Roadblock or Accelerator? The Effect of Electric Vehicle Subsidy Elimination

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Nafisa Lohawala*

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Abstract

Federal and state governments in many countries subsidize the early adopters of electric vehicles (EVs). These programs often use quotas or deadlines to phase out the subsidies, which can create dynamic incentives for car manufacturers. Since most of the literature studies the effect of introducing subsidies on market outcomes in static settings, little research has addressed the dynamic effects of subsidy-capping designs. This paper explores those effects in the US vehicle market. I develop a structural model of consumers' vehicle choices and manufacturers' pricing decisions in the US automobile industry. I then estimate the model using comprehensive data on new vehicle registrations, prices, characteristics, and subsidies in 30 states between 2011 and 2017. Based on the primitives generated from the model, I conduct counterfactual simulations to compare three designs: a marketwide deadline, a per-manufacturer deadline, and a per-manufacturer quota. The simulations show that for a given government expenditure, the quota leads to up to 18 percent lower EV sales than the deadlines. Moreover, each design influences the sales of conventional vehicles, consumer surplus, manufacturer profits, and liquid fuel consumption differently.

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1 Introduction

Consumer subsidies and rebates are a popular means to promote advanced technology vehicles in several countries, such as the United States, Canada, China, and Norway (Beresteanu and Li 2011; Chandra, Gulati, and Kandlikar 2010; Jenn, Azevedoa, and Ferreira 2013). Policymakers typically use provisions such as quotas and deadlines to cap these subsidies. Despite this wide use, little work has been done to understand their effect on market outcomes. This paper extends the literature by considering the dynamic effects of such provisions. I show that different provisions have different effects that can reinforce the intended policy objectives or create unintended consequences that partly undo the benefits of the subsidy.

Policymakers subsidize plug-in electric vehicle (EV) purchases to address various externalities. EV adoption has a positive environmental externality due to zero tailpipe emissions.[1] It can enhance the energy security of oil-importing countries by not relying on gasoline. It has information spillovers to the extent that EV consumers help spread information about it. It also makes entry attractive for charging stations, which is crucial for developing a charging network and further encouraging demand. In addition, a policy goal may be to integrate EVs into the automobile industry by overcoming the most significant barrier to their adoption—high up-front cost—by making EVs price competitive with conventional vehicles.

The traditional Pigouvian solution to externalities is to subsidize the externality-generating activity equivalent to the marginal external benefit at the optimal quantity. Policymakers typically allow these subsidies to end after a certain period, with several possible reasons for doing so. First, subsidies can be prohibitively expensive if sales surge due to higher budgetary requirements, administrative costs, or other political reasons. Second, marginal gains from informational spillovers are likely to fade as EVs integrate into the automobile industry. Finally, the marginal cost, and therefore the price, is likely to come down as manufacturers find cheaper ways to produce the battery.

Policymakers worldwide use different strategies to cap the subsidies, such as limiting the total expenditure, imposing a deadline, or combining both. For instance, in 2012, Norway planned to remove financial incentives for EVs after 2018 or once there were 50,000 such vehicles on the road (Steinbacher, Goes, and Jörling 2018).[2] In 2020, China planned to cut EV subsidies progressively between 2020 and 2022, with complete expiration in 2022.[3] The US federal EV tax-credit program initiated by the Energy Improvement and Extension Act of 2008 capped the incentives by giving each manufacturer a quota of 200,000 vehicles, after which its credit phased out. The Inflation Reduction Act of August 2022 (IRA) replaced this cap with a single deadline for purchase subsidies. Vehicles produced by all EV manufacturers now qualify for the subsidy until 2032 (provided they meet some additional requirements).

1. Questions have been raised in the literature on the environmental benefits of driving EVs because charging the battery increases pollution at the power plant (see Babaee, Nagpure, and DeCarolis (2014), Archsmith, Kendall, and Rapson (2015), Holland et al. (2016), and Buekers et al. (2014)). The cleaner the grid, the greater the environmental benefits of replacing a gasoline vehicle with an EV.

2. Although the 50,000 target was reached early in 2015, Norway later extended the incentives.

3. See https://www.globaldata.com/data-insights/automotive/china-will-end-ev-subsidies-after-30-cuts-in-2022/.

For a given level of expenditure, are these designs equally effective in raising EV penetration? What are their implications for market outcomes such as consumer surplus, EV manufacturers' profits, and overall gasoline consumption? This paper takes a step toward answering these questions.

I focus on the US federal EV tax-credit program, which provides nonrefundable income tax credits of up to $7,500 to EV consumers.[4] Before the IRA, the program had a unique subsidy-capping design (see Figure 1). The phaseout was triggered when a given manufacturer delivered the 200,000th subsidy-qualifying vehicle. In that quarter and the next, the per-vehicle subsidy remained unchanged. It then reduced to half for that manufacturer's vehicles for the next two quarters, one-fourth for another two quarters, and then zero. Given the timing component in this design, pushing the sale of the 200,000th vehicle to the following quarter (e.g., in July instead of June) could delay the phaseout by a quarter.

I examine the short-term dynamic incentives created by this design. To do that, I break the design into two components. The first is a per-manufacturer quota, in which each manufacturer faces a separate quota on the total number of qualifying vehicles. Similar to the actual US design, if the manufacturer sells fewer EVs than its quota in any period, then all EVs that it sells in the next period also qualify for the subsidy. The second component is a per-manufacturer deadline, where each manufacturer faces a separate deadline. The actual design in the program can be considered as a combination of a per-manufacturer quota of 200,000 vehicles and three per-manufacturer deadlines corresponding to the 50%, 75%, and 100% subsidy cuts. I compare these components with a marketwide deadline as instituted by the IRA.[5] Comparing these different designs helps understand the dynamic implications of replacing the earlier design with a marketwide deadline.

I first use a stylized two-period monopoly model to illustrate how this quota can potentially incentivize manufacturers to reduce their EV sales as they get close to the quota, thereby undermining the effectiveness of the subsidy. The incentive arises because by staying below the quota in a given period, the manufacturer can ensure that all EVs sold in the following period also qualify. Because the manufacturer has market power, it can retain some benefits of the subsidies. As a result, it can earn higher profits from all the EV sales made during an additional period. In contrast, capping the subsidy using a deadline does not create this incentive because the manufacturer cannot control when the subsidy expires.

Next, to quantify the effects of each design, I develop and estimate a structural model of the US automobile industry. The demand side follows a discrete-choice framework, where consumers choose a vehicle among all available fuel types. Because the EV market is still nascent, adoption may depend on information gains from early adopters and mobility gains from the development of a charging network (Kalish and Lilien 1983; Heutel and Muehlegger 2015; Springel 2021; Li et al. 2017). I capture this network effect in the model by allowing consumers to care about the number of EVs previously sold in their local geographic area. In contrast, the supply side is an oligopoly

4. Starting in 2024, the subsidy will be available as a "point-of-sale rebate" rather than a tax credit.

5. The IRA also made other changes to the program. For instance, it added a final assembly requirement, whereby the subsidy is only available for EVs that were assembled in North America, and a price cap, an income cap, and restrictions on sourcing critical battery minerals. Because my focus is on understanding the effect of the subsidy-capping designs, I do not consider these other changes.

with product differentiation where car manufacturers compete in prices.

The model's key feature is that, in addition to current profits, it allows manufacturers to care about the following year's profits when choosing vehicle prices. Such two-period pricing captures manufacturers' responses to the dynamic incentives induced by the subsidy caps, which a static model would miss. The two-period model also allows manufacturers to internalize the demand-side network effect. Given a per-manufacturer quota, the network-effect-induced incentives work in the opposite direction to quota-induced incentives. On the one hand, exhausting the quota shrinks the future EV demand by eliminating the subsidy; on the other hand, attracting early adopters increases the future EV demand due to the network effect. Thus, the manufacturer's pricing response is a priori ambiguous and depends on market parameters such as own- and cross-price elasticities and the network effect.

Next, I estimate these demand parameters using product-level data on vehicle registrations, characteristics, and federal and state-level subsidies in 30 states between 2011 and 2017. Based on the estimated demand parameters and the first-order conditions of the manufacturers' profit functions, I then recover the vehicle markups and marginal costs in 2017. Finally, based on these primitives, I recompute pricing equilibria under three counterfactual designs: a marketwide deadline, a per-manufacturer deadline, and a per-manufacturer quota. I compare these designs with a counterfactual with no subsidy.

