S.T. Yau High School Science Award

Research Report

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Title of Research Report

The Effects of Federal Incentives on the Automotive Market and Greenhouse Gas Emissions

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Abstract

This paper examines the role of the federal Clean Vehicle Tax Credit (CVTC) in shaping consumer vehicle choices and greenhouse gas emissions in the United States. Using a structural random-coefficient logit model estimated on quarterly sales data covering 62 brands and 397 car models from 2015Q1–2025Q2, we evaluate how federal incentives influence demand for electric vehicles (EVs) and gasoline vehicles (GVs) and simulate the consequences of the early termination of the CVTC under the One Big Beautiful Bill Act. The results show that the CVTC has a significant impact on EV adoption. Counterfactual simulations suggest that eliminating the CVTC would result in a reduction of 1,387,367 qualified EV sales, with most displaced demand shifting to GVs. These reallocations increase annual CO_2 emissions by 4,276 kilotons and total greenhouse gas emissions by 4,501 kilotons, alongside $1,647.86 million in additional fuel costs. The findings highlight the central role of federal incentives in sustaining EV demand and achieving climate and energy policy goals.

Keywords: Clean Vehicle Tax Credit, random-coefficient model, greenhouse gas emissions, automotive market, climate policy.

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1. Introduction

Automobile pollution, particularly from gasoline- and diesel-powered vehicles, is a major contributor to both local air quality problems and global climate change. In the United States, the transportation sector accounts for about 28–31% of total energy-related CO_2 emissions, with passenger cars and light-duty trucks responsible for more than half of that share [1]. A typical passenger vehicle emits roughly 4.6 metric tons of CO_2 per year, equivalent to approximately 400 grams per mile [2]. These emissions not only accelerate global warming but also contribute to harmful pollutants such as nitrogen oxides, volatile organic compounds, and fine particulate matter, which worsen air quality and pose serious health risks [3]. To address these challenges, policymakers have pursued a range of interventions to accelerate the transition from gasoline-powered vehicles (GVs) to electric vehicles (EVs). Early approaches included fuel economy standards, zero-emission vehicle mandates, and state- or federal-level purchase subsidies.

More recently, federal legislation has dramatically expanded the scope of EV support. The Inflation Reduction Act (IRA), signed into law on August 16, 2022, represents the largest U.S. investment in decarbonizing light-duty transportation [4]. The law created a new Clean Vehicle Tax Credit (CVTC) that provides up to $7,500 for qualifying new EVs and $4,000 for used EVs, with eligibility tied to income limits, vehicle price caps, and sourcing requirements for batteries and minerals [5]. Early market evidence suggests the program has boosted EV adoption: U.S. clean vehicle sales reached about 1.46 million in 2023, a nearly 50 percent increase from 2022, with much of this growth attributed to IRA incentives [6]. Independent projections by the International Council on Clean Transportation likewise suggest that the IRA will substantially increase EV market share over the next decade compared to a no-IRA baseline, although these are forecasts

rather than evaluations based on post-IRA data [7]. Together, these findings indicate that the IRA has become the central federal driver of EV adoption in the United States.

However, the One Big Beautiful Bill Act (OBBB), passed in July 2025, accelerates the expiration of the CVTC, along with the used and commercial EV credits, which were originally scheduled to run until 2032 [8]. Under OBBB, these credits will no longer be available for vehicle purchases made after September 30, 2025. The early termination of the CVTC raises the possibility of significant shifts in consumer behavior and, ultimately, greenhouse gas emissions. Once the subsidy is removed, many consumers who would have chosen EVs are likely to substitute back into gasoline or hybrid vehicles, while some may defer purchase altogether. If GVs dominate the substitution margin, this reallocation implies a substantial rebound in fossil fuel consumption. As a result, the removal of the credit not only reduces EV adoption but also increases aggregate greenhouse gas emissions.

Motivated by these rapid changes in CVTC policies, we use a unique national-level dataset from the U.S. automotive industry and a widely adopted structural model to evaluate the consequences of the federal Clean Vehicle Tax Credit. Our study has three objectives. First, we quantify the effect of the CVTC on national-level sales of both EVs and GVs. Second, we conduct counterfactual simulations to predict the consequences of removing the CVTC, examining how displaced demand reallocates across EVs, GVs, and hybrid cars. Third, we assess the environmental implications of these shifts by calculating how the increase in GV sales translates into higher CO_2 and total greenhouse gas (GHG) emissions.

To accomplish this, we adopt a structural random-coefficient logit demand model, similar to Berry, Levinsohn, and Pakes (1995, henceforth BLP) [9]. A structural framework is essential in this context because it directly models how households choose among competing vehicles,

allowing us to recover underlying consumer preferences and substitution patterns across EVs, GVs, and hybrids. Unlike a traditional logit model, which suffers from the independence of irrelevant alternatives (IIA) property and thus assumes proportional substitution across all products, the random-coefficient specification incorporates consumer heterogeneity in tastes for price and product attributes such as fuel economy and powertrain type. The structural nature of the model also makes it well-suited for policy analysis: by embedding incentives directly into the utility function, we can simulate counterfactual scenarios such as the early termination of the CVTC under the OBBB and evaluate both sales reallocations and environmental outcomes in a consistent behavioral framework. Importantly, incorporating consumer heterogeneity is critical for generating realistic substitution patterns for the counterfactual analysis. Without it, simpler models would imply that all vehicle types experience the same percentage change in market share when incentives are removed, ignoring meaningful differences in how consumers actually substitute across gasoline, hybrid, and EV models. For example, consumers are more likely to switch to another EV or hybrid than to a gasoline car model.

After obtaining the counterfactual sales reallocations, we translate these demand shifts into environmental and economic outcomes. Specifically, we combine the predicted changes in gasoline vehicle sales with vehicle-level fuel economy and emissions data from the U.S. Department of Energy. Following the Environmental Protection Agency (EPA) conventions on annual driving distances and fuel carbon content, we calculate the additional CO_2 and total greenhouse gas emissions associated with increased gasoline use. At the same time, multiplying fuel consumption by prevailing fuel costs provides an estimate of the added household expenditures on gasoline. In this way, the counterfactual analysis links policy-induced shifts in consumer demand directly to their environmental and economic consequences.

Our analysis is supported by a unique dataset that consolidates information from multiple sources. We compile quarterly car model-level sales from Automotive News, vehicle characteristics, including fuel economy, CO_2 emissions, manufacturer's suggested retail price (MSRP), body type, powertrain, and trim availability, from the U.S. Department of Energy's FuelEconomy.gov, and supplemental brand and model attributes from Ward's Automotive Yearbook and Cars.com. We further link these data with federal and state-level incentive information from the Department of Energy's Alternative Fuels Data Center. This integration yields a rich dataset covering 62 brands and 397 car models in the U.S. passenger car market from the first quarter of 2015 through the second quarter of 2025. Together, the structural model and comprehensive data allow us to provide the national-level evidence on how the CVTC shapes vehicle demand and emissions outcomes.

