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Modeling the Demand for Electric Vehicles and the Supply of Charging Stations in the United States

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The information in this paper is preliminary and is being circulated to stimulate discussion and critical comment as developmental work for analysis for the Congress.

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Abstract

This paper presents a simulation model of the markets for light-duty electric vehicles (EVs) and the associated public charging infrastructure, as well as the network interactions between them. It illustrates the model's attributes by simulating the effects of federal subsidies for public electric vehicle chargers and of an extension of tax credits for electric vehicles. I project that by the early 2030s the charger subsidies, which were signed into law in 2021 as part of the Infrastructure Investment and Jobs Act, will have increased the size of the charger network enough to meet the demand for charging through the middle of that decade. That includes the additional demand that the expansion itself will induce: I project that through 2030, sales of EVs will rise more than 20 percent more rapidly with the expanded charger network than they would have otherwise. Including the additional effect of the EV tax credits that were signed into law as part of the 2022 reconciliation act, as well as past growth in EV sales, I project that EVs will constitute between 27 percent and 60 percent of new light-duty vehicle sales by 2032, compared with about 6.5 percent in 2022. After the subsidy funding from the Infrastructure Investment and Jobs Act has been spent and the available EV tax credits claimed, EV charger networks and the EV fleet will remain somewhat larger than they would have been in the absence of those policies.

Keywords: Electric vehicles, charging infrastructure, network effects, tax credits, subsidies

JEL Classification: H23, H54, L98

Contents

1. Introduction

This paper provides an overview of an analysis that jointly models the demand for light-duty, plug-in electric vehicles (EVs) and the supply of public EV chargers. As the Congress considers or adopts a range of policies that would subsidize sales of plug-in electric vehicles, either directly or indirectly, this model gives the Congressional Budget Office an additional tool for estimating the effects of those policies on the federal budget, carbon dioxide emissions, and the demand for electricity and gasoline. The model projects sales of new electric vehicles—including plug-in hybrid-electric vehicles—as a share of sales of all new passenger vehicles. That share is modeled as a function of predicted vehicle costs (production, operation, and maintenance); the size of the EV charger network (including slower level 2, or L2, chargers with respect to the number of registered EVs and faster L3, or "DC fast," chargers with respect to the size of the national highway system); and consumers' preferences for EVs or similar cars with internal combustion engines. The model also projects the stock of EV chargers as a function of the predicted cost of supplying a charger and the projected size of the electric vehicle fleet.

The model builds on recent work by Cole et al. (2023), who model the demand for EVs and the supply of EV chargers as jointly determined.[1] The demand for EVs is presented as depending on the size of the EV charger network: The larger that network, the more utility an EV provides, because it can be driven to more places and recharged more easily. Similarly, in Cole et al. (2023) the supply of chargers depends on sales of EVs: The larger the EV fleet, the more use each EV charger receives and the more revenue it generates per unit of time.

The model described here takes a similar approach but with two important differences. First, it incorporates into its base case the anticipated effects of up to $7.5 billion in federal EV charger subsidies provided by the Infrastructure Investment and Jobs Act (IIJA; Public Law 117-58) in 2021, along with the anticipated effects of the EV tax credits provided by the 2022 reconciliation act (P.L. 117-169).[2]

Before the enactment of the 2022 reconciliation act, CBO and the staff of the Joint Committee on Taxation (JCT) prepared an estimate of its budgetary effects (CBO 2022). As required by the Congressional Budget Act of 1974, CBO estimated the effects of the spending provisions, and JCT estimated the effects of the tax provisions. By statute, the cost estimate for the 2022 reconciliation act published by CBO directly incorporated JCT's estimates of the budgetary effects of the energy-related tax provisions of that bill, including those related to electric power,

[1] Cole et al. (2023), citing Zhou and Li (2018) and Springel (2021).

[2] The base case presented in this paper is not an input to CBO's budget baseline. It is an output of a stand-alone CBO model based on recent market trends and findings from the literature.

electric vehicles, carbon capture and sequestration, and clean energy manufacturing. The model described in this working paper was not used in preparing that cost estimate.

The second difference from the approach taken by Cole et al. (2023) is that I calibrate the model so that its base-year supply of chargers matches the most recent full-year number reported in the Alternative Fuels Data Center's station locator database and so that, once the IIJA subsidies are exhausted, it projects a ratio of L2 chargers to EVs approximately equal to the current ratio of about 3 charging ports per 100 EVs.[3] That serves as my estimate of the optimal (profit-maximizing) ratio for charger suppliers, even as the number of registered EVs continues to increase. Cole et al. (2023) calibrate their model to a future ratio that is about three times higher.

In this paper, I discuss the demand for EVs and particularly my approach toward attribute drift, or changes in certain attributes of EV ownership that affect consumers' preferences for EVs or internal combustion engine vehicles (ICEVs). (Those attributes, which are not otherwise specified in my model, include the availability and performance of EV chargers, social influences, and many attributes of the vehicles themselves.) The attribute drift term allows the model to more accurately account for recent trends in EV sales. Those sales exceed what the model would predict solely on the basis of the other terms in the demand equation: the relative ownership costs of EVs and ICEVs, the number of publicly accessible chargers per EV and per highway mile, and past sales of EVs.

Next, I discuss the supply of EV chargers. The model has a supply equation giving the number of charging stations by year as a function of the size of the EV fleet, the cost of supplying a charger that year compared with the anticipated lower cost the next year, and the number of charging stations that existed the previous year. If in any year it is optimal, in the model, for suppliers to add no new EV chargers, the size of the charger network will decline that year by the number of chargers that will fail, based on rates of failure that increase with charger age. The discussion of charger supply also describes how I model the federal IIJA subsidies for EV chargers.

I use the model to project annual sales of new EVs and the supply of new charging stations through 2050. The demand and supply equations interact: The size of the charger network affects EV demand, and the size of the EV fleet affects the supply of chargers. Details about the values used for the model's parameters and six sensitivity analyses of influential parameters are provided in Appendix A and Appendix B, respectively.

The model described in this paper provides CBO with a tool for estimating the effects of developments in the automobile industry, and in federal policy toward EV sales, on the federal

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[3] The number of EV chargers per charging station varies, currently averaging about 2 chargers per station according to the station locator database. EV chargers may have multiple ports for charging more than one vehicle at a time, just as fuel pumps with multiple nozzles can refuel more than one vehicle at a time at a gas station.

budget and the economy. This paper provides transparency into that model, which was developed while the Treasury Department was developing guidance on eligibility requirements for electric vehicles to qualify for tax credits. The percentage of EVs that will ultimately qualify for those credits is not known with precision. The projections provided in this paper reflect that and other sources of uncertainty (see Appendix A).

2. Demand for Electric Vehicles

In the model, vehicle buyers choose between electric and internal combustion versions of their desired vehicle. I analyze cars and light trucks separately but do not distinguish between different vehicle makes and models. In the vehicle sales data used in this simulation model, I classify plug-in hybrid vehicles as EVs and non-plug-in hybrid vehicles as ICEVs.

A consumer's choice of an EV or an ICEV depends on expected ownership costs, the density of the EV charger network, and shifts in consumers' preferences for EVs (as modeled by attribute drift). I estimate a vehicle's expected ownership cost as its purchase price—accounting for the EV tax credits contained in the 2022 reconciliation act—plus its expected operating and maintenance costs over its first eight years, discounted to the date of purchase.[4] I measure the density of the charger network in terms of the number of rapid chargers per highway mile and the number of slower chargers per EV.[5]

Attribute drift can be thought of as reflecting the effects on consumers' preferences for EVs or ICEVs of factors not otherwise included in the model. Examples of such factors include improvements in EVs or the charger network, breadth and availability of EV models relative to ICEVs, and social influences such as proportion of EV ownership among acquaintances and other drivers. Without attribute drift, the model would project future EV sales solely on the basis of trends in vehicle costs and network density. I calibrate the drift term so that the model's

[4] In valuing expected future savings on maintenance and operating costs for an EV versus an ICEV, I use a discount rate of about 10 percent. That rate combines a preference for receiving value today versus in the future with an observed tendency for consumers to undervalue future savings from energy-efficient technologies. I use 3 percent as consumers' rate of time preference, and I model consumers as undervaluing future savings in energy and maintenance costs by an average of 25 percent. (The actual reduction comes from a probability density that averages 25 percent.) See Allcott and Wozny (2014); see also Helfand and Wolverton (2011). Finally, I model consumers as valuing future savings over eight years rather than over the expected life of the vehicle. The combination of those factors amounts to discounting future savings at an annual rate of about 10 percent. In sensitivity testing I find that counting just five years of expected savings does not substantially change the model's projections.

[5] Although my EV projections do not account for panel trucks or other freight-delivery vehicles, those vehicles will typically recharge in private fleet facilities overnight or at dedicated truck stops and will thus not tend to compete with passenger vehicles for access to the public charging infrastructure. L3 rapid chargers can recharge most cars to about 80 percent of capacity in about 20 minutes and are most suitable for placement along highways. Slower L2 chargers take four or five hours to provide a comparable charge and are more suitable for placement in parking facilities. For charging times, see Alternative Fuels Data Center, "Developing Infrastructure to Charge Electric Vehicles."

projected EV sales through 2030—ignoring the expected influence of the federal IIJA charger subsidies and EV tax credits—are consistent with the observed EV sales trend over the past several years. (The next section presents EV sales projections that are based on different assumptions about attribute drift.) Finally, I adjust the intercept and attribute drift terms so that, given the other parameter values in the model, its base-year EV sales match observed totals from most recent full year, currently 2021.

2.1 Factors That Influence EV Market Share

I model the demand for EVs as arising from an underlying consumer utility function:

$$u_{i,j,t} = \alpha_j + ln(p_{j,t}) \cdot \beta_p + ln(L2_t/TotEV_{t-1}) \cdot \beta_{L2} + ln(L3_t/HwyMiles) \cdot \beta_{L3} + \psi_t + \epsilon_{i,j,t},$$

where i indexes individual consumers, j is vehicle type (car or light truck), and t is time in years. The β terms are parameters associated with, respectively, the sensitivity of the demand for EVs to changes in the following: ownership cost $p_{j,t}$ of an EV of type j in year t relative to that for a comparable ICEV; the number of slower L2 chargers per registered EV in year t; and the number of faster L3 chargers per highway mile.[6] Finally, ψ_t is attribute drift, and $\epsilon_{i,j,t}$ is an idiosyncratic taste shock distributed as type I (Gumbel) extreme value (Cole et al. 2023). I further describe the parameters below.

To ensure that EV and ICEV ownership costs ($p_{j,t}$) are compared on an equal basis, I calculate the costs for both types of vehicle using the number of miles that a potential buyer would expect to drive in an EV. Until recently, EVs were estimated to be driven only about 60 percent as many miles as ICEVs, on average (Burlig et al. 2021). With expansion in the EV charger network and improved battery capacities, that ratio appears to be increasing over time. To reflect that, I model the ratio of miles driven by EVs versus ICEVs as currently averaging 60 percent and gradually increasing to 100 percent by 2035.

That increase contributes to growth in the projected demand for EVs, because it means that expected annual energy savings from EVs versus ICEVs are also increasing. Some current evidence suggests that many EVs are already being driven as many miles as comparable ICEVs (Spiller et al. 2023). If so, current demand for EVs may already reflect much of those energy savings, and thus the model may be slightly overstating that source of growth in projected demand. However, the contribution of higher future energy savings to growth in the demand for EVs is relatively small.

[6] I treat *HwyMiles* as constant, although it may increase gradually over time. I also hold constant the energy efficiency of EVs (although battery costs continually decline, which is equivalent to increasing energy efficiency from the perspective of ownership costs) and ICEVs after model year 2026 because corporate average fuel economy (CAFE) standards for later model years have not yet been specified. Through 2026, I treat both average ICEV fuel economy and manufacturing costs as rising with increasingly stringent CAFE standards (see Appendix A).

Like the effect of anticipated growth in EV miles driven, the rate of decrease in EV battery costs is also favorable to EVs. That rate could slow if it became more difficult to mine the scarce materials used in batteries. Conversely, innovations in battery technology, which would be spurred by concerns about the scarcity of materials, could sustain or increase battery cost reductions (see Appendix A).

Existing empirical research on the sensitivity of EV demand to the size of the charger network does not distinguish between L2 and L3 chargers. Thus, I assign the same value to both β_{L2} and β_{L3}. Even so, with about 15.4 registered EVs per highway mile in the United States at the end of 2022—a ratio that will increase over time—each additional L3 charger is therefore modeled as having $ln(TotEV/HwyMiles) = ln(15.4) = 2.7$ times more influence on EV demand at present than each new L2 charger has.[7]

That consumer utility function—or, more precisely, the type I extreme-value term reflecting variation in individuals, vehicles, and time in consumers' preferences for passenger vehicles—yields a tractable and logically appealing expression (its values range from 0 to 1) for the market share of EVs versus ICEVs. With that utility function, the shares of EVs among all new light-duty vehicles are given by a pair of logistic functions, one each for cars and light trucks. Logistic functions' familiar S-shaped curves are useful for modeling technology diffusion because they asymptote at shares of 0 and 1:

$$EVshare_{j,t} = \frac{e^{\left(\alpha_j + X_t \beta_j + \psi_t\right)}}{1 + e^{\left(\alpha_j + X_t \beta_j + \psi_t\right)}},$$

where α_j is a calibration parameter for setting the model's initial EV share for new vehicles of type $j \in \{car, truck\}$ to the currently observed value; X_t is matrix shorthand for the factors $p_{j,t}$, $(L2_t/TotEV_{t-1})$, and $(L3_t/HwyMiles)$ that underlie the demand for EVs in this model; β_j is vector shorthand for the three corresponding demand-response parameters β_p, β_{L2}, and β_{L3}; and Ψ_t is the attribute drift parameter, discussed in greater detail in the next section.

