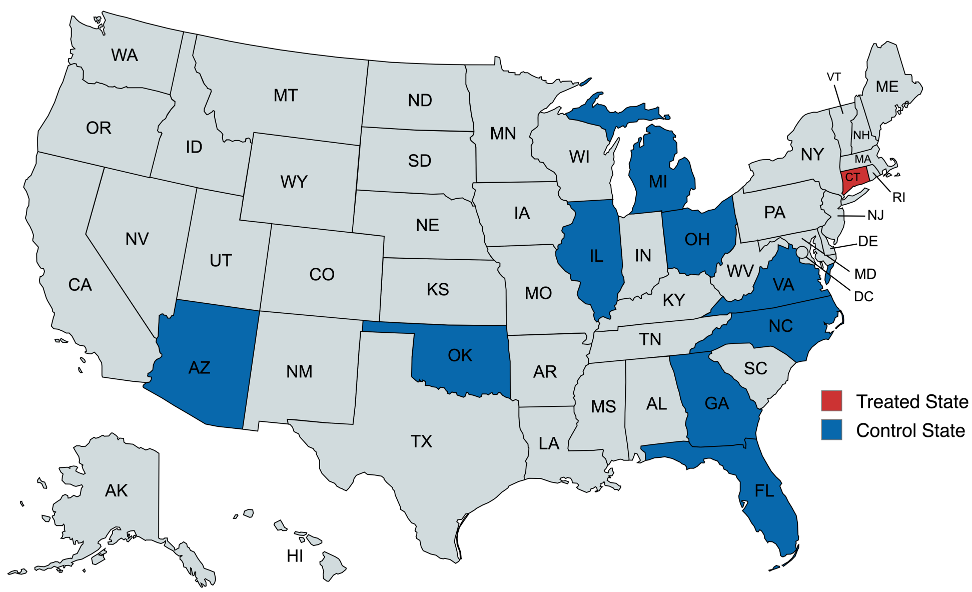
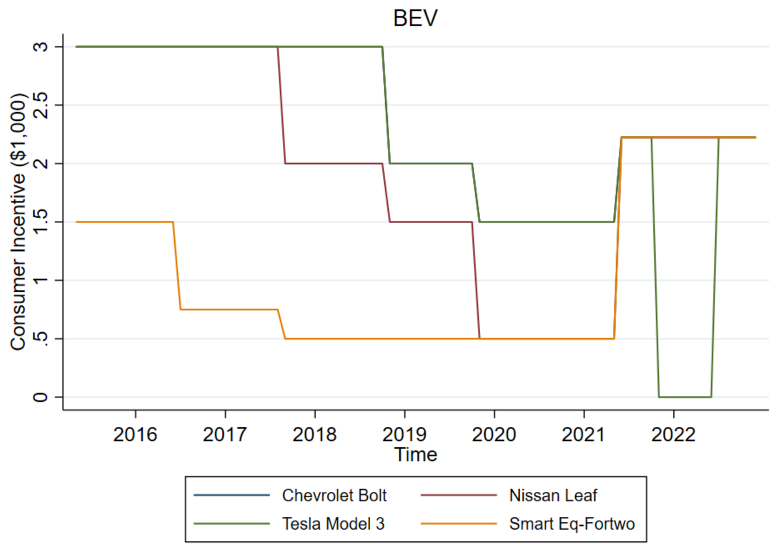


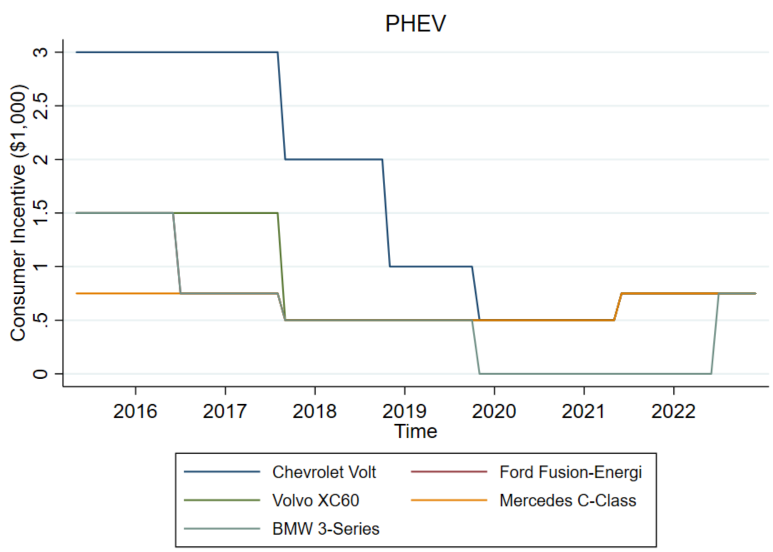
Figure 2: CHEAPR Eligibility Rule and Subsidy Amounts

	Consumer Incentive - BEV		Consumer Incentive - PHEV		Dealer Incentive		Max MSRP
	Rebate Amount	Required Battery Capacity	Rebate Amount	Required Battery Capacity	Rebate Amount	Eligibility	
5/9/15 - 6/30/16	\$3000 \$1500 \$750	$>$ 18 kWh 7-18 kWh $<$ 7 kWh	\$3000 \$1500 \$750	$>$ 18 kWh 7-18 kWh $<$ 7 kWh	\$300	Any vehicle eligible for consumer incentive	\$60,000
7/1/16 - 8/14/17	\$3000 \$1500 \$750	$>$ 25 kWh 20-25 kWh $<$ 20 kWh	\$3000 \$1500 \$750	$>$ 18 kWh 10-18 kWh $<$ 10 kWh	\$300	Any vehicle eligible for consumer incentive	\$60,000
8/15/17- 10/14/18	\$3000 \$2000 \$500	$\geq$ 175 mi 100-174 mi $<$ 100 mi	\$2000 \$500	$\geq$ 40 mi $<$ 40 mi	\$150	Any vehicle eligible for consumer incentive	\$60,000
10/15/18- 10/14/19	\$2000 \$1500 \$500	$\geq$ 200 mi 120-199 mi $<$ 120 mi	\$1000 \$500	$\geq$ 45 mi $<$ 45 mi	\$150	Any vehicle eligible for consumer incentive	\$50,000
10/15/19- 6/06/21	\$1500 \$500	$\geq$ 200 mi $<$ 200 mi	\$500	Any PHEV	\$125 \$75	200+ mi range Other eligible vehicles	\$42,000
6/7/21- 6/30/22	\$2250	Any BEV	\$750	Any PHEV	\$125 \$75	Eligible BEV Eligible PHEV	\$42,000
7/1/22- 12/31/22	\$2250	Any BEV	\$750	Any PHEV	\$125 \$75	Eligible BEV Eligible PHEV	\$50,000

Figure 3: Consumer incentive variation over time, EV type, and battery capacity



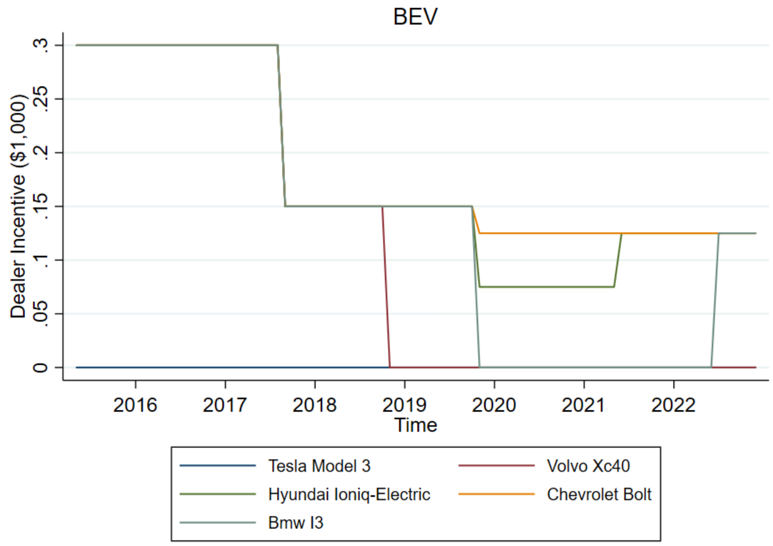
(a) BEV



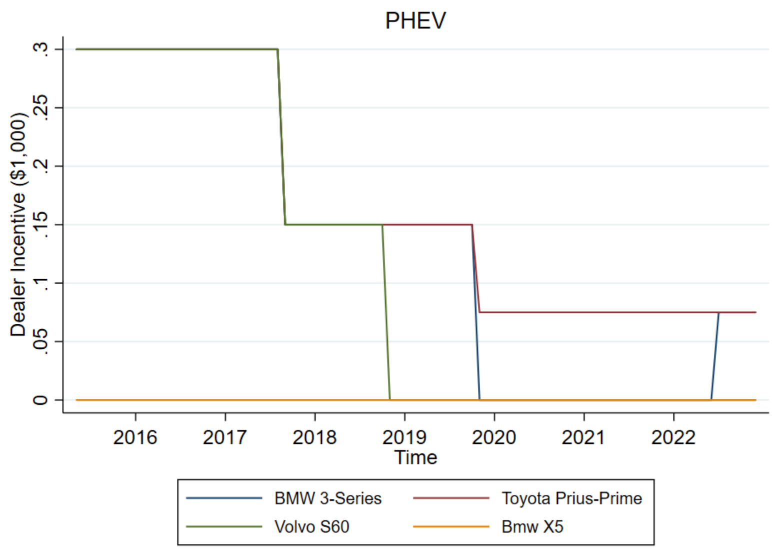
(b) PHEV

Note: The figures above plot the consumer subsidy amount for representative EV models under the CHEAPR program. These figures illustrate the cross-sectional and temporal variation in consumer subsidies.

Figure 4: Dealer incentive variation over time, EV type, and battery capacity



(a) BEV



(b) PHEV

Note: The figures above plot the dealer subsidy amount for representative EV models under the CHEAPR program. These figures illustrate the cross-sectional and temporal variation in dealer subsidies.

3 Data

We compiled a rich dataset of new car purchases in CT and nine other states (Figure 1) from 2018 to 2022 using several data sources. Our main dataset is vehicle registration data from the U.S. car market collected by S&P Global Mobility. We supplement this dataset with data on charging stations, fuel economy, fuel cost, state and federal incentives, and demographics.

Our vehicle registration dataset contains monthly new vehicle registrations at the state level for every car model. Each vehicle model is defined as a make, model name, model year, fuel type, trim, and style. Following previous literature on demand estimation for the automobile market, we treat new registrations as sales. For each model sold in a state in a month, we observe the reported transaction prices. To our best knowledge, these are the prices excluding any subsidies or discounts.

We obtain a wide range of car characteristics using DataOne's VIN Decoder. These characteristics include but are not limited to MSRP, vehicle size (length, height, width), vehicle weight (curb weight, wheelbase), horsepower, fuel economies, and battery capacity. We obtain the publicly available dataset listing the number of charging stations from the EIA and aggregated the number of charging stations to the state-month level. We collect monthly fuel costs (including gas, electricity, and diesel prices) for each state in our dataset from EIA and supplement this data with EPA data on electric range and fuel economy. We can calculate dollar-per-miles for each model using the fuel cost and fuel economy.

We also obtain demographics at the state level from the American Community Survey (ACS), such as income per capita and population. We use ACS data to build income distributions at the state-month level for the structural model. Using the household income draws from the ACS data, we can fit the mean and variance of a log-normal distribution.

We obtain the CHEAPR program rule on consumer and dealer subsidies for EVs from the program's website. In addition, we gather information on other states' consumer subsidies and federal credits from the Alternative Fuels Data Center (AFDC). This information allows us to assign state—and federal-level subsidy amounts for each EV model.

For the demand estimation, we aggregate the data up to the state-month-product level where a product is defined as a make/model/model year/fuel type (e.g., 2018 Chevrolet Volt PHEV). Fuel types include gasoline, hybrid, battery electric (BEV), plug-in hybrid (PHEV), diesel, and flex-fuel. We use the characteristics of the most frequently sold trim for each product. We reduce the size of the data further by leaving out cars with MSRP above $110,000 and keeping only new car purchases. For estimation tractability, we set the potential market size equal to the total number of cars registered in a given state each year. The final data consists of 363,100 product-month-state product observations. Tables 1 and 2 provide detailed summary statistics.

Table 1: Summary Statistics for CT

	2018	2019	2020	2021	2022
BEV					
Transaction Price	45.753	52.931	53.834	51.491	58.631
Net Price	36.678	46.418	48.595	45.883	54.133
Consumer Incentive	1.575	0.910	0.482	0.674	0.786
Dealer Incentive	0.102	0.070	0.043	0.043	0.042
Federal Credit	7.500	5.604	4.757	4.934	3.712
Sales	1368	1870	2214	4312	4742
Dollar-per-mile	0.07	0.08	0.08	0.08	0.10
Curb weight	3682	4079	4267	4296	4721
PHEV					
Transaction Price	44.812	45.433	51.919	49.238	53.091
Net Price	38.958	39.606	45.883	42.982	47.413
Consumer Incentive	0.532	0.377	0.184	0.239	0.269
Dealer Incentive	0.104	0.085	0.028	0.028	0.027
Federal Credit	5.322	5.450	5.852	6.017	5.409
Sales	1481	812	741	2432	2163
Dollar-per-mile	0.13	0.14	0.15	0.17	0.20
Curb weight	4210	4172	4436	4455	4585
Non-EV					
Transaction Price	36.849	38.733	40.262	42.624	45.198
Net Price	36.849	38.733	40.262	42.624	45.198
Consumer Incentive	0	0	0	0	0
Dealer Incentive	0	0	0	0	0
Federal Credit	0	0	0	0	0
Sales	160401	141843	106087	107202	76899
Dollar-per-mile	0.14	0.14	0.15	0.18	0.21
Curb weight	3993	4024	4083	4149	4180

Notes: Mean values of key characteristics for treated state

Table 2: Summary Statistics for Other States

	2018	2019	2020	2021	2022
BEV					
Transaction Price	44.384	51.330	57.317	55.245	64.196
Net Price	36.884	45.670	52.867	50.488	60.498
Consumer Incentive	0	0	0	0	0
Dealer Incentive	0	0	0	0	0
Federal Credit	7.500	5.659	4.451	4.757	3.698
Sales	1573.6	1829.4	1924.7	3764	4569.5
Dollar-per-mile	0.07	0.08	0.08	0.09	0.10
Curb weight	3745	4046	4306	4323	4727
PHEV					
Transaction Price	44.650	44.850	54.774	54.889	57.986
Net Price	39.319	39.426	48.861	48.771	52.567
Consumer Incentive	0	0	0	0	0
Dealer Incentive	0	0	0	0	0
Federal Credit	5.331	5.423	5.913	6.118	5.419
Sales	938.4	615.9	463.8	1707.9	1768.9
Dollar-per-mile	0.13	0.14	0.15	0.17	0.20
Curb weight	4234	4177	4460	4502	4590
Non-EV					
Transaction Price	36.832	39.402	42.751	47.101	50.012
Net Price	36.832	39.402	42.751	47.101	50.012
Consumer Incentive	0	0	0	0	0
Dealer Incentive	0	0	0	0	0
Federal Credit	0	0	0	0	0
Sales	317609	285039	203273	186753	135926
Dollar-per-mile	0.14	0.14	0.15	0.19	0.21
Curb weight	4007	4031	4096	4173	4186

Notes: Mean values of key characteristics for control states that do not have any incentive for EVs during the 2018-2022 time period

4 Impacts of Consumer and Dealer Subsidies on EV Prices and Sales

In this section, we estimate the effects of consumer and dealer subsidies on EV prices and sales. We begin with the reduced-form model specification used to estimate these effects. This is followed by an event-study approach, where we separately estimate the effect of consumer and dealer subsidies on EV sales and prices.