This study makes three key contributions. First, it provides the structural evidence on how the CVTC shapes consumer demand, offering an *ex post* evaluation of a federal incentive program that has previously been studied mostly at the state level or through forward-looking projections. We demonstrate that the CVTC has a significant impact on consumers' choices when shopping for new cars. Second, it goes beyond aggregate adoption to uncover substitution patterns across electric, gasoline, and hybrid vehicles, showing that the loss of EV sales from subsidy removal is not evenly spread, with the greatest percentage increase in the CVTC unqualified EVs. Counterfactual analysis indicates that a full elimination of the CVTC reduces CVTC-qualified EV sales by 68.36% (1,387,367 units). As the consumer demand shifts, other EV models (CVTC unqualified EVs) experience a dramatic 43.70% increase (223,416 units). GVs have a modest 2.68% gain (817,571 units) relative to their existing market share. Hybrid vehicles show similar modest percentage gains (2.76%, or 4,854 units). Moreover, there is a loss of 341,526 sales as

consumers choose not to purchase a new vehicle. Third, it links these behavioral shifts to broader consequences for both the environment and household finances, quantifying the resulting increases in greenhouse gas emissions and fuel expenditures. The elimination of the CVTC adds 4,276 kilotons of CO_2 emissions and 4,501 kilotons of total GHG emissions annually, alongside $1,647.86 million in additional fuel costs.

Before presenting our empirical analysis, we first review the existing literature on EV incentives to position our contribution, then provide essential institutional background on the CVTC and OBBB, and finally describe our data sources and structural modeling approach.

2. Literature Review

2.1. *The Effect of Federal and State EV Incentives Prior to the IRA*

There are studies on both federal and state-level government incentives and how these might influence consumers' choices and the demand for EVs. Both provide evidence that government incentive programs increase EV adoption. At the federal programs level, Gallagher and Muehlegger (2011) show that hybrid vehicle sales in the U.S. respond positively to both fuel prices and federal tax incentives, establishing the foundation for understanding how fiscal policy shapes clean vehicle demand [10]. Building on this, Li (2019) uses vehicle-level data to show that federal tax credits under the Energy Improvement and Extension Act and the American Recovery and Reinvestment Act significantly boosted EV demand [11]. Synthesizing results across many contexts, Hardman et al. (2017) similarly conclude that financial purchase incentives are generally effective in stimulating battery electric vehicle sales [12].

State-level studies reinforce and extend these findings. Jenn, Springel, and Gopal (2018) conduct a comprehensive analysis across all U.S. states, estimating that each additional $1,000 of

rebate or tax credit raises EV sales by 2.6%, while non-monetary incentives such as HOV lane access further increase adoption [13]. Muehlegger and Rapson (2018) examine California's Clean Vehicle Rebate Project and show that it increased adoption, with higher participation among upper-income households [14]. Clinton and Steinberg (2019) likewise highlight that subsidies often flow disproportionately to wealthier buyers, shaping who responds to incentives [15]. Sheldon and Dua (2019) provide further evidence that while subsidies consistently increase uptake, the incremental effect depends on design features and consumer heterogeneity [16]. Policy reversals also confirm these effects: Xing, Leard, and Li (2021) document that when Georgia eliminated its $5,000 EV subsidy in 2015, new registrations fell by nearly two-thirds compared to neighboring states [17]. Finally, Springel (2021) shows that beyond direct purchase subsidies, state investments in charging infrastructure are also effective in raising EV adoption, in some cases more so than equivalent spending on rebates [18].

Taken together, federal and state evidence provide a consistent conclusion: government incentives are powerful drivers of EV adoption, but the scale and distribution of their effects depend heavily on program design and market context.

2.2. The effect of the Inflation Reduction Act

The passage of the IRA in 2022 marked a turning point in U.S. climate policy. Several recent studies have evaluated its broader implications. Bistline, Mehrotra, and Wolfram (2023) model U.S. energy and economic outcomes under the IRA, projecting that the legislation could reduce U.S. greenhouse gas emissions by 33–40% below 2005 levels by 2030 [19]. Cole et al. (2023) developed a two-sided model of the EV market to simulate the effects of the IRA and the Infrastructure Investment and Jobs Act (IIJA) [4]. They show that IRA subsidies, particularly the

$7,500 new EV credit, substantially increase EV penetration, though at high fiscal cost, with projected expenditures up to $382 billion through 2031. Allcott et al. (2024) conducted the first ex post welfare analysis of IRA EV credits, finding that credits were largely passed through to consumers, but that restrictions on domestic content led to large shifts toward leasing, exploiting the so-called "leasing loophole" [20]. Their equilibrium model shows that while IRA credits generate significant environmental benefits, they come at a cost of $23,000–$32,000 per incremental EV sold.

2.3. Structural Demand Models in Environmental Policy Evaluation

A growing literature employs structural demand models, particularly the BLP random-coefficient logit framework, to evaluate environmental and energy policies in the automotive sector. These studies demonstrate the value of estimating consumer preferences and substitution patterns when assessing policy effectiveness. Bento et al. (2009) use a structural approach to evaluate the distributional and efficiency impacts of increased gasoline taxes in the United States, modeling consumer choices across new, used, and scrapped vehicles while accounting for household heterogeneity [21]. Grigolon et al. (2018) apply a random-coefficients logit model to a panel of European countries to examine consumer valuation of fuel costs and the effectiveness of alternative tax policies [22]. Li et al. (2017) develop a structural model incorporating indirect network effects to study the electric vehicle market, estimating how EV adoption and charging station deployment mutually reinforce each other [23]. Together, these studies suggest that modeling consumer heterogeneity through structural frameworks is essential for capturing realistic substitution patterns across powertrains and for conducting credible policy counterfactuals.

2.4. Research Gap and Contribution

While previous literature highlights the IRA's scale, costs, and welfare implications, they primarily focus on aggregate emissions projections, macroeconomic effects, or policy design trade-offs. By contrast, our study complements this work by shifting attention to the market-reallocation consequences of CVTC termination: when qualified EVs lose the federal credit, how does displaced demand reallocate across unqualified EVs, GVs, hybrids, and the outside option?

Our study advances this literature along three dimensions. First, we are among the first to directly measure the impact of the CVTC on sales of different types of vehicles, including EVs, GVs, and hybrids. Prior work has documented how subsidies raise EV adoption and how IRA provisions affect welfare, credit incidence, leasing behavior, and trade-related policy outcomes. We extend this work by constructing a national quarterly vehicle-level panel covering 62 brands and 397 car models from 2015Q1 through 2025Q2. This broad panel spans the pre-IRA and IRA periods and allows us to evaluate the CVTC within the broader new-vehicle market rather than focusing only on EV adoption. Second, our BLP random-coefficient logit specification explicitly recovers consumer heterogeneity in preferences and generates realistic substitution patterns across EVs, GVs, and hybrids. This is important because the consequences of subsidy removal depend on the composition of replacement choices, not simply on the number of EV sales lost. The model, therefore, allows demand displaced from qualified EVs to reallocate flexibly across unqualified EVs, GVs, hybrids, and the outside option. Thirdly, in terms of policy insight, we use the estimated model to simulate the early termination of the CVTC under the One Big Beautiful Bill Act. The counterfactual analysis quantifies not only the decline in qualified EV sales but also the resulting increases in GV sales, CO_2 emissions, total greenhouse gas emissions, and household fuel expenditures. By linking subsidy removal to market-wide substitution patterns and downstream environmental and economic outcomes, the paper provides evidence on

how ending a major federal EV incentive reshapes the new-vehicle market and its broader policy consequences.

The next section provides the institutional background needed to interpret this analysis. We first describe the environmental challenge motivating federal EV policy, then discuss the design and eligibility criteria of the CVTC under the IRA, and finally explain the policy reversal introduced by the OBBB Act.