The β_j parameters reflect how sales of new EVs respond to changes in vehicle ownership costs (including purchase price) or in the charger network and have the following signs: $\beta_p < 0$ (increases in ownership costs reduce the demand for EVs), $\beta_{L2} > 0$, and $\beta_{L3} > 0$ (increases in L2 chargers per EV or in L3 chargers per highway mile increase the demand for EVs). The β_j parameters are related to elasticities of demand when demand is measured in terms of market

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[7] As of December 2022, there were about 3.4 million electric vehicles registered in the United States, including EVs and plug-in hybrid EVs (Alternative Fuels Data Center, "Electric Vehicle Registrations by State"). The National Highway System in the United States currently includes about 224,000 miles of highway, including about 67,000 miles of interstate highways and other freeways and 157,000 miles of other principal arterial highways (Federal Highway Administration 2021).

share (rather than unit sales). For example, the price elasticity of market share for new EVs, in year *t*, is given by $\beta_p \cdot (1 - EVshare_t)$—meaning that a 1 percent decrease in the relative ownership cost of an EV versus an ICEV would increase the market share of new EVs by $\beta_p \cdot (1 - EVshare_t)$ percent in year *t*.[8]

As long as the market share of new EVs remains small, the price elasticity of market share will approximately equal β_p. The elasticity will decline as the share of new EVs increases. Ultimately, as the share of new EVs approaches 100 percent, the elasticity will approach zero.

The charger network elasticities of market share for new EVs have the same form as the price elasticity: An increase of 1 percent in the number of L2 chargers per EV, or in L3 chargers per highway mile, would increase the market share of new EVs by $\{\beta_{L2} \; or \; \beta_{L3}\} \cdot (1 - EVshare_t)$.

Appendix A lists the parameter values and data used in the model, along with their sources. Vehicle sales are aggregate totals for plug-in vehicles (EVs and plug-in hybrid EVs) and vehicles that do not plug in (ICEVs that run on gasoline or diesel and hybrid EVs that do not plug in). Vehicle production costs and fuel costs are given for representative vehicles: EVs rather than plug-in hybrid EVs because EVs outsell them by a substantial margin, and gasoline-powered ICEVs (of average fuel efficiency) rather than diesel or non-plug-in hybrid EVs, for the same reason (EIA 2022b). EV production costs reflect estimates for car batteries with a capacity of 70 kilowatt-hours and batteries for light trucks with a capacity of 120 kilowatt-hours, both providing a range of 240 miles. Future decreases in battery production costs are treated as reducing the prices of new EVs.[9] Appendix B presents the results of sensitivity analyses on the most influential parameters in the model, including the $\beta_{j,t}$ terms relating to the ownership cost and network size elasticities of demand for new EVs.

2.2 Attribute Drift

The term *attribute drift* refers to changes in unspecified attributes of EV ownership (including attributes of the vehicles themselves; their availability in the new-vehicle marketplace relative to ICEVs; attributes of EV charger networks, including availability and performance of vehicle chargers; and the influence of social factors) that affect consumers' preferences for EVs relative to ICEVs. In the EV demand equation, attribute drift at time *t* is

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[8] Relative ownership costs of EVs and ICEVs depend on purchase prices and the present value of expected lifetime costs of fuel and maintenance, given an assumed number of miles traveled per year as a vehicle ages. Purchase prices are estimated as markups of projected production costs, including the cost of EV batteries. The price- and charger-supply elasticities of demand are drawn from probability densities that reflect the range and quality of estimates found in the literature (see Appendix A).

[9] The technological advances that those cost decreases represent could instead be used to increase battery range while holding vehicle prices fixed; either use would increase EV sales.

$$\psi_t = \mu + \psi_{t-1} + \zeta_t,$$

where ψ_0 = 0, μ is a constant time trend, and ζ_t is a mean-zero annual departure from that trend. Greater attribute drift—a higher trend value μ—projects a more rapid shift to EVs. In the model's simulations, trend μ is randomly drawn, with a mean value that depends on β_p: The more responsive consumers are to changes in the relative costs of EV ownership, the more rapidly the shift to EVs would occur with decreases in those costs. Both μ and ζ_t are drawn from normal density functions:

$$\mu \sim N\left(a \cdot \left|\beta_p\right|, b \cdot \left|\beta_p\right|\right), \qquad \zeta_t \sim N(0, c \cdot |\mu|).$$

That functional form for attribute drift follows Cole et al. (2023), who cite Archsmith et al. (2021).

To specify drift, the modeler specifies parameters *a, b,* and *c,* with *a* being the key parameter because it directly affects the demand trend. The parameters *b* and *c* specify variances for trend μ and departure ζ_t, respectively. At each iteration of a policy simulation, a new price elasticity is drawn from a specified probability distribution.[10] That selection determines the value of β_p that will be used for that iteration. With β_p determined, trend μ is then selected: On average it will have a value of $a \cdot \left|\beta_p\right|$, although with a variance of $b \cdot \left|\beta_p\right|$. When a high (low) price elasticity is drawn, for that iteration consumers will be more (less) responsive every year to changes in the factors that affect consumers' preferences for EVs versus ICEVs. With μ determined, a new ζ_t is drawn for each year of each iteration, determining the random, annual departure from long-term attribute drift μ. That departure will be zero on average, with a variance of $c \cdot |\mu|$.

2.3 Model Calibration Adjustment to Attribute Drift Term

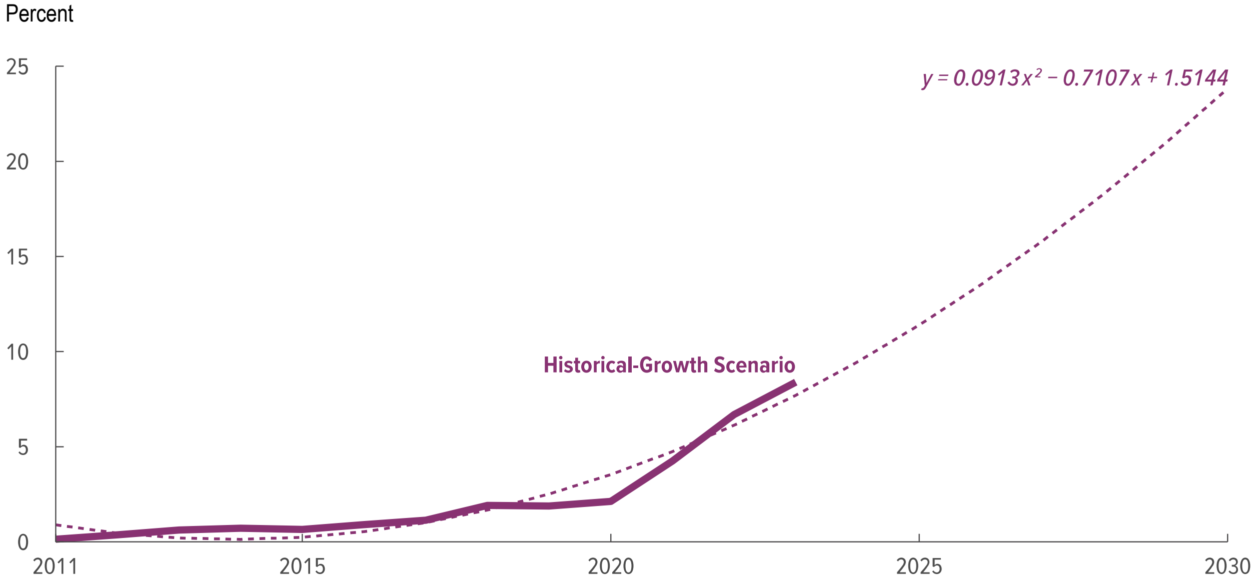
On average, the value of attribute drift ψ_t will change by $a \cdot \left|\beta_p\right|$ each year. Thus, the parameter *a* directly influences projected shares of new EVs. To provide an empirical basis for the value of *a* that is used in the model, I consider trends in actual U.S. sales of light-duty EVs over the past decade.

Plotting new-EV market shares since 2011 shows that EV sales have been rising at an increasing rate (see Figure 1). Until 2017, the market share for new EVs had been increasing by less than 0.2 percentage points per year, on average. Since then, the new-EV share has increased by about 1 percentage point per year, and it has risen even more rapidly since 2020. The relationship between EV market share and year is well described by a quadratic trend line.

[10] That distribution reflects the range of estimated EV price elasticities in the refereed studies CBO relied on for those estimates (see Appendix A).

Figure 1.

Market Share of New Plug-in EVs, With Quadratic Trend Line



Data source: Congressional Budget Office, using data from Argonne National Laboratory, Energy Systems and Infrastructure Analysis Division. See www.cbo.gov/publication/58964#data.

EV = electric vehicle.

Fitting a quadratic curve to new-EV market shares since 2011 yields the equation

$$\textit{EV share} = 1.514 - 0.711 * \textit{years} + 0.091 * \textit{years}^2.$$

The trend line projects an EV share of 24 percent in 2030. I calibrate the model so that its base-year EV market share matches the observed share for 2022 and so that, on average, its projected 2030 value (in the absence of the federal charger subsidies in the 2021 IIJA and the federal EV tax credits in the 2022 reconciliation act) matches the 2030 value projected from the historical data in Figure 1. Results presented in this paper all reflect that calibration.

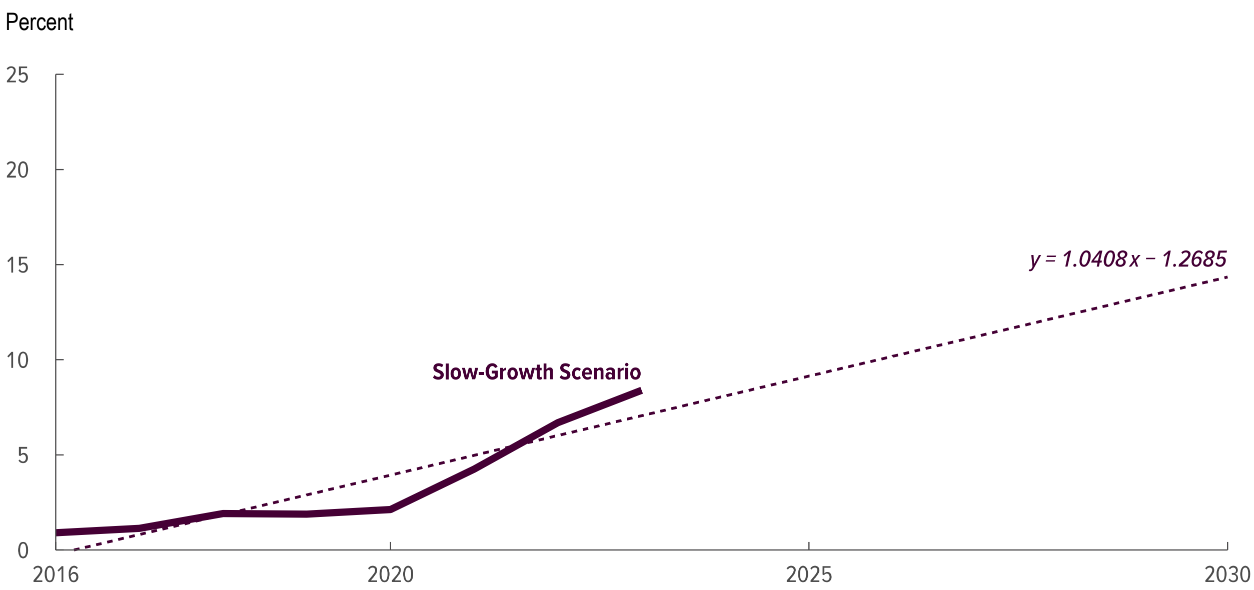
The a parameter, which determines the average trend in attribute drift, is the parameter that I adjust to calibrate the model's 2030 projected value. For the b and c parameters of attribute drift, I set $b = a/4$ (so that variance in the attribute drift trend is one-fourth of the mean trend) and $c = 2$ (so that variance in the departure-from-trend term is twice the mean absolute trend), following Cole et al. (2023).

Figure 1 raises the question of why I did not simply estimate the model's attribute drift parameters econometrically, by fitting the data on EV sales from 2011 through 2022 to the model's demand equation. I decided against that approach for two reasons. First, there are only 12 data points with which to estimate the five parameters in that equation (plus three additional parameters in the charger supply equation introduced below). And second, I would also need to have data on the size of the EV charging network in each of those years. I have data on the estimated current number of EV chargers, their installation dates, and the dates they were last confirmed to be working. But I have no information about chargers that have become unavailable, whether taken out of service or otherwise abandoned, so I cannot determine whether older chargers are undercounted. Instead, I populate the model with parameter estimates taken from the refereed literature or, for the attribute drift term, with the value that causes the model's projections for 2030 to match those of the simple quadratic equation of Figure 1, given the model's other parameter values.

To illustrate the sensitivity of the results to other possible calibrations of the model, I consider two additional projections, which I call the slow-growth and rapid-growth scenarios. I develop the slow-growth scenario to approximate the values projected by a linear trend, fitted to EV market shares since 2016.[11] That trend line projects a market share of more than 14 percent in 2030 (see Figure 2).

Figure 2.

Market Share of New Plug-in EVs, With Linear Trend Line



Data source: Congressional Budget Office, using data from Argonne National Laboratory, Energy Systems and Infrastructure Analysis Division. See www.cbo.gov/publication/58964#data.

EV = electric vehicle.

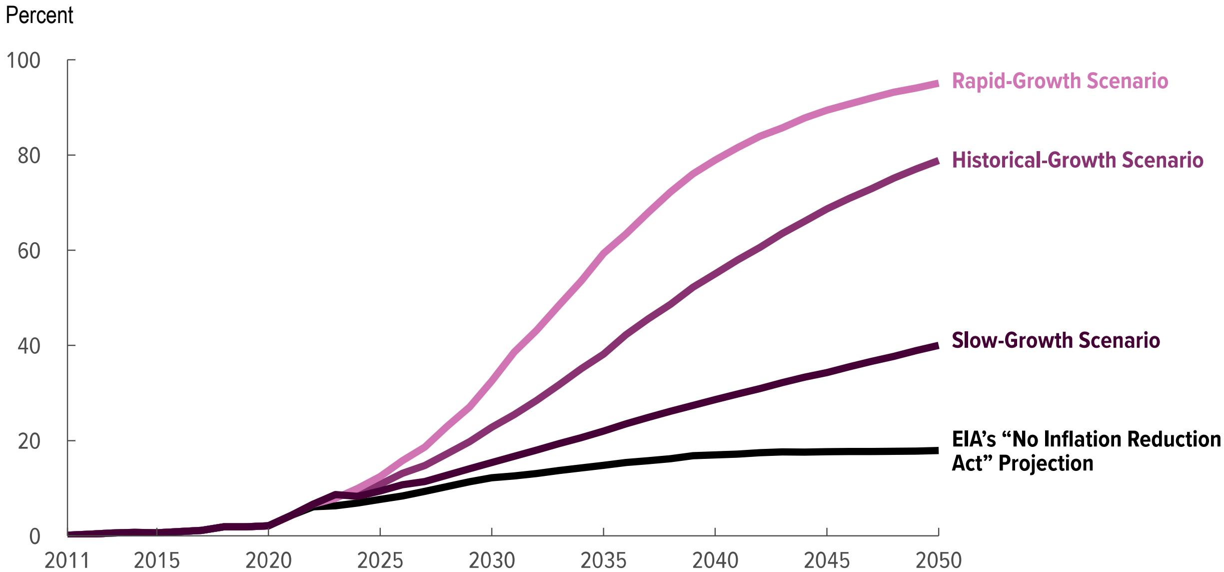
[11] New-EV market share began growing steadily in 2016 as automakers began selling light-truck EVs, primarily sport-utility vehicles, in appreciable numbers. Fitting a linear trend to data going back to 2011 projects an EV market share for 2030 of 10 percent, just a few percentage points higher than the actual EV share observed in 2023.