The simulations show that even though all subsidy-capping designs boost the EV market penetration, there are not equally effective. For a given government expenditure, a per-manufacturer quota can lead to much lower EV sales compared to the deadlines. In my experiments, the per-manufacturer quota reduces EV sales by up to 18 percent compared to the deadlines. Two factors drive this result. First, staying below the quota in any period allows a manufacturer to qualify for the subsidy on all EVs it sells in the following period, which allows it to earn higher profits. Second, because the subsidy is only eliminated for manufacturers that exhaust the quota, not doing so protects manufacturers from competition from manufacturers below the quota. In contrast, as deadlines do not allow manufacturers to control when the subsidy expires, they can be more cost-effective in increasing EV market penetration. These results suggest that, all else equal, replacing the earlier design with a marketwide deadline will likely boost the EV market penetration closer to subsidy expiration.

In addition to the effect on market penetration, the subsidy-capping designs can have spillover effects on conventional vehicles' sales and can affect consumer surplus, manufacturers' profits, and liquid fuel consumption. They also affect profit distribution across manufacturers. Compared to a marketwide deadline, a per-manufacturer deadline shifts profits away from the manufacturers that face the limit. A per-manufacturer quota does not necessarily do so, because it allows them to control when the subsidy expires. This finding sheds light on the argument made by the dominant EV manufacturers, such as Tesla, General Motors (GM), and Nissan, which have claimed that the per-manufacturer cap put them at a competitive disadvantage compared to newly entering rivals. EV subsidies became a topic of vigorous debate during the tax reform of 2017 partly because of this cap; the dominant manufacturers and other supporters formed an EV-drive coalition and argued (among other reforms) to remove the cap. After the original design survived that tax reform, the top EV manufacturers that initially lobbied to preserve these incentives started favoring their removal altogether (Lambert 2018). The results suggest that, all else equal, replacing the earlier design with a marketwide deadline is likely to impact the distribution of profits and other market outcomes mentioned above.

The paper adds to multiple strands of the literature. First, it contributes to the growing economic literature on the role of government policies in decarbonizing transportation. According to the Paris Agreement, many governments from different countries have set a target to achieve net-zero emissions by 2050. Transitioning from conventional vehicles to EVs is essential to this goal (Williams et al. 2012). Some papers, such as DeShazo, Sheldon, and Carson (2017), Jenn, Springel, and Gopal (2018), and Clinton and Steinberg (2019), analyze the effectiveness of incentives in encouraging consumer adoption of EVs and generally find that consumers respond to subsidies and other incentives. Other papers, such as Li et al. (2017), Li (2018), and Springel (2021), explore the positive feedback loop between EV purchases and charging infrastructure. This body of literature suggests an indirect network effect that is important for policy design. Yet other papers, such as Aghion et al. (2016), Jacobsen (2013), and Gillingham (2022), model vehicle manufacturers' responses to environmental regulation. I contribute by analyzing how the subsidy design can help improve EV market penetration, accounting for manufacturers' responses to the dynamics of subsidy elimination. Comparing the market outcomes under different designs allows for systematic policymaking—based on arraying alternative designs and comparing the advantages and disadvantages of each. Recognizing the importance of the network effect on manufacturers' pricing decisions, I internalize it by allowing consumers' utility to depend on previous EV purchases in their geographic area.

More broadly, the paper contributes to the literature investigating the role of government incentives in promoting green technology. Examples include Beresteanu and Li (2011), Gallagher and Muehlegger (2011), and Jenn, Azevedoa, and Ferreira (2013) on hybrid vehicles, Van Benthem, Gillingham, and Sweeney (2008), Crago and Chernyakhovskiy (2017), and Langer and Lemoine (2022) on solar power, and Hitaj (2013) on wind power development. Most papers study the effect of introducing subsidies on prices and welfare in a static equilibrium but ignore the dynamics of subsidy elimination. For instance, Beresteanu and Li (2011) build an equilibrium model of the new car market and estimate that federal income-tax credits for hybrid vehicles accounted for about 20 percent of such sales in 2006. My paper adds to the literature by explicitly modeling the responses of forward-looking vehicle manufacturers to the subsidy-capping designs in a microfounded model. The analysis is relevant for other countries, as well as other environmentally friendly products, such as fuel-cell vehicles, solar panels, small wind turbines, and geothermal heat pumps, where policymakers use similar subsidy-capping designs.

Finally, my paper adds to the literature on the incidence effects of subsidy programs. Some papers on US clean energy subsidies include Sallee (2011), Borenstein and Davis (2016), Gulati, McAusland, and Sallee (2017), and Pless and Van Benthem (2019). Examples from other subsidy contexts include Cabral, Geruso, and Mahoney (2018) on health insurance, Polyakova and Ryan (2019) on the Affordable Care Act, and Fan and Zhang (2022) on cellphones. This paper adds to the incidence literature by highlighting that, for a given value of the subsidy, the incidence depends on program design. I take a structural approach that allows for a detailed analysis of mediating factors and a simulation of market outcomes under the counterfactual subsidy-capping designs.

The rest of the paper is organized as follows. Section 2 provides a brief background of the US plug-in EV industry. Section 3 describes an illustrative example to provide economic intuition and identifies the key parameters governing manufacturers' responses to the subsidy-capping designs. Section 4 outlines the utility specification and the supply-side problem. Section 5 reports data and summary statistics. Section 6 discusses identification, estimation, and results. Section 7 describes the counterfactual experiments and discusses the findings. Section 8 concludes.

2 Industrial Background

This section begins with a brief description of the US plug-in EV market and the federal tax-credit program that is the focus of this paper. It then describes the key mechanisms of interest in the federal program. Finally, it describes other regulations that have influenced EV development.

2.1 Plug-In EV Market and Federal Tax Credits

Plug-in EVs are road vehicles powered by batteries that can be recharged by plugging into the electric grid. They come in two varieties: (i) battery EVs (BEVs), which are powered exclusively through electricity, and (ii) plug-in hybrid EVs (PHEVs), which use an electric motor as the primary power source and the internal combustion engine as a backup. Both differ from fuel-cell EVs (FCEVs), such as the Honda Clarity, and conventional hybrids (HEVs), such as the Toyota Prius, neither of which can be plugged into an electric grid.

The US plug-in EV market mostly developed after Nissan introduced the Leaf in late 2010. With fuel efficiency and environmental regulations becoming increasingly stringent, most US vehicle manufacturers have added plug-ins to their portfolios. As of 2023, Tesla is the highest-selling manufacturer, followed by GM and Nissan.

The US federal government started a tax-credit program for PHEVs and BEVs under the Energy Improvement and Extension Act of 2008. The program offered nonrefundable tax credits for purchases made after December 31, 2009 (IRS 2009). The credit varied by car model and was worth \$2,500 plus \$417 for each kilowatt-hour of battery capacity over 4 kWh, capped at \$7,500.[6] BEVs qualify for a higher credit than PHEVs due to their larger battery capacity. Popular BEVs, such as all Tesla models and Chevrolet Bolt, qualified for the full \$7,500 subsidy.

Until 2022, the US program used a unique phaseout provision. As summarized in Figure 1, the phaseout triggered for a manufacturer once it sold 200,000 subsidy-qualifying cars for US use after

6. A consumer's purchase needed to meet specific requirements to be eligible. See Internal Revenue Code Section 30D for details.

December 31, 2009. The credit was unchanged in the quarter when the manufacturer delivered the 200,000th vehicle and the next quarter. It reduced to 50 percent for the next two quarters, 25 percent for the next two quarters, and then zero. All eligible plug-in vehicles sold during the phaseout period qualified for the credit.