4.1 EV Prices

We estimate the effect of consumer and dealer subsidies on the out-of-pocket price that customers pay for EVs. Exploiting the cross-sectional and temporal variation in both consumer and dealer subsidy levels, we estimate the following specification:

$$P^c_{jst} = \theta_c CustSub_{jst} + \theta_d DealerSub_{jst} + \beta_1 FedCredit_{jt} + \beta_2 X_{jst} + \mu_j + \mu_s + \mu_{Jt} + \epsilon_{jst} \tag{1}$$

Our dependent variable, denoted by P^c_{jst}, is consumers' out-of-pocket for vehicle j at month i in state s. P^c_{jst} equals the transaction price less consumer subsidies at the state level and federal credit. A vehicle j is defined at a granular level: make - model – model year – fuel – trim level. $CustSub_{jst}$ and $DealerSub_{jst}$ are the consumer and dealer subsidy amount available for vehicle j at month t in state s. Since most EVs during this time are also eligible for federal credit, we include the amount of federal credit as a control variable. X_{jst} is a vector of control variables, including MSRP, number of charging stations, horsepower, curb weight, years since vehicle introduction, body type, and drive type. μ_j are vehicle fixed effects where a vehicle is defined as the combination of make and model (e.g. Chevrolet Bolt). μ_s are state fixed effects. μ_{Jt} are month-EV type fixed effects where J is the EV type (BEV or PHEV) containing vehicle j and t is the month vehicle j is purchased. Our data covers 60 months and 10 states.

Our main parameters of interest are θ_c and θ_d, measuring the extent to which consumer and dealer subsidies affect the out-of-pocket price consumers pay for EVs. These coefficients can be interpreted as the fraction of consumer and dealer subsidies passed through to consumers. Either θ_c or θ_d equal to 0 would imply that none of the subsidy amounts is passed through to consumers. In this case, the dealer is the only beneficiary of the respective subsidy. On the other hand, either θ_c or θ_d equal to -1 would imply that consumers obtain the total amount of the respective subsidy. We can interpret $100 \cdot |\theta_c|$ as the percentage of consumer subsidy that the consumer obtains and $100 \cdot |\theta_c|$ as the percentage of dealer subsidy that the consumer obtains.

In our model specification, we use prices of similar EVs that are not receiving subsidies to estimate the counterfactual prices of EVs that receive subsidies at a given month. In our analysis, we implement this by incorporating the month-EV type fixed effects to control for underlying changes in price. We assume that other vehicles in the same EV type (BEV or PHEV) that are not receiving subsidies in a given month are a valid counterfactual for the prices that would have been obtained in the absence of subsidies.

Table 3 reports the estimated results of Eq 1. Column 5 is our preferred model specification. The coefficient of consumer subsidy suggests a decrease in EV prices of approximately \$730 per thousand dollars of consumer subsidy. This implies that around 73% of consumer subsidy is passed through to consumers. The coefficient of dealer subsidy is statistically indistinguishable from zero. This implies that none of the dealer subsidies are passed on to consumers. We also find a negative and significant effect of federal credit on EV prices, implying that most of the federal credit (71%) is passed through to consumers.

We confirm these findings using an event-study approach. In the event-study approach, we analyze only EV purchases that took place nine months before and after a consumer or dealer subsidy reduction. To identify the effect of consumer subsidy separately, we restrict the data to a set of EVs that experienced a $1000 reduction in consumer subsidy only in October 2018 (no change in dealer subsidy). To identify the effect of dealer subsidy separately, we restrict the data to a set of EVs that experienced a 50% reduction in dealer subsidy only (from $150 to $75) in October 2019 (no change in consumer subsidy). In both cases, EVs purchased in CT are the treated group, and the same EVs purchased in other states belong to the control group. We estimate the following model specification:

$$P^c_{jst} = \sum_{k=-9}^{k=9} \delta_k \cdot (Treat_{js} \cdot 1[t=k]) + X_{jt} + \mu_j + \mu_t + \mu_s + \epsilon_{jts} \tag{2}$$

Our dependent variable is the out-of-pocket price consumers pay for vehicle j at time t in state s. t denotes months since the reduction of one of the subsidies, meaning t=0 for treatment month, t is negative for before-treatment months, and t is positive for after-treatment months. $Treat_{js}$ is a binary variable equal to 1 for EVs purchased in CT (treated state) and 0 for EVs purchased in other states. $1[t=k]$ is a binary variable for each time period. X_{jt} include federal credit amount and MSRP. μ_s are state fixed effects. μ_j are make-model fixed effects. μ_t are month fixed effects.

Our parameters of interest are the δ_k. $\delta_{-9}, \delta_{-8}, ..., \delta_{-2}$ denote the effect for months before one of the subsidies decreases. Similarly, $\delta_0, \delta_1, ..., \delta_9$ denote the effect for months after one of the subsidies decreases. We omit the effect at t=-1, and thus, when interpreting the results, everything is relative to that omitted effect.

Figure 5 shows the estimated coefficients of Eq 2 where a subset of EVs saw a $1000 reduction in consumer subsidy only. We did not see many changes in EV prices for a few months before the reduction of consumer subsidies. Once the reduction occurs, we see significant EV price increases two months later. Before the subsidy reduction, the average price difference between the treated and control groups is approximately $1,067. This difference increases to $1,640 after the consumer subsidy reduction. In other words, a $1,000 decrease in consumer subsidy results in $571 increase in EV prices. This implies that the consumer obtains nearly 60% of the consumer subsidy, which is in the 95% confidence interval of the effect of consumer subsidy found in the previous regression. The result of this event-study approach confirms our finding that consumers obtain the majority of consumer subsidies.

Figure 6 plots the estimated coefficients of Eq 2 where a subset of EVs saw a 50% reduction in dealer subsidy from $150 to $75. When the dealer subsidy reduction takes effect, we do not see any significant changes in EV prices. In other words, a 50% decrease in dealer subsidy results in zero change in EV prices. This confirms our previous finding that consumers do not obtain any part of the dealer subsidy.

4.2 EV Sales

In this section, we study the extent to which consumer and dealer subsidies affect EV purchases. We aggregate data to vehicle-month-state level where a vehicle is now defined as combination of make-model (e.g. Chevrolet Bolt). We estimate the following model specification to identify the effects of consumer and dealer subsidies on EV sales:

$$log(\text{Sales Per Cap}_{jst}) = \alpha_c CustSub_{jst} + \alpha_d DealerSub_{jst} + \beta_1 FedCredit_{jt} + \beta_2 X_{jst} + \mu_{Js} + \mu_{Jt} + \epsilon_{jst} \tag{3}$$

Our dependent variable, denoted by $log(\text{Sales Per Cap}_{jst})$, is the log of electric vehicle j sales per thousand residents in state s in month t. $CustSub_{jst}$ and $DealerSub_{jst}$ are the consumer and dealer subsidy amount available for vehicle j at month t in state s. Since most EVs during this time are also eligible for federal credit, we include the amount of federal credit as a control variable. X_{jst} is a vector of control variables including car characteristics (log(horsepower/curb weight), years since vehicle introduction, body type, drive type), number of available charging stations, dollar-per-mile, state direct sales policy and state demographics (per capita income and population). μ_{Js} denotes state-make fixed effects. μ_{Jt} denotes month-make fixed effects. ϵ_{jst} denotes the error term. We allow each state to have a separate time-invariant preference for each EV brand with state-make fixed effects. We control for national trends in vehicle sales, vehicle availability, EV policies, and macroeconomics by incorporating month-make fixed effects.

Our parameters of interest are α_c and α_d. α_c denotes the percentage change in EV sales per capita for a \$1,000 consumer subsidy. Similarly, α_d denotes the percentage change in EV sales per capita for a \$1,000 dealer subsidy. We identify these two coefficients off cross-state variation in EV brand sales trends.

Table 4 presents the estimated results for Eq 3 on various sets of explanatory variables. Column 3 is our preferred specification. The results suggest an increase in per capita EV sales of approximately 4.5% per thousand dollars of consumer subsidy. This estimate is positive, statistically significant, and robust across different specifications. However, we do not find a statistically significant effect of dealer subsidy on EV sales. Therefore, we cannot reject the hypothesis that dealer subsidy has no effect on EV sales. Unsurprisingly, we find strong evidence that federal credit is positively correlated with EV adoption. A \$1,000 increase in federal credit is associated with a 4.2% increase in EV sales.

We further confirm our findings from this model specification by using an event-study approach. In the event-study approach, we analyze only EV purchases that took place nine months before and after a consumer or dealer subsidy reduction. To identify the effect of consumer subsidy separately, we restrict the data to a set of EVs that experienced a \$1000 reduction in consumer subsidy only in October 2018 (no change in dealer subsidy). To separately identify the effect of dealer subsidy, we restrict the data to a set of EVs that experienced a 50% reduction in dealer subsidy only (from \$150 to \$75) in October 2019 (no change in consumer subsidy). In both cases, EVs purchased in CT are the treated group, and the same EVs purchased in other states belong to the control group. We estimate the following model specification:

$$log(\text{Sales Per Cap}_{jst}) = \sum_{k=-9}^{k=9} \delta_k \cdot (Treat_{js} \cdot 1[t = k]) + X_{jst} + \mu_j + \mu_t + \mu_s + \epsilon_{jts} \tag{4}$$

The dependent variable, denoted by $log(\text{Sales Per Cap}_{jst})$, is the log of electric vehicle j sales per thousand residents in state s in time t. t denotes months since the reduction of one of the subsidies, meaning t=0 for treatment month, t is negative for before-treatment months, and t is positive for after-treatment months. $Treat_{js}$ is a binary variable equal to 1 for EVs purchased in CT (treated state) and 0 for EVs purchased in other states. $1[t = k]$ is a binary variable for each time period. X_{jst} is a vector of control variables, some of which are defined by only j and t (federal credit), some depend on s and t (number of charging stations, direct sales dummies, income per capita, population) and some depend on all three (dollar-per-mile). μ_j are make-model fixed effects. μ_t are month fixed effects. μ_s are state fixed effects.

Our parameters of interest are the δ_k. $\delta_{-9}, \delta_{-8}, ..., \delta_{-2}$ denote the effect for months before one of the subsidies decreases. Similarly, $\delta_0, \delta_1, ..., \delta_9$ denote the effect for months after one of the subsidies decreases. We omit the effect at t=-1, and thus, when interpreting the results, everything is relative to that omitted effect.

Figure 5 plots the estimated coefficients of Eq 4 in the case where a subset of EVs saw a \$1000 reduction in consumer subsidy only. We do not observe significant changes in EV sales for many months before the reduction of consumer subsidy. After the reduction takes place, there are significant reductions in EV sales starting in month 3. On average, before the subsidy reduction, the difference in average per capita EV sales between the treated and control groups is 2.6%. This difference is -2.7% after the consumer subsidy reduction. In other words, a \$1000 decrease in consumer subsidy results in a 5.6% decrease in per capita EV sales. This estimate is within the 95% confidence interval of the effect of consumer subsidy on EV sales in Eq 3. This result confirms that consumer subsidies significantly increase EV adoption.

Figure 6 illustrates the estimated coefficients from Equation 4, focusing on a scenario where a subset of EVs experienced a 50% reduction in dealer subsidies, dropping from \$150 to \$75. Despite this reduction, there are no noticeable changes in per capita EV sales. In other words, a 50% decrease in dealer subsidies leads to no measurable impact on EV adoption. This reinforces our earlier conclusion that dealer subsidies have a negligible effect on promoting EV adoption

The results from the reduced-form model highlight the distinct impacts of consumer and dealer subsidies on EV market outcomes. Specifically, a reduction in consumer subsidies leads to significant price increases and a noticeable drop in EV adoption, underlining their effectiveness in influencing consumer behavior and market outcomes. On the other hand, dealer subsidies appear to have little to no effect on prices or sales, suggesting they are less effective tools for promoting EV adoption. This sets the stage for a deeper inquiry into the underlying mechanisms and the potential for more targeted subsidy allocation to optimize both economic and environmental objectives.

Table 3: Effect of Consumer and Dealer Incentive on EV Price

	(1) Net Price	(2) Net Price	(3) Net Price	(4) Net Price	(5) Net Price
Consumer Incentive	-0.613***	-0.636***	-0.764***	-0.708***	-0.730***
	(0.113)	(0.110)	(0.118)	(0.121)	(0.117)
Dealer Incentive	7.430	7.654	5.363	4.136	4.268
	(7.313)	(7.340)	(7.100)	(7.206)	(7.116)
Federal Credit	-0.783***	-0.732***	-0.745***	-0.711***	-0.711***
	(0.0430)	(0.0641)	(0.0706)	(0.0717)	(0.0761)
MSRP	0.661***	0.661***	0.658***	0.467***	0.472***
	(0.0126)	(0.0126)	(0.0143)	(0.0303)	(0.0292)
Years since intro		-0.748	-0.742	-0.712	-0.706
		(0.460)	(0.463)	(0.461)	(0.463)
Charging Station			0.00223***	0.00225***	0.00226***
			(0.000422)	(0.000390)	(0.000391)
Log(Horsepower/Curbweight)				11.86***	12.16***
				(1.395)	(1.577)
Constant	20.15***	19.94***	14.14***	55.13***	55.65***
	(0.634)	(0.681)	(0.706)	(5.618)	(5.822)
Month×EV-type FE	Y	Y	Y	Y	Y
State FE	Y	Y	Y	Y	Y
Make-model FE	Y	Y	Y	Y	Y
Body-type FE					Y
Drive-type FE					Y
Observations	180896	180896	180896	180896	180896
Mean Net Price	51.51	51.51	51.51	51.51	51.51
R^2	0.825	0.825	0.826	0.831	0.831

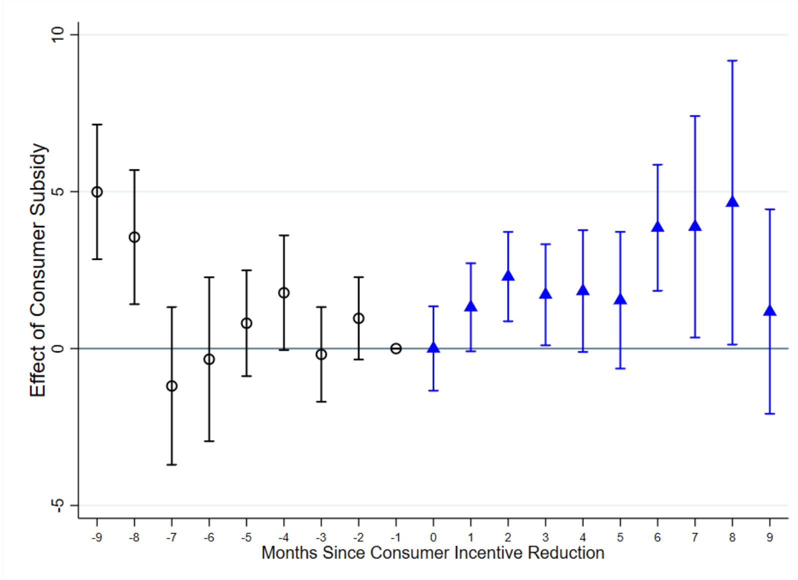
Notes: * $p < 0.1$, ** $p < .05$, *** $p < .01$. Standard errors clustered at the state level. This table reports the effects of consumer and dealer incentives on consumer's out-of-pocket prices, which equal transaction prices less consumer subsidy and federal credit. Column 5 is our preferred model specification, corresponding to Eq (1).