Finally, I set the rapid-growth scenario so that it is approximately symmetrical to the slow-growth scenario, with respect to the historical-growth projection lying between them. The scenarios are determined by their *a* parameter value in the equation given in Section 2.1. For each scenario, I set that parameter so that, on average, its projected EV share for 2030 matches the target value.

For 2030 I set the rapid-growth scenario so that it projects an EV market share of 34 percent, versus the 24 percent projected by the historical-growth scenario. The slow-growth scenario, with the *a* parameter set close to zero, projects a 2030 EV share of 16.5 percent of new light-duty vehicle sales (see Figure 3). By comparison, the Energy Information Administration's (EIA's) most recent projection for 2030 is 15.2 percent (EIA 2023b). Cole et al. (2023) calibrate their model so that it projects an average EV market share of 36.6 percent in 2030, to be consistent with a projection by IHS Markit (2021), a private purveyor of market information and analysis.

Figure 3.

Projected Market Share of New Light-Duty EVs Under Various Growth Scenarios



Data sources: Congressional Budget Office; Energy Information Administration (EIA). See www.cbo.gov/publication/58964#data.

Projections are from my electric vehicle (EV) projection model, under three scenarios using different values for attribute drift. EIA's "No Inflation Reduction Act" projection is from its *Annual Energy Outlook 2023* (EIA 2023a). The Inflation Reduction Act is also known as the 2022 reconciliation act.

All projections exclude the effects of the charger subsidies in the Infrastructure Investment and Jobs Act and the EV tax credits in the 2022 reconciliation act.

3. Supply of EV Chargers

The markets for EVs and EV chargers are inextricably linked. The demand for EV charging is determined by the size of the EV fleet, and the feasibility of EV ownership depends on the size of the charger network and the locations of its charging stations. Growth in the EV fleet has allowed potential revenues from new EV chargers to be forecast more accurately, reducing the investment risk for companies that supply those chargers. Growth in the charger network has, in turn, made EVs more appealing by making it easier for EV drivers to find charging stations and take long trips.

EV chargers are supplied by private, profit-maximizing firms that can freely enter and exit the market. In deciding to build a new station, a supplier compares the fixed cost of construction with the discounted stream of revenues anticipated from that station, given the size of the EV fleet. With free entry, firms will, in equilibrium, continue to build new charging stations to the point where they are indifferent about adding one more station this year or waiting until next year.

Under those conditions, the total number of charging stations available each year will increase with the number of registered EVs and decrease with the anticipated difference between the cost of installing a charger next year and installing it in the current year. I use 2 percent for the rate at which suppliers expect costs to decline each year.[12] In the model, even if revenues from a charger were lower than expected, the supplier would keep that charger in place until it failed, because its installation is a sunk cost. (The supplier's decision then, about whether to replace the charger, would depend on expected future profits at that time, not on past performance.) As a result, if in any year the profit-maximizing size of the charger network is less than it was in the previous year—because of a decrease in the size of the EV fleet or a change in the expected cost of a charger—the network will not shrink by more than the number of aging chargers that stop working. That number will be the greater of the profit-maximizing number of chargers, which is based on EV fleet size and charger costs, or the number of existing chargers that have not failed over the past year.

Following Cole et al. (2023), for each type of charger L_k, $k \in \{2, 3\}$, I model the number of chargers in logarithmic form—making the parameters γ_1 and γ_2 elasticities—as

$$ln\left(L_{k,t}\right) = max\left\{\delta_k + \gamma_1 \cdot ln(EVstock_t) - \gamma_2 \cdot ln\left(\Delta Cost_{k,t}\right), \sigma_v \cdot ln\left(L_{k,t-1}\right)\right\},$$

where:

- t is year.
- δ_k are the y-intercepts. The model is calibrated so that the projected initial supply of chargers matches the number reported by the Alternative Fuels Data Center ("Electric Vehicle Charging Stations"). Cole et al. (2023) use their δ_k terms to tune their model so that at "full

[12] The smaller the expected rate of decrease in charger costs, the larger the number of chargers that will be supplied in the current year.

penetration," when all passenger vehicles are EVs, their projected number of chargers achieves a predefined level thought necessary to serve an EV fleet of that size.

- γ_1 and γ_2 are, respectively, the elasticity of charger supply with respect to the stock of EVs and the elasticity of charger supply with respect to $\Delta Cost_{k,t}$. The empirical literature on those elasticities is somewhat thin but suggests that they have similar values.
- $EVstock_t$ is the number of registered EVs for year t, equal to initial EV fleet size plus annual sales minus annual vehicle scrappage. I use a scrappage rate of 4.4 percent of the EV fleet each year (Bento et al. 2018).
- $\Delta Cost_{k,t} \equiv Cost_{k,t} - Cost_{k,t+1}/(1+\rho)$ is the discounted expected change in costs to build and install a charger of type k, between years t and $t+1$. I model suppliers as expecting charger costs to decline at a real 2 percent each year (see Appendix A). Suppliers discount the next year's costs by their average cost of capital ρ, which is set at 8 percent for this analysis.[13]
- σ_v is the average annual survival rate in the charger network when the network's average charger age is v years. Annual changes in the size of the charger network reflect both new installations and replacements of failed chargers. For that reason, σ_v only comes into play when charger suppliers' optimal level of investment is zero.[14] That can occur when charging infrastructure subsidies are exhausted after inducing suppliers to build enough chargers to support a larger EV fleet than exists when the subsidies end. The survival term $\sigma_v \cdot ln(L_{k,t-1})$ is needed because I model suppliers as not anticipating future growth in the EV fleet. Details about σ_v are provided later in this paper in the discussion of IIJA subsidies.

The parameter values for the charger supply equation are listed in Appendix A, along with those from the EV demand equation.

4. Model Base Case: Federal Charger Subsidies and EV Tax Credits

The results presented in this paper reflect the projected effects of two recent federal policies on the EV charger network and on EV sales: the federal charger subsidies provided by the IIJA and

[13] Eight percent is the approximate average estimated cost of capital for 2011 to 2022 in five industries whose products and services are inputs in the supply of EV chargers: automotive, electric utilities, electrical equipment, electronics, and engineering and construction. For cost-of-capital estimates by year and industry, see Damodaran (2023).

[14] Because the supply equations are in terms of stocks rather than flows of chargers, charger failures are implicitly accounted for in years when the network expands.

the EV tax credits provided by the 2022 reconciliation act. The projections establish a base case against which other policy options could be assessed.

The IIJA, signed into law in November 2021, provides for up to $7.5 billion in federal EV charger subsidies. The 2022 reconciliation act, signed into law in August of that year, provides tax credits of up to $7,500 for EV purchases, subject to qualifications on, for instance, buyer income, vehicle price, domestic content of battery materials, and location of vehicle production. Because those programs are now current law, I incorporate my projection of their effects into the base case of the EV simulation model.

This section compares projected new-EV market shares and projected L2 and L3 charger network sizes under three policy scenarios: a current-law projection that reflects the effects of the federal subsidies for EV chargers under the IIJA and the EV tax credits in the 2022 reconciliation act; a projection of the effects of the IIJA subsidies alone; and, for comparison, a historical-growth projection, which excludes the effects of both of those policies. Together, the three scenarios allow the projected effects of the IIJA subsidies and the EV tax credits to be separately identified.

4.1 Federal Charger Subsidies: Description of Modeling Approach

The IIJA charger subsidies cover 80 percent of the private cost of building and installing a new charger. (The private cost of a new charger is currently about $100,000 for an L3 charger, and $5,000 for an L2 charger, with two ports, or charging cables, per charger.) In 2022, $1.3 billion of that funding became available. The remaining funds will become available in increasing amounts in each succeeding year through 2026, from $1.4 billion in 2023 to $1.7 billion in 2026.

On the basis of historical spend-out rates for federal highway funding, CBO projects that states will continue to spend from that funding through 2032. Expenditures from the IIJA charger-subsidy funds will ramp up gradually for several years, peaking at nearly $1 billion per year in the late 2020s, and then declining as remaining funds are spent (CBO 2023).

The subsidies were initially available in such limited amounts that they did not affect supplier behavior in 2022. However, I model suppliers as anticipating their technology costs (including subsidy funding) one year ahead. I expect that by 2024 the IIJA subsidies will be widely available. As a result, I also model charger suppliers as restraining their 2023 investments in anticipation of the 80 percent drop in their costs the next year. The $\Delta Cost_{k,t}$ terms in the supply equations operationalize that one-year investment slowdown.

Of the up to $7.5 billion in IIJA subsidies, $6.25 billion is for charger installations along highways. That amount includes all of the $5 billion allocated in the IIJA to the National Electric Vehicle Infrastructure (NEVI) formula program, as well as half of the $2.5 billion allocated to the Charging and Fueling Infrastructure (CFI) grant program. Given the costs of L2 and L3 chargers and the numbers of each that have been installed to date, I estimate that about

88 percent of expenditures on charger installations to date have been for L3 chargers. I use that estimate as the basis for projecting future spending on highway charger installations. Thus, in my projections, I allocate 88 percent of each year's available federal highway-charger subsidies to L3 chargers, with the remainder going to the slower L2 chargers.

The remaining $1.25 billion in funding under the CFI grant program is available to support the expansion of the refueling infrastructure for both EVs and alternative-fuel vehicles more generally, including vehicles powered by fuel cells, propane, or compressed natural gas—at workplaces, shops and restaurants, multifamily housing developments, and the like. Rapid charging is not essential at such locations (unlike charging along highways) because drivers can be occupied in other activities—working, shopping, dining, or being at home—while their vehicles are charging. Thus, most of the EV chargers installed with that funding will probably be L2 chargers.

It is not known what fraction of the CFI funding will be used to build infrastructure for other types of alternative-fuel vehicles. I project that most of the funding will probably be used to support EV charger installations, and thus I assign 80 percent of the simulated CFI funding to that purpose. Those projections can be revised as evidence emerges about how that funding is being used.

Using the Alternative Fuels Data Center's data on charger installations in 2022 and on the relative costs of L2 and L3 chargers, I estimate that about 25 percent of 2022 expenditures for charger installations—including both highway and community installations—went toward L2 chargers.[15] Thus, of the CFI funding that will be spent on EV chargers, I expect that 25 percent will be used to build L2 chargers, with the remainder used for L3 chargers. Because L2 chargers cost only about 5 percent of what an L3 charger costs, more L2 than L3 chargers will be built with both types of subsidies: the $6.25 billion in NEVI funding and the up to $1.25 billion in CFI funding that is used to build EV chargers.

4.2 Federal EV Tax Credits: Description of Modeling Approach

Electric vehicles help automakers achieve regulatory targets specified in the corporate average fuel economy (CAFE) standards and the vehicle greenhouse gas emissions standards. Thus it is likely that new-EV buyers will receive close to the full amount of the EV tax credit that they qualify for, as long as those standards influence automakers' product and pricing decisions.[16] Indeed, proposed increases in the stringency of the vehicle emissions standards might, if adopted,

[15] For a list of EV charging stations in the United States, see Alternative Fuels Data Center, "Electric Vehicle Charging Stations."

[16] Until an automaker's CAFE ratings are well above the CAFE standards, each EV sold has an economic value to the automaker beyond its profit margin: The sale helps the company avoid a fine for being out of compliance with the CAFE standards and helps it sell more-profitable ICEVs that lower the company's CAFE ratings.

induce automakers to adjust the prices of their vehicles to make EVs more attractive relative to ICEVs. This paper examines that possibility (see Appendix C).

In my model, automakers do not raise the prices of their EVs in response to consumers' receiving tax credits on those EVs. As a result, a tax credit of $7,500 will reduce the price of an EV by about 10 percent to 20 percent (for EVs priced between about $35,000 and $80,000). Eligibility restrictions on the income of the vehicle buyer, the price of the vehicle, and the domestic content of its battery and assembly will limit the uptake of the tax credits and the amount of tax credit that consumers may qualify for.

Automakers will have to invest in domestic EV battery-production facilities to meet the domestic-content requirements of those credits. Currently, at least 40 percent of the "critical minerals" in the batteries of qualifying EVs must have been extracted or processed in the United States or a free-trade partner nation. (That requirement increases in stringency with each model year, until it reaches 80 percent after 2026.) In addition, 50 percent of the value of the battery's components in 2023 (rising to 100 percent after 2028) must have been manufactured or assembled in North America. The two restrictions are independent: Buyers of EVs that meet one restriction but not the other will qualify for half of the available credit, or $3,750.

Further, buyers with income above specified thresholds—$150,000 for single taxpayers, $225,000 for heads of household, and $300,000 for married couples filing jointly—will not qualify for the credits. The credits are also restricted to EVs priced below $55,000 (cars) and $80,000 (light trucks, including crossovers and sport-utility vehicles). Households with high income purchase an even greater share of high-priced EVs than they do of new EVs generally.

Beginning in 2024, when the additional requirements on the sources of critical minerals and domestic manufacturing will apply, only a small fraction of EV sales may initially qualify for the credit. For instance, China—which is not a qualifying source—currently possesses about 80 percent of the world's lithium-based EV battery manufacturing capacity, whereas the United States has about 5 percent.[17] However, over time more EVs will probably qualify for the tax credits as the domestic production capacities of automakers and battery manufacturers increase.[18] To satisfy the tax-credit eligibility requirements on vehicle prices, automakers will probably also expand the number of lower-priced EV models they offer.

I model the effects of those requirements by adopting a set of estimates developed by the International Council on Clean Transportation (ICCT; Slowik et al. 2023). They estimate that, on

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[17] LeafScore (2023), citing a report by Benchmark Minerals Intelligence, an industry analyst.