3. Institutional Background

Having established that federal incentives are powerful drivers of EV adoption, we now turn to the specific institutional context that motivates our analysis. The CVTC introduced by the IRA represents a fundamental restructuring of federal EV policy, and its early termination under the OBBB Act creates a natural policy experiment for evaluating the consequences of subsidy removal. To properly specify our empirical model and interpret our counterfactual simulations, we must understand three key institutional elements: (1) the magnitude of transportation sector greenhouse gas emissions that motivate federal EV policy, (2) the specific design features and eligibility criteria of the CVTC, and (3) the policy reversal enacted through OBBB. We address each in turn.

3.1. Transportation Greenhouse Gas

The transportation sector represents the largest source of greenhouse gas emissions in the United States, accounting for 28% of total U.S. greenhouse gas emissions in 2022 and constituting a critical environmental challenge that demands urgent attention [24]. Over 94% of transportation fuel consumption relies on petroleum-based products, primarily gasoline and diesel, resulting in direct carbon dioxide emissions that fundamentally drive anthropogenic climate change [25]. Gasoline-powered passenger vehicles constitute a substantial portion of this environmental burden,

with passenger cars alone responsible for 20% of transportation sector emissions, while light-duty trucks including sport utility vehicles, pickup trucks, and minivans contribute an additional 37% [26]. Combined, cars and light-duty trucks account for 57% of all transportation emissions, highlighting their disproportionate environmental impact [26]. The scale of individual vehicle contributions is significant, as a typical passenger vehicle emits approximately 4.6 metric tons of carbon dioxide annually, with each gallon of gasoline combustion producing 8,887 grams of CO_2 emissions [2]. This substantial emissions profile from GVs not only contributes to global warming and climate change but also generates local air pollutants that compromise public health, underscoring the urgent need for comprehensive transportation decarbonization strategies and the accelerated adoption of clean vehicle technologies, highlighting their disproportionate environmental impact.

3.2. The inflation Reduction Act and Clean Vehicle Tax Credit

The Inflation Reduction Act (IRA), signed into law on August 16, 2022, represents the most extensive U.S. investment in climate action to date, described by the Biden Administration as "the most ambitious investment in combating the climate crisis in world history" [27]. It represents a transformative shift in federal electric vehicle policy, fundamentally restructuring clean vehicle incentives to promote domestic manufacturing while accelerating EV adoption nationwide. It is not only an environmental measure but also a strategy to bolster domestic manufacturing and supply chain security [27]. In pursuit of these goals, the IRA centers on broad tax incentives for low-carbon technologies produced within the United States and allied nations. Among these provisions, credits for EVs stand out as a cornerstone of the legislation. Analysts emphasize that EV incentives are intended to accelerate adoption while simultaneously linking U.S. climate objectives to economic resilience and energy independence [28],[5].

At the center of the IRA's transportation provisions is the New Clean Vehicle Tax Credit (CVTC, Internal Revenue Code §30D), which restructured the earlier federal EV incentive program beginning January 1, 2023, and extends it through December 31, 2032 [28]. The credit provides up to $7,500 for new clean vehicles and up to $4,000 for qualifying used EVs, subject to strict eligibility rules. New vehicles must be plug-in EVs or fuel-cell vehicles with a gross vehicle weight rating below 14,000 pounds, final assembly in North America, and (for plug-ins) a battery capacity of at least 7 kWh from a qualified manufacturer [29]. In addition, purchase price thresholds—$55,000 for cars and $80,000 for SUVs, vans, and pickup trucks—ensure that subsidies target mainstream vehicles rather than luxury models [28]. Moreover, the EV batteries should satisfy the year-specific sourcing tests (critical minerals and battery components rules). Thus, the number of vehicles eligible for the CVTC changes from year to year. In 2023, following the implementation of the April 18 rules, 23 models qualified—14 eligible for the full $7,500 credit and 9 for the partial $3,750 credit. In 2024, the number dropped to 19 models (11 at $7,500 and 8 at $3,750). By 2025, after several supply-chain recertifications, 16 models qualified, all eligible for the full $7,500 credit. A list of eligible vehicles by model year is available on the U.S. Department of Energy's website: https://fueleconomy.gov/feg/tax2023.shtm

3.3. The One Big Beautiful Bill Act

The political landscape for EV incentives shifted dramatically with the passage of the *One Big Beautiful Bill Act* (OBBB) in July 2025. While the IRA had initially extended the CVTC through 2032, OBBB curtailed its duration by eliminating eligibility for new purchases after September 30, 2025. This accelerated sunset represents a fundamental reversal in federal clean vehicle policy with two major implications: first, it creates a near-term incentive for consumers to accelerate EV purchases before the deadline, potentially leading to a short-term sales spike; second,

it raises the likelihood of a longer-term decrease in EV adoption, as the removal of the federal subsidy increases the relative cost of qualifying vehicles. Thus, it is critical to assess how the early termination of the CVTC reshapes vehicle sales patterns and the resulting environmental impacts.

4. Data

We consolidate our data from various sources. Our dataset covers 62 brands (e.g., Honda) and 397 car models (e.g., Honda Civics) sold in the U.S. passenger car market from Quarter 1 of 2015 to Quarter 2 of 2025. We end our sample at Quarter 2 of 2025 to provide a clean evaluation window. The passage of OBBB in July 2025 creates strong incentives for consumers to advance their EV purchases before the September deadline. Including data after this point would capture these policy-induced spikes rather than the underlying demand response to the CVTC, thereby biasing estimation. Following prior literature, we exclude ultra luxury cars priced over $150,000, as these are unlikely to be in the consideration set of mainstream car shoppers [9].

We collect car model-specific attributes, such as miles per gallon (MPG), CO_2 emission per mile (CO_2), annual fuel cost(FCOST), Powertrain type (i.e., EV, GV, Hybrid), and body type (i.e., sedan, minivan, pickup trucks, SUV, others) from the U.S. Department of Energy website www.fueleconomy.gov. In this study, we classify plug-in hybrid electric vehicles together with battery electric vehicles under the "EV" category, since both rely on external charging and qualify for the CVTC. By contrast, conventional hybrids such as the Toyota Prius are categorized as "Hybrid" because they cannot be plugged in, do not qualify for the CVTC, and their small batteries are charged only through regenerative braking and the internal combustion engine. We obtain country of origin (i.e., Korean, European, U.S., and Japanese) and product segment (i.e., luxury and economy) from Ward's Automotive Yearbook. Out of the 397 car models in the dataset, 192 are economy models, and 205 are luxury models. Powertrain availability is distributed as 53 EVs,

335 GVs, and 9 Hybrids. By body style, we observe 170 SUVs, 165 sedans, 11 minivans, 16 pickups, and 35 other types (e.g., sports car, micro car, and coupe).

We obtain the quarterly sales of each car model from the Automotive News Market Data Book. An average EV car model is sold 7,946.56 units each quarter during our sample period. That number is 17,066.38 and 6,513.15 for GVs and hybrid cars, respectively. The best-selling brand is Ford, with an average of 515,168.95 units sold each quarter. The best-selling GV car model is the Ford F-Series, with 199,463 units sold each quarter. The best-selling EV car is the Tesla Model Y, with sales of 61,747.62 per quarter. The data on manufacturer-suggested retail list price (MSRP) are obtained from cars.com.