Table 4: Effect of Consumer and Dealer incentive on EV Sales

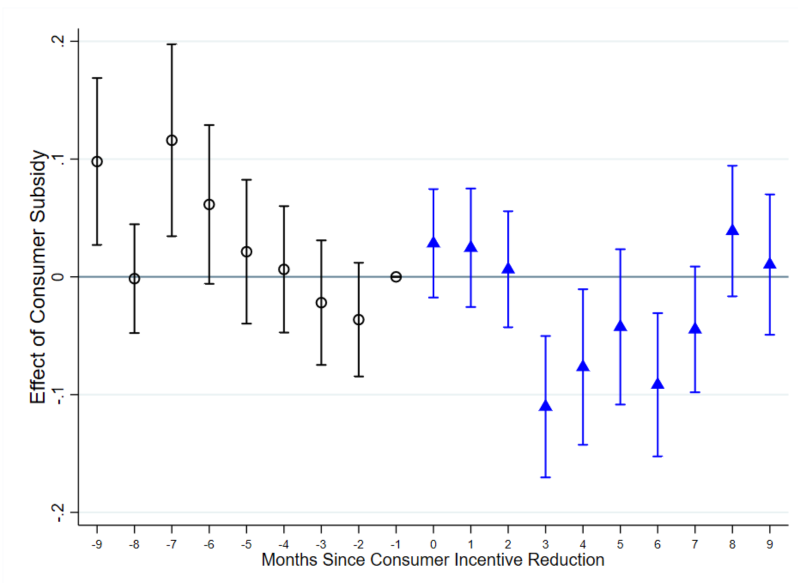
	(1) log(sales per capita)	(2) log(sales per capita)	(3) log(sales per capita)
Consumer Incentive	0.0641***	0.0440**	0.0446**
	(0.0152)	(0.0170)	(0.0185)
Dealer Incentive	0.220	0.319	0.364
	(0.365)	(0.455)	(0.455)
Federal Credit	0.0474***	0.0415***	0.0415***
	(0.00935)	(0.00709)	(0.00710)
Years since intro	-0.400***	-0.408***	-0.408***
	(0.0601)	(0.0603)	(0.0600)
Log(Horsepower/Curbweight)	-0.579***	-0.588***	-0.589***
	(0.144)	(0.144)	(0.143)
Charging Station		-0.0000677***	-0.0000393
		(0.0000187)	(0.0000297)
Dollar-per-mile		-1.366*	-1.377
		(0.735)	(0.756)
Income per cap			-0.0334*
			(0.0168)
Population			-0.00000827
			(0.0000899)
Constant	-9.045***	-8.722***	-6.766***
	(0.411)	(0.389)	(1.468)
State $\times$ Make FE	Y	Y	Y
Make $\times$ Month FE	Y	Y	Y
Bodytype	Y	Y	Y
Drivetype	Y	Y	Y
Observations	18183	17854	17854
R^2	0.658	0.659	0.660

Notes: * $p < 0.1$, ** $p < .05$, *** $p < .01$. Standard errors clustered at the state level. This table reports the effects of consumer and dealer incentives on per capita EV sales. Column 3 is our preferred model specification, corresponding to Eq (3).

Figure 5: Event-Study: Effects of Consumer Incentive Reduction



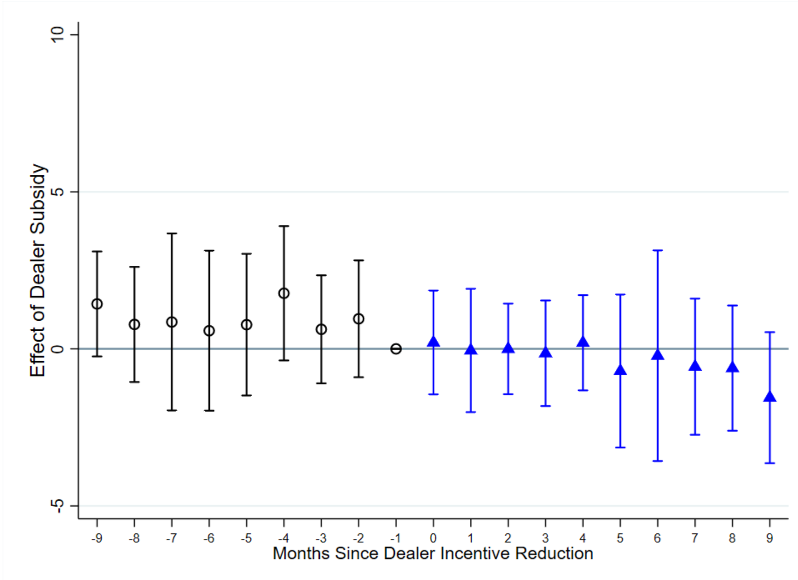
(a) EV Prices



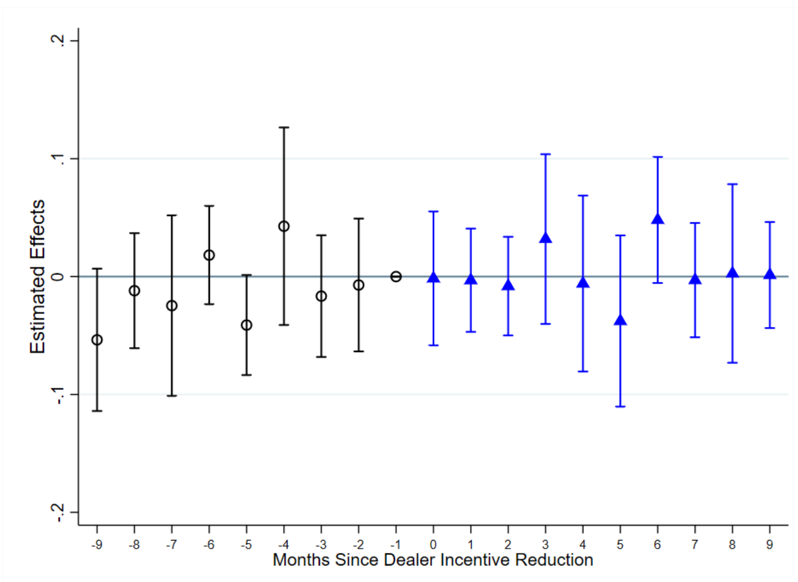
(b) EV Sales

Note: The figures above plot estimates from Eq.(2) and Eq.(4) and show the difference in EV prices and sales between treated and control states in the months leading up to and after the $1,000 reduction in consumer incentive. To separately identify the effect of consumer incentives, we restrict the data to a set of EVs that experienced a $1000 reduction in consumer subsidy only in October 2018 (no change in dealer incentive). The solid horizontal line denotes a point estimate of zero. The whiskers represent 95 percent confidence intervals.

Figure 6: Event-Study: Effects of Dealer Incentive Reduction



(a) EV Prices



(b) EV Sales

Note: The figures above plot estimates from Eq.(2) and Eq.(4) and show the difference in EV prices and sales between treated and control states in the months leading up to and after the 50% reduction in dealer incentive. To separately identify the effect of dealer subsidy, we restrict the data to a set of EVs that experienced a 50% reduction in dealer subsidy only (from $150 to $75) in October 2019 (no change in consumer subsidy). The solid horizontal line denotes a point estimate of zero. The whiskers represent 95 percent confidence intervals.

5 Empirical Model

The reduced-form analysis suggests consumer subsidies are more effective than dealer subsidies in reducing upfront purchasing costs and increasing EV adoption. However, we require a structural model to further understand the mechanisms at play and explore how subsidies can be allocated more efficiently while keeping total subsidy spending constant. This model allows us to capture more realistic substitution patterns and incorporate the equilibrium effects on the supply side—elements that are not fully accounted for in the linear reduced-form model.

In this section, we introduce a structural model of demand and supply for new car purchases. This will enable us to examine the effects of both types of subsidies on dealer pricing decisions and conduct various policy counterfactuals to identify the optimal subsidy allocation. The model focuses on two key economic agents: heterogeneous consumers who make purchase decisions to maximize utility and dealers who set prices to maximize profits. Additionally, the marginal cost function is specified to allow for differential responses by dealers to consumer and dealer subsidies, as indicated by the reduced-form results.

5.1 Vehicle Demand

Consumer vehicle demand follows the discrete-choice framework of Berry et al. (1995). Consumers choose the vehicle, maximizing their indirect utility and exhibiting heterogeneous preferences over prices. A market t is defined as a state observed in a month. Each consumer i chooses one of the differentiated products j where $j = 1, ..., J$ or chooses the outside option $j = 0$. The outside option here is not buying a new vehicle. Consumer i's indirect utility from purchasing a vehicle j is given by:

$$u_{ijt} = \delta_{jt} + \mu_{ijt} + \epsilon_{ijt}$$

$$u_{ijt} = \alpha p^c_{jt} + \beta X_{jt} + \xi_{jt} + \Sigma p^c_{jt}\nu_i + \Pi \frac{p^c_{jt}}{y_i} + \epsilon_{ijt} \tag{5}$$

The mean utility, δ_{jt}, is common to all consumers within a state and month. μ_{ijt} is the mean-zero individual deviation from the mean utility. ϵ_{ijt} is a consumer-specific unobserved taste shock assumed to be i.i.d. Type-I extreme value distributed.

In the mean utility, p^c_{jt} is the consumers' purchase price. Consumers pay a purchase price equal to reported transaction prices less state subsidies and federal subsidies. State subsidies vary across fuel types, vehicle models, and markets. Federal subsidies vary across fuel type, vehicle models, and time. X_{jt} is a vector of product fixed effects that capture all vehicle characteristics and control variables. ξ_{jt} is an unobserved characteristic of vehicle j in market mt.

μ_{ijt} denotes individual deviation from the mean utility. In the individual deviation from the mean utility, ν_i is drawn from a standard normal distribution. Individual income, denoted by y_i, follows a log-normal distribution.

Consumer i chooses vehicle j if $U_{ijt} \geq U_{ij't}$ for all $j^{'}$. The market share for vehicle j is obtained by integrating over individual choices:

$$s_{jt} = \int\int \frac{exp(\delta_{jt} + \mu_{ijt})}{1 + \sum_{k=1}^{J} exp(\delta_{kt} + \mu_{ikt})} dF(\nu)dG(y) \tag{6}$$

where F(.) is the joint CDF of the unobserved taste shocks and G(.) is the income distribution. The observed market share is defined as $s_{jt} = \frac{q_{jt}}{M_t}$ where q_{jt} is the observed quantity of vehicle j, and M_t is the number of consumers in each market. We defined M_t as the total number of car registrations in a year in each state.

5.2 Vehicle Supply

We model the profit-maximizing price of multi-product dealers for each month. We take the product and characteristics set to be given. Dealers receive the transaction price p_{jt}^{trans} from consumers, which equals the consumer's purchase price plus state and federal subsidies, $p_{jt}^c + cinc_{jt} + fed_{jt}$, and the dealer incentive directly from the state, $dinc_{jt}$. Dealers thus maximize profits by setting consumer prices of all available vehicles at the state level. Dealer f's profit maximization problem is given by:

$$\max_{p^c} \pi_{ft} = \sum_{j \in J_{ft}} (p_{jt}^c + cinc_{jt} + fed_{jt} + dinc_{jt} - mc_{jt}) s_{jt} M_t \tag{7}$$

This supply model accommodates the consumer and dealer incentives in CT. p_{jt}^c is the out-of-pocket price paid by consumers, $cinc_{jt}$ is the consumer incentive, $dinc_{jt}$ is the dealer incentive and fed_{jt} is the federal credit. Then, the transaction price received by dealers is $p_{jt}^c + cinc_{jt} + fed_{jt}$. mc_{jt} denotes the marginal cost of selling vehicle j in market t. M_t is the size of market t and s_{jt} is the market share. The first-order conditions can be expressed as:

$$\frac{d\pi_{ft}}{dp_{jt}^c} = s_{jt} + \sum_{k \in J_{ft}} (p_{kt}^c + cinc_{kt} + fed_{kt} + dinc_{kt} - mc_{kt}) \frac{ds_{kt}}{dp_{jt}^c} = 0 \tag{8}$$

Assuming Nash Bertrand competition in prices, from the first-order conditions (Eq 9), we can back out markups and marginal costs. Let Δ_p be a JxJ matrix with entry k and l such that $\Delta_{lk} = \frac{ds_{kt}}{dp_{jt}^c}$ if k and l are sold by the same firm and zero otherwise. The first-order conditions and marginal cost (net of subsidies) can be rewritten as:

$$s + (p^c + cinc + fed + dinc - mc)\Delta_p = 0 \tag{9}$$

$$\widehat{MC} = mc - cinc - fed - dinc = p^c + s\Delta_p^{-1} \tag{10}$$

where s is the vector of market shares. The markup is given by this term, $s\Delta_p^{-1}$. p^c is the vector of consumers' purchase prices. mc is the vector of marginal costs. $cinc$, $dinc$, and fed are vectors of consumer subsidy, dealer subsidy, and federal credit, respectively. Thus, $\widehat{MC}$ denotes marginal costs net of state, federal, and dealer subsidies. The expression of net marginal cost implies that an increase in either consumer or dealer subsidy is equivalent to a marginal cost decrease for the dealers.

5.3 Marginal Cost Specification

We specify a log-linear marginal cost function. The marginal cost function is given by:

$$log(\widehat{MC}_{jt}(q_j t, \omega_j t; \theta_s)) = \gamma w_{jt} + \omega_{jt} \tag{11}$$

where w_{jt} are vehicle characteristics and observed cost-shifters and ω_{jt} captures unobserved cost shocks. We let the marginal cost function depend on consumer subsidy, dealer subsidy, federal credit, purchase time, and several observed vehicle characteristics, such as EV type, size, weight, and battery size. By including the incentives on the right-hand side, we allow dealers to react differently to the consumer and dealer subsidies. We also include firm, state, and drive-type fixed effects. All remaining unobserved cost-shifters are included in the ω_{jt} term. The vector of parameters to be estimated is γ.