[18] Since the 2022 reconciliation act was signed into law, many automakers have begun building—or have announced plans to build—EV battery-manufacturing facilities in the United States. See, for instance, Plante and Rindels (2022).

the basis of income only, 68 percent of EV buyers currently qualify for the tax credits, rising to 77 percent in 2030 as automakers introduce new EV models that more households with qualified income would buy. Independent of that, they estimate that 87 percent of new-EV purchases will qualify on the basis of price. They estimate that approximately 70 percent to 80 percent of new EVs sold after 2025 will satisfy the law's critical minerals requirement, with a smaller fraction (I use 50 percent) qualifying in 2024. Finally, they assume that, for now, all new EVs will satisfy the requirement for domestic battery assembly, qualifying those vehicles for half of the $7,500 tax credit.[19]

The Treasury Department recently determined that most leased EVs qualify for a commercial clean-vehicle tax credit of $7,500, on the basis of their incremental cost over comparable ICEVs and not limited by their status with respect to critical minerals, domestic production, or price (Internal Revenue Service 2022).[20] Since the Treasury Department issued that ruling, EV leasing has increased substantially. Automakers that pass along the value of the tax credit to their leasing customers are said to be leasing about twice as many EVs now as they were before the ruling, whereas automakers not passing along the credit have experienced no such increase (St. John 2023).

In principle, every new EV might qualify for the EV tax credit, because consumers wishing to buy a new EV that would not otherwise qualify for a credit—or consumers who do not themselves qualify for the credit—might simply lease the vehicle instead. To allow for that possibility, I model half of such consumers as leasing rather than buying their new EV. (The observed increase in EV leasing is roughly consistent with that treatment.) The other half will have—for a variety of possible reasons—sufficiently strong preferences that they will buy rather than lease, forgoing the credit. In sensitivity testing I consider, alternately, that no consumers lease or that every consumer leases who does not otherwise qualify for the tax credit (see Appendix B).

The 2022 reconciliation act makes separate provision, beyond the EV tax credits, for subsidizing the manufacture and sale of EVs. The act also includes a section 45X advanced manufacturing production credit for EV batteries, tied to the capacity of the battery. The credit is $35 per kilowatt-hour of capacity in each battery cell, plus $10 per kilowatt-hour for each module. For the 70 kilowatt-hour car battery capacities I use in this analysis, the credit amounts to $3,150 per

[19] Beginning in 2024, EVs qualifying on domestic-assembly grounds cannot contain battery components sourced from countries designated as "foreign entities of concern." Beginning in 2025, that exclusion will extend to minerals used in those batteries as well. It is not yet known what fraction of currently qualifying EVs will be disqualified by those conditions. My analysis therefore does not account for that effect, other than to describe how any given fraction of disqualified vehicles would affect my results.

[20] For compact plug-in hybrid EVs the incremental cost, and thus the available clean-vehicle credit, is less than $7,500.

car. For trucks, the credit is $5,400 per vehicle with a 120 kilowatt-hour battery. Initially, manufacturers may share those credits with their customers, in the form of lower vehicle prices, to promote the sale of those EVs. As with the EV tax credits, I use ICCT's share-parameter estimates: 25 percent in 2023, 50 percent from 2024 through 2029, then descending in equal increments to 12.5 percent in 2032, and zero thereafter (Slowik et al. 2023). The sensitivity analysis that I conduct on the ICCT parameter values, described above, includes those estimated shares of the section 45X production credits.

4.3 Policy Effects on EV Charger Networks

To estimate the expansion that may occur each year in the charger networks as a result of the IIJA funding, relative to the expansion that would have occurred in the absence of the funding, I shift the charger supply curves out to reflect the 80 percent drop in installation costs for the subsidized chargers. Initially, while the charger network remains relatively small, the implied charger supply expansion is less than the number of subsidized chargers. In those years, some of the funding therefore subsidizes some chargers that would have been supplied anyway. In later years, the network expands by the full number of subsidized chargers, relative to the expansion that would have occurred in the absence of the funding.

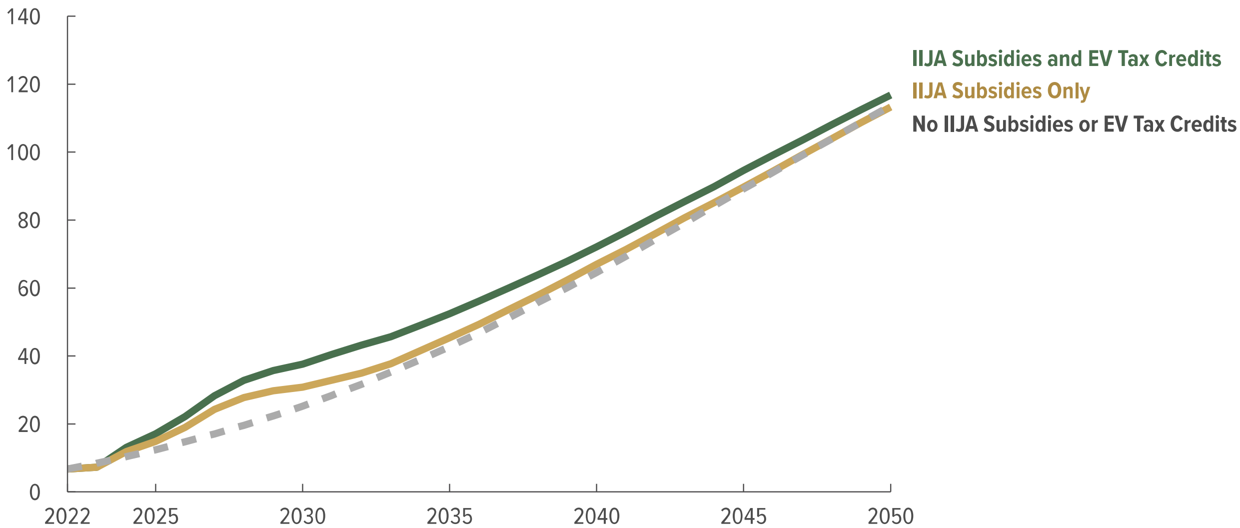
Under that approach, the EV model's median projection is that by 2030 the IIJA subsidies will have increased the number of L3 charging stations by more than 20 percent, to almost 31,000, compared with slightly more than 25,000 stations projected in the absence of those subsidies (see Figure 4). In addition, the EV tax credits will indirectly increase the size of the charger network by increasing the demand for public chargers as sales of new EVs increase. After about 2030, new station construction will slow as remaining subsidy funds decline, because the charger network will slightly exceed the demand for charging services at that time.[21] With continued growth in the EV fleet, described below, the supply of and demand for EV chargers will ultimately come back into balance, and growth in the charger networks will again increase, without federal subsidies.

[21] The abundance of available chargers will encourage more consumers to choose an EV when purchasing their next new vehicle.

Figure 4.

Median Projected Supply of L3 Charging Stations

Thousands of Charging Stations



Data source: Congressional Budget Office. See www.cbo.gov/publication/58964#data.

EV = electric vehicle; IIJA = Infrastructure Investment and Jobs Act.

In anticipation of the IIJA subsidy funds, I project that construction of L3 charging stations will initially slow, in 2023, compared with the pre-policy trajectory. (That initial slowdown is apparent in Figure 4.) But I project that by 2040 there will be about 67,000 L3 charging stations under the IIJA scenario—and about 72,000 of them under the IIJA plus EV tax-credit scenario, enough to be placed throughout the interstate highway system and the U.S. highway system at a density greater than that of gas stations along the Pennsylvania and Ohio Turnpikes.[22] According to the Alternative Fuels Data Center, there were about 7,000 L3 charging stations in the United States at the end of 2022. Although I project that the market would have supplied nearly as many L3 chargers by 2040 without either policy in place, the difference is that the two policies will have hastened the switch from ICEVs to EVs.

Figure 4 suggests that in the long run, through 2050, the IIJA subsidies and the EV tax credits will ultimately have only a small effect on the size of the L3 charger network compared with what it would have been without those policies. The primary effect of those policies will be the faster adoption of EVs. Even so, I project that the charger network will remain slightly larger for

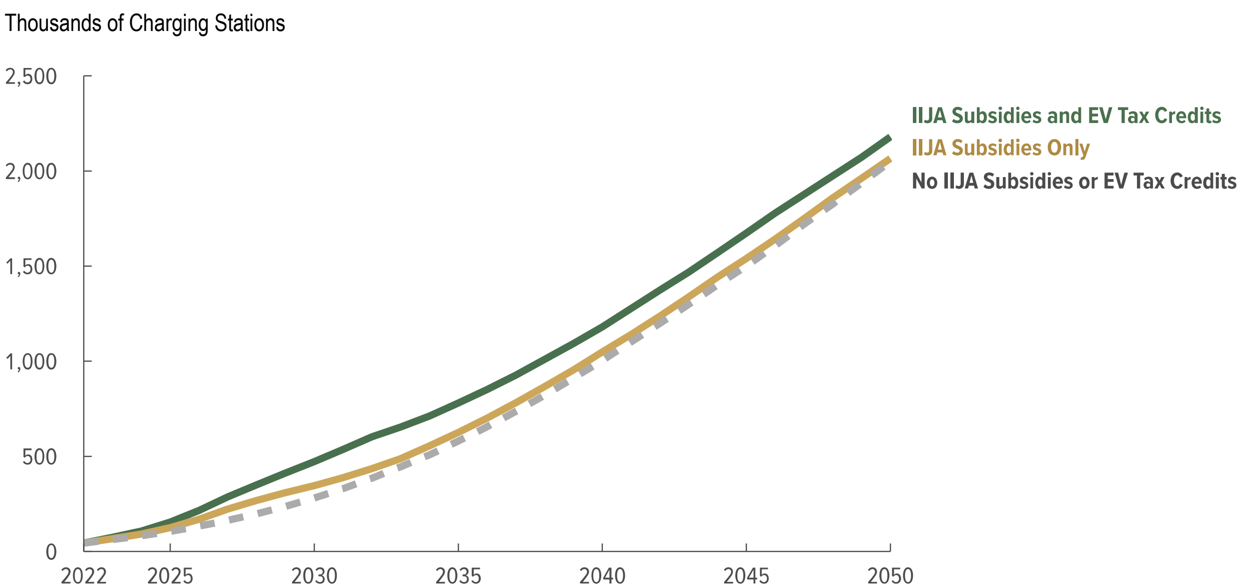
[22] Because rapid-charging an EV takes about 20 minutes, compared with about 5 minutes to refuel an ICEV, the density of EV chargers along highways would need to be greater than that of gas pumps to avoid queueing and to serve the same number of vehicles as those gas pumps serve.

many years than it would have been without those policies: The large expansion of the charger networks in the 2020s and 2030s will cause a long-term increase in the sale of EVs—many of which will remain on the road for a decade or more. That expansion of the EV fleet (see the next section) will increase the demand for and supply of chargers throughout that time.

The IIJA subsidies will affect the L2 charger network in a similar fashion. My median projection for 2030, with the IIJA subsidies, is that the network of L2 chargers will expand to 345,000 stations—from about 45,000 at the end of 2022—versus about 280,000 L2 stations if the IIJA subsidies were not available (see Figure 5).[23] Including the effect of the EV tax credits, I project that the network will expand to more than 600,000 L2 stations by 2032—with about 43,000 additional L3 stations located along highways. If each station has two chargers, each with two ports, that implies that there will be about 2.5 million EV charging ports by 2032. By comparison, there are currently about 150,000 gas stations in the United States (American Petroleum Institute 2021). If a typical gas station has 6 to 12 pumps, that implies that there are currently between 0.9 million and 1.8 million gasoline pumps in the United States.

Figure 5.

Median Projected Supply of L2 Charging Stations



Data source: Congressional Budget Office. See www.cbo.gov/publication/58964#data.

EV = electric vehicle; IIJA = Infrastructure Investment and Jobs Act.

[23] Those numbers exclude L2 chargers at workplaces and private homes.

4.4 Effects on Market Share of New EVs

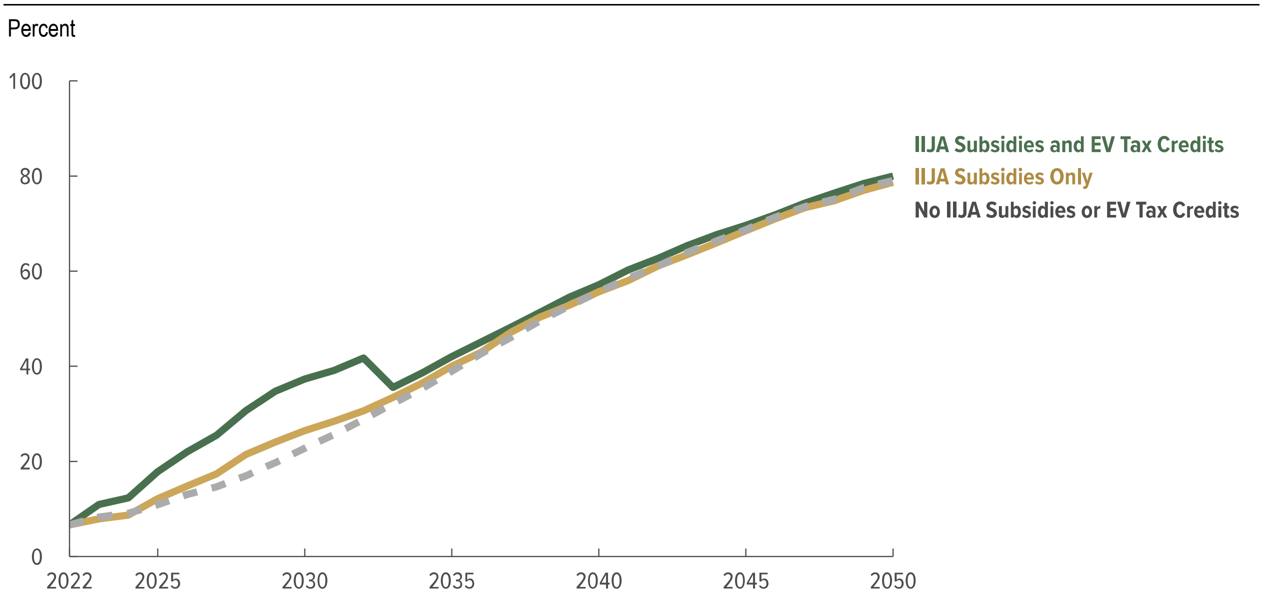
By the late 2020s the IIJA charger subsidies, by themselves, would have boosted the new-vehicle market share of EVs by more than 4 percentage points (see Figure 6). Even though that effect will decline once the IIJA funding has been spent, the expanded charger network encourages slightly greater EV sales—as a share of total sales of new light-duty vehicles—for some years after that.