We obtain both federal and State Laws and incentives during our sample period from the US. Department of Energy https://afdc.energy.gov/laws. During our sample period, the IRA is the only federal incentive that applies to new car purchases. We also obtain the list of eligible EVs from the same website. Importantly, not all vehicles meeting the assembly and price rules qualify for the full credit. The IRA divides the $7,500 incentive into two equal parts: one tied to critical mineral sourcing and the other to battery component manufacturing in North America. Vehicles that meet only one of these requirements are eligible for half the credit, while those that satisfy both qualify for the full amount. Given the heterogeneous nature of vehicle models eligible for the CVTC, we distinguish between two distinct categories, (1) pure EV models, including Tesla Model Y, Rivian R1T, and other car models that exclusively offer electric powertrains, and (2) mixed powertrain models, including traditional vehicle car models like the BMW X5 that offer both CVTC-qualifying electric variants and conventional gasoline options within the same model line. Because our dataset is at the car model level, we do not directly observe the sales split between EV and gasoline trims within mixed models such as the BMW X5. To address this, we collected

supplemental information from publicly available primary and secondary sources, including official manufacturer disclosures, investor reports, reputable industry publications, and major automotive news outlets. AI-assisted search tools (ChatGPT-5) were used to help identify potential data sources and relevant documents, similar to a structured search engine query. All numerical figures used in the analysis were manually verified by the authors and extracted directly from these documented sources. For the vast majority of mixed models, we obtained model-specific EV sales or reported EV share ratios. In a small number of cases where model-level splits were unavailable, we relied on brand-level EV share information as a proxy. This procedure allowed us to split mixed models into separate gasoline and EV trims, ensuring consistency with the structure of our demand model.

There are 23 state-level government incentives that were applied to new car purchases during our sample period. These programs vary widely in structure but generally fall into two categories: direct purchase subsidies and tax benefits or fee reductions. We report the descriptive statistics in Table 1.

Table 1. Descriptive Statistics

Variable	Mean	Max	Min	S.D.
Sales	16,419.92	238,128.00	100.00	24,795.85
Market share	0.03	0.47	0.00	0.04
MSRP ($)	41,105.79	169,900.00	12,660.00	2,2339.33
MPG (Miles per Gallon)	29.26	137.00	10.50	19.79
CVTC-Pure EV ($)	56.44	7500.00	0.00	634.62
CVTC-Mixed EV ($)	53.30	7500.00	0.00	598.21
Incentive at state level ($)	12.20	524.00	0.00	61.29

Note: market share is multiplied by 10. Therefore, the original mean is 0.003.

5. Model and Estimation

5.1. Empirical Model

We estimate a random coefficient logit model on the sales data to uncover the impact of CVTC on consumers' preferences [9],[30]. We consider a market with utility-maximizing households that shop for passenger cars. We assume that each household chooses from a set of $M_t=\{1,2,\ldots J_t\}$ car models offered by a group of brands indexed by i in time t. A household also has the option of not buying any of the car models, in which case it is considered to purchase an outside good denoted by $j = 0$. Household h maximizes its utility by making the optimal purchase decision:

$$\max_j u_{hjt} = \boldsymbol{\alpha} CVTC_{jt} + \beta_{1h} Price_{jt} + \boldsymbol{\beta_{2h} X_{jt}} + \gamma_j + \epsilon_{hjt} \quad (1)$$

In the above equation, u_{hjt} is the indirect utility that household h derives from buying car model j (e.g., Toyota Camry) at time t. $CVTC_{jt}$ is the primary policy variable of interest, measuring the dollar amount of the CVTC available for model j at time t. We estimate separate CVTC coefficients, $\boldsymbol{\alpha} = \{\alpha^{pure}, \alpha^{mix}\}$, for pure EV car models and mixed powertrain models that offer an EV trim, recognizing that consumer sensitivity to tax incentives may differ systematically between contexts where buyers are choosing among exclusively electric options versus deciding between electric and gasoline versions of the same underlying vehicle platform.

In Equation (1), $Price_{jt}$ is MSPR price of car model j at time t. It directly captures sensitivity to vehicle prices. X_{jt} is a vector of control variables, including MPG_{jt}, EV_j, GV_j, $State_{jt}$, and $Season_{jt}$. MPG_{jt} is miles per gallon, reflecting consumers' preference for gas-efficient cars. EV_j and GV_j are EV indicators and GV indicators, respectively, capturing consumers' preferences for powertrain type with hybrid cars as the base. $State_{jt}$ is the State-level incentives and is included to account for additional subsidies. $Season_{jt}$ is quarterly dummies that capture seasonality and recurring calendar fluctuations in auto demand, such as higher sales at year-end. Finally, model fixed

effects γ_j absorb time-invariant characteristics such as body type or brand reputation. As a result, we do not include any of the car characteristics that do not change over time, such as luxury vs economy indicators. The only exception is the powertrain indicators, which are essential for capturing realistic substitution patterns among EVs and GVs in our policy simulations. We are able to separately identify both car model fixed effects and powertrain dummy coefficients by omitting one car model within each powertrain category as the baseline, effectively creating separate reference points for EV and GV categories. Please note we take the natural log of all continuous variables, including $CVTC_{jt}$, $Price_{jt}$, MPG_{jt}, and $State_{jt}$.

Importantly, we follow the classic BLP model to account for household heterogeneity by assuming that the coefficients $\beta_h = \{\beta_{1h}, \beta_{2h}\}$ in Equation (1) are normally distributed. Allowing these coefficients to be random across consumers is essential for accurately capturing demand in the automobile market. It reflects the reality that different households place different values on price, fuel savings, or new technologies such as EVs. Some consumers are highly price sensitive, while others are not, and some strongly favor EVs, while others strongly prefer GVs. Incorporating this heterogeneity directly addresses the well-known independence of irrelevant alternatives (IIA) property of the simple logit model, which unrealistically implies proportional substitution across all products. By allowing for random taste variation, the model generates more realistic substitution patterns—for instance, when a federal EV credit is reduced, displaced demand flows disproportionately toward other EVs or hybrids rather than evenly across all vehicle types. This richer structure is critical for evaluating CVTC policies, where the effectiveness of incentives depends on how heterogeneous consumers substitute between qualifying EVs, non-qualifying EVs, and gasoline cars.

The utility of choosing the outside good is: $u_{h0t} = \epsilon_{h0t}$. Assuming ϵ_{hjt} in Equation (1) to be extreme value distributed, we derive a logit model of consumer choice. The probability of a consumer choose model *j* at time *t* is

$$S_{hjt} = \frac{\exp(E(u_{hjt}))}{1+\sum_j \exp(E(u_{hjt}))} \quad (2)$$

The probability of a consumer choosing the outside option at time *t* is

$$S_{h0t} = \frac{1}{1+\sum_j \exp(E(u_{hjt}))} \quad (3)$$

Therefore, the market share of car model *j* at time *t* is

$$S_{jt} = \int_{\beta_h} S_{hjt} \times P(\beta_h) d\beta_h \quad (4)$$

where $P(\beta_h)$ is the distribution over the elements of $\beta_h = \{\beta_{1h}, \beta_{2h}\}$. We use simulation to compute the integral in Equation (4). We randomly draw *n* vectors of β_h from the distribution of $P(\beta_h)$ in simulating *n* households. We then obtain an approximation to the integral in Equation (4) as:

$$s_{jt} = \frac{1}{n}\sum_{h=1}^{n} s_{hjt} \quad (5)$$

In order to calculate the outside share S_{0t}, we need to obtain the market size (MS_t) of the passenger car market. Following prior research [9], we calculate the quarterly market size as follows:

MS_t= [No. of Households(*t*)*No. of cars per household(*t*)]/[Average age of car*4] (6)

We obtain annual data on the number of households from the US. Census Bureau website www.census.gov. According to the Simmons database, the average US household owned 1.83

passenger cars in the sample period. The average age of a car in the US was 12.6 years during the same period, according to Ward's Automotive Yearbook.