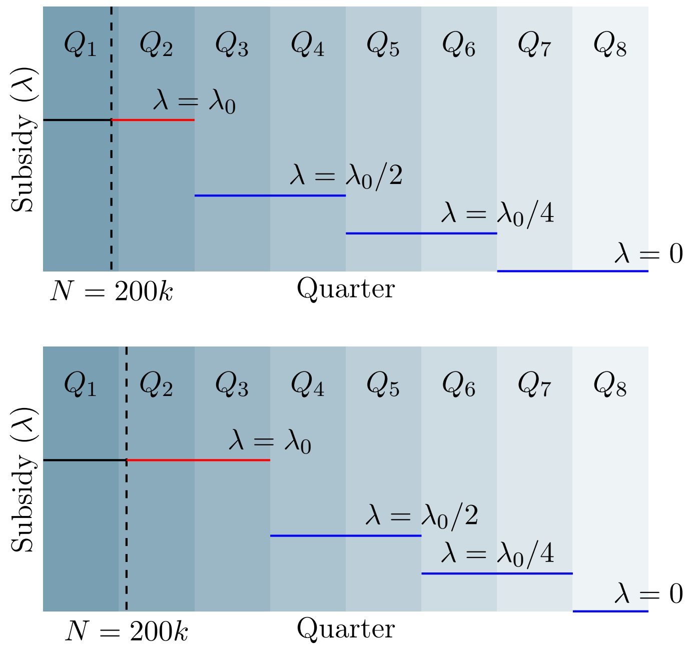
This design followed the tax-credit program for conventional hybrid vehicles (Energy Policy Act, 2005), allegedly designed to prevent dominant foreign manufacturers, such as Toyota and Honda, from benefiting more than domestic manufacturers over the program's life (Lazzari 2006; Leonhardt 2006). The first two manufacturers that hit the threshold (Tesla and GM) are American. Tesla delivered the 200,000th qualifying vehicle in July 2018; Tesla cars qualified for a \$7,500 credit July–December 2018, \$3,750 January–June 2019, and \$1,875 July–December 2019 (IRS 2018). GM delivered the 200,000th qualifying vehicle in November 2018 and faced the subsidy expiration in April 2020 (IRS 2019). The IRA replaced this phaseout design with a marketwide deadline of 2032. All manufacturers, including the ones with the 200,000th vehicle before 2022, are eligible until 2032, provided their vehicles meet additional requirements, such as domestic assembly.[7]

Because only two EV manufacturers have faced the elimination of purchase subsidies, I rely on structural methods to understand the implications of different subsidy-capping designs. Specifically, I develop and estimate a structural model of the US automobile industry, explicitly accounting for consumers' and manufacturers' decisions. I use the estimated market parameters to simulate pricing equilibrium under the counterfactual designs and compare market outcomes across different designs. Appendix A shows time-series evidence that EV sales responded differently to the per-manufacturer quota and the per-manufacturer deadline, based on Tesla and GM's experiences.

In contrast to the EV tax-credit program studied here, the conventional hybrid tax-credit program initiated by the Energy Policy Act (2005) would allow better data availability during and after the subsidy elimination because the program expired in 2010. Nonetheless, I focus on the plug-in EV tax-credit program for two reasons. First, in contrast to plug-in EVs, conventional hybrids compared better than the dominant alternatives from a consumer's perspective, as they combine the benefits of gasoline engines and electric motors. As a result, hybrids were already in high demand before the tax credits started. Second, the hybrid program offered tax credits only up to \$3,150 with a much lower per-manufacturer cap of 60,000. Toyota exhausted the quota within a few months (IRS 2006). Due to these reasons, vehicle manufacturers are more likely to care about the consumer subsidies in the EV market and, hence, more likely to respond to their elimination.

7. See IRS (2023) for details.

Figure 1: Subsidy-Capping Design Adopted in the United States

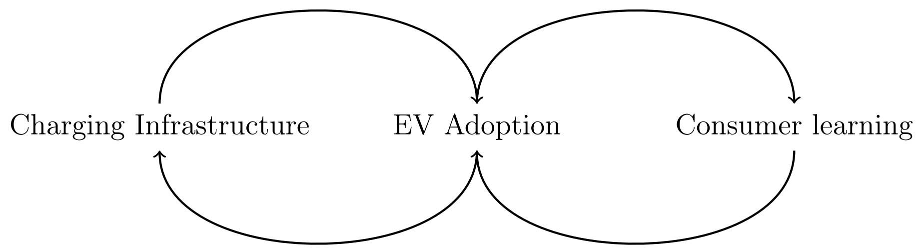


Notes: Panel (a) explains how the subsidy would evolve if the manufacturer exhausted the 200,000 threshold at the end of quarter $Q1$. The phaseout is triggered in the second quarter after the electric vehicle (EV) manufacturer delivers the 200,000th subsidy-qualifying vehicle ($Q3$). In the first six months of the phaseout, a qualifying vehicle from that manufacturer receives 50 percent of the original subsidy. In the second six months, the subsidy reduces to 25 percent. It is eliminated thereafter. The number of vehicles that can receive subsidies during the phaseout period is unlimited. Panel (b) shows the subsidy evolution if the manufacturer hit the threshold at the beginning of $Q2$ instead, indicating a substantial incentive to reduce EV sales at the end of $Q1$ because doing so prolongs the subsidy for another quarter.

2.2 Key Features of the Federal Subsidy Design

The design in Figure 1 is a combination of a per-manufacturer quota of 200,000 vehicles and three per-manufacturer deadlines. The first two reduce the value of the credit, and the final deadline eliminates it. Compared to the per-manufacturer deadline, the quota incentivizes manufacturers to reduce their EV sales for two reasons. First, the quota holds up the first deadline. The subsidy reduces to half in the second quarter after the 200,000th subsidy-qualifying EV is delivered. Thus, pushing the sale of that vehicle to the next quarter can delay the phaseout by three months. Second, the subsidy is eliminated only for those manufacturers who exhaust the quota; doing so before others exposes an EV manufacturer to increased competition because other manufacturers continue to qualify. By reducing the sales of subsidy-qualifying vehicles, EV manufacturers can avoid this situation. On the other hand, the deadlines that followed the quota create no such incentive because manufacturers cannot control when the subsidy expires.

Figure 2: Network Effect



Notes: The figure depicts the positive feedback effect (or the network effect) of electric vehicle (EV) adoption on future demand through two independent channels. Adoption allows potential consumers to experientially infer the quality of plug-in EVs, which increases future adoption. Similarly, it makes entry more appealing for charging stations, and more charging stations allow more consumers to purchase an EV.

An EV manufacturer's response to the per-manufacturer quota can be more complex if it anticipates gains from selling early. Such gains may arise due to multiple reasons. On the demand side, early sales may create a network effect that encourages later sales through two mechanisms described in Figure 2. The first mechanism is consumer learning, whereby "word of mouth" effects mitigate the uncertainty in product quality (Kalish and Lilien 1983; Heutel and Muehlegger 2015) for future car buyers. When buyers see more EV adoption, their exposure to this new technology increases, which may increase their willingness to purchase EVs instead of conventional vehicles. As a result, early sales can shift the future EV demand to the right. This, in turn, can lead to more consumer learning and even higher adoption.

The second mechanism is developing charging infrastructure, which creates a similar feedback effect: more EVs on the road make entry more appealing for charging stations, and more charging stations allow more consumers to adopt EVs. Thus, early sales can shift the future EV demand to the right by facilitating the entry of charging stations. The role of charging infrastructure may not seem obvious, considering that consumers can plug EVs into an ordinary electric outlet. However, that process is very slow and not viable for traveling long distances that would exceed the's battery capacity. Fast-charging infrastructure is crucial to ensure mobility, especially for BEVs, because they do not have a gasoline backup. In addition to these demand-side gains, early sales may offer supply-side gains by helping manufacturers reduce costs through innovation and self-perfection (learning by doing).

Given such gains, a per-manufacturer quota creates two conflicting forces. On the one hand, surpassing the quota means forgoing future subsidies. On the other hand, staying below it means forgoing the network gains from additional sales. As a result, the response would depend on the relative strengths of the two channels. I discuss this mechanism further in Section 3 and account for the network effect in my model by allowing consumer utility to depend on the previous EV sales by the manufacturer. For simplicity, I do not model the supply-side gains separately.

2.3 State-Level Subsidies and ZEV Mandates

Some state and local governments also offer monetary or nonmonetary incentives. Monetary incentives are up to $5,000 per consumer (on top of the federal tax credits) in states such as California. Nonmonetary incentives include access to carpool lanes and free meter parking.

California's ZEV program has also significantly influenced the development of the plug-in EV market. Designed by the California Air Resources Board in the 1990s to achieve the state's long-term emission reduction goals, the program requires a growing percentage of manufacturers' overall sales to have low emissions. Nine other states (collectively called "ZEV states") also adopt the ZEV regulations and, together with California, represent nearly 30 percent of the US car market.

Although ZEV mandates do not affect consumer decisions, they affect manufacturers' profit function. The program works through a credit system, where each manufacturer must show ZEV credits as a percentage of vehicle sales in the ZEV states in each model year. Manufacturers with a shortfall can use credits accumulated in other years or buy credits from other manufacturers. Conversely, manufacturers that exceed their credit requirements can bank credits for later years or sell them. For instance, Tesla and Nissan sold relatively higher BEV volumes than other manufacturers starting in 2012 and sold credits to others. I discuss the ZEV program further in Section 4 and incorporate it into my model by including the value of ZEV credits in the firms' profit functions.

3 An Illustrative Model

This section demonstrates the effect of subsidy-capping designs on EV sales using a monopoly example. Although the full model involves an oligopoly with strategic interactions, this simple example provides economic intuition and identifies the key parameters governing the designs' effect. Section 4 generalizes to the full oligopoly model, which I estimate and use for counterfactual experiments.