The EV tax credits will have a direct and much larger effect on sales of new EVs. It will take some time for automakers to develop processes for producing EVs that qualify for the credits. My median projection for 2032 is that, by that year, the EV tax credits will have increased the EV share of new light-duty vehicle sales in the United States to 42 percent—11 percentage points beyond what the IIJA subsidies would have achieved by themselves. Without either policy, my median projected EV sales share in the U.S. market would have been about 29 percent in 2032.

Those median projections are just one set among thousands of projections produced in every simulation exercise. The middle two-thirds of those projections constitutes the likely range of values produced by the simulations; the median is the 50th percentile projection. On the basis of those projections, the likely range of EV market shares in 2032, with both IIJA subsidies and EV tax credits in place, is from 27 percent to 60 percent (see also Section 4.5).

Figure 6.

Median Projected Market Share of New Light-Duty EVs



Data source: Congressional Budget Office. See www.cbo.gov/publication/58964#data.

EV = electric vehicle; IIJA = Infrastructure Investment and Jobs Act.

A comparison of projected EV sales with and without the tax-credit policy suggests that many of the credits claimed will be "inframarginal"—that is, going to consumers who would have purchased an EV anyway. Restrictions on credit eligibility based on vehicle price and buyer income will help limit claims by consumers with the means to buy high-priced vehicles. But such restrictions cannot eliminate inframarginal credits entirely: Some consumers may be able to receive the value of the credit by leasing an EV, and many consumers with income below the allowable maximum will have strong enough preferences for EVs that they will purchase one even if they do not receive a credit.

After the credits expire, the EV share of new light-duty vehicle sales in the United States will return to a value close to what it would have been in the absence of the tax credits. The share will remain slightly elevated because the additional EV sales resulting from the tax credits will cause more public EV chargers to be supplied. That larger charger network will encourage additional sales of EVs, relative to projected sales in the absence of either policy. After 2032 the projected number of EVs per L2 charger is slightly higher under the two federal policies than under the IIJA subsidies alone, leading to slightly smaller projected EV shares over the 2040s. However, as discussed below, the projected size of the EV fleet is larger throughout the 2040s under the two federal policies than it is in the other two scenarios.

The ICCT parameter values that I use in the model imply that, on average, about 64 percent of EV sales will qualify outright for an EV tax credit. Furthermore if, as I model it, half of consumers who would not qualify for the tax credit—or who choose an EV that would not qualify—lease instead of buying in order to qualify for the credit, then credits will be claimed on another 18 percent of new EVs each year. But those estimated rates are preliminary: The actual number of credits that will be claimed depends on factors that have not yet been finalized. Those include processes for determining the percentage of the value of a battery's critical minerals that counts toward the tax credit's critical minerals requirement and of the value of battery components that were manufactured or assembled in North America.

In addition, the Treasury Department has not yet issued final guidance on the "foreign entity of concern" (FEOC) restrictions on the EV tax credits (section 13401(e)(2) of the 2022 reconciliation act). Beginning in 2024 the restrictions will be applied to new EVs with battery components manufactured or assembled by a FEOC, and in 2025 they will apply to EVs in which critical minerals used in the batteries were extracted, processed, or recycled by a FEOC. Because many EV batteries and minerals—such as lithium—come from or are processed in countries such as China that have been designated as FEOCs, those restrictions could substantially reduce the number of EVs eligible for the tax credits, especially after 2025.

It is not yet possible to estimate how great the reduction will be; as a result, my simulations do not account for the effects that the FEOC provisions might have. If, for example, the FEOC provisions reduce credit uptake by 80 percent, the effect of the EV tax credits, as plotted in

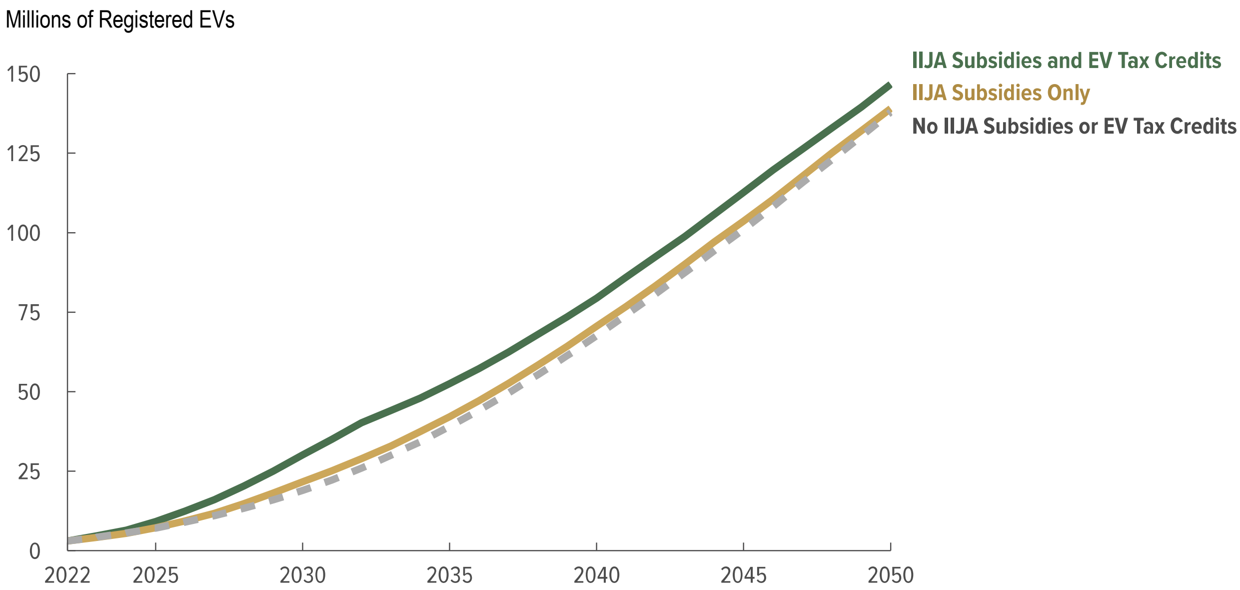
Figure 6, will decrease by about 80 percent of the distance between the top (EV tax credit) and middle (IIJA charger subsidy) lines in the figure. The actual decrease will be slightly more than 80 percent because fewer EV chargers will be supplied and that, in turn, will slightly discourage EV sales independent of the reduction in EV tax-credit eligibility.

Whatever the initial reduction in tax-credit eligibility that may occur because of the FEOC restrictions, automakers are actively seeking other sources for battery minerals and components. To the extent that they succeed before 2032, the effect of the FEOC restrictions will decline over time.

The increase in EV market shares under the two federal policies, relative to the projected trend without those policies, has a long-lived effect on the size of the EV fleet of vehicles of all ages (see Figure 7). The simulation model projects that after 2032, when the tax credits expire, the number of registered EVs in the United States, of all ages, will remain a couple of years ahead of where it would have been in the absence of those policies. I project that, allowing for vehicle scrappage and retirements, the U.S. EV fleet will reach 50 million vehicles by mid-2035, about two-and-a-half years sooner than it would have without those policies. Once the policies expire, the projected trends in EV fleet size converge somewhat, across the three scenarios. But the gap remains about two years even as the projected EV fleet size reaches 100 million in the mid-2040s.

Figure 7.

Median Projected Size of the EV Fleet for Vehicles of All Ages



Data source: Congressional Budget Office. See www.cbo.gov/publication/58964#data.

EV = electric vehicle; IIJA = Infrastructure Investment and Jobs Act.

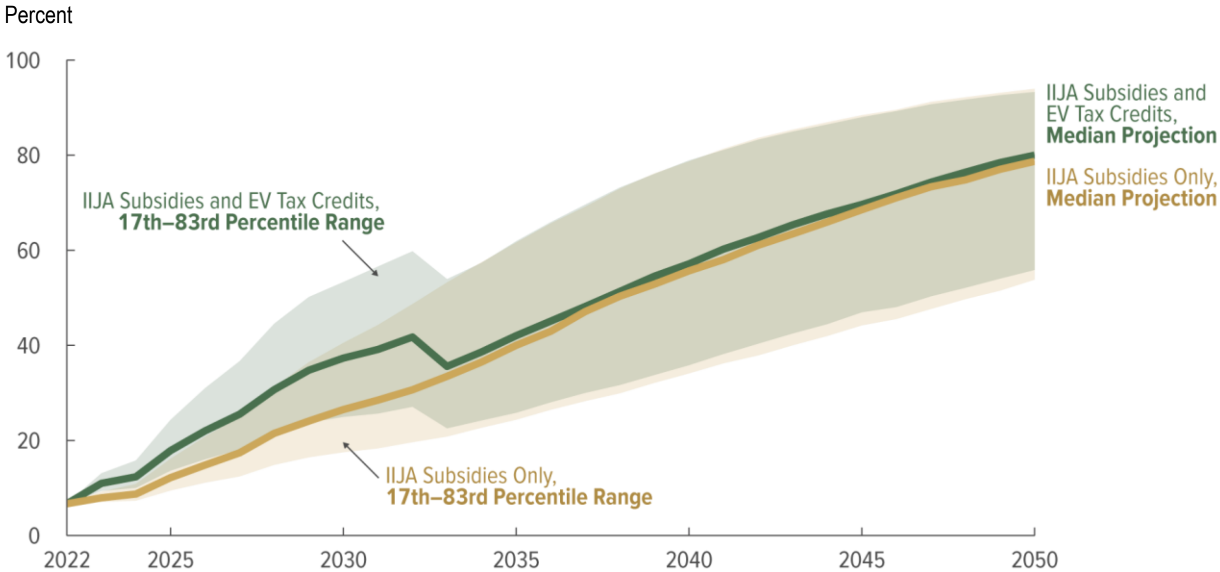
4.5 Model Uncertainty

Parameter values are an important source of uncertainty in the EV model's projections. Most of the parameter values used are drawn from probability distributions to reflect that uncertainty. Values for each parameter are drawn from distributions defined over a range of estimated values for that parameter from the peer-reviewed research literature. The figures presented above provide no sense of the magnitude of those uncertainties and report only median projections—the central values from simulations that were repeated thousands of times.

Model uncertainty can be ascertained by plotting additional projections away from the center of the range of simulated outcomes. By convention, the 17th percentile and 83rd percentile projections are used: The difference between them spans the middle two-thirds of projected values, the likely range for a modeled outcome. For instance, where the model's median projected market share for new EVs in 2033 is about 36 percent under the scenario with IIJA subsidies plus EV tax credits—the likely range extends from about 23 percent to about 54 percent (see Figure 8). Although the model parameter values are drawn from symmetrical probability densities, the likely range is not symmetrical about the 36 percent median projection: The 17th percentile projection lies 13 percentage points below the median, and the 83rd percentile projection is 18 percentage points above it. There is more latitude for increased gains than for reduced gains in EV share, in a market where EV sales over the past several years had been trending toward an EV share of more than 20 percent by 2030 even before the charger-subsidy and EV tax-credit policies were initiated.

Figure 8.

Projected Market Share of New Light-Duty EVs



Data source: Congressional Budget Office. See www.cbo.gov/publication/58964#data.

EV = electric vehicle; IIJA = Infrastructure Investment and Jobs Act.

4.6 Comparison of CBO's and Other Projections

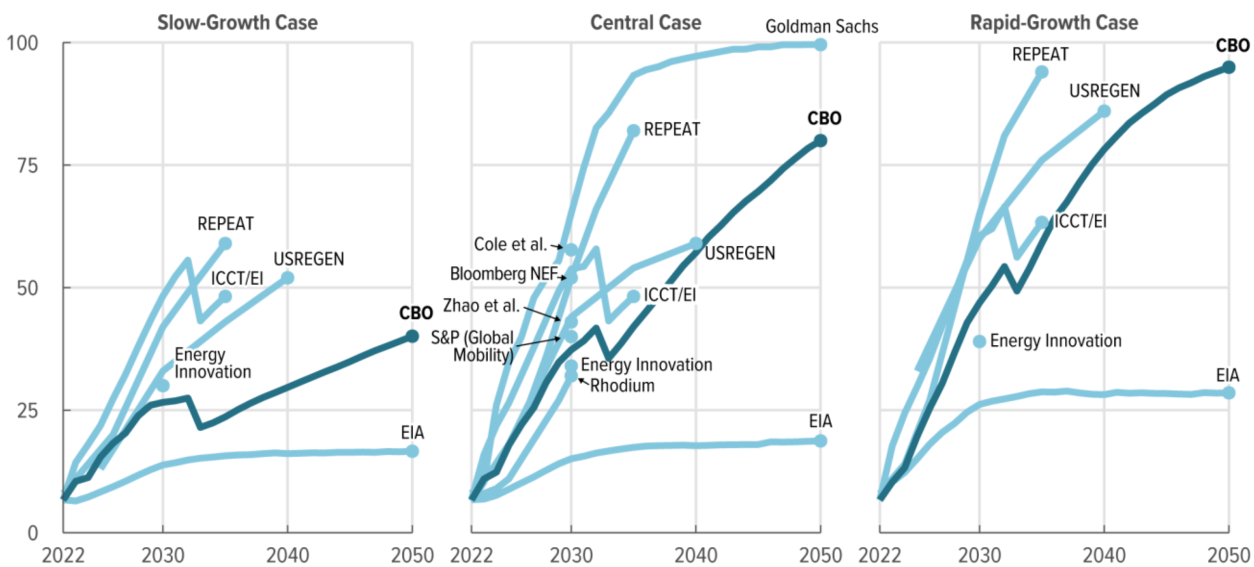
The EV market-share projections I present in this paper add to a growing number of similar projections by other organizations (see Figure 9). For my central, historical-growth case I set the attribute drift term so that, with neither IIJA subsidies nor EV tax credits, the model's projected EV share for 2030 would match the recent, quadratic trend in EV sales growth, extrapolated to 2030. Variation in the projections by other analysts may reflect differences in their models' parameter values (such as for vehicle ownership costs or the effects of changes in supply, demand, or price), in their treatment of state and federal policies toward EVs, or in their calibration of those models.

The projections under my rapid- and slow-growth scenarios illustrate how my model can accommodate different forecasts of the pace of innovation or the evolution of consumer preferences. (Figure 9 includes analogous projections by other organizations, where available.) The rapid-growth projection reflects a particular setting of the attribute drift parameter. I could choose different values for that parameter to produce higher or lower rates of growth in EV demand, in any of my three scenarios. (See Appendix B for a sensitivity analysis of attribute drift.)

Figure 9.