5.2. Endogeneity of Price and Estimation

Price is endogenous because firms may make adjustments to their marketing strategy when anticipating demand shocks unobserved by researchers. For example, when introducing a new year version on a car model with a better design (e.g., car facelift), a firm may offer cash back incentives and increase its advertising budget on that car model. Such missing variables (e.g., product aesthetic appearance) may increase demand, leading to biased estimates of price and advertising.

To address the endogeneity of vehicle prices, we adopt the instrumental variables (IV) strategy introduced by BLP. Consistent with prior applications in the automobile industry, the instruments are constructed from functions of both a product's own characteristics and those of its competitors [31]. The procedure begins by classifying each vehicle into similarity groups defined along three categorical dimensions: country of origin (U.S., Japan, Europe, Korea), body type (sedan, minivan, pickup truck, SUV, other), and market segment (economy vs. luxury). For every model, we form two groups of similar products: (1) vehicles that share the same origin and segment, and (2) vehicles that share the same body type and segment. Instruments are then created by calculating the sum of observable characteristics (such as fuel economy and fuel savings) across products within the same brand and across rival brands for each similarity group. For instance, the Volkswagen Jetta, classified as a European economy sedan, would be compared with (1) all European economy cars and (2) all economy sedans, and the sums of characteristics would be calculated separately within Volkswagen and across competing brands. These instruments are relevant because equilibrium prices are determined in part by a product's own attributes and by the attributes of competing vehicles.

Our estimation procedure uses the generalized method of moments (GMM) combined with a contraction mapping technique, similar to BLP (1995) [9]. Additional details of this estimation procedure can be found in Nevo (2000) [30]. We use Gauss (Kernel Rev. 6.0.8, GUI Rev. 6.0.3) to estimate the models. Maxlik pack is used for finding the optimum estimates for the GMM objective function (https://faculty.washington.edu/ezivot/maxlik.htm).

6. Results

6.1. Estimation Results

To examine the data patterns and validate our empirical approach, we begin by presenting results from three progressively refined model specifications in Table 2. Model 1 serves as a baseline OLS estimation to establish the fundamental relationships in the data. It employs the natural logarithm of quarterly sales as the dependent variable, providing a straightforward examination of how the CVTC and other factors influence aggregate vehicle sales. Model 2 is a special case of our proposed model where consumers are homogeneous. The proposed full model was reduced to a linear equation with the difference between log market share and log outside share, $\ln(Sjt) - \ln(S_{0t})$, as the dependent variable. It is estimated using two-stage least squares (2SLS). Model 3 represents our preferred specification that addresses key econometric concerns inherent in demand estimation. The progression across these three models reveals consistent coefficient estimates, lending credibility to our empirical findings. However, we focus our discussion on Model 3, which represents the full model.

Table 2. Estimation Results

	Model 1 (OLS)	Model 2 (2SLS)	Model 3 (Full Model)
	Y_{jt}=ln($Sales_{jt}$)	Y_{jt}=ln(S_{jt})-ln(S_{0t})	
Means			
CVTC: Pure EV	0.06(0.01)***	0.05(0.01)***	0.15(0.03)***
CVTC: Mixed EV	-0.05(0.03)	0.07(0.03)**	0.34(0.18)*
EV	0.03(0.13)	0.74(0.13)***	-3.85(0.31)***
GV	4.53(0.20)***	5.17(0.22)***	8.48(0.06)***
MSRP	0.56(0.02)***	-0.97(0.03)***	-1.31(0.16)***
MPG	0.17(0.04)***	0.44(0.05)***	0.62(0.03)***
Q1	-0.04(0.02)***	-0.02(0.01)*	-0.20(0.18)
Q2	0.03(0.02)**	0.04(0.01)***	0.14(0.22)
Q3	-0.01(0.02)	-0.01(0.01)	0.02(5.18)
State Incentives	0.37(0.02)***	0.39(0.02)***	0.66(0.06)***
Standard Deviations			
EV			3.93(0.72)***
GV			2.47(1.65)
MSRP			0.11(0.20)
MPG			0.80(0.16)***
Car Model FE	Yes	Yes	Yes

Note: Standard Error is reported in parentheses.

*** p<0.01, ** p<0.05, * p<0.10

6.2. Main Policy Variable: Clean Vehicle Tax Credit (CVTC)

The central parameter of interest is the CVTC. In Model 3, which is our preferred specification, we estimate the effect of the CVTC separately for pure EV trims and mixed trims (models offering both gasoline and EV versions). The results show that the mean coefficient for CVTC is positive and statistically significant for both categories: 0.15 ($p < 0.01$) for pure EVs and 0.34 ($p < 0.10$) for mixed trims. These coefficients imply that the CVTC substantially raises the chance of consumers choosing a qualifying vehicle, with larger effects observed when the subsidy is attached to mixed trims where consumers directly compare EV and gasoline options within the same model line.

6.3. Powertrains Preference, Price Sensitivity, and the Effects of Other Control Variables

The inclusion of random coefficients sheds light on consumer preferences for different powertrains. Using hybrids as the reference category (i.e., preference for hybrid equals zero), the mean utility for GVs is strongly positive (8.48, $p < 0.01$). In contrast, the mean utility for EVs is negative (–3.85, $p < 0.01$). This pattern indicates that, on average, consumers prefer GVs over hybrids, and hybrids over EVs. However, the large and highly significant standard deviation for EVs (–3.93, $p < 0.01$) reveals substantial heterogeneity in preferences: while most households don't prefer EVs, a notable subset of consumers exhibit positive utility for EV adoption. By contrast, the standard deviation for GVs (2.47) is not statistically significant, suggesting relatively little heterogeneity around the strong baseline preference for gasoline models.

The manufacturer's suggested retail price (MSRP) coefficient of -1.31 ($p<0.01$) confirms the expected negative relationship between price and demand. Note that in Model 1 (OLS), MSRP is positive, highlighting the importance of the correction for price endogeneity. Moreover, the estimated standard deviation of the MSRP coefficient is not statistically significant, suggesting limited evidence of heterogeneous price responsiveness across households

Fuel economy (measured by MPG) has a positive and statistically significant mean effect (0.62, $p < 0.01$), indicating that, on average, consumers prefer vehicles with higher fuel efficiency. The large and significant standard deviation (0.80, $p < 0.01$) further suggests strong heterogeneity: while many households place high value on MPG, others show little or no responsiveness once EV status and fuel savings are accounted for. This highlights the importance of modeling consumer heterogeneity when evaluating the effects on fuel economy.

The coefficients on the quarterly seasonality controls are small and statistically insignificant, indicating no systematic differences in vehicle demand across quarters once other

factors are accounted for. State-level incentives have a positive and significant effect (0.66, $p < 0.01$), confirming that additional rebates or credits at the state level further stimulate EV demand beyond the federal program.

In random-coefficient logit models, the estimated parameters represent distributions of preferences across heterogeneous consumers rather than direct elasticities. Following standard practice in the structural demand literature, we rely on counterfactual simulations in next subsection to translate these preference parameters into economically interpretable policy effects.