Consider a monopolist that maximizes the sum of profits across two periods. The market demand in the first period is linear in the consumer price:

$$Q_1(P_1) = A - BP_1,$$

where A and B are positive scalars. The market demand in the second period is similar but depends on the first-period adoption to account for the network effect:

$$Q(P_1, P_2) = (A - BP_2) + \eta Q_1(P_1).$$

Here, η represents the network effect. The higher its value is, the more valuable the early adopters are. As described in Section 2, such a network effect may be relevant for new technologies due to consumer learning or charging network development.

Let λ_t denote the purchase subsidy in period t. The consumer price is the difference between the manufacturer-set price p_t and the subsidy λ_t. The firm produces at a constant marginal cost c

in both periods and chooses the prices p_1^* and p_2^* to maximize the sum of profits in both periods:

$$(p_1^*, p_2^*) = \underset{p_1, p_2}{\operatorname{argmax}}\ (p_1 - c)Q_1(p_1 - \lambda_1) + (p_2 - c)Q_2(p_1 - \lambda_1, p_2 - \lambda_2).$$

Consider two subsidy-capping designs inspired by the current US phaseout. The first design introduces a deadline so that only the first-period buyers qualify for the subsidy:

$$\lambda_t = \begin{cases} s, & \text{if } t = 1 \\ 0, & \text{if } t = 2. \end{cases}$$

In contrast, the second design introduces a cap Γ on the number of qualifying sales. All first-period buyers are eligible. Second-period buyers qualify only if first-period sales fail to exceed the quota Γ:

$$\lambda_t = \begin{cases} s, & \text{if } t = 1 \\ s\mathbf{I}[Q_1(p_1 - s) < \Gamma], & \text{if } t = 2. \end{cases}$$

The crucial distinction between the two designs is that the latter grants the firm control over the second-period subsidy. Correspondingly, the privately optimal responses would differ. For the exposition, Figure 3 plots the optimal first-period sales under the deadline and quota designs as a function of quota Γ under different hypothetical parameter values. Panel (1) uses parameter values $A = 300$, $B = 12$, $c = 20$, and $\eta = 0$. The first-period sales can vary substantially under the quota or deadline. The firm sells 90 vehicles in the first period when facing a deadline. When facing a quota $\Gamma < 90$, it sells only Γ cars in the first period to secure the subsidy in the second period.

The difference in the privately optimal prices and sales across the two designs depends on the underlying parameters, such as price sensitivity B and network effect η. Panels (2) and (3) demonstrate this by varying B and η. In Panel (2), I reduce the price sensitivity to $B = 10$ while keeping the network effect as 0, as in Panel (1). The effect of the subsidy on consumer demand is lower compared to Panel (1) due to the lower price elasticity of demand. As a result, the firm facing a quota stays below it only if $\Gamma > \Gamma^*$. When $\Gamma < \Gamma^*$, the firm behaves as if facing a deadline, and the two designs produce equivalent market outcomes.

In Panel (3), I increase the network effect η to 0.2 while keeping the price sensitivity as in Panel (2). Because of the network effect, the firm facing a deadline sells more EVs in the first period than in Panels (1) and (2). The firm with a quota now faces a nontrivial dilemma: exhausting the quota shrinks the second-period demand due to reduced subsidy, but attracting adopters in the first period increases second-period demand due to the network effect. Although Γ^* is the same as in Panel (2), the difference in sales between the deadline and quota is larger.

Several lessons emerge from this simple analysis. First, a per-manufacturer quota can incentivize manufacturers to sell fewer EVs. In the monopoly example, this incentive arises because by staying below the quota in a given period, the manufacturer can ensure that all EVs sold in the following period also qualify. This incentive will be reinforced in an oligopoly because staying below the quota also protects the firm from competition from other manufacturers. Second, the effect of the subsidy-capping designs on market outcomes depends on parameters such as own-price elasticity and the network effect. In an oligopoly, market outcomes, such as profit distribution, will also depend on the cross-price elasticities. By recovering the key parameters, I can answer how the designs affect market penetration, gasoline consumption, consumer surplus, and firms' profits.

4 Full Model

I now describe the complete model with the consumer and manufacturer decision problems in the US automobile industry. I observe new vehicle sales in M geographic markets (indexed by $m = 1, 2, \ldots, M$) over T years (indexed by $t = 1, 2, \ldots, T$). Each year has a fixed set of firms that produce an exogenous set of products.

The demand specification follows the discrete-choice framework of Berry, Levinsohn, and Pakes (1995), where consumers choose a single vehicle from all available fuel types. Including all fuel types allows for simulating what happens to the entire market of automobiles under the counterfactual scenarios. To ease computation, I assume that consumers are myopic in that they do not consider the future evolution of prices or infrastructure and only purchase if the vehicle serves their present driving needs. In contrast, the supply side is an oligopoly with product differentiation where manufacturers choose prices for all vehicles in their portfolio. I use the estimated demand elasticities to recover the marginal costs in 2017 and investigate what would have happened if the subsidy elimination began in 2017 under different subsidy-capping designs. In practice, the subsidy elimination began in 2018. However, as discussed later, I avoid this year in the estimation to ensure that the demand elasticities are not influenced by intertemporal substitution. Although the 2017 data are imperfect to directly inform the effect of the actual subsidy-capping design, it allows examining the dynamic trade-offs highlighted in Section 3 and predicting the effect that different designs would have had during 2017. I elaborate on consumer demand and manufacturers' decision problems next.

4.1 Demand

Each period, consumers arrive at the market. The products available in market m in model year t are indexed by $j \in \mathcal{J}_{mt}$. Consumer i's indirect utility from choosing vehicle j is a function of vehicle and individual characteristics:

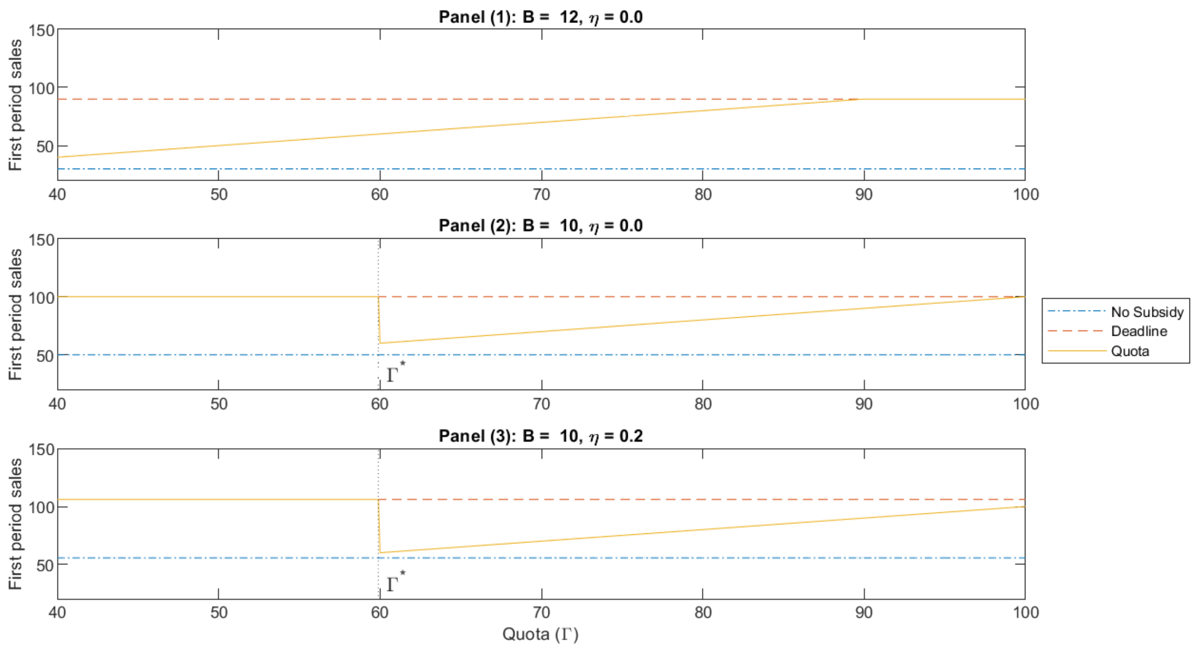
$$U_{ijmt} = -\alpha_i p_{jmt} + x_{jt}\beta_i + N_{jmt}\eta + \xi_{jmt} + \epsilon_{ijmt}, \tag{1}$$

where p_{jmt} represents the consumer price and equals the manufacturer's suggested retail price (MSRP) minus all purchase incentives:

$$p_{jmt} = MSRP_{jt} - \underbrace{RD_{jt}}_{\text{Retail discount}} - \underbrace{\lambda^0_{jt}}_{\text{Federal subsidy}} - \underbrace{\lambda_{jmt}}_{\text{local subsidy}}.$$

In equation 1, x_{jt} is a $K \times 1$ vector of vehicle attributes, including size, performance, cost of

Figure 3: Deadline vs. Quota in a Monopoly



Notes: This figure shows the first-period sales as a function of quota Γ in three different situations. Each panel fixes $c = 20$ and $A = 300$ but changes either the price coefficient B or the network effect η.