Comparison of CBO's and Other Projections of EV Market Share

Percent



Data source: Congressional Budget Office. See www.cbo.gov/publication/58964#data.

Details about the projections are given in the following references: Bloomberg NEF (McKerracher et al. 2023); Cole et al. (2023); EIA (2023a); Energy Innovation (EI) (Baldwin and Orvis 2022); Goldman Sachs (2023); ICCT/EI (Slowik et al. 2023); REPEAT (Jenkins et al. 2023); Rhodium (Larsen et al. 2022); S&P Global Mobility (Brinley 2023); USREGEN (Bistline et al., forthcoming); Zhao et al. (2022).

EV = electric vehicle.

Appendix A: Parameter Values

Table A-1 lists the parameters that appear in the simulation model, along with their values and the sources of those values.

Table A-1.

Parameter Values Used in CBO's Analysis

	Mean Value	Notes
Vehicle Costs		UBS (2017) via Lutsey and Nicholas (2019)
Power Train		
ICEV	$6,800	Constant (Cost savings from learning by doing are fully realized)
EV battery	$8,750 (Cars) $15,000 (Light trucks)	70 kWh battery, $125/kWh (240-mile range) 120 kWh battery, $125/kWh (240-mile range) Average annual decrease = 6% ~N(0.06, 0.006) to a minimum of $50/kWh
EV, other components	$3,200	Average annual decrease = 1.6%, ~N(0.016, 0.0016)
Assembly		
ICEV	$12,700	Constant (Cost savings from learning by doing are fully realized)
EV	$12,246	Average annual decrease = 0.7%, ~N(0.007, 0.0007)
Indirect Costs		Includes depreciation, amortization, administrative, and research and development costs
ICEV	$4,000	Average annual increase = 1.6%, ~N(0.016, 00008) through 2026 for increases in CAFE stringency
EV	$5,800	Average annual decrease = 10% ~N(0.1, 0.015) to a minimum of $3,200
Markups		
Dealers	15%	
Manufacturers		
ICEV	5% (Cars), 15% (Light trucks)	
EV	1% (Cars), 3% (Light trucks)	EV producer markups increase by equal amounts each year until they equal ICEV markups in 2035
Taxes	8.5%	
Maintenance		
ICEV	6.1 cents/mile (Cars); 9.4 cents/mile (Light trucks)	
EV	2.6 cents/mile (Cars); 3.9 cents/mile (Light trucks)	
Operating Costs		
Energy Consumption		
ICEV	On-road fuel economy averages 76% of CAFE ratings (NHTSA 2022), rising to 45.1 mpg (2026 cars), 33.9 mpg (2026 light trucks)	CAFE final rule standards through 2026 (CAFE 2022); CAFE stringency held constant after 2026, the latest year for which standards have been specified
EV	0.29 kWh/mile (Cars, e.g., Bolt) 0.5 kWh/mile (Light trucks)	Implies 240-mile range from a 70 kWh battery Implies 240-mile range from a 120 kWh battery; equal to least-efficient EV

Continued

Parameter Values Used in CBO's Analysis

	Mean Value	Notes
Operating Costs (Continued)		
Energy Prices		
ICEV	Gasoline price projections from EIA	EIA (2023a)
EV	Electricity price projections from EIA	EIA (2023a)
Vehicle Miles		
ICEV	Costs compared using EV vehicle miles traveled	Oak Ridge National Laboratory (2022)
EV	60% of age-specific average vehicle miles traveled for all passenger vehicles, rising to 100% by 2035	Oak Ridge National Laboratory (2022)
EV Chargers		
Current Costs		
L2	$5,000 (includes two plugs)	Nicholas (2019)
L3 (DC Fast)	$200,000 (includes four plugs)	Nicholas (2019)
Future Costs	Decreasing by 2% per year	Following Cole et al. (2023), ICCT uses 3%; see Slowik et al. (2023)
Initial Network Size		
L2	45,000 chargers	Alternative Fuels Data Center, "Alternative Fueling Station Locator"
L3	6,750 chargers	
Other Parameters		
Vehicle Fleet Size		
ICEV	Projected annual sales totals for cars and light trucks (ICEVs and other non-EV alternative fuels)	EIA (2022b)
EV	Aggregated monthly sales Totals by year, cars and light trucks, EVs and plug-in hybrids	Argonne National Laboratory
Discounting		
Future capital costs	8% annual discount rate	Damodaran (2023)
Future consumer costs, savings	3% annual discount rate	Cole et al. (2023); Clinton et al. (2020) use 5%
Consumer foresight	8-year horizon at purchase (On average, consumers consider only 75% of future costs of operation and maintenance)	Valuation factor ~U[0.5,1]; see Cole et al.(2023)
Elasticities		
EV demand	Own price elasticity ~N(-2, 0.25)	Relative price, or price(EV)/price(ICEV) Cole et al. (2023)
	Charger network size elasticity ~N(0.4,0.01)	Springel (2021)
Charger supply	Own cost elasticity ~N(0.65,0.01)	Springel (2021); Li et al. (2017)
	EV fleet size elasticity ~N(0.65,0.01)	Springel (2021); Li et al. (2017)

Data source: Congressional Budget Office.

CAFE = corporate average fuel economy; EV = electric vehicle; ICCT = International Council on Clean Transportation; ICEV = internal combustion engine vehicle; kWh = kilowatt-hour; mpg = miles per gallon; NHTSA = National Highway Traffic Safety Administration.

Appendix B: Sensitivity Analyses

This appendix presents sensitivity analyses for four comparatively influential parameters:

- The elasticity of the market share of new electric vehicles (EVs) with respect to the relative ownership cost of an EV compared with that of a comparable internal combustion engine vehicle (ICEV);
- The elasticity of new-EV market share with respect to the number of EV chargers;
- The time trend of the attribute drift term described in Section 2.2 of this paper; and
- The rate at which EV production costs change over time.

Additionally, this appendix considers the sensitivity of the results to a set of parameter values taken from the International Council on Clean Transportation (ICCT), on eligibility for the EV tax credits specified in the 2022 reconciliation act, and, separately, on my own modeling of consumer leasing behavior.

For most of the other parameters in the model, changes to their values—within plausible ranges, singly or in small groups of related parameters—do not dramatically affect my projections. Those analyses are not reported in this paper.

I report the sensitivity results in terms of their effects on the model's base case reflecting current law, with charger subsidies provided in the Infrastructure Investment and Jobs Act (IIJA), EV tax credits from the 2022 reconciliation act, and an attribute drift term reflecting the historical-growth projection from previous years' EV sales totals.

Sensitivity Analysis 1: Change the Price Elasticity of New-EV Market Share by 25 Percent

Some analysts expect the price elasticity of the demand for new EVs to increase, in absolute value, as automakers supply more moderately priced EVs that price-sensitive consumers would consider buying. This sensitivity test considers the effects that such a broadening of demand would have on the simulation model's projected EV share of new vehicles. For the sake of completeness, I also consider the opposite scenario—that of demand for EVs narrowing to include only consumers who are less sensitive to price than is simulated in the rest of the paper.

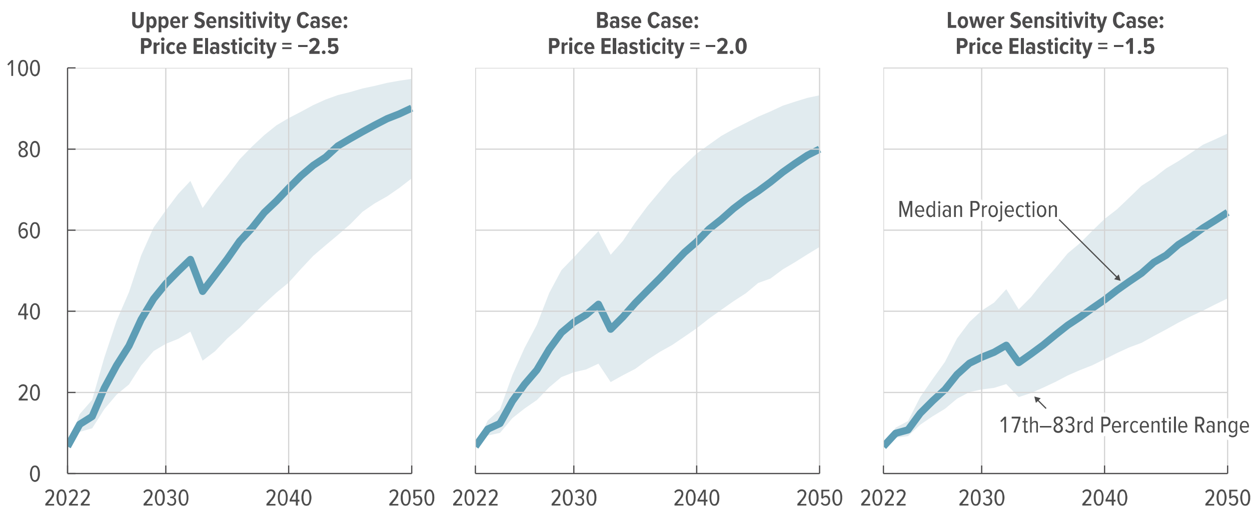
For those tests I change the price elasticity of new-EV market share, β_2 in the demand equation, by 25 percent in absolute value, from −2.0 to either −2.5 (more price-sensitive) or −1.5 (less price-sensitive). The β_2 parameter determines how changes in $p_{j,t}$ in the demand equation affect projected EV market shares. I perform all simulations using the scenario with IIJA subsidies and EV tax credits. As I did for the base case (a price elasticity of −2.0), for the two sensitivity cases I draw new elasticity values for each simulation from normal probability distributions with means of either −1.5 or −2.5, depending on the case, and standard deviations of 0.35.

For the simulations with an average price elasticity of −2.5—indicating greater sensitivity to relative EV ownership costs than I model elsewhere in this paper—my median projection for 2032 (the last year of EV tax-credit availability) is a 53 percent EV share of new light-duty vehicle sales. That is 11 percentage points higher than I project with a price elasticity of −2. By contrast, with a lower elasticity of −1.5 the median projected EV market share drops to 32 percent, 10 percentage points lower than with a price elasticity of −2 (see Figure B-1). Those differences are similar to, and slightly inside, the upper and lower bounds of the model's likely range of projected EV shares, as I described in Section 4.5.[1]

Figure B-1.

Sensitivity of Projections of New-EV Market Share to 25 Percent Changes in Price Elasticity

Percent



Data source: Congressional Budget Office. See www.cbo.gov/publication/58964#data.

EV = electric vehicle.

Sensitivity Analysis 2: Change the Sensitivity of EV Demand With Respect to EV Chargers by 25 Percent

In the analyses presented in this paper, I use a charger elasticity of EV demand of 0.4, meaning that a 10 percent increase in the number of chargers would induce a 4 percent increase in the

[1] The likely range reflects random variation in the model's parameter values, whereas the median projections plotted in Figure B-1 reflect predetermined differences in the mean price elasticity values for each case.

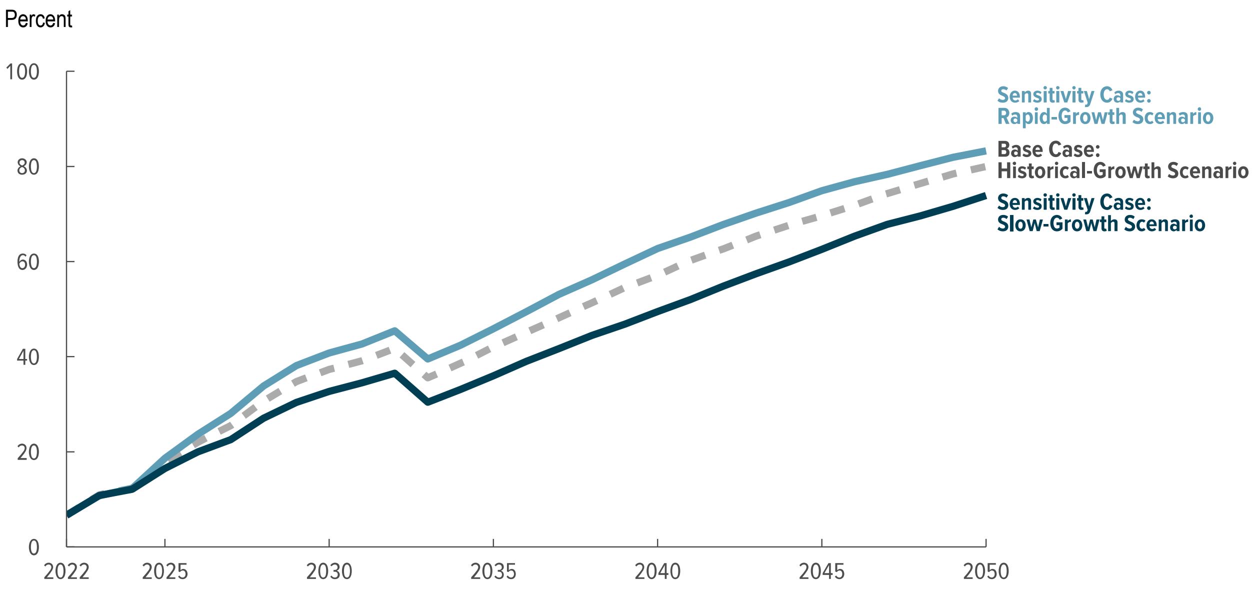
market share of new EVs (Springel 2021). An earlier analysis found evidence for a demand response about twice as large (Zhou and Li 2018).

Here I explore the effect that an increase—or a decrease—in the value of the charger elasticity parameter would have on projected EV market share. In these tests, I change the sensitivity of EV demand by plus or minus 25 percent with respect to the size of the charger network. Increasing the charger elasticity from 0.4 to 0.5 causes the median projected EV market share for 2032 to increase from 42 percent (with a likely range of 27 percent to 60 percent) to 45 percent (likely range: 31 percent to 65 percent).[2] Decreasing that demand sensitivity to charger supply, from 0.4 to 0.3, reduces the median projection for 2032 to 37 percent (likely range: 23 percent to 56 percent; see Figure B-2).

As with the price elasticity of demand, increases in the charger elasticity of demand have a slightly larger effect on projected EV shares than do decreases of the same size. That is because any increase (decrease) in market share is reinforced by a charger supply response: More (fewer) chargers will be supplied as demand for charging services varies with the size of the EV fleet.

Figure B-2.

Sensitivity of Projections of New-EV Market Share to 25 Percent Changes in Charger Elasticity



Data source: Congressional Budget Office. See www.cbo.gov/publication/58964#data.