6.4. Counterfactual Analysis: the Impact of Removing CVTC on GHG Emissions

The purpose of our counterfactual analysis is twofold. First, we simulate how vehicle sales would change under alternative policy scenarios with 10%, 20%, 50%, and 100% reductions in CVTC. Second, we evaluate the environmental consequences of these shifts, since lower EV adoption and higher gasoline vehicle sales are expected to increase greenhouse gas emissions. To implement this, we use our estimated BLP demand parameters to recalculate predicted market shares and sales volumes by adjusting the CVTC variable in the utility function while holding other parameters constant. The 100% reduction scenario directly corresponds to the policy environment following the passage of the One Big Beautiful Bill Act, which terminates the CVTC after September 30, 2025. Unlike reduced-form approaches that capture only aggregate sales responses, the counterfactual analysis based on the structural model allows us to calculate both the demand reallocations across EVs, hybrids, and GVs, and the resulting changes in emissions when heterogeneous consumers adjust their choices in response to policy changes.

The counterfactual simulations reveal substantial and progressive impacts of CVTC reductions on vehicle sales patterns(Table 3). As the tax incentive decreases from 10% to 100%, CVTC qualified EV sales decline correspondingly from 234,073 units (-11.53%) to 1,387,367

units (-68.36%), demonstrating the strong relationship between subsidy levels and EV adoption. Under the complete elimination scenario (100% reduction), which corresponds to the policy environment following the OBBB, the 1.39 million unit decline in qualified EV sales triggers significant market reallocation.

Notably, only 1.05 million of these displaced sales substitute for other vehicle types, while approximately 0.34 million sales (24.6% of displaced qualified EV sales) flow to the outside option, indicating that a substantial fraction of consumers exit the new car market entirely when subsidies are removed. In our discrete choice framework, the outside option represents consumers who choose not to purchase any new vehicle in a given quarter, either deferring their purchase to a later period, holding onto their current vehicle longer, or exiting the new car market entirely. This substantial flow to the outside option indicates that the CVTC influences not only *which* vehicle consumers choose but also *whether* they enter the new vehicle market at all. The finding suggests that federal subsidies play a critical role at both the intensive margin (substitution among vehicle types) and the extensive margin (participation in the market), with roughly one-quarter of consumers who would have purchased a subsidized EV choosing instead to forgo a new vehicle purchase when the incentive is removed.

Table 3. Simulated Change in Car Sales with Reduced Tax Incentive

sales change	Tax incentive reduced 10%	Tax incentive reduced 20%	Tax incentive reduced 50%	Tax incentive reduced 100%
CVTC qualified cars	-234,072.75 (-11.53%)	-435,494.02 (-21.46%)	-899,294.10 (-44.31%)	-1,387,367.44 (-68.36%)
CVTC unqualified cars	172,771.56 (0.55%)	322,306.19 (1.03%)	670,704.27 (2.15%)	1,045,841.22 (3.36%)
- unqualified EV cars	24,636.09 (4.82%)	49,064.67 (9.60%)	119,950.86 (23.46%)	223,416.19 (43.70%)
-unqualified Gas cars	147,260.00 (0.48%)	271,627.17 (0.89%)	547,501.58 (1.80%)	817,570.65 (2.68%)
-unqualified Hybrid cars	875.48 (0.50%)	1,614.35 (0.92%)	3,251.83 (1.85%)	4,854.38 (2.76%)

Note: Percentage changes to sales before policy change are reported in parentheses.

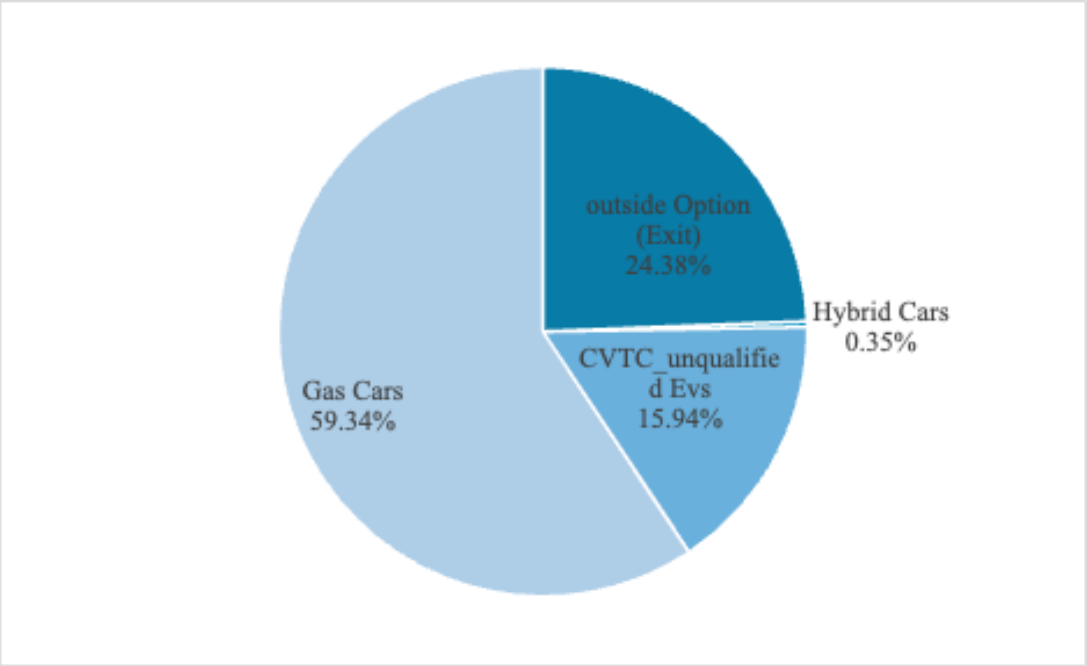
Table 4: Simulated Environmental Impact with Reduced Tax Incentive

sales change	Tax incentive reduced 10%	Tax incentive reduced 20%	Tax incentive reduced 50%	Tax incentive reduced 100%
Added CO_2 emission per year (K tons)	770.02	1420.39	2863.25	4276.12
Added GHG emission per year (K tons)	810.55	1495.14	3013.95	4501.17
Added Fuel cost per year (M$)	296.79	547.44	1103.49	1647.86

The substitution pattern among unqualified vehicles reveals important heterogeneity in consumer preferences with important climate implications. Most notably, CVTC unqualified EV models experience a dramatic 43.70% increase (223,416 units), a growth rate more than fifteen times larger than other vehicle categories. This substantial proportional increase suggests that many consumers who lose access to CVTC-qualified vehicles remain strongly committed to electric powertrains and actively seek out non-qualifying EV alternatives. However, despite this remarkable proportional shift toward EVs, GVs capture the largest absolute increase at 817,571 units, representing a concerning majority of displaced qualified EV sales. While this translates to only a modest 2.68% gain relative to their existing market dominance, the sheer volume of this shift carries significant environmental consequences, as these additional GVs will generate substantially higher lifetime carbon emissions compared to their displaced EV counterparts. Hybrid vehicles show similarly modest percentage gains (2.76%, or 4,854 units).

Figure 1 illustrates the destination of displaced CVTC-qualified EV sales under the full credit elimination scenario, disaggregating the 1,387,367-unit decline into its constituent substitution flows. The largest share of displaced demand, 59% (817,571 units), flows to GVs. A notable 25% of displaced sales (341,526 units) flow to the outside option, meaning these consumers exit the new car market entirely rather than substitute into another vehicle type. The remaining 16% (223,416 units) are allocated toward CVTC-unqualified EVs. Hybrid vehicles absorb a negligible share of displaced demand (less than 1%, or 4,854 units). Taken together, this substitution pattern reveals that GVs, not alternative clean vehicles, are the primary beneficiary of CVTC elimination, with direct consequences for greenhouse gas emissions and the trajectory of vehicle fleet electrification.