Panel (1): The price coefficient $B = 12$, and the network effect $\eta = 0$. When facing a quota, the firm always stays below the quota to secure the future subsidy, which may result in fewer sales compared to a deadline.

Panel (2): The network effect is as in case (1), but the price coefficient is lowered to $B = 10$. The firm reduces the first-period sales only when the quota is higher than Γ^*.

Panel (3): The price coefficient remains as in case (2), but the network effect is raised to $\eta = 0.2$. As in case (2), the firm reduces the first-period sales only when the quota is higher than Γ^*. However, the network effect leads to a larger difference in first-period sales between deadline and quota compared to case (2).

driving, battery range, fuel type indicators, and 14 vehicle segment indicators based on market orientations. α_i denotes the marginal utility from price, assumed to follow a log-normal distribution with parameters α and σ_α. In other words, $log(\alpha_i) = \alpha + \sigma_\alpha v_{i\alpha}$, where $v_{i\alpha}$ follows a standard normal distribution. β_i is a $K \times 1$ vector of taste coefficients, assumed to follow a normal distribution with parameters β and $\sigma_{\beta l}$ for the l^{th} dimension of β_i. N_{jmt} indicates a vector of the network effect variables and includes the interaction of BEV and PHEV indicators with the log cumulative EV sales by the manufacturer of vehicle j in market m up to year $t-1$, along with the interaction of BEV and PHEV indicators with the log cumulative EV sales by all manufacturers whose EVs use the same type of Level 3 charger in market m up to year $t-1$. ξ_{jmt} represents the average, or common, utility from the attributes of vehicle j in market m and year t that is unobservable to the researcher but known to consumers and producers; these may include quality, promotional activity, or systematic demand shocks. I model $\xi_{jmt} = \xi_m + \xi_t + \Delta\xi_{jmt}$. Econometrically, ξ_m is captured by market-specific dummies that control for time-invariant market-level variations, such as the quality of public transit or local inclinations to be green. ξ_t is captured by time dummies that control for national factors that do not vary across markets, such as national macroeconomic, climate, and global fuel price shocks. $\Delta\xi_{jmt}$ is left as an econometric error term. Finally, ϵ_{ijmt} represents idiosyncratic tastes assumed to follow i.i.d. type-I extreme value distribution.

The specification incorporates the network effect in a reduced-form fashion by allowing consumer utility from an EV to depend on the cumulative EV sales from the same manufacturer until the previous period and the cumulative EV sales from all manufacturers with compatible Level 3 chargers until the previous period.[8] The rich dataset includes car registrations since the recent development of the US plug-in EV market. It allows me to calculate the cumulative EV sales in each geographic market precisely. The rationale for including previous adoption of EVs from the same manufacturer is that adopters help spread information about that manufacturer's EVs among the new consumer pool. When car buyers observe more EVs produced by a given manufacturer, they may be more willing to buy its EVs. Therefore, the signs of these network-effect variables are expected to be positive. The rationale for including the previous adoption of all EVs that use a compatible Level 3 charger is that it is associated with the available charging infrastructure network vital to guarantee drivers' mobility. However, previous adoption of EVs produced by competing manufacturers also increases consumers' exposure to competing EVs, which may induce them to purchase those vehicles instead. Therefore, the signs of these network-effect variables are theoretically ambiguous.

Modeling the vehicle purchase decisions as static is reasonable for buyers of conventional gasoline-powered vehicles, as these do not evolve substantially over time. However, EV buyers may also time their purchases to take advantage of better prices. For instance, if they believe that subsidies will expire, they may buy earlier. To ensure that the demand parameters reflect actual purchase choices and not an intertemporal substitution, I estimate the demand model using data unaffected

8. Although Level 1 and Level 2 charging standards are uniform across all vehicle brands, Level 3 charging stations were offered through three incompatible standards during the sample period. Tesla used its own Supercharger network. Nissan, Mitsubishi, Kia, and Toyota used the Japanese-developed CHAdeMO standard. FCA, GM, Ford, Volkswagen, and BMW used the SAE International Combo standard.

by the subsidy changes (2011–2017). The static choice framework is a good approximation for EV purchasing decisions during these years because the federal price incentives were put in place in 2009—well before the start of the EV market—and did not phase out until 2018. As a result, the subsidy-induced timing effects are unlikely to be relevant, and the elasticities will likely reflect the actual changes in vehicle choice. Although eliminating subsidies may induce changes in purchase timing, it is unlikely to affect the true parameters governing vehicle choice behavior. As a result, I can apply the demand parameters estimated from the 2011–2017 data in the counterfactual experiments.

EV buyers may also care about the timing of their purchases if they believe that the charging network or quality will improve. The static assumption imposes that car purchase behavior is governed by present driving needs, which is reasonable because consumers may be limited in changing their residence or workplace location in the short run. Moreover, as discussed in Section 5.2, the improvements in battery range have been slow, suggesting that consumers would have to wait for a long time for significant upgrades.

Consumers make their purchase by maximizing their utilities across all vehicle options with the outside option of purchasing a used vehicle or nothing. As they are myopic, the outside good does not include purchasing the vehicle in the future. The utility from choosing the outside choice is

$$U_{i0mt} = \xi_{0mt} + \epsilon_{i0mt}.$$

The mean utility of the outside good is not identified, so I normalize $\xi_{0mt} = 0$. Consumer i chooses a model j if and only if

$$U_{ijmt} \geq U_{ij'mt}, \forall j' \neq j.$$

The choice probability is

$$\begin{aligned} Pr_{ijmt} &= \int I(\epsilon | U_{ijmt} \geq U_{ij'mt} \forall j') dF(\epsilon) \\ &= \frac{exp(-\alpha_i p_{jmt} + x_{jt}\beta_i + N_{jmt}\eta + \xi_{jmt})}{1 + \sum\limits_{j' \in \mathcal{J}_{mt}} exp(-\alpha_i p_{j'mt} + x_{j't}\beta_i + N_{j'mt}\eta + \xi_{j'mt})}. \end{aligned}$$

Correspondingly, the share of vehicle j in the market market m and period t is

$$s_{jmt} = \int \frac{exp(-\alpha_i p_{jmt} + x_{jt}\beta_i + N_{jmt}\eta + \xi_{jmt})}{1 + \sum\limits_{j' \in \mathcal{J}_{mt}} exp(-\alpha_i p_{j'mt} + x_{j't}\beta_i + N_{j'mt}\eta + \xi_{j'mt})} dF(\alpha_i, \beta_i).$$

Let H_{mt} denote the number of households in market m and period t. The demand for vehicle j in market m and period t is $Q_{jmt} = H_{mt} s_{jmt}$.

4.2 Supply

I model the market as served by a multifirm, differentiated-product industry where firms engage in Bertrand price competition. Given the market primitives, each firm f chooses prices for all vehicles in its portfolio to maximize the sum of profits in the current and following year across all its products in all the geographic markets, assuming that product offerings, marginal costs, state-level subsidies, and demand shocks stay as in period t. Vehicle characteristics other than the price evolve exogenously, which is reasonable because manufacturers typically make product decisions over a longer horizon than pricing decisions. The profit for firm f is

$$\Pi_{ft} = \sum_{m} \sum_{j \in \mathcal{J}_{ft}} \left[(p_{jt} - c_{jt} + h_{jmt}) Q_{jmt}(p_{.t}) + \; (p_{j,t+1} - c_{jt} + h_{jmt}) Q_{jm,t+1}(p_{.t}, p_{.t+1}) \right]. \tag{2}$$

The price p_{jt} is uniform across all markets and equals the MSRP minus retail discounts:

$$p_{jt} = MSRP_{jt} - \underbrace{RD_{jt}}_{\text{Retail discount}}.$$

MSRPs and retail discounts are constant across markets within a model year. I do not observe and therefore do not consider market-specific discounts. c_{jt} is the marginal cost, and h_{jmt} is the value of ZEV credits for model j in market m. For non-ZEV states, h_{jmt} takes the value 0. For ZEV states, h_{jmt} is the product of the value of the credit for model j and the price of ZEV credit. In 2017, battery EVs, plug-in hybrids, and hydrogen fuel-cell vehicles earned credits depending on their battery charge time and range. Vehicles with a range of fewer than 50 miles earned one credit; those with a range of more than 300 miles and a recharge time of fewer than 15 minutes earned nine credits. In addition, conventional hybrids, such as the Honda Civic and Toyota Prius (AT-PZEV), earned up to 0.8 of a credit, and gasoline vehicles with lower emissions (PZEV) than federal standards earned up to 0.2 of a credit. Although the ZEV credit market does not have price transparency, literature has backed out prices from the revenues reported by the manufacturers. Following McConnell and Leard (2021), I assume that the value of ZEV credits in 2017 was USD 2,218.