6 Estimation

In this section, we discuss the identification and estimation of the demand and cost parameters. We first describe the demand and supply instruments used in our analysis to overcome the endogeneity issue and identify the parameters of interest. This is followed by a discussion of our approach to dealing with zero market share and the estimation of demand and supply models.

6.1 Identification

Estimation of the demand-side parameters suffers from an endogeneity issue. Price choices may be correlated with unobserved vehicle characteristics. In this analysis, we hold the standard assumption that other product characteristics besides prices are exogenous. Instruments are used to overcome this endogeneity issue and help identify the price and random coefficients.

Gandhi and Houde (2019) pointed out that the classic BLP instruments (sums of product characteristics) perform poorly and proposed differentiation IVs for demand estimation. We use two sets of differentiation IVs.

The first set is local instruments that count products close in characteristic space. These include those considering own-firm products and those considering rival-firm products: $Z_{jt}^{D,k,local} = \sum_{l\in J\setminus\{l\}}\{1|d_{jlt}^k| < sd(d^k)\}$. $|d_{jlt}^k|$ is the absolute value of the difference between products j and l in vehicle characteristics k, $sd(d^k)$ is the standard deviation of characteristics k across all markets, and J denotes the set of products. We build the local instruments for continuous characteristics such as curb weight and wheelbase. In addition, we also build local instruments for a price index, which we obtain from regressing the out-of-pocket price that the consumers pay on demand and cost shifters.

The second set is a discrete instrument that counts the number of products with the same values of characteristics: $Z_{jt}^{D,k,discrete} = \sum_{l\in J\setminus\{l\}} 1\{|d_{jlt}^k| = 0\}$ where $|d_{jlt}^k|$ is the absolute value of the difference between products j and l in vehicle characteristics k as before. This set of instruments includes those considering own-firm products and those considering rival-firm products of the same drive type, body type, and number of doors. We also create discrete instruments for EV type.

These two sets of differentiation instruments shift markups and thus help identify price sensitivity parameters. In particular, these instruments allow a car that faces stronger competition to earn a lower markup, and a car with little or no competition in a characteristic space would see a higher markup due to limited substitution to similar products.

We also use another set of price instruments to identify price coefficients. These include state EV incentives, federal EV incentives, and manufacturing wages. Federal EV subsidies vary by fuel type, battery capacity, and over time. Conditional on fuel type and battery capacity, this instrument is uncorrelated with unobservables. We assume that dealers do not choose components of unobservables based on the federal subsidy.

State EV incentives vary by state and vehicle and over time. Conditional on state fixed effects, changes in state subsidies over time, differences in subsidies across states or vehicles, and differences in subsidies across car models within states are uncorrelated with unobservables. To the best of our knowledge, the timing of changes in state subsidies was not announced very far in advance. The structure of the subsidies is also exogenous after controlling for characteristics such as range or battery capacity.

State and product fixed effects are included in all specifications. State fixed effects help control state-level factors that are invariant between 2018 and 2022, such as the public inclination to be green. Product fixed effects, where a product is defined at the granular level of make-model-year-fuel, help capture all vehicle characteristics and vehicle-level factors, such as a vehicle's popularity.

Using the set of demand instruments allows us to identify the parameters of the demand model. Mean utility parameters are identified by variations in market shares (across state and time) and observed characteristics (across vehicles and time). The price coefficient δ is identified by variation in market shares and prices across the market. The local and discrete instruments described above help identify the random coefficient Σ and Π.

On the supply side, price choices can be correlated with unobserved marginal cost shocks. We address this endogeneity issue by using a set of cost-shifters, including wages, fuel costs, lithium battery prices, and state policy regarding direct car sales. We also include observed exogenous car characteristics in the marginal cost function since these characteristics were set beforehand.

6.2 Zero market shares

This paper studies the U.S. automobile industry between 2018 and 2022 when Covid heavily disrupted the industry, and thus, zero units of some new vehicles were sold in some states and time periods. Moreover, even though not being in its inception, the electric vehicle industry in the U.S. was growing through major changes during this period (e.g., car manufacturers expanded the number of markets where EVs are offered). This growth in the EV market results in some EV models not being sold in some states and periods.

In this paper, we focus on new vehicle purchases, excluding any used vehicle purchases. We assume each new make-model-year-fuel will be available for sale for approximately one year. For example, new purchases of a 2018 vehicle are assumed to be until December 2018. Any vehicles bought after the model year are not considered new purchases and thus are dropped in this analysis.

We define the zeros as when vehicles are available for sale but not purchased by consumers. Vehicles not offered for sale in a market are dropped from estimation. A product is defined as not offered for sale when the total monthly sales for this product are zero across all states in the data.

Zero shares in the demand model could pose a problem as the estimation procedure is poorly defined. However, deleting observations with zero market shares is problematic since it alters market structure and affects our counterfactual analyses later. One approach to deal with zero shares is proposed by D'Haultfœuille et al. (2019). The market share is corrected as:

$$s_{jt}^{c} = \frac{q_{jt}^{obs} + 0.5}{M}$$

where q_{jt}^{obs} is the observed number of vehicle j sold in a given market. M is the defined market share. This approach allows us to minimize the bias of $log(s_{jt})$ and thus estimate the demand model consistently.

6.3 Estimation

The parameters to be estimated in the demand model are denoted by $\theta_d = (\alpha, \beta^x, \Sigma, \Pi)$.[4] We allow for random coefficients on prices because we believe consumer heterogeneity on prices is essential in automobile demand. This is particularly true for EV purchases, as the purchase price is considered the most significant barrier to adoption. We include purchase year and dollar per mile in the mean utility. We also add state and product fixed effects in the mean utility. All the remaining unexplained variation is captured in unobservables denoted by ξ_{jt}. We interact unobservables with the demand instruments described in the previous section to form demand moment conditions: $E[z_{jt}^D \xi_{jt}] = 0$.

On the supply side, the parameters to be estimated on the supply side are denoted by $\theta_s = (\gamma)$. As mentioned in the previous section, we specify marginal cost as a function of subsidies and observed characteristics, such as EV type, battery size, weight, and size. We also include brand, state, and drive-type fixed effects. All remaining unobserved marginal cost shifters are collected in ω_{jt}. From the first-order condition, we solve for supply-side unobservable vector ω_{jt}. We interact this vector with the supply-side instruments to build supply moment conditions, $E[z_{jt}^S \omega_{jt}] = 0$.

We stack the demand and supply moments to form:

$$g(\theta) = \begin{bmatrix} g_D(\theta) \\ g_S(\theta) \end{bmatrix} = \frac{1}{N} \begin{bmatrix} \sum_{j,t} Z_{jt}^D \, \xi_{jt} \\ \sum_{j,t} Z_{jt}^S \, \omega_{jt} \end{bmatrix}$$

We then minimize the following GMM objective function:

$$\min_{\theta} g(\theta)' W g(\theta)$$

where W is a positive definite weighting matrix. The estimator and its econometric properties are described in detail in Berry et al. (1995) and Berry et al. (2004).

7 Empirical Results

Table 5 reports the estimated vehicle demand parameters in the utility function. This result comes from the full structural estimation. In the demand model, we allow consumers to have heterogeneous sensitivity to car prices, resulting in variation in the marginal utility of these terms across consumers. Table 5 shows the mean valuation for the price term and the individual deviation from this mean.

We find that car attributes enter the consumer utility with the expected sign. The coefficient for price is negative and significant, suggesting consumers dislike high prices. There is significant heterogeneity in consumers' sensitivity to price. The negative and significant price standard deviation term suggests substantial variation in how different consumers react to changes in price, with some consumers being highly price sensitive. As expected, the interaction term between price and

[4] We estimate the demand parameters and marginal costs using PyBLP (Conlon and Gortmaker, 2020).

inversed income has a negative effect. As consumers' income increases, they become slightly less price sensitive, which aligns with standard economic intuition.

All else equal, consumers have significantly lower demand for cars in more recent years, which might seem counterintuitive. However, considering this study time period of 2018 to 2022 in which the pandemic happened and negatively affected the automotive market, it is intuitive to see significantly lower demand for cars closer to 2022. This could be due to several pandemic-related factors. First, since the pandemic caused substantial economic downturn and uncertainty, consumers decided not to proceed with large purchases such as cars, resulting in lower demand in later years. Second, the pandemic significantly shifted consumers' preferences regarding modes of transportation and mobility needs. Thus, consumers are more likely to opt for the outside option (including used cars or keeping current vehicles). Finally, it is well-known that the pandemic disrupted the global supply chain, reducing the availability of new cars. Higher prices and limited consumer choices could drive lower demand during this period. Overall, the robustness of this term suggests that the pandemic had a measurable and significant impact on vehicle demand across the study period.

Consumers dislike higher fuel costs, as the negative coefficient in the mean utility suggests. Overall, cars with higher fuel costs are less attractive to consumers since they drive up the overall cost of driving a car. This implies that consumers prefer cars with lower operating costs, consistent with the general public's preference for fuel-efficient vehicles.

The median own-price elasticity is -6.31. Figure A1 presents the empirical cumulative distribution of the estimated own-price elasticities. Our estimated own-price elasticity falls within the range of estimates in prior work on demand estimation for the new car market[5]. Table 7 presents selected car models' mean own- and cross-price elasticities in 2018. Each elasticity in a column-row combination implies the change in market share of the row vehicle as the price of the column vehicle increases by 1%. For example, as the price of 2018 Honda Cr-V gasoline increases by 1%, the market share of the 2018 Chevrolet Bolt EV goes up by 0.004%. Overall, the demand for new cars is relatively elastic, suggesting consumers are sensitive to price changes.

Table 6 reports a dealer's marginal cost estimates from Eq 11, obtained from the full structural estimation with the demand model. On the marginal cost side, all subsidy terms negatively affect the dealer's marginal cost, as expected. Consumer incentives operate equivalent to a significant reduction in dealer marginal costs, as evidenced by the negative parameter on the consumer incentive term. For every $1,000 increase in consumer incentives, dealers adjust prices as though marginal costs decrease by roughly 3% (approximately $1,000 on average). Since consumer incentives boost demand for EVs (as shown in the reduced-form analysis results), dealerships can move inventory more quickly, reduce holding costs, and increase turnover rates. This increase in dealers' efficiency due to consumer incentives reduces the cost of selling a car. In addition, since consumer incentives stimulate demand for EVs, dealers might have more opportunities to negotiate better terms with manufacturers, lowering their marginal cost.

Dealer incentives also affect dealer behavior similar to a reduction in marginal costs, though the coefficient is not statistically significant. For every $1,000 increase in dealer incentive, the dealers adjust prices as though marginal costs fall by 0.7% (approximately $252 on average). Dealerships

[5]The following list presents estimates of price elasticities from previous papers that used a similar demand model: Beresteanu and Li (2011): -10.91; Berry et al. (1995): -3.928; Reynaert and Sallee (2021): -5.45; Klier and Linn (2012): -2.6.

often face several challenges[6] when selling EVs, which generally make it more expensive than selling traditional internal combustion cars. The dealer incentive is expected to lower the financial burden for dealerships.

Other variables in the marginal cost have the expected signs and magnitudes. Like consumer incentives, federal credits also boost demand for EVs and thus affect dealer behavior. Between 2018 and 2022, marginal costs for dealerships increased potentially due to rising input costs of vehicles and supply chain disruption exacerbated during the pandemic period. Heavier cars are more costly to sell because these cars are more costly to produce; thus, higher production costs are passed on to dealerships. A negative coefficient for height implies that taller vehicles, such as SUVs and trucks, are less costly for dealerships. These vehicles tend to have higher profit margins and faster turnover rates due to higher popularity among consumers, resulting in reduced costs of holding and promoting them.

Overall, selling BEVs is more costly than other fuel types, holding all else equal. This finding aligns with economic intuition, as BEVs require high-cost components such as drivetrains and advanced battery systems, which may raise dealership procurement costs. Additionally, BEVs require additional training, marketing, and infrastructure investments, further contributing to increased operational costs. On the other hand, a larger battery size slightly reduces marginal cost for dealers, though the coefficient is not statistically significant at the traditional statistical level. This may reflect higher consumer demand for longer-range EVs or the fact that larger batteries often come in higher-end EV models, which could carry a higher profit margin, allowing dealers to offset some of the associated costs.

The marginal cost results are consistent with the reduced-form findings, providing a more detailed understanding of the mechanisms behind the observed price and sales effects. From the marginal cost estimates, we find that a $1,000 increase in consumer incentives affects dealers equivalently to a 3% reduction in marginal costs or approximately $1,080 on average. This translates to a 100% cost pass-through rate. This aligns with the reduced-form results, where 74% of the consumer subsidy is passed on to consumers through lower prices, resulting in a 4.5% increase in EV sales.

In the reduced form analysis, a $1,000 dealer incentive has no significant effect on either EV prices or sales, and the event-study analysis similarly shows no change in EV prices or sales even as dealer incentives are reduced by 50%. These reduced form results indicate that dealer incentives do not substantially shift consumer-facing prices or influence purchase decisions. The supply-side results reinforce this finding. While the estimates suggest that a $1,000 dealer incentive is equivalent to a marginal cost reduction of 0.7% (or approximately $252), the effect is not statistically significant due to the relatively large standard error. This lack of significance suggests that dealer incentives do not meaningfully affect dealer behavior in a way that would translate into lower prices for consumers.

Several factors may explain why dealer incentives fail to affect dealer behavior and directly affect prices and adoption. First, the average dealer incentive among eligible EVs is relatively small at $114, which represents less than 0.24% of the average marginal cost of an EV ($47,105) and only a fraction of the average markup of an EV ($6,350). Given the size of the dealer incentive relative to these more significant cost components, the incentive may simply be too small to induce dealerships to adjust their pricing strategies in any significant way.

[6] Dealers face higher upfront costs for EVs due to production and holding costs, promotional expenses, and investments in infrastructure like test drives and charging stations. Dealer incentives help reduce these financial burdens by lowering acquisition, promotion, and sales costs

A specific comparison between the 2019 Chevrolet Bolt EV and the 2019 Chevrolet Blazer gasoline model provides additional context for why dealer incentives may not be effective. The Chevrolet Bolt EV has a markup of \$6,133 (MSRP = \$39,173), while the gasoline-powered Chevrolet Blazer has a slightly higher markup of \$6,252 (MSRP = \$39,150). Even if we add the average dealer incentive of \$114 to the markup of the Bolt EV, the total markup would not be significantly higher than that of the gasoline model. This suggests that the dealer incentive is insufficient to meaningfully influence dealerships' preferences toward selling EVs over gasoline vehicles. Given the difference in markups between EVs and gasoline cars, dealer incentives fail to nudge dealerships toward promoting EV sales over traditional gasoline models.

Other factors include heterogeneity across dealerships. Dealer incentives often target specific EV models based on criteria like MSRP caps, which can obscure their overall average effect across all dealerships. For instance, while Chevrolet EV models are consistently eligible for dealer incentives, none of the Audi EV models qualify, resulting in a more substantial impact on Chevrolet dealerships and a negligible effect on Audi dealerships. This discrepancy can lead to statistical insignificance when averaging the impacts across all manufacturers.