Figure 1 Destination of Displaced CVTC-Qualified EV Sales under Full Credit Elimination



Based on the simulated sales reallocations in Table 3, we next calculate the environmental and economic consequences of reducing or eliminating the CVTC. We obtain each car model's CO_2 emissions in grams per mile and annual fuel cost in USD from the U.S. Department of Energy's fuel economy database. To translate per-mile CO_2 emissions into annual values, we follow the U.S. Environmental Protection Agency's convention of assuming 12,000 miles (19312 km) of driving per year for typical passenger vehicles and 15,000 (24140 km) miles for light trucks, [24] Beyond carbon dioxide, passenger vehicles also emit other greenhouse gases such as methane (CH_4) and nitrous oxide (N_2O) from the tailpipe, as well as hydrofluorocarbons (HFCs) from leaking air conditioners. Unlike CO_2, which can be directly estimated from fuel consumption, these gases are tied to vehicle miles traveled or maintenance conditions and are much harder to quantify precisely. Following the EPA's approach, we assume that CO_2 accounts for approximately 95% of total vehicle GHG emissions, with the remaining 5% contributed by CH_4, N_2O, and HFCs. Accordingly, total vehicle GHG emissions are calculated as $CO_2 \times (100/95)$ [2].

By multiplying the predicted increase in GV sales under each counterfactual scenario by the corresponding per-vehicle emissions and fuel cost figures, we generate estimates of the aggregate environmental and economic costs associated with the policy-induced shift away from electric vehicles. Table 4 reports the results. Even modest cuts to the CVTC generate measurable increases in emissions: a 10% reduction adds roughly 770 thousand tons of CO_2 per year, equivalent to about 810 thousand tons of total GHGs, and increases annual fuel expenditures by nearly $297 million. As the credit is reduced further, these costs rise steeply. A 50% cut adds 2.9 million tons of CO_2 and over $1.1 billion in fuel costs annually. Under complete elimination, the added burden reaches 4.3 million tons of CO_2 (4.5 million tons of total GHGs) each year, alongside an additional $1.65 billion in fuel costs.

Taken together, the findings in this counterfactual analysis reveal two important dynamics. First, it highlights how strongly EV adoption depends on federal incentives and how the removal of these incentives risks both a sharp drop in the EV market and an increase in GV sales. Second, the fact that more than 300,000 lost sales are not replaced at all suggests that removing the CVTC not only shifts consumers toward higher-emitting vehicles but also reduces overall new vehicle turnover, potentially slowing the replacement of used, less efficient cars. Third, the impact of federal EV incentives extends well beyond the car market: reducing the CVTC not only decreases EV sales but also substantially increases carbon emissions and household fuel expenses. The additional emissions from a full elimination of the CVTC are equivalent to putting nearly one million gasoline cars back on the road, while the rise in fuel costs represents a significant transfer of household income to fuel expenditures. Together, this analysis demonstrates that federal EV subsidies are a powerful lever not only for shaping consumer demand but also for mitigating greenhouse gas emissions and reducing fuel dependence.

7. Robustness Checks

7.1. Potential Endogeneity of CVTC and State Level Incentives

A potential concern is that CVTC eligibility may be endogenous. Because manufacturers actively decide whether a vehicle meets the battery sourcing, mineral content, and assembly requirements under the IRA, certification status is not randomly assigned. If manufacturers simultaneously adjust unobserved product quality, dealership incentives, or marketing intensity for models expected to qualify for the CVTC, estimates of the incentive effect could be biased. In addition, state-level incentives may also respond to local market conditions, introducing a second potential source of endogeneity.

We address these concerns through both institutional arguments and empirical robustness checks. Institutionally, qualification for the CVTC depends on battery supply chains, mineral sourcing contracts, and assembly location decisions that are typically determined within multi-year product development cycles (often three to five years between major redesigns). These substantial adjustment frictions limit manufacturers' ability to rapidly manipulate eligibility in response to short-term demand shocks. Moreover, our specification includes car model fixed effects, which absorb all time-invariant differences in product quality, baseline marketing intensity, and brand reputation. Remaining bias would therefore require time-varying marketing investments precisely aligned with certification timing.

To further assess robustness, we conduct two additional analyses. First, because CVTC eligibility is less likely to be endogenous immediately following the IRA's implementation, we restrict the sample to the first six quarters after introduction (2023 Q1–2024 Q2). In this shorter window, manufacturers had a limited opportunity to reconfigure supply chains or systematically reallocate marketing resources. The estimated CVTC coefficients remain statistically significant and economically meaningful.

Second, we implement the Gaussian Copula correction proposed by Park and Gupta (2012), which provides a control-function–type adjustment for endogenous regressors in

nonlinear models without requiring external instruments [32]. This approach relies on the non-normality of the potentially endogenous regressor. Our diagnostic tests yield mixed evidence: the Kolmogorov–Smirnov and skewness/kurtosis tests reject normality, whereas the Jarque–Bera test does not. Accordingly, we interpret the copula results cautiously. Nevertheless, the copula-adjusted estimates remain qualitatively similar to the baseline model, and the counterfactual simulation results, particularly the magnitude and direction of sales reallocations and emissions impacts, are not materially altered.

We acknowledge that causal interpretation of the CVTC coefficients of the main model rests on institutional arguments discussed above rather than a randomized or quasi-experimental design. However, the consistency of the CVTC coefficients across all four model specifications, OLS, 2SLS, and the full random-coefficient model with and without Gaussian Copula correction, substantially strengthens confidence that the positive relationship is not driven solely by a particular estimation approach. However, the possibility of remaining unobserved factors means that the estimates should be interpreted under the maintained assumptions of the structural framework rather than as definitive causal estimates from randomized variation.

7.2. Robustness to Mixed-Model Allocation Procedure

As described in the Data section, for models offering both gasoline and EV trims under the same model name, total sales are reported only at the aggregate level. We therefore split total model sales into EV and gasoline components using documented trim-level information. However, in a small number of cases, we approximate the EV portion using the brand's overall EV sales share. This procedure may introduce measurement error if brand-level shares do not perfectly reflect model-specific trim composition.

To evaluate whether our findings are sensitive to this allocation approach, we conduct a robustness check excluding the four models for which brand-level EV shares were used to split total sales (Lincoln Aviator, Lincoln Corsair, BMW X5, and BMW 3 Series). These

models account for 4 out of 397 total models (approximately 1% of the full sample) or 4 out of 58 EV models (6.9% of EV models). Re-estimating the model after removing these observations yields results that are consistent with the baseline specification. The estimated CVTC effects and counterfactual simulation outcomes remain materially unchanged, indicating that our core conclusions are not driven by the sales allocation method for mixed models.

8. Conclusion, Limitations, and Implications

8.1. Conclusion

This study evaluates the impact of the federal Clean Vehicle Tax Credit (CVTC) on vehicle demand and emissions in the United States, with particular focus on the consequences of its early termination under the One Big Beautiful Bill Act (OBBB) of 2025. Using a structural random-coefficient logit model estimated on a comprehensive national dataset covering 62 brands and 397 car models between the first quarter of 2015 and the second quarter of 2025, we quantify how federal incentives shape consumer vehicle choices and how these choices in turn affect greenhouse gas emissions.