A two-period pricing model is vital to examine how firms respond when the dynamics of subsidy elimination become relevant. For instance, firms facing a per-manufacturer quota may increase EV prices to delay exhausting it. A static model will fail to capture such adjustments. The two-period model is also crucial for the firms to internalize the network effect and react strategically to the subsidy elimination based on their expectations of how current prices affect future EV demand. For instance, the model allows the firms facing a per-manufacturer quota to keep prices low and surpass the quota if they believe that raising prices would diminish their future profits. Although the two-period assumption is guided by computational simplicity, it is not restrictive, because if firms care about a longer horizon, that is similar to solving the same problem with a lower discount factor.

The prices chosen in period t affect the profits in period $t+1$ by influencing only a set of commonly observed state variables: the subsidy value and network effect. Given these state variables, all firms simultaneously choose prices for all the products in period $t+1$. I derive the optimality conditions using backward induction. Given $p_{.t}$, the optimal price vector $p^*_{.t+1}(p_{.t})$ in period $t+1$ is the solution to the system of J first-order conditions:

$$\sum_m \left[Q_{jm,t+1} + \sum_{k \in \mathcal{J}_{ft}} \left((p_{k,t+1} - c_{kt} + h_{kmt}) \frac{\partial Q_{km,t+1}}{\partial p_{j,t+1}} \right) \right] = 0.$$

The optimal price vector $p^*_{.t+1}(p_{.t})$ can be used to simulate the optimal profit vector $\Pi^*_{f,t+1}(p_{.t})$ as a function of $p_{.t}$. In period t, the vector of prices $p_{.t}$ maximizes

$$\Pi_{ft} = \sum_m \sum_{j \in \mathcal{J}_{ft}} \left[(p_{jt} - c_{jt} + h_{jmt}) \, Q_{jmt}(p_{.t}) \right] + \Pi^*_{f,t+1}(p_{.t}).$$

In 2017, all EV manufacturers were far behind the quota. As a result, their profit maximization problems in 2017 are not constrained by it, ensuring that $\Pi^*_{f,t+t}(p_{.t})$ is differentiable in $p_{.t}$. Therefore, the necessary optimality condition in period t with respect to the price of product j is

$$\sum_m \left[Q_{jmt} + \sum_{k \in \mathcal{J}_{ft}} \left((p_{kt} - c_{kt} + h_{kmt}) \frac{\partial Q_{kmt}}{\partial p_{jt}} \right) \right] + \frac{\partial \Pi^*_{f,t+1}(p_{.t})}{\partial p_{jt}} = 0. \tag{3}$$

These first-order conditions involve own and cross-price derivatives of the demand for each product, calculated as the weighted sums of individual derivatives:

$$\frac{\partial Q_{kmt}}{\partial p_{jt}} = H_{mt} \frac{\partial s_{kmt}}{\partial p_{jt}} = \begin{cases} -H_{mt} \int s_{ijmt}(1 - s_{ijmt}) \alpha_i dF(\alpha_i, \beta_i), & \text{if } j = k \\ H_{mt} \int s_{ijmt} s_{ikmt} \alpha_i dF(\alpha_i, \beta_i), & \text{otherwise.} \end{cases} \tag{4}$$

The derivatives $\frac{\partial \Pi^*_{f,t+1}(p_{.t})}{\partial p_{jt}}$ can be computed numerically. I use these first-order conditions to recover the marginal costs for all products in 2017.

The model has some caveats. First, firms control sales only through short-run price changes. In practice, firms can use more ways to reduce EV sales. For example, given a per-manufacturer quota, they can lower the production of subsidy-qualifying vehicles; this would create an artificial shortage and keep the sales below the quota. In the absence of data on vehicle inventories, I do not model this mechanism. Such simplification affects how firms respond to the counterfactual subsidy-capping designs, which I discuss further in Section 7. Second, throughout the analysis, I abstract from entry and exit decisions. In practice, the designs may also affect firms' entry into the EV market. Although this concern was important when the subsidy was enacted in 2009, it is less relevant today because most major vehicle manufacturers already have some EVs in their portfolio.

Finally, other overlapping regulations imposed on vehicle manufacturers, such as federal corporate average fuel economy (CAFE) and greenhouse gas (GHG) standards, also incentivize manufacturers to increase EV sales. CAFE and GHG standards influence the market on the supply side by imposing limits on the average fuel economy and GHG emissions of the vehicles that a manufacturer sells each year. Both regulations grant extra credits to EVs, incentivizing manufacturers to sell more EVs. For simplicity, I do not account for these regulations in the manufacturers' profit function. One concern is that these incentives may interact with the dynamic incentives created by a per-manufacturer quota. For instance, a manufacturer nearing its quota may want to sell more EVs to offset CAFE liabilities, even if it means exceeding the quota and forgoing future subsidies. Such concern is irrelevant to the estimation because it relies on the years before subsidy elimination. It is also unlikely to be restrictive for counterfactual analysis because both CAFE and GHG programs allow additional flexibilities, such as banking credits from overcompliance to use for compliance in another model year. As a result, a manufacturer facing a quota on EV subsidies can use such flexibilities to meet their CAFE and GHG requirements. Thus, ignoring these regulations still provides a good approximation of the market outcomes under different subsidy-capping designs.

5 Data

5.1 Data Sources

The data for this paper come from various sources. The vehicle sales data were purchased from a market research company and contain new light-duty vehicle registrations in 30 states during the calendar years 2011–2017. The selected states captured the highest EV market share in 2016. I use these states to define a geographic market. As the EV market primarily developed after 2010, the data capture it from the outset. A vehicle is a unique model year, make, model, and fuel type. I use registrations for all fuel types (except fuel cell) to account for substitution between fuel types.[9] I exclude exotic vehicles, such as Ferrari and Lamborghini. For each market, I estimate its size using the US Census Bureau's state-level annual estimates of housing units and calculate the market shares by dividing the state-level sales volume by the number of households in that year. The market share of the outside good is the difference between 1 and the sum of inside goods market shares.

The distinction between a calendar year and a model year presents a technical issue in defining the choice sets. A model year is a manufacturer's annual production period, including January 1 of the calendar year. It typically runs from October to September of the next year (e.g., 2016 models were released around October 2015.) I define the choice sets based on model year, thus assuming that all vehicles released in any model year sell in the same model year and that model years perfectly align for each manufacturer. I do not observe the 2011 models sold in the 2010 calendar year, so I use 2011 data to calculate cumulative EV sales in each market but not the demand estimation. The sample comprises 62,186 observations of vehicle shares over 30 states during 2012–2017.

I obtain vehicle-level characteristics from the WARDS Intelligence Data Center and Environmental Protection Agency and fill in missing values based on the information from Edmunds. Additionally, I obtain market segmentation data from Automotive News. Although I observe vehicle characteristics at the trim level, registrations are at the make-model-fuel level. Hence, I average the characteristics across different trims to match the registrations. Vehicle characteristics include MSRP, size-related measures (wheelbase and width), horsepower, curb weight, fuel type, fuel effi-

9. I drop fuel-cell vehicles from the sample, as I do not observe state-level hydrogen prices. These observations comprise less than 0.01 percent of the total US sales during 2011–2017.

ciency, and battery range (for EVs). The demand model allows consumer utility to depend on the size, performance, cost of driving, and battery range. I measure size by the product of wheelbase and width and performance by the ratio of horsepower and curb weight. For gasoline and diesel vehicles, I calculate the cost of driving as the state-level fuel price per gallon divided by the vehicle's fuel economy; the fuel prices come from the US Energy Information Administration (EIA) and are expressed in dollars per million British thermal units (Btu). I convert these into dollars per gallon using the Btu content of each fuel.[10] For BEVs, I calculate the cost of driving by dividing the electricity price per kW-hrs by the vehicle electricity consumption in kW-hrs/mile.[11] Finally, I calculate the cost of driving for PHEVs by assuming that they run 50 percent of the time on electricity and 50 percent on gas or diesel. It varies with two sources: fuel economy and market-level fuel prices. Thus, a high gas price in a state raises the cost of driving all gasoline vehicles in that state.