EV = electric vehicle.

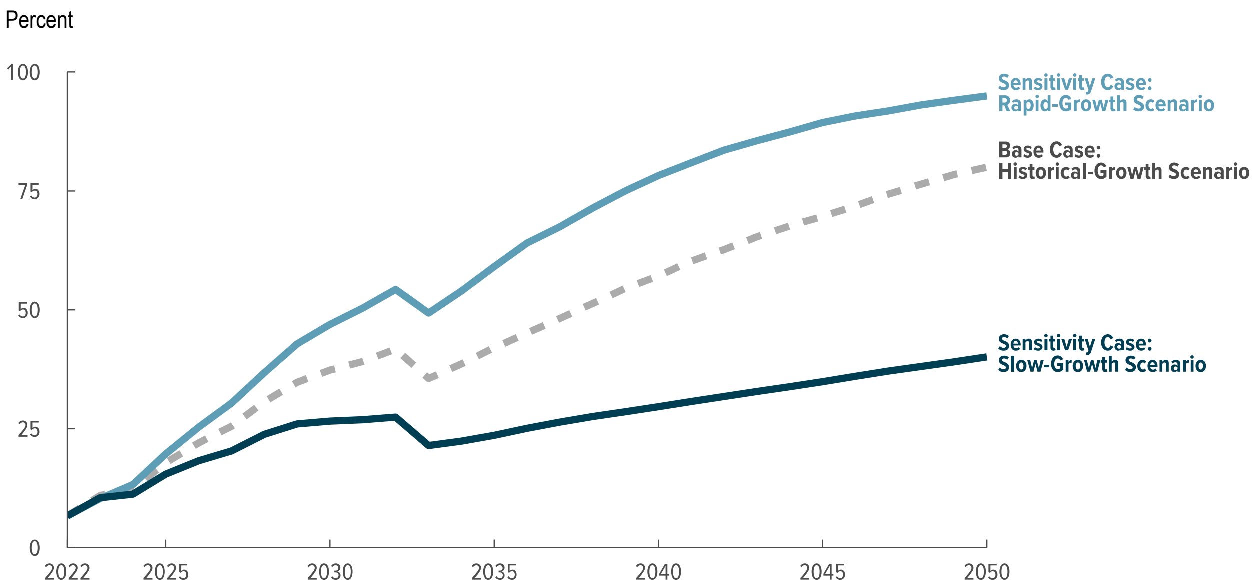
[2] Those likely ranges could be presented as a three-panel figure like Figure B-1, but their differences are smaller than those plotted in Figure B-1 and thus would be less easily discerned if presented in separate panels.

Sensitivity Analysis 3: Alternative Time Trends for the Attribute Drift Term

The attribute drift term includes a time-trend parameter that directly influences the model's projections. The three model calibration options shown in Figure 3 differ solely in the underlying value of that parameter. Applied to the model's base case, which includes the current-law IIJA subsidies and EV tax credits, those three growth scenarios project median EV market shares for 2032 of 27 percent, 42 percent, and 54 percent, respectively (see Figure B-3). After that, the projections continue to diverge until about 2041 when, under the rapid-growth scenario, the rate of increase slows as projected new-EV shares first exceed 80 percent on the approach to a 100 percent share of the market.

Figure B-3.

Sensitivity of Median Projection of Current-Law New-EV Market Share to Changes in Trend in Attribute Drift



Data source: Congressional Budget Office. See www.cbo.gov/publication/58964#data.

EV = electric vehicle.

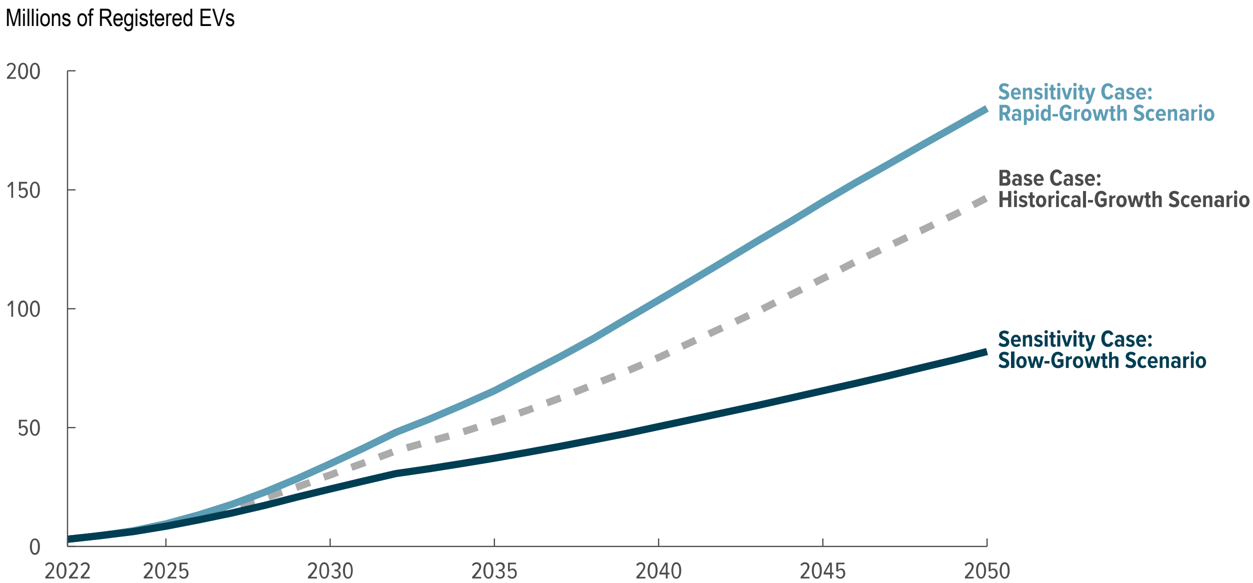
Growth in the share of EVs sold each year has a compounding effect on the total number of registered EVs. The middle, historical-growth scenario projects that there will be 100 million EVs on the road by 2044—and about 150 million EVs by 2050, equal to more than half the number of light-duty vehicles currently registered in the United States (Bureau of Transportation Statistics). The sensitivity cases presented in this appendix all affect that projection. Within those sensitivity cases, the largest effects are produced by the slow- and rapid-growth scenarios. We provide those alternate EV fleet-size projections here.

Under the rapid-growth scenario the nation's fleet of light-duty EVs is projected to reach 100 million vehicles by 2040, four years sooner than in the historical-growth scenario (see

Figure B-4). The slow-growth scenario projects that the nation's EV fleet will not reach the 100 million threshold until after 2050. As of 2022 there were 3.4 million light-duty EVs in the United States, including plug-in hybrids (1.0 million) and EVs powered purely by battery (2.4 million) (Alternate Fuels Data Center, "Electric Vehicle Registrations by State").

Figure B-4.

Sensitivity of Median Projection of EV Fleet Size to Changes in Trend in Attribute Drift



Data source: Congressional Budget Office. See www.cbo.gov/publication/58964#data.

EV = electric vehicle.

Sensitivity Analysis 4: Change the Rate of Decrease in EV Production Costs by 50 Percent

This sensitivity analysis addresses the possibility that EV production costs might decline more slowly or rapidly than modeled. The results of this analysis indicate that the model's EV share projection parameters are not very sensitive even to large changes in the rate of change in certain EV costs. In part that is because growth in the demand for EVs does not only depend on declining production costs of EVs. It also depends on EVs' expected lower costs of operation and maintenance, growth in the number of EV chargers, and growth in consumer demand for EVs as a result of other, unspecified attributes of the vehicles, as captured in the attribute drift term.

The table in Appendix A lists the EV cost parameter values used in this analysis. Battery costs are $8,750 for cars and $15,000 for light trucks, based on $125 per kilowatt-hour (kWh) for a battery with a range of 240 miles (70 kWh for a typical car and 120 kWh for a light truck); lately, those costs have been declining by 6 percent per year, and that is the value I use in the simulations—to a minimum of $50 per kWh. Other power train component costs are $3,200, declining by 1.6 percent per year; assembly costs are $12,246 for a typical car, declining by 0.7 percent per year; and indirect costs (depreciation, amortization, administration, and research and development) are $5,800 per vehicle, declining by 10 percent per year, to a minimum of $3,200. EV costs are decreasing as the technologies are improved and as automakers refine their vehicle designs and manufacturing processes. By contrast, automakers have been designing and producing ICEVs for more than a century. Thus, those costs are relatively more stable. My analyses allow for a gradual increase in indirect costs associated with ICEV production if I wish to model the effect of gradually increasing stringency in vehicle fuel economy standards. However, for this analysis I hold ICEV indirect costs fixed after 2026 to reflect that corporate average fuel economy (CAFE) standards are not currently specified in law beyond that model year of vehicles.

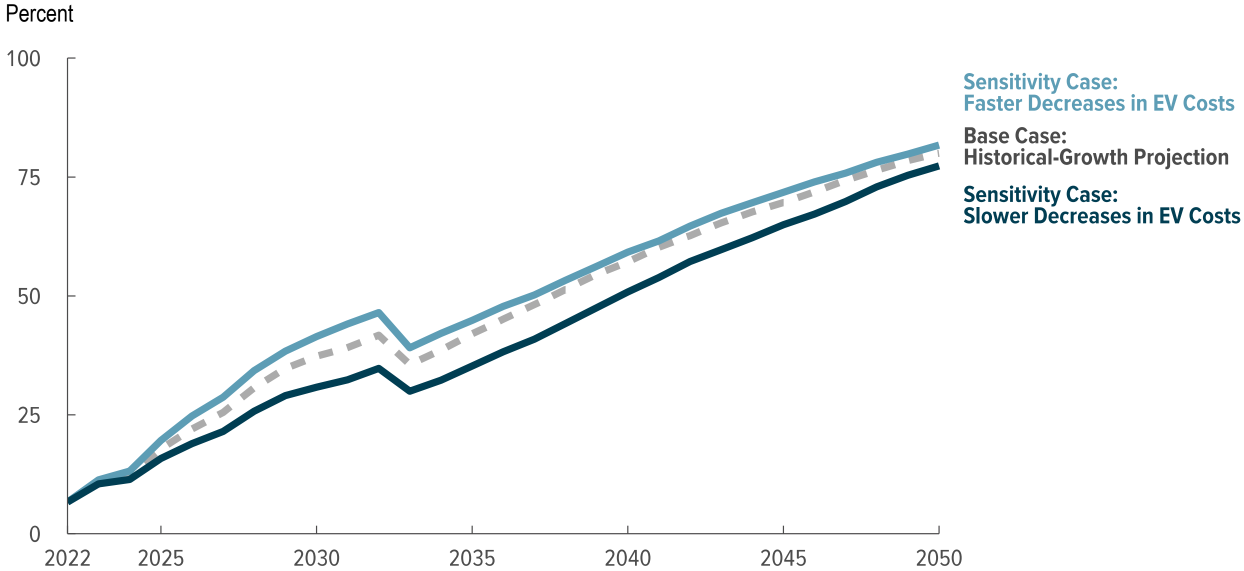
Because my analysis takes current demand for EVs as given—the model is calibrated to project EV shares from current values—changing the dollar costs used in the model would not affect the model's projections. Given the observed demand for EVs—the level from which future EV shares are projected—doubling the cost values used in the model would have no effect other than to double the amount that consumers in the model are implicitly willing to pay for an EV.

Instead, for this sensitivity analysis I alter the rate of change in those costs, by plus or minus 50 percent. For example, slowing the rates of change by 50 percent means that battery costs would decrease by 3 percent per year, other power train costs would decrease by 0.8 percent, assembly costs by 0.35 percent, and indirect costs by 5 percent.

Slower declines in EV costs would slow growth in the demand for EVs, relative to the base case, because consumers would have to pay more for the vehicles. For example, from a peak projected new-EV share of 42 percent in the base case in 2032—with EV tax credits and IIJA charger subsidies still available—slowing the rate of decrease in EV costs by half reduces the peak projection to 35 percent for that year (see Figure B-5). By contrast, using a more rapid rate of decrease, more rapid by half than in the simulations presented in the paper—so that battery costs decrease by 9 percent per year, for example—would yield an EV share projection of 47 percent in 2032. The effect is slightly asymmetrical—slowing the rate of change in EV costs has a slightly bigger effect on the projection than increasing the rate does—because there are lower bounds to some components of EV costs and because the difference between the two sensitivity cases, in their rates of cost decrease, is a little more important in the early years when those component costs are a larger share of the total lifetime costs of an EV.

Figure B-5.

Sensitivity of Median Projection of New-EV Market Share to a 50 Percent Change in the Rate of EV Cost Decreases



Data source: Congressional Budget Office. See www.cbo.gov/publication/58964#data.

EV = electric vehicle.

Sensitivity Analysis 5: Compare ICCT's Low, Moderate, and High Cases for EV Tax-Credit Eligibility

Before it is known how successful automakers' efforts will be to produce EVs that qualify for the tax credits offered in the 2022 reconciliation act, the number of EV tax credits that will be claimed can only be estimated with uncertainty. In recognition of that, ICCT has developed three sets of estimates, which they label as their low, moderate, and high cases, for the percentage of EV transactions that will qualify for the tax credits on various criteria (see Table B-1). I use their moderate case estimates for the results presented in this paper.

Table B-1.