Overall, these findings on marginal cost function reinforce our reduced-form analysis result. Consumer subsidies play a crucial role in shaping dealer behavior, leading to lower prices for consumers and ultimately driving greater adoption of electric vehicles (EVs). In contrast, dealer subsidies don't have meaningful impacts on dealer behavior or consumer prices and adoption decisions. The asymmetric information on dealer subsidies could explain the difference in market outcomes between the two subsidies. In our setting, consumer subsidies are explicitly advertised and communicated to consumers and dealers (Figure A4). Conversely, dealer subsidies are often not disclosed publicly to consumers but are well-known among dealerships (Figure A5).

According to Ausubel et al. (2002), a negotiating party with incomplete information about its opponent would obtain a smaller share of surplus in the bargaining process compared to if they receive the full information. Based on this theory, buyers would obtain a larger share of consumer subsidies, which they are well-informed about, and they would obtain a smaller share of dealer subsidies, which they are unlikely to know about. This matches our findings, and thus, the asymmetric information on dealer subsidies could be one of the explanations for the distinct impacts of consumer and dealer subsidies.

Table 5: Vehicle Demand Estimation Results

	Coefficient	Standard Error
Demand: Means		
Price	-0.173	(0.013)
Purchase year	-0.310	(0.006)
Dollar-per-mile	-1.937	(1.191)
Demand: St. Dev		
Price	-1.132	(0.063)
Demand: Interaction		
Price/Income	-1.669	(1.539)
Median own-price elasticity	-6.31	

Notes: This table reports the estimated coefficients and standard errors for new vehicle demand using GMM estimation. Aggregated data include 363,100 observations where an observation is product (j) in state (s) and month (m). State and Product Fixed Effects are included in vehicle demand.

Table 6: Vehicle Supply Estimation Results

	Coefficient	Standard Error
Consumer Incentive	-0.030	(0.011)
Dealer Incentive	-0.007	(0.133)
Federal Credit	-0.018	(0.001)
Purchase year	0.082	(0.00003)
Battery size	-0.0001	(0.0002)
Curb weight	0.0003	(0.00001)
Height	-0.010	(0.0002)
BEV	0.037	(0.014)

Notes: This table reports the estimated coefficients and standard errors for the vehicle supply side using GMM estimation. State-, Make-, and Drive type Fixed Effects are included on vehicle supply side. The outcome variable is the logarithm of marginal cost.

Table 7: Mean own- and cross-price elasticities for selected vehicles

	Chevrolet Bolt EV	Honda Clarity PHEV	Honda CrV Gasoline	Ford Fusion Energi PHEV	Toyota Rav4 Hybrid	Tesla Model3 EV	Chevrolet Volt PHEV
Chevrolet Bolt EV	-4.39477	0.00044	0.00917	0.00006	0.00162	0.00256	0.00025
Honda Clarity PHEV	0.00013	-3.09393	0.00687	0.00005	0.00128	0.00234	0.0002
Honda CrV Gasoline	0.00013	0.00038	-4.39870	0.00006	0.00136	0.00267	0.00022
Ford Fusion Energi PHEV	0.00013	0.00043	0.00903	-4.05515	0.00159	0.00241	0.00025
Toyota Rav4 Hybrid	0.00014	0.00039	0.00739	0.00006	-4.84541	0.00278	0.00022
Tesla Model3 EV	0.00015	0.00041	0.00818	0.00006	0.00156	-7.46685	0.00024
Chevrolet Volt PHEV	0.00013	0.00040	0.00753	0.00005	0.00140	0.00263	-3.63936

Notes: This table reports the mean own- and cross-price elasticities of selected vehicle of different fuel types in 2018.

8 Counterfactual

We used the estimated demand and supply models to determine how to allocate the subsidy better to maximize EV adoption by conducting several policy counterfactuals. For each counterfactual policy, we use the following procedure. First, we alter the amount of subsidy to a counterfactual level. Keeping the market structure the same, we calculate new marginal costs and equilibrium prices, allowing us to calculate the equilibrium market shares. Then, we calculate the number of vehicles sold by multiplying the equilibrium market shares by the market size.

8.1 The Role of Consumer Incentive

This section evaluates the effect of consumer incentives in the CHEAPR program on EV adoption, vehicle prices, and environmental outcomes by conducting several counterfactual policy simulations. First, we explore market outcomes in the absence of consumer incentives to gauge the reliance of EV markets on these subsidies. We then analyze the impact of increasing the budget for consumer incentives based on findings that consumer subsidies are more effective than dealer incentives in reducing prices and encouraging EV purchases. Lastly, we examine various redistribution strategies for the additional funds: (1) targeting EVs with high price elasticity among low-income populations, (2) prioritizing EVs with high North American value-added content, and (3) focusing on EVs with the highest overall price elasticity. Each scenario provides insights into how to allocate subsidies best to maximize EV adoption while balancing broader economic and environmental objectives.

Table 8 shows the outcomes for these scenarios[7]. The "Status quo" column includes simulated outcomes based on structural model estimates. Figure A2 confirms no significant difference between observed and simulated data, indicating that the model fits the real-world data well. The average out-of-pocket price for EVs (including state and federal subsidies) is $44,541, and non-EVs are priced lower at $40,733. This suggested that CHEAPR's consumer subsidy and federal credit play a significant role in bridging the price gap between EVs and ICE vehicles and thus make EVs more competitive with traditional ICE cars.

In the absence of consumer subsidy, the price of EVs rises by $394 (0.88%), leading to a decline in EV sales by 7.11% as fewer consumers are willing to bear the higher upfront costs. Given the findings that consumer incentives reduce prices and increase EV purchases, we explore the impacts of a slight increase in the consumer incentive budget equal to the dealer incentive budget. We first distribute this additional budget equally across all eligible EVs. On average, each eligible EV receives an additional $29 of consumer subsidy, resulting in a slight decrease in prices (0.05%) and a small rise in adoption (0.49%).

When reallocating the additional budget to focus on low-income households, we observe a modest increase in EV sales (0.57%), surpassing the gains from a general increase in consumer incentives, as shown previously for a lower level of consumer incentive. This policy scenario taps into the greater price sensitivity of low-income consumers. Since these consumers are more responsive to price changes due to budget constraints, directing subsidies toward them not only increases EV adoption but also promotes equity. From a welfare perspective, this approach ensures that the

[7]This table reports annual average sales, consumer price, consumer incentive, consumer surplus, CO_2 emissions and CO_2 damages. Following Conlon and Gortmaker (2020), consumer surplus is calculated using the following equation: $CS_{it} = log(1 + \sum_{j \in J_t} expV_{ijt})/(\frac{-\partial V_{i1t}}{\partial p1t})$ where $\frac{-\partial V_{i1t}}{\partial p1t}$ is the derivative of utility for the first product with respect to its price. And $V_{ijt} = \delta_{jt} + \mu_{ijt}$

benefits of subsidies are distributed more equitably across income groups, potentially democratizing access to cleaner technology.

Another scenario involves redistributing the additional budget to support EVs with a high percentage of North American value-added content[8]. This approach results in a similar increase in EV sales by 0.57%, comparable to the low-income household targeting scenario. However, the environmental impact is slightly more favorable, with CO_2 damages decreasing marginally more than the low-income household targeting case. This policy has broader industrial implications. Supporting vehicles with high North American content not only boosts EV adoption but also fosters local economic growth by encouraging the production and sale of vehicles with a significant proportion of domestic parts. This may align with policymakers' objectives of promoting domestic industries while simultaneously addressing environmental goals.

The most economically efficient scenario occurs when subsidies are targeted at EVs with high own-price elasticity. This approach leads to the highest adoption increase (0.59%). From an economic standpoint, this scenario maximizes the market response per dollar spent. Since high own-price elasticity indicates that consumers are more sensitive to price reductions, reallocating subsidies to these vehicles leads to the most significant boost in adoption for the same amount of subsidy spending. This option is particularly attractive when the objective is to optimize the cost-effectiveness of government spending on subsidies.

This analysis highlights the significant role of consumer incentives in reducing vehicle prices and boosting sales, reinforcing the importance of targeting consumers directly to drive adoption. Additionally, the redistribution of dealer incentive total budget can be tailored to meet different policy objectives, including cost-effectiveness, equity, and domestic economic and environmental goals.

[8] the percentage of U.S./Canadian equipment (parts) content. Data from the National Highway Traffic Safety Administration's Part 583 American Automobile Labeling Act Reports.

Table 8: Counterfactual Analysis of the Impact of Consumer Incentives

	Status quo	Counterfactuals (1) No Inc	(2) Eligible EVs	(3) Low-income	(4) NA-value-added	(5) Price-elastic
Sales						
EV	4,720	-335.8 (↓ 7.11%)	23.1 (↑ 0.49%)	27.0 (↑ 0.57%)	26.7 (↑ 0.57%)	27.9 (↑ 0.59%)
PHEV	1,697	-81.1 (↓4.78%)	6.9 (↑0.41%)	5.3 (↑0.31%)	1.8 (↑0.10%)	5.5 (↑0.32%)
BEV	3,023	-254.7 (↓8.42%)	16.2 (↑0.54%)	21.7 (↑0.72%)	24.9 (↑0.83%)	22.5 (↑0.74%)
Non-EV	121,868	25.3	-1.8	-2.1	-2.1	-2.2
Consumer Price						
EV	44,541	393.9 (↑0.88%)	-21.4 (↓0.05%)	-17.9 (↓0.04%)	-14.3 (↓0.03%)	-15.3 (↓0.03%)
PHEV	42,968	225.4 (↑0.52%)	-19.9 (↓0.05%)	-16.0 (↓0.04%)	-8.5 (↓0.02%)	-15.5 (↓0.04%)
BEV	46,341	642.9 (↑1.39%)	-23.0 (↓0.05%)	-19.5 (↓0.04%)	-23.1 (↓0.05%)	-13.6 (↓0.03%)
Non-EV	40,733	0.06	-0.01	-0.01	-0.01	-0.01
Consumer Incentive						
EV	537	-537	29.0	18.3	18.0	14.5
PHEV	320	-320	27.5	16.9	12.0	15.9
BEV	885	-885	31.3	19.3	27.3	11.3
Total Spending ($)	14,424,379	-13,533,928 (↓93.83%)	890,451 (↑6.17%)	890,451 (↑6.17%)	890,451 (↑6.17%)	890,451 (↑6.17%)
Consumer Surplus ($)	4,439	-12.2 (↓0.27%)	0.9 (↑0.02%)	1.1 (↑0.02%)	1.0 (↑0.02%)	1.1 (↑0.02%)
CO2 Emissions (tons)	728,382	855.2 (↑0.117%)	-59.1 (↓0.008%)	-68.2 (↓0.009%)	-72.5 (↓0.010%)	-70.4 (↓0.010%)
CO2 Damages ($)	37,147,489	43,612.7	-3,016.4	-3,476.9	-3,698.4	-3,590.8

Notes: This table summarizes results from the counterfactual analysis that examines the market outcomes in the absence of consumer incentives (column 1) and in the scenarios where the budget for consumer incentives slightly increases (columns 2-5). We examine various redistribution strategies for the additional funds: distributing equally among eligible EVs (column 2), targeting EVs with high price elasticity among low-income populations (column 3), prioritizing EVs with high North American value-added content (column 4), and focusing on EVs with the highest overall price elasticity (column 5). Sales, consumer price, consumer incentive, consumer surplus, CO2 emissions and CO2 damages are means values across years.

8.2 Redesign consumer subsidy keeping levels of consumer incentive budget fixed

In this analysis, we focus on redesigning consumer incentives for EVs while keeping the overall levels of state government spending on consumer incentives fixed. Given that the dealer incentives are statistically noisy and that this incentive represents only a small portion (roughly 6%) of the total expenditure on EV subsidies, we shift our attention toward optimizing consumer-side incentives. The objective is to find an alternative allocation of consumer incentives to drive higher sales of EVs without increasing its total budget. Through several policy counterfactuals, we evaluate different distributions of consumer incentives and compare them to the current design with respect to several market outcomes. This analysis allows us to identify the most cost-effective subsidy design that leads to higher EV adoption and environmental sustainability[9]

This counterfactual analysis maintains several critical assumptions: (1) the total government spending on consumer subsidies remains constant, (2) the program's existing MSRP cap for eligibility is kept unchanged, and (3) the market structure remains unchanged. Table 9 summarizes the results under various counterfactual policies. The "Status quo" column includes simulated outcomes based on structural model estimates as before. Columns 1 and 2 report market outcomes when only BEVs or only PHEVs are eligible for consumer incentives. Columns 3-4 represent scenarios where consumer incentives are reallocated to EVs and BEVs, respectively, whose prices consumers are most sensitive to. Column 5 prioritizes EVs with high North American value-added content, and column 6 targets EVs with high own-price elasticity among low-income households.

From our previous counterfactual analysis, we've learned that the current consumer incentive design has increased EV sales by 7.11%, reduced CO_2 emissions by 855.2 tons, and decreased CO_2 damages by $43,613. These findings serve as a benchmark for comparing counterfactual outcomes.

First, we evaluate the effectiveness of consumer subsidy designs that target two different types of electric vehicles (EVs): battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs). Understanding how the allocation of consumer subsidies influences market outcomes is crucial for policymakers aiming to balance EV adoption with environmental goals. BEVs are fully electric and have zero tailpipe emissions, making them crucial to long-term strategies to reduce greenhouse gas emissions. While offering some of the benefits of electrification, PHEVs still rely partially on fossil fuels, thus emitting more CO_2 per mile compared to BEVs. By conducting counterfactuals, we can assess which subsidy structure—targeting BEVs or PHEVs—maximizes EV adoption, minimizes CO_2 emissions, and ensures the most cost-effective use of public funds. These insights are critical as governments seek to design EV incentive programs that accelerate the shift toward cleaner technologies and achieve environmental targets without exceeding budgetary constraints.

In column 1, we consider a policy counterfactual where consumer subsidies are reallocated exclusively to BEVs while keeping the budget constant. PHEVs would receive no consumer subsidy, and

[9] For each vehicle, we estimate the usage of each fuel type (gasoline, diesel, or electricity) and then convert fuel usage to CO_2 emission. Assuming car lifetime to be 10 years and lifetime miles to be 150,000 (following Xing et al. (2021), we estimate that each vehicle is driven 15,000 miles per year. Gasoline or diesel usage is miles per year divided by the vehicle's mpg from gasoline/diesel and CO_2 emission from these fuels is then calculated by multiplying gasoline/diesel usage by grams of CO_2 for gasoline/diesel. Electricity usage is miles per year divided by the vehicle's mpg from electricity and CO_2 emission from electricity usage is calculated by multiplying electricity usage by marginal CO_2 emission (lb/kWh) obtained from Holland et al. (2022). The total CO_2 emission for each vehicle is then the sum of the percentage that the vehicle uses each fuel type times emissions from the respective fuel type.

the spending on PHEVs would be distributed equally among eligible BEVs. On average, each BEV would receive an additional $243.8. This adjustment in the subsidy strategy brings about notable changes in market outcomes. The marginal cost for BEVs decreases by 0.73%, and the price of BEVs falls by 0.64%, leading to a 5.30% rise in BEV sales.