Although average transaction prices are preferred in demand estimation, such data are not readily available. Instead, I combine MSRP data with the manufacturers' retail discounts from Automotive News and federal and state-level subsidies from the US Department of Energy to approximate the prices that consumers and firms face. Federal and state-level subsidies vary across models and time. Given purchase subsidies, the price that enters the firms' profit function differs from the consumer price—it is the difference between MSRP and the average discounts provided by the manufacturer in that year. The consumer price is the difference between MSRP and all purchase incentives, including manufacturer discounts and federal and state subsidies. Federal subsidies are nonrefundable tax credits, so in practice, the amount received by a consumer depends on their income-tax liability. For simplicity, I assume that all consumers can claim the full tax credit. The justification is that the new vehicle market is typically used by wealthy households with high income-tax liabilities. I deflate all vehicle and fuel prices using the Bureau of Labor Statistics Consumer Price Index and adjust them to 2015$.

Finally, I obtain the list of makes produced by each manufacturer from the annual EPA Auto trend reports. Consistent with the regulatory definitions, I assume that different makes of the same parent manufacturer belong to a single firm. For example, Buick, Cadillac, Chevrolet, and GMC are all part of GM.

5.2 Summary Statistics

Table 1 summarizes the sales and sales-weighted average characteristics of vehicles in the sample. The first column reports the model year, and the subsequent columns show the total models, the real price (in thousands of dollars), total sales (in thousands of dollars), size (in thousands of in^2), performance (in HP per 10 lb), cost of driving (in dollars per mile), and battery range (in miles) separately for plug-in EVs and other fuel-type vehicles. The available EV models rose from 9 in

10. See https://www.eia.gov/energyexplained/units-and-calculators/ for details on this calculation.

11. For BEVs, EPA reports fuel economy using an MPGe metric, calculated as 33.705 kWhrs/ gallon divided by the vehicle electricity consumption in kW-hrs/mile. This measures the miles the vehicle can travel on an amount of energy equal to that stored in a gallon of gasoline. I use these values to calculate the vehicle's electricity consumption (kW-hrs/mile) as 33.705 kWhrs/gallon divided by the EPA-reported MPGe values.

2012 to 34 in 2017; their total sales in the sample states rose from 43,000 in 2012 to 207,000 in 2017. Models of other fuel types rose from 315 in 2012 to 348 in 2017; their total sales in the sample states rose from 9.4 million in 2012 to 12.1 million in 2017. The average size of EVs remained fairly stable across both types. The average performance for EVs increased from 0.32 Hp/10 lbs in 2012 to 0.42 Hp/10 lbs in 2017, but that of other fuel types remained stable at around 0.61 Hp/10 lbs. The average cost of driving for EVs remained stable at around $0.05 per mile, but that of other fuel types reduced from $0.16 in 2011 to $0.10 in 2017. The average cost of driving is much lower for EVs due to high fuel economy and low electricity prices. Finally, the average battery range for EVs rose from 53.98 miles in 2012 to 115.43 miles in 2017.

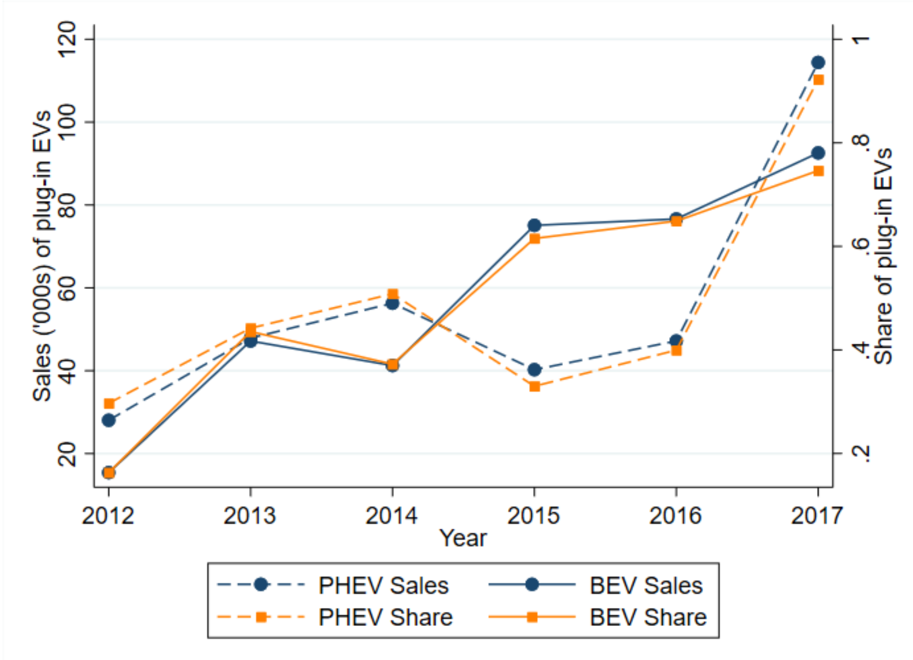
Table 1: New Vehicle Sales and Characteristics in the Sample States

Year	Models		MSRP ($'000)		Sales ('000)		Size ('0000 in^2)		Performance (Hp/10lb)		Driving Cost ($/mile)		Battery Range (miles)	
	EV	Other	EV	Other	EV	Other	EV	Other	EV	Other	EV	Other	EV	Other
2012	9	315	43.11	30.47	43	9,407	0.75	0.81	0.32	0.61	0.04	0.16	53.98	0.00
2013	10	336	43.81	31.16	95	10,739	0.76	0.82	0.38	0.61	0.05	0.15	74.76	0.00
2014	20	349	45.63	31.88	98	10,975	0.75	0.83	0.44	0.61	0.05	0.14	78.94	0.00
2015	21	357	48.96	32.78	115	12,087	0.78	0.83	0.42	0.61	0.04	0.10	99.28	0.00
2016	27	343	60.26	32.85	124	11,685	0.84	0.83	0.52	0.61	0.05	0.09	123.24	0.00
2017	34	348	48.05	33.46	207	12,196	0.80	0.83	0.42	0.61	0.04	0.10	115.43	0.00

Notes: This table shows the evolution of key variables in the sample states between 2012 and 2017. Columns (6)–(9) show the sales-weighted average vehicle characteristics. Size is wheelbase× width (in thousands of in^2), performance is horsepower by curb weight (in Hp/10 lb), driving cost is fuel cost (in dollars per mile), and battery range is the all-electric range (in 10 miles) for electric vehicles.

Figure 4 shows that the annual sales and share of both BEVs and PHEVs went up in the sample states between 2012 and 2017; they represented 1.6 percent of domestic automobile sales in 2017.

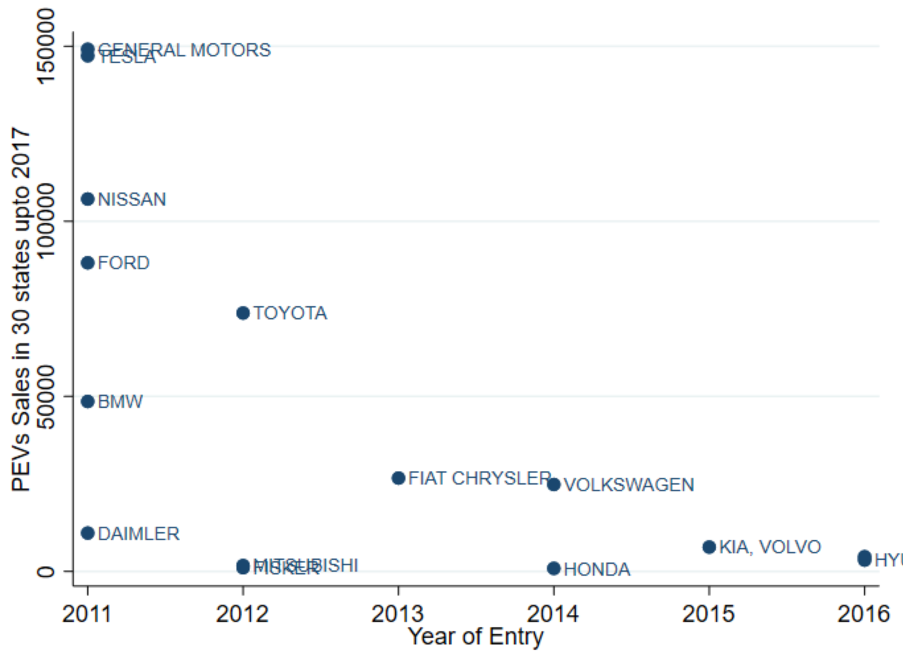
Figure 4: Sales and Share of New Light-Duty Plug-In EVs in the Sample States



Notes: The figure shows the evolution of the US plug-in electric vehicle (EV) industry between 2012 and 2017. The horizontal axis shows the model years. The left and the right axes show the total plug-in EV sales and the share of plug-in EVs in total new-vehicle sales in the sample states, respectively.