Three Estimates of EV Tax-Credit Eligibility

Percent

Tax-Credit Provision	EVs Qualifying for Tax Credit: Low	Moderate	High
Domestic Battery Assembly	100	100	100
Critical Minerals			
2025	76	79	82
2030	56	72	89
2032	55	78	100
Vehicle Price (Manufacturer's Suggested Retail Price)	87	87	87
Buyers' Adjusted Gross Income	68 in 2023, rising to 77 in 2030	68 in 2023, rising to 77 in 2030	68 in 2023, rising to 77 in 2030

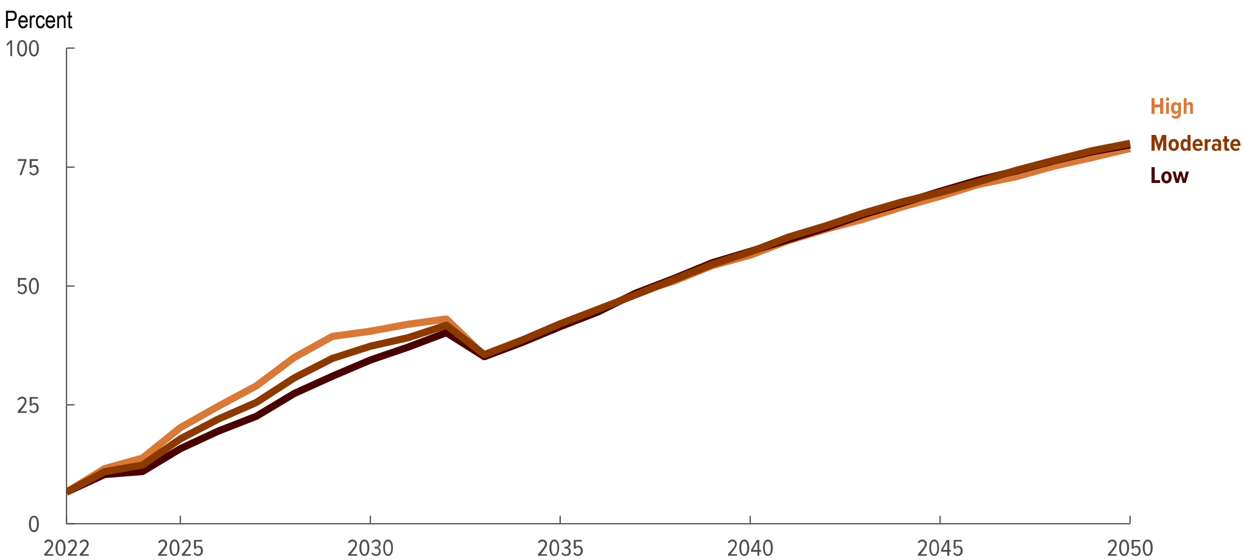
Data source: International Council on Clean Transportation (Slowik et al. 2023). See www.cbo.gov/publication/58964#data.

EV = electric vehicle.

In this sensitivity analysis I compare my projected EV market shares for that moderate case against projections produced using the ICCT's low and high estimates. The maximum divergence in projected EV shares for the low and high cases is about 10 percentage points, in 2028. The comparison reveals that the moderate case is more conservative, with respect to its predictions of EV credits claimed, than the high case: The moderate case projections lie closer to those of the low than of the high case (see Figure B-6).

Figure B-6.

Sensitivity of Median Projection of New-EV Market Share to ICCT's Low, Moderate, and High Cases for EV Tax-Credit Eligibility



Data source: Congressional Budget Office. See www.cbo.gov/publication/58964#data.

EV = electric vehicle; ICCT = International Council on Clean Transportation.

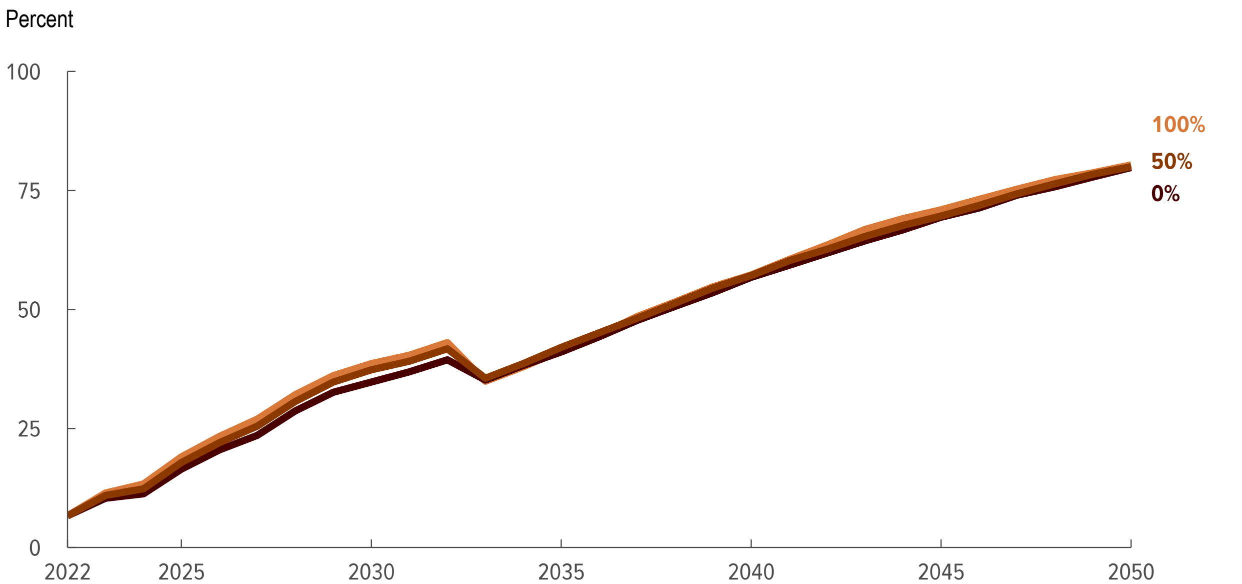
Sensitivity Analysis 6: Change the Amount of EV Leasing That Occurs as a Way of Claiming EV Tax Credits

The Treasury Department recently made a determination that leased EVs are eligible for the EV tax credits in the 2022 reconciliation act even though, if the vehicles had instead been purchased, they would only be eligible on the basis of the criteria listed in Table B-1 (Internal Revenue Service 2022). That means that every electric vehicle sold will qualify for a credit, if the consumer is willing to lease rather than buy the vehicle if necessary. Because not all consumers will be willing to forgo the benefits—as they may perceive them—of owning their vehicle outright, I model that 50 percent of consumers who are not otherwise eligible for a tax credit (including because they have chosen a nonqualifying EV) will lease the vehicle to receive a credit. As discussed previously, that increases the expected number of credits claimed by about one-fourth, compared with no leasing.

In this sensitivity analysis I compare my 50 percent leasing case with the lower- and upper-bounding cases: No leasing occurs, or every consumer who is not otherwise eligible leases in order to receive the credit. My 50 percent leasing case lies approximately in the middle between the zero and 100 percent leasing cases, though slightly closer to the zero case (see Figure B-7).

Figure B-7.

Sensitivity of Median Projection of New-EV Market Share to EV Buyers' Propensity to Lease If They Do Not Otherwise Qualify for an EV Tax Credit



Data source: Congressional Budget Office. See www.cbo.gov/publication/58964#data.

EV = electric vehicle.

The difference between projected EV shares in the zero and the 100 percent leasing cases does not appear very great. At its maximum, in 2030, the difference is about 4 percentage points. From 2023 to 2032 the average difference between those cases is 3 percentage points, equivalent to about 450,000 additional EVs sold—and EV tax credits claimed—per year. For the 50 percent case I project that on average about 265,000 additional EVs will be sold per year as a result of consumers' being able to lease those EVs and receive the value of the tax credit from the automaker as lessor.

I also project, for that case, that an additional 470,000 tax credits will be claimed each year by lessees who would have purchased an EV without a tax credit but who lease in order to receive the credit value. In all, about one-fifth of EV tax credits may be claimed on behalf of EV consumers who lease their vehicles.

Appendix C: A Proposed Rule on Tailpipe Emissions

The Environmental Protection Agency (EPA) recently proposed an extension of the greenhouse gas emissions standards for new light-duty vehicles, through the 2032 model year. Their proposed rule would extend and increase the stringency of the current standards, which apply to vehicles up to model year 2026 (EPA 2023a.)

EPA has said that, depending on how automakers decide to achieve compliance with those standards, by 2032, electric vehicles (EVs) "could account for 67 percent of new light-duty vehicle sales" (EPA 2023b). Automakers might achieve such sales by a combination of means:

- Pricing—increasing the prices of their internal combustion engine vehicles (ICEVs) relative to their EVs;
- Product design—increasing the attractiveness of their EVs relative to their ICEVs; and
- Product offerings—increasing the number of EV models they offer relative to their ICEV models.

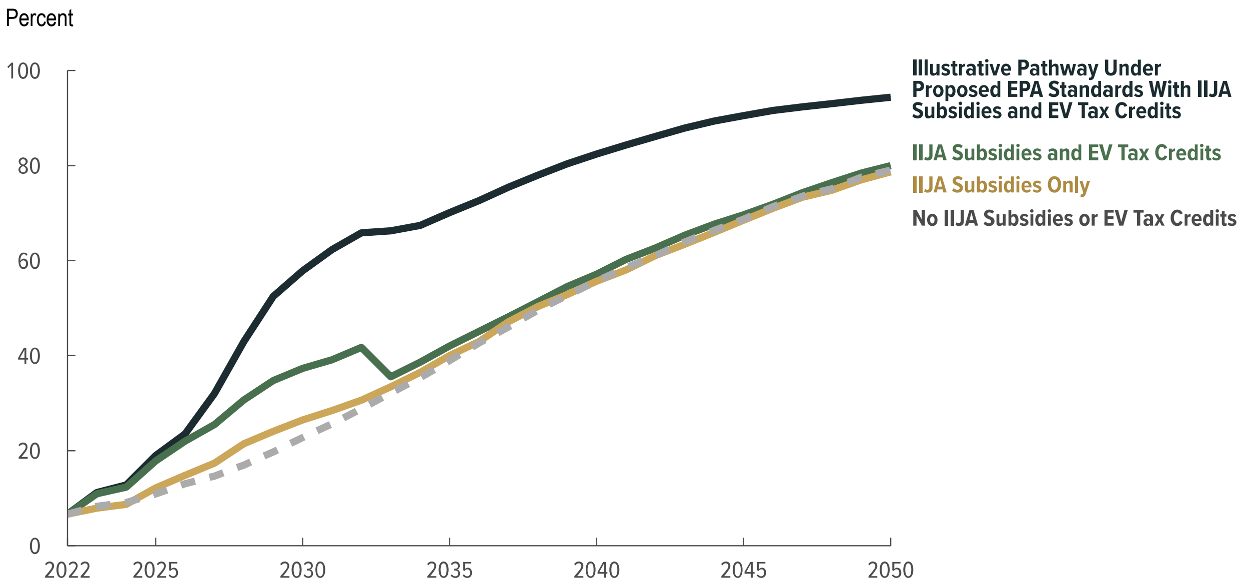
If consumer preferences for EVs increased relative to ICEVs, independent of automakers' efforts to encourage their sale, that would also increase the share of EVs in the market for new light-duty vehicles.

In this scenario, I take EPA's estimated compliance market share of EVs as given, without considering whether or how automakers would achieve it, and I show what such a market would look like.

For the first couple of years after 2032, the effect of the regulatory constraint is apparent because the growth in EV shares pauses at about 67 percent as the EV tax-credit program expires (see Figure C-1). But after that pause, my projections indicate that growth in EV market share will resume, exceeding 80 percent by 2039. Accompanying that growth, charger suppliers continue to add L3 (and L2, not shown) stations, well beyond what can be built using IIJA subsidy funds (see Figure C-2).

Figure C-1.

Median Projected Market Share of New Light-Duty EVs Under Proposed EPA Standards

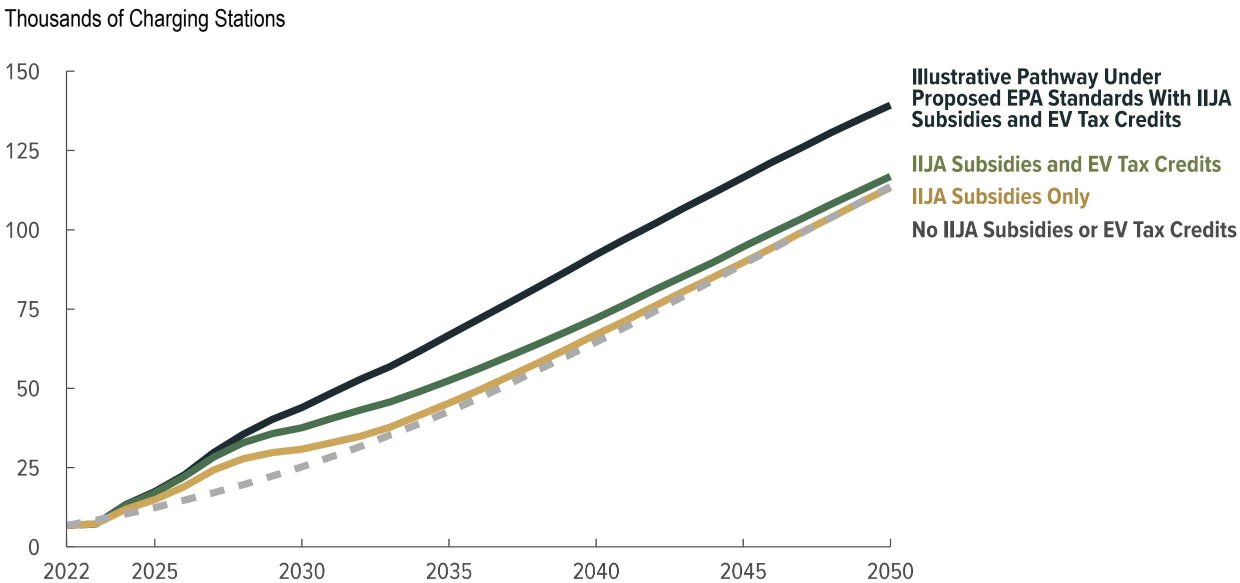


Data source: Congressional Budget Office. See www.cbo.gov/publication/58964#data.

EPA = Environmental Protection Agency; EV = electric vehicle; IIJA = Infrastructure Investment and Jobs Act.

Figure C-2.

Median Projected Supply of L3 Charging Stations Under Proposed EPA Standards



Data source: Congressional Budget Office. See www.cbo.gov/publication/58964#data.

EPA = Environmental Protection Agency; EV = electric vehicle; IIJA = Infrastructure Investment and Jobs Act.

The new standards would cover vehicle models from 2027 to 2032, a period in which the EV tax credits under the 2022 reconciliation act will continue to be available. I project that by the late 2020s, EV sales under the proposed standards will be more than 50 percent higher than they would be under the IIJA charger subsidies and EV tax-credit policies alone. That suggests that the standards, if enacted, would cause a similar—or possibly greater—increase in the number of EV tax credits claimed. The additional EV sales that would occur under the standards would represent a broadening of EV demand to consumers who, by 2032, would not have purchased an EV even with the inducement of the EV tax credits. If those consumers have lower income, on average, than EV buyers who are induced by the tax credits, then credit claiming will be greater, as a share of EVs sold, for the additional EV sales caused by the proposed standards than for the EVs that will be sold even if the standard is not enacted. Similarly, to the extent that automakers lower the prices of their new EVs as part of their strategy for complying with the proposed standards, a greater share of the additional EVs sold under the standard might qualify for a tax credit on the basis of vehicle price, compared with EVs that will be sold if the standard is not enacted.

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