On the other hand, the complete removal of PHEV subsidies leads to a 0.61% increase in marginal cost, a 0.52% increase in prices, and a 4.82% drop in sales for PHEV. Overall, EV sales increase by 1.66%, primarily driven by the substantial boost in BEV sales, as the reduction in their price makes them more attractive to consumers. Annual CO_2 emission decreases slightly by 245 tons (equivalent to a reduction in CO_2 damage[10] of $12,484). Overall, this design outperforms the current design of consumer incentives on both cost-effective and environmental aspects.

The decomposition of effects (Table A1) shows that if we only reduce the PHEV subsidy, the price of EVs increases by 0.31%, and sales decrease by 1.72%, reflecting the impact of reduced affordability for PHEVs. However, the "Difference" column, which isolates the impact of increasing BEV subsidies, indicates that the price of EVs falls by 0.28%, and EV sales rise by 3.38%, which more than compensates for the loss due to the complete removal of PHEV subsidies. This decomposition illustrates that while removing PHEV subsidies negatively affects the market, the targeted increase in BEV subsidies generates enough additional sales to offset these losses, leading to a net positive effect on overall EV adoption. Thus, the policy successfully drives EV growth, primarily by concentrating incentives on the segment consumers respond to most, even as some trade-offs are made within the broader EV market.

By contrast, targeting subsidies solely toward PHEVs results in opposite market outcomes. In column 2, we explore the effects of reallocating all consumer subsidies to PHEVs while completely removing subsidies for BEVs. That is, BEVs would receive no consumer subsidy, and the total spending on BEVs would then be redistributed among eligible PHEVs. On average, each PHEV would receive an additional $918. The marginal cost and prices for EVs reduce by 0.89% and 0.78%, respectively. However, the overall effect shows a slight decline in EV sales of 0.30%, primarily driven by the drop in sales due to the removal of BEV subsidies (Table A2). Furthermore, shifting the financial support to PHEVs increases CO_2 emissions (507 tons) and damages ($25,874). This suggests that subsidizing BEVs delivers not only stronger environmental benefits but also greater market adoption compared to the current structure or a PHEV-focused incentive. Therefore, the BEV-only policy is more aligned with long-term sustainability and environmental objectives, making it the preferred option for policymakers focused on both cost-effectiveness and emissions reduction.

Next, we assess the impact of reallocating subsidies to vehicles whose prices are most sensitive to consumer demand (columns 3 and 4). Given that consumers are more responsive to price changes in some EV models than others, this counterfactual examines how much we can improve EV adoption and environmental outcomes when allocating subsidies to the top price-sensitive models. EV models with average own-price elasticity in the bottom 50% would receive no consumer subsidies. The fixed budget is then distributed equally among targeted EVs. On average, in this scenario, each targeted EV would receive a consumer incentive of $261 (column 3), and each targeted BEV would receive a consumer incentive of $98 (column 4).

In these scenarios, the results indicate that targeting price-sensitive EVs leads to substantial

[10] CO_2 damage is calculated by multiplying CO_2 emissions by the social cost of carbon obtained from Holland et al. (2022)

market gains, whether focusing on all EVs or specifically BEVs. Reallocating subsidies to all price-sensitive EVs (column 3) results in a 3.3% increase in the EV count compared to the current consumer subsidy design. Additionally, this design reduces CO_2 damage by \$20,252 and CO_2 emissions by 397 tons, improving the current incentive design. In addition, focusing subsidies solely on price-sensitive BEVs (column 4) provides even more significant environmental benefits, reducing CO_2 damages by \$29,037 and CO_2 emissions by 569 tons. Vehicle sales increase by 3.67%, making this approach more environmentally effective and cost-efficient in driving EV adoption than the current subsidy design. Refer to Tables A3 and A4 for the decomposition effects of these two counterfactuals.

Another potential strategy involves reallocating subsidies to EVs with high North American value-added content (column 5). This policy not only supports the adoption of cleaner technologies but also promotes domestic industries, fostering economic growth within the North American auto sector. In this scenario, the EV adoption increases by 2.52%, substantially improving the current design. CO_2 damages fall by \$20,519, and emissions decrease by 402 tons compared to the current subsidy design. While the outcomes are slightly less favorable than the price-elasticity targeting approach (columns 3 & 4), this strategy may appeal to policymakers interested in boosting local manufacturing alongside environmental goals. For the decomposition effect of this counterfactual, refer to Table A5.

The final counterfactual (column 6) explores the impact of targeting low-income households, which are often more price-sensitive due to budget constraints. In this scenario, EV adoption increases by 2.55%, and CO_2 damages decline by \$16,333—improvements over the current design. This redistribution strategy promotes EV adoption, reduces emissions, and enhances equity by ensuring low-income households access cleaner vehicle technologies. Given that lower-income households are more likely to forgo EV purchases without subsidies, this approach addresses issues of accessibility and fairness in EV adoption, all while achieving superior environmental benefits compared to the current structure. For the decomposition effect of this counterfactual, refer to Table A6.

The counterfactual analysis highlights the potential for optimizing the design of EV consumer subsidies to achieve higher adoption rates and more significant environmental benefits without increasing the total budget. Specifically, targeting BEVs increases overall EV sales and significantly reduces CO_2 emissions, offering a more cost-effective approach to lowering emissions. The comparison with the current design reveals that reallocating subsidies, especially to price-sensitive BEVs or EVs, generates a further boost in EV adoption and environmental sustainability. Additionally, targeting EVs with high North American value-added content and low-income households achieves domestic economic growth and equity while generating adoption and environmental benefits.

Table 9: Counterfactual Analysis of Consumer Incentive Spending Redistribution

		Counterfactuals					
	Status quo	(1) Target BEVs	(2) Target PHEVs	(3) Price-elastic EVs	(4) Price-elastic BEVs	(5) Top NA value-added	(6) Low income
Sales							
EV	4,720	78.5	-14.2	156.0	173.4	119.0	120.4
		(↑1.66%)	(↓0.3%)	(↑3.3%)	(↑3.67%)	(↑2.52%)	(↑2.55%)
PHEV	1,697	-81.7	241.5	-5.2	-82.1	-57.0	-7.0
		(↓4.82%)	(↑14.23%)	(↓0.31%)	(↓4.84%)	(↓3.36%)	(↓0.41%)
BEV	3,023	160.2	-255.7	161.1	255.5	176.0	127.5
		(↑5.30%)	(↓8.46%)	(↑5.33%)	(↑8.45%)	(↑5.82%)	(↑4.22%)
Non-EV	121,868	-7.9	-0.1	-15.8	-17.6	-11.5	-11.8
Consumer Price ($)							
EV	44541	13.8	-346.4	88.3	264.4	186.6	103.1
		(↑0.03%)	(↓0.78%)	(↑0.20%)	(↑0.59%)	(↑0.42%)	(↑0.23%)
PHEV	42968	225.2	-1023.9	-109.2	225.1	100.3	-43.5
		(↑0.52%)	(↓2.38%)	(↓0.25%)	(↑0.52%)	(↑0.23%)	(↓0.10%)
BEV	46341	-296.5	642.8	402.5	354.2	315.2	340.5
		(↓0.64%)	(↑1.39%)	(↑0.87%)	(↑0.76%)	(↑0.68%)	(↑0.73%)
Non-EV	40733	-0.1	0.02	-0.2	-0.2	-0.1	-0.1
Marginal Cost ($)							
EV	38,236	13.5	-341.8	86.9	260.6	183.9	101.6
		(↑0.04%)	(↓0.89%)	(↑0.23%)	(↑0.68%)	(↑0.48%)	(↑0.27%)
PHEV	36,682	222.1	-1010.1	-107.7	222.1	98.9	-42.9
		(↑0.61%)	(↓2.75%)	(↓0.29%)	(↑0.61%)	(↑0.27%)	(↓0.12%)
BEV	40,014	-292.7	634.0	396.6	348.8	310.6	335.5
		(↓0.73%)	(↑1.58%)	(↑0.99%)	(↑0.87%)	(↑0.78%)	(↑0.84%)
Consumer Incentive							
EV	537	-98.2	205.7	-275.4	-438.6	-289.6	-251.2
PHEV	320	-320.3	917.9	-16.3	-320.3	-151.9	-47.2
BEV	885	243.8	-885.4	-701.2	-664.2	-515.8	-595.2
Consumer Incentive Budget ($)	13,533,928	-0	-0	-0	-0	-0	-0
CO2 Emissions (tons)	728,382	-244.8	507.3	-397.1	-569.4	-402.3	-320.3
		(↓0.03%)	(↑0.07%)	(↓0.05%)	(↓0.08%)	(↓0.06%)	(↓0.04%)
CO2 Damages ($)	37,147,489	-12483.5	25873.7	-20252.0	-29037.2	-20519.3	-16333.6

Notes: This table summarizes results from the counterfactual analysis that examines the market outcomes of alternative consumer incentive designs, keeping the consumer incentive spending level fixed. Sales, consumer price, consumer incentive, consumer surplus, CO2 emissions, and CO2 damages are means values across years. We examine various redistribution strategies for the total government spending: only BEVs (column 1), only PHEVs (column 2), only EV and BEV models above median own-price elasticity (columns 3-4), only EV models with top North American value-added (column 5) and target low-income population (column 6).

8.3 Redesign consumer incentive keeping total government spending fixed

Our findings suggest that prioritizing consumer-side incentives is crucial for policymakers aiming to accelerate the transition to EVs. Therefore, this analysis examines the market outcomes when redistributing the total state government spending to only consumer subsidies. We evaluate different consumer incentive designs through several policy counterfactuals while keeping total spending constant and comparing the market outcomes to the no-incentive baseline. This counterfactual analysis maintains several critical assumptions: (1) the total government spending on subsidies remains fixed, (2) the program's existing MSRP cap for eligibility is kept unchanged, (3) the market structure remains unchanged, and (4) the reduction in dealer incentive has no effect on dealer behavior and EV market outcomes (based on our reduced-form and structural model findings).

Table 10 summarizes the results under various counterfactual policies. The "No Incentive" column includes market outcomes without EV subsidies. Columns 1 and 2 report market outcomes when only BEVs or PHEVs are eligible for consumer incentives. Columns 3-4 represent scenarios where consumer incentives are reallocated to EVs and BEVs, respectively, whose prices consumers are most sensitive to. Column 5 prioritizes EVs with high North American value-added content, and column 6 targets EVs with high own-price elasticity among low-income households.

Across all scenarios, the redistribution of incentives leads to an increase in overall EV sales compared to the "No Incentive" baseline. The most substantial gains are observed in the scenarios where we target price-elastic EVs and BEVs (columns 3 and 4), where sales rise by 11.9% and 13.31%, respectively. These results highlight the critical role that price sensitivity plays in consumer adoption of EVs. By concentrating subsidies on EVs with high price elasticity, policymakers can maximize the adoption of these vehicles, particularly among consumers who are more responsive to price changes.

In addition to stimulating EV adoption, targeting price-sensitive EVs or BEVs generates positive environmental outcomes. The most significant reductions in CO_2 emissions occur in the price-elastic BEV-targeting scenario (column 3), with emissions dropping by 1,509 tons (equivalent to $77,005). Targeting price-elastic EVs also leads to significant improvement in environmental sustainability (CO_2 emission and damages dropping by 1,329 tons and $67,769, respectively)

Columns 5 and 6, which focus on EVs with high North American value-added content and those targeting low-income households, also lead to decent increases in EV adoption and decreases in CO_2 emissions. Furthermore, these approaches not only advance environmental goals but also promote equity and domestic economic growth by supporting local manufacturing and making EVs more accessible to under-served communities. Overall, the analysis suggests that more targeted subsidies drive adoption and yield measurable reductions in emissions, foster economic equity, and contribute to sustainable domestic growth.

Table 10: Counterfactual Analysis of Total Incentive Spending Redistribution

		Counterfactuals					
		(1)	(2)	(3)	(4)	(5)	(6)
	No Incentive	Target BEVs	Target PHEVs	Price-elastic EVs	Price-elastic BEVs	Top NA value-added	Low income
Sales							
EV	4,384	447.1	343.6	521.8	539.7	482.2	484.0
		(↑10.2%)	(↑7.84%)	(↑11.9%)	(↑13.31%)	(↑11%)	(↑11.04%)
PHEV	1,616	-0.7	344.7	80.5	-1.0	25.5	78.5
		(↓0.04%)	(↑21.33%)	(↑4.98%)	(↓0.06%)	(↑1.58%)	(↑4.86%)
BEV	2,769	447.7	-1.1	441.3	540.7	456.7	405.5
		(↑16.17%)	(↓0.04%)	(↑15.94%)	(↑19.53%)	(↑16.49%)	(↑14.65%)
Non-EV	121,893	-36.1	-27.2	-43.6	-45.4	-39.0	-39.4
Consumer Price ($)							
EV	44,935	-404.5	-791.0	-322.6	-136.4	-218.4	-306.8
		(↓0.90%)	(↓1.76%)	(↓0.72%)	(↓0.30%)	(↓0.49%)	(↓0.68%)
PHEV	43,194	-0.2	-1335.2	-353.2	-0.3	-131.8	-283.7
		-	(↓3.09%)	(↓0.82%)	(↓0.001%)	(↓0.31%)	(↓0.66%)
BEV	46,984	-998.2	-0.1	-253.6	-304.0	-345.1	-319.0
		(↓2.12%)	-	(↓0.54%)	(↓0.65%)	(↓0.73%)	(↓0.68%)
Non-EV	40,733	-0.2	-0.04	-0.2	-0.3	-0.2	-0.2
Consumer Incentive							
EV	0	458.8	789	276	104	261	302
PHEV	0	0	1315	321	0	177	288
BEV	0	1177.6	0	194	233	389	306
Total Spending ($)	0	14,424,378	14,424,378	14,424,378	14,424,378	14,424,378	14,424,378
Consumer Surplus ($)	4,427	17.3	13.2	22.2	23.2	19.1	19.7
		(↑0.39%)	(↑0.30%)	(↑0.50%)	(↑0.52%)	(↑0.43%)	(↑0.45%)
CO2 Emissions (tons)	727,447	-1,186.4	-362.5	-1,328.8	-1,509.9	-1,333.3	-1,247.1
		(↓0.16%)	(↓0.05%)	(↓0.18%)	(↓0.21%)	(↓0.18%)	(↓0.17%)
CO2 Damages ($)	37,099,789	-60,509	-18,485	-67,769	-77,005	-67,997	-63,601

Notes: This table summarizes results from the counterfactual analysis that examines the market outcomes of alternative consumer incentive designs, keeping the total spending level fixed. Sales, consumer price, consumer incentive, consumer surplus, CO2 emissions, and CO2 damages are means values across years. We examine various redistribution strategies for the total government spending: only BEVs (column 1), only PHEVs (column 2), only EV and BEV models above median own-price elasticity (columns 3-4), only EV models with top North American value-added (column 5) and target low-income population (column 6).