Our results highlight three central findings. First, the CVTC has a significant positive effect on EV adoption, and federal tax incentives play an important role in tipping consumer preferences toward electric vehicles. Second, counterfactual simulations show that eliminating the CVTC would lead to a dramatic reduction in qualified EV sales, with losses of approximately 1.39 million units. Much of this displaced demand reallocates to GVs (817,571 units) while a smaller but proportionally larger increase is observed for unqualified EVs (223,416 units) and hybrids (4,854 units). Importantly, about 341,526 units are lost to the outside option, reflecting deferred or foregone purchases in new car market. Third, these shifts have substantial environmental and economic implications. Full elimination of the CVTC adds 4,276 kilotons of CO_2 emissions and 4,501 kilotons of total greenhouse gas emissions annually,

alongside $1,647.86 million in additional fuel costs for households. These findings indicate the importance of federal EV incentives not only for sustaining market demand but also for mitigating climate change and reducing consumer fuel expenditures.

8.2. *Limitations*

While the study provides novel evidence on the consequences of the CVTC, several limitations should be acknowledged.

First, our analysis relies on aggregate sales data at the model level, which necessitated approximations for mixed trims. Although we carefully split model sales into EV and gasoline trims using supplemental sources and manual verification, errors in these allocations could introduce measurement noise. Future work using micro-level registration data or proprietary manufacturer records would help validate and refine these splits.

Second, while our structural model accounts for heterogeneity in consumer preferences, it does not capture all behavioral complexities. For example, factors such as consumer learning about EV technology, range anxiety, charging infrastructure availability, and peer effects are not explicitly modeled but may play an important role in adoption decisions. Incorporating these dynamics into structural frameworks would provide a richer understanding of how incentives interact with evolving consumer beliefs and social influences.

Third, the counterfactual simulations assume that vehicle characteristics and firm strategies remain fixed. In practice, automakers may adjust MSRP, marketing, or product portfolios in response to policy changes, which could dampen or amplify the simulated outcomes. For instance, manufacturers may lower prices or increase promotional spending to offset the loss of subsidies. While our framework provides clean estimates of the demand-side response, future research should integrate firm behavior to deliver a more comprehensive general equilibrium assessment.

Fourth, our emissions calculations are based on standardized assumptions of annual mileage (12,000 miles for cars, 15,000 for light trucks) and EPA conversion factors. Actual emissions may vary depending on driving conditions, maintenance, and regional fuel mixes. Moreover, while we incorporate methane, nitrous oxide, and hydrofluorocarbons through EPA multipliers, these values are averages and may not reflect real-world variability. Extending this work with detailed lifecycle analysis or region-specific emissions data would enhance the precision of the environmental assessment.

Fifth, while our counterfactual analysis identifies that approximately 341,526 sales flow to the outside option when the CVTC is eliminated, our static discrete-choice framework cannot distinguish between consumers who permanently exit the new vehicle market and those who temporarily defer their purchases to future periods. This distinction carries meaningful implications for policy evaluation. If the majority of outside-option flows represent temporary deferrals, the long-run environmental costs of CVTC removal may be smaller than our static estimates suggest, as pent-up demand eventually materializes in subsequent periods and consumers ultimately replace their vehicles with newer, cleaner models. Conversely, if consumers permanently exit the new vehicle market, for instance, by extending the life of their existing vehicles for several additional years, the environmental consequences are compounded beyond what our static emissions estimates capture. Older, less fuel-efficient vehicles remaining on the road longer would generate higher cumulative emissions than our estimates suggest, suggesting that our reported figures represent a lower bound on the true environmental cost of CVTC removal. The roughly one-quarter of displaced EV buyers who flow to the outside option therefore represent a policy-critical margin whose behavioral dynamics remain unresolved in our framework. Future research employing household-level panel data or vehicle registration records over multiple periods could decompose the outside option into these distinct

mechanisms and provide a more complete picture of the dynamic adjustment process following policy changes.

Sixth, our sales data record only new vehicle purchases and do not separately identify lease transactions. In our BLP framework, lease transactions are therefore embedded within the outside option. Because the CVTC can stimulate both purchases and leases of qualifying vehicles, our estimates likely understate the full market response to the policy. In this sense, the policy effects we document should be interpreted as conservative lower bounds on the total impact of the CVTC on EV adoption. Incorporating the leasing channel would likely strengthen, rather than weaken, our central conclusion that the CVTC is a powerful driver of EV demand and that its removal entails substantial environmental and economic costs. Future research using transaction-level data that distinguishes between purchase and lease decisions would allow for a more complete quantification of the policy's overall market effects.

Seventh, our analysis is grounded in the U.S. institutional context, drawing on a dataset that covers the U.S. passenger vehicle market. As a result, the findings are most directly applicable to high-income, market-driven economies with established vehicle markets, mature EV supply chains, and tax-based subsidy delivery mechanisms. Developing economies face substantially different structural conditions, including lower average household incomes, less developed charging infrastructure, weaker consumer familiarity with EV technology, and alternative subsidy instruments such as import duty waivers or direct cash transfers rather than income tax credits. These differences could lead to markedly different consumer responses to incentive programs, both in magnitude and in the distribution of benefits across income groups. We therefore caution against direct extrapolation of our quantitative estimates to emerging market contexts. Examining how structural incentive effects differ across economies at varying stages of EV market development represents a valuable and policy-relevant direction for future research.

Finally, our time frame ends in the second quarter of 2025, just before the OBBB takes effect. While this cutoff avoids the confounding short-term purchase acceleration caused by the pending subsidy expiration, it also means that we cannot empirically observe how consumers actually respond once the policy change is implemented. Future work using post-OBBB data would provide valuable validation of the counterfactual predictions.

8.3. *Implications*

Despite these limitations, the study offers several important implications for research, policy, and industry.

For researchers, this paper demonstrates the value of structural models in evaluating climate and energy policy. Unlike reduced-form approaches that provide average treatment effects, our framework uncovers heterogeneous consumer responses and realistic substitution patterns, offering a richer picture of policy impacts. Future empirical work could build on this foundation by incorporating dynamic considerations such as repeat purchasing, fleet turnover, and firm competition, thereby extending the scope of policy evaluation in automotive markets.

For policymakers, the findings highlight the critical role of federal incentives in accelerating EV adoption and reducing greenhouse gas emissions. The simulations show that removing the CVTC would not simply slow the growth of EV sales but would actively reverse adoption, with nearly 1.4 million lost EV sales translating into a rebound of over four million tons of annual CO_2 emissions. This evidence suggests that abrupt withdrawal of subsidies risks undermining broader climate targets, and that a more gradual or targeted phase-out may be necessary to sustain progress. In addition, the results demonstrate that a significant portion of displaced demand flows into GVs, which has direct consequences for fossil fuel dependence and consumer fuel costs. Designing policies that smooth the transition—such as infrastructure investment, hybrid incentives, or manufacturer mandates—could mitigate these adverse effects.

For industry stakeholders, the results underscore the vulnerability of EV demand to policy shocks. Automakers and dealers should anticipate sharp demand contractions in the absence of subsidies and consider proactive strategies such as cost reductions, consumer education, and bundling with financing or charging benefits. The heterogeneity in consumer preferences also implies that while some buyers will adopt EVs regardless of incentives, others remain highly sensitive to upfront price differences. Targeted marketing and financing solutions could help bridge this gap.

Taken together, these implications reinforce the central message of this paper: federal incentives are not merely marginal supports but fundamental drivers of EV adoption, emissions reduction, and consumer welfare. Abrupt policy reversals risk not only stalling the transition to cleaner transportation but also reversing environmental gains already achieved. By quantifying these dynamics in a rigorous structural framework, this study provides timely and policy-relevant evidence on the importance of sustained federal support for the EV market.

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