9 Conclusion

This paper provides new evidence on the distinct effects of consumer and dealer subsidies in the electric vehicle (EV) market. The results imply that statutory incidence plays a crucial part in shaping the economic incidence of EV subsidies. Our reduced-form model results show that consumer subsidies are significantly more effective at maximizing EV adoption than dealer subsidies. Specifically, a substantial portion of consumer subsidies are passed through to buyers, resulting in higher EV sales. On the other hand, dealer subsidies have little to no impact on either EV prices or adoption.

Our structural model for new vehicle purchase, accounting for both demand- and supply-side responses in equilibrium, supports the findings from the reduced-form analysis. We find that dealers react as if their marginal cost had decreased by 3% for every thousand-dollar increase in consumer subsidies. However, dealer subsidies fail to induce similar responses from dealerships. This result could be due to insufficient magnitude, limited salience, or asymmetric information on dealer subsidies. These findings reveal that dealers are more responsive to demand-side incentives, highlighting the effectiveness of targeting subsidies directly at buyers.

Our counterfactual analyses explore how different subsidy designs could optimize EV adoption and environmental benefits under a fixed government spending level. We find that reallocating subsidies to battery electric vehicles (BEVs) and price-elastic EV models significantly increases adoption and leads to more significant reductions in carbon emissions. Additionally, policymakers could consider targeting EVs with high North American value-added and low-income households to achieve broader policy objectives, such as promoting equity and supporting domestic manufacturing while maximizing adoption and environmental benefits.

This paper illustrates how targeted consumer subsidies—whether directed at BEVs, price-sensitive or domestic models, or low-income households—can be more effective at optimizing vehicle adoption and emission reduction. These insights offer practical guidance for subsidy programs for green technology in the U.S. and other countries seeking to accelerate the adoption of environmentally friendly innovations and the energy transition.

References

Allcott, H., Kane, R., Maydanchik, M. S., Shapiro, J. S., and Tintelnot, F. (2024). The Effects of "Buy American": Electric Vehicles and the Inflation Reduction Act. NBER Working Paper Series No. 33032.

Alliance for Automotive Innovation (2021). Electric vehicle dashboard. https://www.autosinnovate.org/EVDashboard.

Armitage, S. and Pinter, F. (2022). Regulatory Mandates and Electric Vehicle Product Varietys. Working paper.

Ausubel, L. M., Cramton, P., and Deneckere, R. J. (2002). Bargaining with incomplete information. Handbook of game theory with economic applications, 3:1897–1945.

Barwick, P. J., Kwon, H.-S., and Li, S. (2024). Attribute-based Subsidies and Market Power: an Application to Electric Vehicles. NBER Working Paper Series No. 32264.

Barwick, P. J., Kwon, H.-s., Wang, B., and Zahur, N. B. (2023). Pass-through of Electric Vehicle Subsidies: A Global Analysis. AEA Papers and Proceedings, (113):323–328.

Bennett, B. and Isaac, J. (2023). The true cost of electric vehicles: Uncovering the hidden environmental and consumer impacts. Texas Public Policy Foundation.

Beresteanu, A. and Li, S. (2011). Gasoline Prices, Government Support, and the Demand for Hybrid Vehicles in the United States. International Economic Review, 52(1):161–182.

Berry, S., Levinsohn, J., and Pakes, A. (1995). Automobile Prices in Market Equilibrium. Econometrica: Journal of the Econometric Society, pages 841–890.

Berry, S., Linton, O. B., and Pakes, A. (2004). Limit theorems for estimating the parameters of differentiated product demand systems. The Review of Economic Studies, 71(3):613–654.

Bloomberg NEF (2021). Electric vehicle outlook 2021. https://bnef.turtl.co/story/evo-2021/page/1.

BLS (2023). Charging into the future: The transition to electric vehicles. https://www.bls.gov/opub/btn/volume-12/charging-into-the-future-the-transition-to-electric-vehicles.htm.

Busse, M. R., Knittel, C. R., Silva-Risso, J., and Zettelmeyer, F. (2012). Did “Cash for Clunkers” Deliver? The Consumer Effects of the Car Allowance Rebate System. Working paper.

Chandra, A., Gulati, S., and Kandlikar, M. (2010). Green Drivers or Free Riders? An Analysis of Tax Rebates for Hybrid Vehicles. Journal of Environmental Economics and management, 60(2):78–93.

CHEAPR (2023). Cheapr - resources. https://portal.ct.gov/deep/air/mobile-sources/cheapr/cheapr—resources.

CHEAPR (2024). Cheapr implementation manual. https://portal.ct.gov/deep/air/mobile-sources/cheapr/cheapr—resources.

Chetty, R., Looney, A., and Kroft, K. (2009). Salience and Taxation: Theory and Evidence. American Economic Review, 99(4):1145–1177.

Clinton, B. C. and Steinberg, D. C. (2019). Providing the Spark: Impact of Financial Incentives on Battery Electric Vehicle Adoption. Journal of Environmental Economics and Management, 98:102255.

Conlon, C. and Gortmaker, J. (2020). Best Practices for Differentiated Products Demand Estimation with PyBLP. The RAND Journal of Economics, 51(4):1108–1161.

Connecticut DEEP (2016). Electric vehicle roadmap for connecticut: A policy framework to accelerate electric vehicle adoption.

D’Haultfœuille, X., Durrmeyer, I., and Février, P. (2019). Automobile Prices in Market Equilibrium with Unobserved Price Discrimination. The Review of Economic Studies, 86(5):1973–1998.

European Commission (2022). European commission announces measures to boost electric vehicle market. https://ec.europa.eu/commission/presscorner/detail/en/ip_22_6462.

Gallagher, K. S. and Muehlegger, E. (2011). Giving Green to Get Green? Incentives and Consumer Adoption of Hybrid Vehicle Technology. Journal of Environmental Economics and Management, 61(1):1–15.

Gandhi, A. and Houde, J.-F. (2019). Measuring Substitution Patterns in Differentiated-products Industries. NBER working paper, (w26375).

Holland, S. P., Kotchen, M. J., Mansur, E. T., and Yates, A. J. (2022). Why marginal co2 emissions are not decreasing for us electricity: estimates and implications for climate policy. Proceedings of the National Academy of Sciences, 119(8):e2116632119.

Jacqz, I. and Johnston, S. (2024). Electric Vehicle Subsidies and Urban Air Pollution Disparities. Journal of the Association of Environmental and Resource Economists, (forthcoming).

Jenkin, F. (1872). On the Principles which Regulate the Incidence of Taxes. Proceedings of the Royal Society of Edinburgh, 7:618–631.

Jiménez, G., Martinez-Miera, D., and Peydró, J.-L. (2020). Who Truly Bears (Bank) Taxes? Evidence from Only Shifting Statutory Incidence.

Johnson, C., Anderson, J., Appenzeller, N., Williams, B., Santulli, C., and Pallonetti, N. (2016). Evaluating the connecticut dealer incentive for electric vehicle sales. Transparency Specialist Evaluation.

Kaul, A., Pfeifer, G., and Witte, S. (2016). The Incidence of Cash for Clunkers: Evidence from the 2009 Car Scrappage Scheme in Germany. International Tax and Public Finance, 23(6):1093–1125.

Kelley Blue Book (2021). New vehicle prices surge to record highs for fifth straight month, according to kelley blue book. https://mediaroom.kbb.com/2021-09-14-New-Vehicle-Prices-Surge-to-Record-Highs-for-Fifth-Straight-Month,-According-to-Kelley-Blue-Book.

Klier, T. and Linn, J. (2012). New-vehicle characteristics and the cost of the corporate average fuel economy standard. The RAND Journal of Economics, 43(1):186–213.

Li, S., Tong, L., Xing, J., and Zhou, Y. (2017). The Market for Electric Vehicles: Indirect Network Effects and Policy Design. Journal of the Association of Environmental and Resource Economists, 4(1):89–133.

Linn, J. (2022). Balancing Equity and Effectiveness for Electric Vehicle Subsidies. Resources for the Future Working Paper 22-7.

Liu, J. (2022). Who Should be Subsidized for Electric Vehicles? Demand Estimation and Policy Design under Network Effects. Working paper.

Lohawala, N. (2023). Roadblock or Accelerator? The Effect of Electric Vehicle Subsidy Elimination. Resources for the Future Working Paper 23-13.

Muehlegger, E. and Rapson, D. S. (2022). Subsidizing Mass Adoption of Electric Vehicles: Quasi-experimental Evidence from California. Journal of Public Economics, 216:104752.

Pless, J. and van Benthem, A. A. (2019). Pass-through as a Test for Market Power: An Application to Solar Subsidies. American Economic Journal: Applied Economics, 11(4):367–401.

Remmy, K. (2023). Adjustable Product Attributes, Indirect Network Effects, and Subsidy Design: The Case of Electric Vehicles. Working paper.

Reynaert, M. and Sallee, J. M. (2021). Who benefits when firms game corrective policies? American Economic Journal: Economic Policy, 13(1):372–412.

Sallee, J. M. (2011). The Surprising Incidence of Tax Credits for the Toyota Prius. American Economic Journal: Economic Policy, 3(2):189–219.

Sinyashin, A. (2021). Optimal Policies for Differentiated Green Products: Characteristics and Usage of Electric Vehicles. Working paper.

Springel, K. (2021). Network Externality and Subsidy Structure in Two-sided Markets: Evidence from Electric Vehicle Incentives. American Economic Journal: Economic Policy, 13(4):393–432.

The White House (2021). Fact sheet: President biden announces steps to drive american leadership forward on clean cars and trucks. https://www.whitehouse.gov/briefing-room/statements-releases/2021/08/05/fact-sheet-president-biden-announces-steps-to-drive-american-leadership-forward-on-clean-cars-and-trucks/.

Wang, J. and Xing, J. (2023). Subsidizing Industry Growth in a Market with Lemons: Evidence from the Chinese Electric Vehicle Market. Working paper.

Xing, J., Leard, B., and Li, S. (2021). What Does an Electric Vehicle Replace? Journal of Environmental Economics and Management, 107:102432.

10 Appendix - Tables

Table A1: Decomposition Effects - Counterfactual 1: Targeting BEVs

	Status quo	Total change	Change from subsidy decrease for PHEV	Difference
Marginal Cost ($)				
EV	38,236	0.04%	0.35%	-0.32%
PHEV	36,682	0.61%	0.61%	0%
BEV	40,014	-0.73%	0%	-0.73%
Consumer Price ($)				
EV	44,541	0.03%	0.31%	-0.28%
PHEV	42,968	0.52%	0.52%	-0.0002%
BEV	46,341	-0.64%	0.00002%	-0.64%
Non-EV	40,733	-0.0002%	-0.000002%	-0.0002%
Sales				
EV	4,720	1.66%	-1.72%	3.38%
PHEV	1,697	-4.82%	-4.80%	-0.02%
BEV	3,023	5.30%	0.01%	5.29%
Non-EV	121,868	-0.007%	0.005%	-0.012%
Consumer Incentive ($)				
EV	537	-98	-197	98.76
PHEV	320	-320	-320	0
BEV	885	244	0	243.83
Consumer Incentive Spending ($)				
EV	13,533,928	-0.98	-4,241,648	4,241,647
PHEV	4,241,648	-4,241,648	-4,241,649	1.00
BEV	9,292,280	4,241,647	0	4,241,647

Notes: This table reports the decomposition effects for counterfactual 1, where consumer subsidies are targeted toward BEVs. The "Change from subsidy decrease for PHEV" column reports the changes in market outcomes (compared to the status quo) when consumer subsidies for PHEVs reduce to 0. The "Total change" column reports the changes in market outcomes (compared to the status quo) when consumer subsidies for PHEVs are reduced to 0. The spending on PHEVs is then distributed among eligible BEVs. The difference between these two effects is reported in the last column.

Table A2: Decomposition Effects - Counterfactual 2: Targeting PHEVs

	Status quo	Total change	Change from subsidy decrease for BEV	Difference
Marginal Cost ($)				
EV	38,236	-0.89%	0.66%	-1.56%
PHEV	36,682	-2.75%	0%	-2.75%
BEV	40,014	1.58%	1.58%	0%
Consumer Price ($)				
EV	44,541	-0.78%	0.58%	-1.35%
PHEV	42,968	-2.38%	0.0002%	-2.38%
BEV	46,341	1.39%	1.39%	0%
Non-EV	40,733	0.00005%	0.0001%	-0.00005%
Sales				
EV	4,720	-0.30%	-5.39%	5.09%
PHEV	1,697	14.23%	0.02%	14.21%
BEV	3,023	-8.46%	-8.43%	-0.03%
Non-EV	121,868	-0.0001%	0.016%	-0.016%
Consumer Incentive ($)				
EV	537	206	-340	546
PHEV	320	918	0	918
BEV	885	-885	-885	0
Consumer Incentive Spending ($)				
EV	13,533,928	-1	-9,292,280	9,292,279
PHEV	4,241,648	9,292,279	0	9,292,279
BEV	9,292,280	-9,292,280	-9,292,280	0

Notes: This table reports the decomposition effects for counterfactual 2, where consumer subsidies are targeted toward PHEVs. The "Change from subsidy decrease for BEV" column reports the changes in market outcomes (compared to the status quo) when consumer subsidies for BEVs reduce to 0. The "Total change" column reports the changes in market outcomes (compared to the status quo) when consumer subsidies for BEVs are reduced to 0. The spending on BEVs is then distributed among eligible PHEVs. The difference between these two effects is reported in the last column.

Table A3: Decomposition Effects - Counterfactual 3: Targeting Top Price-Elastic EVs

	Status quo	Total change	Change from subsidy decrease for non-targeted EVs	Difference
Marginal Cost ($)				
EV	38,236	0.23%	0.62%	-0.40%
PHEV	36,682	-0.29%	0.32%	-0.62%
BEV	40,014	0.99%	1.07%	-0.08%
Consumer Price ($)				
EV	44,541	0.20%	0.54%	-0.34%
PHEV	42,968	-0.25%	0.28%	-0.53%
BEV	46,341	0.87%	0.94%	-0.07%
Non-EV	40,733	-0.0004%	-0.00001%	-0.00038%
Sales				
EV	4,720	3.30%	-2.37%	5.67%
PHEV	1,697	-0.31%	-2.69%	2.38%
BEV	3,023	5.33%	-2.20%	7.53%
Non-EV	121,868	-0.013%	0.007%	-0.020%
Consumer Incentive ($)				
EV	537	-275	-397	122
PHEV	320	-16	-211	195
BEV	885	-701	-712	11
Consumer Incentive Spending ($)				
EV	13,533,928	0	-6,313,804	6,313,804
PHEV	4,241,648	-1,554,849	-2,892,500	1,337,651
BEV	9,292,280	1,554,849	-3,421,304	4,976,153

Notes: This table reports the decomposition effects for counterfactual 3, where consumer subsidies are targeted toward top price-elastic EVs. The "Change from subsidy decrease for non-targeted EVs" column reports the changes in market outcomes (compared to the status quo) when consumer subsidies for non-targeted EV models reduce to 0. The "Total change" column reports the changes in market outcomes (compared to the status quo) when consumer subsidies for non-targeted EVs are reduced to 0. The spending on these vehicles is then distributed among top price-elastic EVs. The difference between these two effects is reported in the last column.

Table A4: Decomposition Effects - Counterfactual 4: Targeting Top Price-Elastic BEVs

	Status quo	Total change	Change from subsidy decreases for non-target EVs	Difference (%)
Marginal Cost ($)				
EV	38,236	0.68%	0.79%	-0.10%
PHEV	36,682	0.61%	0.61%	0%
BEV	40,014	0.87%	1.07%	-0.20%
Consumer Price ($)				
EV	44,541	0.59%	0.68%	-0.09%
PHEV	42,968	0.52%	0.52%	0%
BEV	46,341	0.76%	0.94%	-0.17%
Non-EV	40,733	-0.0005%	-0.000004%	-0.00048%
Sales				
EV	4,720	3.67%	-3.13%	6.80%
PHEV	1,697	-4.84%	-4.79%	-0.05%
BEV	3,023	8.45%	-2.19%	10.64%
Non-EV	121,868	-0.014%	0.009%	-0.02%
Consumer Incentive ($)				
EV	537	-439	-463	25
PHEV	320	-320	-320	0
BEV	885	-664	-712	48
Consumer Incentive Spending ($)				
EV	13,533,928	0	-7,662,952	7,662,952
PHEV	4,241,648	-4,241,648	-4,241,648	0
BEV	9,292,280	4,241,648	-3,421,304	7,662,952

Notes: This table reports the decomposition effects for counterfactual 4, where consumer subsidies are targeted toward top price-elastic BEVs. The "Change from subsidy decrease for non-targeted EVs" column reports the changes in market outcomes (compared to the status quo) when consumer subsidies for non-targeted EV models reduce to 0. The "Total change" column reports the changes in market outcomes (compared to the status quo) when consumer subsidies for non-targeted EVs are reduced to 0. The spending on these vehicles is then distributed among top price-elastic BEVs. The difference between these two effects is reported in the last column.

Table A5: Decomposition Effects - Counterfactual 5: Targeting Top North-American Value-Added EVs

	Status quo	Total change	Change from subsidy decrease for non-target EVs	Difference
Marginal Cost ($)				
EV	38,236	0.48%	0.53%	-0.05%
PHEV	36,682	0.27%	0.46%	-0.19%
BEV	40,014	0.78%	0.61%	0.16%
Consumer Price ($)				
EV	44,541	0.42%	0.47%	-0.05%
PHEV	42,968	0.23%	0.39%	-0.16%
BEV	46,341	0.68%	0.54%	0.14%
Non-EV	40,733	-0.0003%	0.00001%	-0.00031%
Sales				
EV	4,720	2.52%	-2.29%	4.81%
PHEV	1,697	-3.36%	-3.98%	0.62%
BEV	3,023	5.82%	-1.34%	7.16%
Non-EV	121,868	-0.009%	0.006%	-0.02%
Consumer Incentive ($)				
EV	537	-290	-294	5
PHEV	320	-152	-234	82
BEV	885	-516	-385	-131
Consumer Incentive Spending ($)				
EV	13,533,928	0	-5,317,230	5,317,230
PHEV	4,241,648	-3,099,916	-3,505,228	405,312
BEV	9,292,280	3,099,916	-1,812,002	4,911,918

Notes: This table reports the decomposition effects for counterfactual 5, where consumer subsidies are targeted toward top North-American (NA) value-added. The "Change from subsidy decrease for non-targeted EVs" column reports the changes in market outcomes (compared to the status quo) when consumer subsidies for non-targeted EV models reduce to 0. The "Total change" column reports the changes in market outcomes (compared to the status quo) when consumer subsidies for non-targeted EVs are reduced to 0. The spending on these vehicles is then distributed among top NA value-added. The difference between these two effects is reported in the last column.

Table A6: Decomposition Effects - Counterfactual 6: Targeting Low-income Population

	Status quo	Total change	Change from subsidy decrease for non-target EVs	Difference
Marginal Cost ($)				
EV	38,236	0.27%	0.42%	-0.15%
PHEV	36,682	-0.12%	0.28%	-0.40%
BEV	40,014	0.84%	0.66%	0.18%
Consumer Price ($)				
EV	44,541	0.23%	0.36%	-0.13%
PHEV	42,968	-0.10%	0.24%	-0.34%
BEV	46,341	0.73%	0.58%	0.16%
Non-EV	40,733	-0.0002%	-0.00001%	-0.00019%
Sales				
EV	4,720	2.55%	-1.66%	4.21%
PHEV	1,697	-0.41%	-2.51%	2.10%
BEV	3,023	4.22%	-1.17%	5.39%
Non-EV	121,868	-0.010%	0.004%	-0.014%
Consumer Incentive ($)				
EV	537	-251	-296	45
PHEV	320	-47	-190	143
BEV	885	-595	-497	-98
Consumer Incentive Spending ($)				
EV	13,533,928	0	-4,803,559	4,803,559
PHEV	4,241,648	-1,440,089	-2,771,000	1,330,911
BEV	9,292,280	1,440,090	-2,032,559	3,472,649

Notes: This table reports the decomposition effects for counterfactual 6, where consumer subsidies are targeted toward EVs with high own-price elasticity among low-income households. The "Change from subsidy decrease for non-targeted EVs" column reports the changes in market outcomes (compared to the status quo) when consumer subsidies for non-targeted EV models reduce to 0. The "Total change" column reports the changes in market outcomes (compared to the status quo) when consumer subsidies for non-targeted EVs are reduced to 0. The spending on these vehicles is then distributed among EVs with high own-price elasticity among low-income households. The difference between these two effects is reported in the last column.

11 Appendix - Figures

Figure A1: Empirical CDF of Own-Price Elasticity

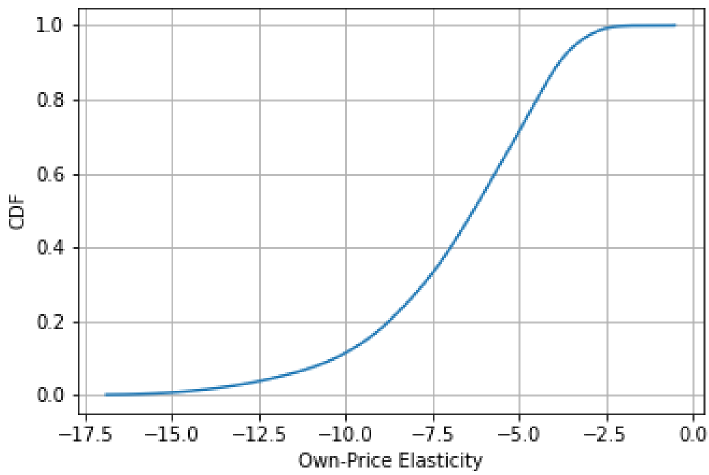
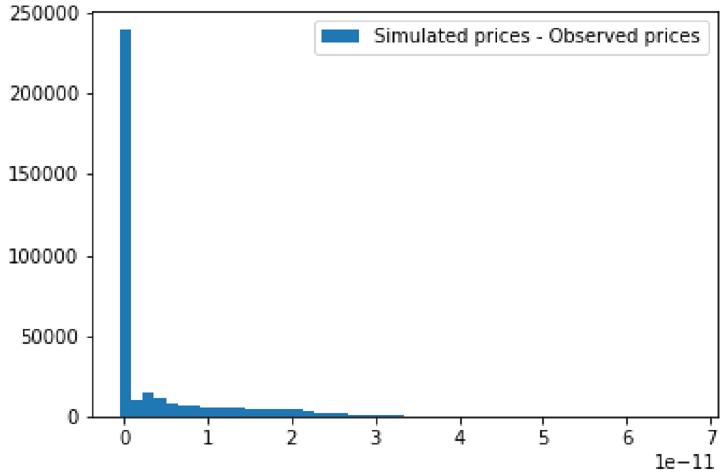
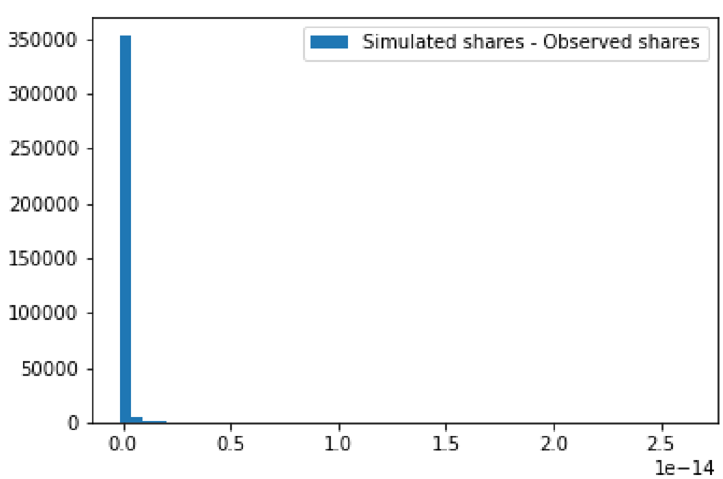


Figure A2: Difference between Observed Data and Simulated Data



(a) Prices



(b) Shares

Note: Figures show the difference between the observed data and simulated data using demand and supply estimates

Figure A3: CHEAPR consumer subsidy assignment (Source: Johnson et al. (2016))

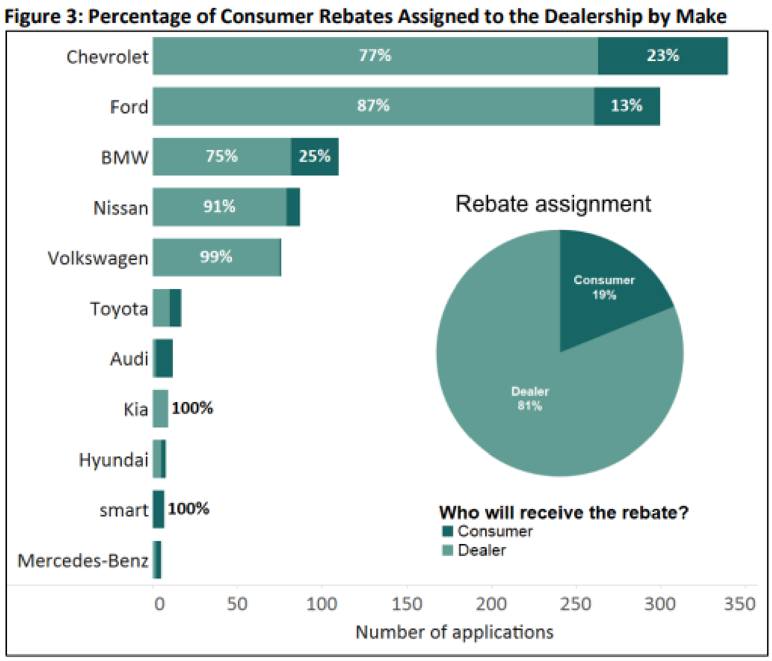


Figure A4: CHEAPR Overview Information Flyer (Source: CHEAPR (2023))

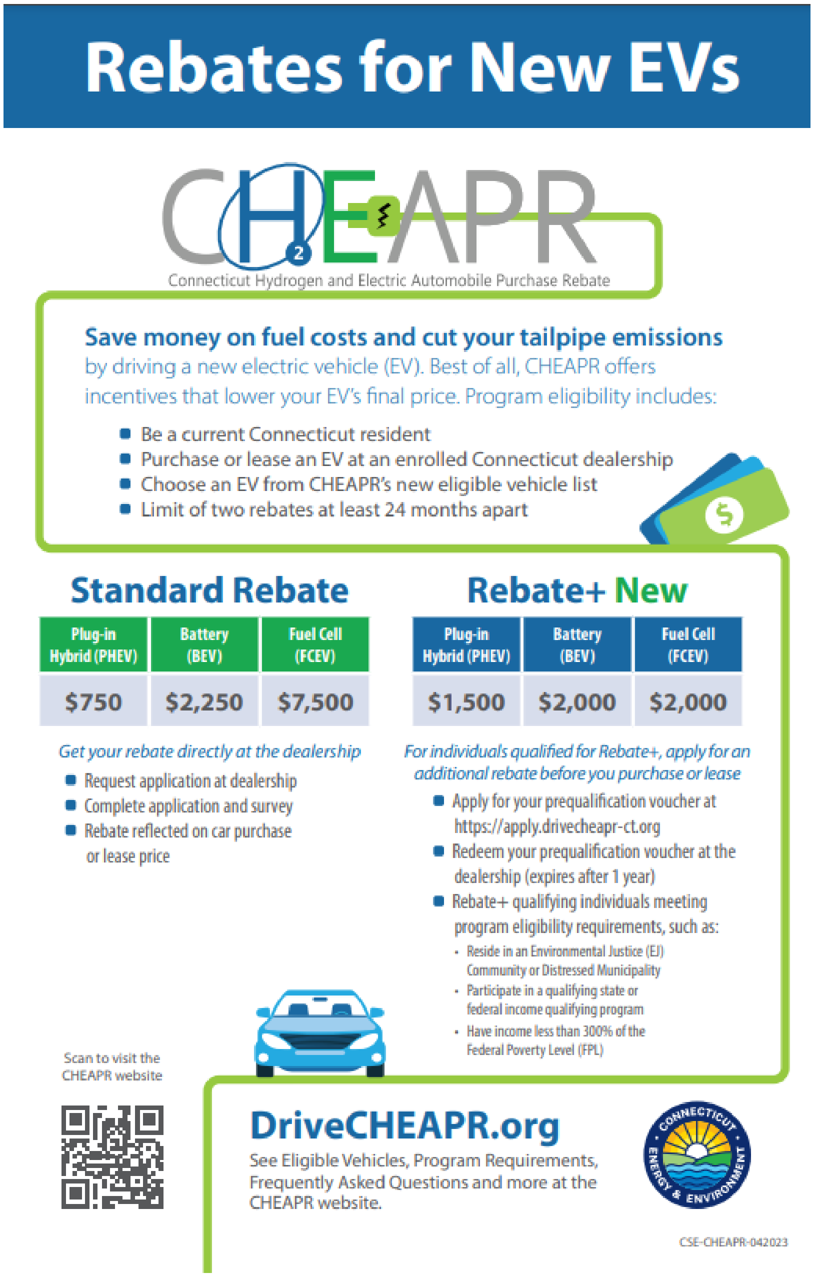


Figure A5: Dealer Incentive Briefly Mentioned in the Program Implementation Manual (Source: CHEAPR (2024))

4.2 Dealership Incentive

The dealership incentive is designed to reduce the barrier for dealerships to sell or lease BEVs, PHEVs, or FCEVs. **OEMs with distribution locations that only sell BEVs are not eligible for a dealer incentive, nor are dealerships that only sell used vehicles.** To be eligible to receive a dealer incentive, dealerships must apply for an incentive on behalf of an Applicant.

Connecticut franchised new automobile dealers are eligible to receive a dealer incentive on approved applications of:

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