Figure 5 shows all EV manufacturers with their year of entry on the horizontal axis and the total vehicles sold in the sample states between 2011 and 2017 on the vertical axis. Tesla and GM sold around 150,000 EVs; Nissan sold around 110,000. Table 2 summarizes the plug-in models and the nominal value of federal subsidies for each manufacturer in 2017. The subsidy ranged from $3,793 for PHEVs such as BMW I8 to $7,500 for BEVs such as Tesla Model 3. It remained unchanged for all models during the sample period.

Figure 5: Major Players in the Plug-In EV Industry



Notes: This figure shows the major US plug-in electric vehicle (EV) manufacturers. For each manufacturer, the x-coordinate shows the year in which its first plug-in EV sale appears in the sample. The y-coordinate shows the total plug-in sales between 2011 and 2017.

Table 2: Federal Subsidies for Plug-In EVs

Manufacturer	Plug-in EV Models	Subsidy Range (USD)
Bmw	BMW 330, BMW 740, BMW I3, BMW I8, BMW X5	3,793–7,500
Daimler	Mercedes-Benz B-Class, Mercedes-Benz GLE, Smart Fortwo	4,460–7,500
Fiat Chrysler	Chrysler Pacifica, Fiat 500	7,500
Ford	Ford C-Max, Ford Focus, Ford Fusion	4,007–7,500
General Motors	Cadillac CT6, Chevrolet Bolt, Chevrolet Volt	7,500
Hyundai	Hyundai Ioniq, Hyundai Sonata	4,919–7,500
Kia	Kia Optima, Kia Soul EV	4,919–7,500
Mitsubishi	Mitsubishi i-MiEV	7,500
Nissan	Nissan Leaf	7,500
Tesla	Tesla Model 3, Tesla Model S, Tesla Model X	7,500
Toyota	Toyota Prius Prime	4,502
Volkswagen	Audi A3, Porsche Cayenne, Volkswagen Golf	4,502–7,500
Volvo	Volvo XC90	4,585

Notes: This table summarizes the plug-in electric vehicle models and federal consumer subsidies in 2017 for each manufacturer.

Table 3 summarizes the plug-in EV sales and regulations in all 30 states in 2017. Columns (1) and (2) list the total sales in each state and their share as a percentage of overall new-vehicle sales. Sales are highest in California (3.67 percent) and lowest in Oklahoma (0.15 percent). Columns (3) and (4) show purchase incentives and ZEV mandates. Six states provide some subsidies for plug-in EVs, and eight have the ZEV requirement. States with subsidies or ZEV mandates have higher EV sales.

Table 3: State-Level EV Sales and Incentives

Market	Plug-In Sales	Percent of Total Sales	Plug-In Incentives	ZEV State
Arizona	10,374	0.68		-
California	350,563	3.67	Yes	Yes
Colorado	12,527	1.10	Yes	-
Connecticut	7,607	0.80	Yes	Yes
Florida	25,983	0.43		-
Georgia	27,448	1.29		-
Hawaii	7,158	2.30		-
Illinois	14,553	0.49		-
Indiana	3,760	0.30		-
Maryland	11,575	0.76	Yes	Yes
Massachusetts	14,060	0.77	Yes	Yes
Michigan	14,064	0.46		-
Minnesota	4,691	0.39		-
Missouri	3,915	0.33		-
Nevada	3,766	0.57		-
New Hampshire	2,354	0.50		-
New Jersey	16,694	0.57		Yes
New York	30,238	0.57	Yes	Yes
North Carolina	8,041	0.37		-
Ohio	8,166	0.27		-
Oklahoma	1,189	0.15		-
Oregon	14,869	2.00		Yes
Pennsylvania	11,883	0.35		-
Tennessee	4,266	0.34		-
Texas	21,619	0.30		-
Utah	4,368	0.87		-
Vermont	2,592	1.17		Yes
Virginia	9,849	0.51		-
Washington	27,804	2.05		-
Wisconsin	6,205	0.48		-

Notes: Columns (1) and (2) show the total plug-in electric vehicle (EV) sales and their share as a percentage of overall new car sales during 2011–2017 based on data for the 30 states in the sample. Column (3) and (4) shows the availability of state-level plug-in EV incentives and ZEV requirement.

6 Estimation and Results

The next step is to estimate the structural model described in Section 4. I estimate the demand system and recover marginal cost, assuming that the data are generated by Nash-Bertrand equilibrium behavior. The benefit of sequential estimation is that demand estimation does not rely on supply-side conduct. Section 6.1 describes the estimation and identification of the demand parameters, and Section 6.2 reports the results from estimating the structural model.

6.1 Estimation and Identification

The fundamental issue that motivates demand estimation is the price endogeneity arising from two sources. First, the model implies that price and quantity are determined in equilibrium, so the price partly depends on the unobservable product characteristics $\Delta\xi_{jmt}$. For instance, vehicle characteristics, such as comfort, ride smoothness, and expected resale value, cannot be measured directly. However, the price will likely reflect them if they are costly for the manufacturer or affect demand. Similarly, advertisement efforts are unobserved but may be correlated with the pricing discounts. Second, I do not observe the average vehicle transaction price and instead approximate it using MSRP minus purchase incentives. As a result, variations in the vehicle transaction price across markets enter $\Delta\xi_{jmt}$ in equation 1. Both cases result in price endogeneity.

Identification requires a set of exogenous instruments. Vehicle characteristics other than price are valid instruments for themselves, as they are part of an exogenous development process. Appropriate instruments for price include any factors that are correlated with the price but not with $\Delta\xi_{jmt}$. I follow Berry, Levinsohn, and Pakes (1995) and use the sum over the characteristics of firm's other vehicles and the sum over the characteristics of all the competing vehicles as instruments for price. Specifically, for each vehicle characteristic k (constant, size, performance, driving cost, and battery range), I include the following terms as instruments for price:

$$z^k_{jmt} = (x^k_{jt}, \sum_{r\neq j, r\in\mathcal{J}_{fmt}} x^k_{rt}, \sum_{r\neq j, r\notin\mathcal{J}_{fmt}} x^k_{rt}). \tag{5}$$

Overall, there are 10 excluded instruments.

These instruments vary over vehicle models in each market and across time. They are relevant because they proxy for the degree and closeness of competition that a brand faces, thus affecting the firm's markups. The rationale for separately including firms' own vehicles and other firms' vehicles is that when a firm prices its vehicles, it would treat the substitution with its own and other firms' vehicles differently, as consumers who will switch away to another of its vehicles following a price increase do not represent as much of a loss. The identifying assumption is that the demand unobservables $\Delta\xi_{jmt}$ are mean independent of the observed characteristics. The underlying timing assumption is that car manufacturers do not observe $\Delta\xi_{jmt}$ when choosing vehicle characteristics.

The identification issues associated with including cumulative sales as a product characteristic are similar to those involved in using a lagged dependent variable as a regressor. Specifically, consistent estimation of the network-effect parameters requires that demand unobservables are not serially correlated. I assume that, conditional on the market and year fixed-effects, this is the case.

Following Berry, Levinsohn, and Pakes (1995) and Nevo (2000), I estimate the demand parameters using the simulated Generalized Method of Moments using the population moment condition that is a product of the described instrumental variables and unobservable demand shocks $\Delta\xi_{jmt}$.

6.2 Results

Table 4 shows the results from the estimating demand derived from the indirect utility specification in Equation 1.[12] The first eight rows show the coefficients measuring the mean parameters α and β. Most coefficients are precisely estimated and have expected signs. Vehicle size and the horsepower-to-weight ratio have positive coefficients, indicating that consumers value size and performance. The negative coefficient on the cost of driving per mile implies that consumers prefer high fuel efficiency, which reduces the cost per mile. The sign on the BEV indicator is negative, indicating that in the absence of a network (i.e., zero cumulative EV sales) and ceteris paribus, BEVs are less preferred to conventional models, possibly because they do not have a gasoline backup. Moreover, the coefficient on the PHEV indicator is positive, indicating that consumers value vehicles with a gasoline backup.

The next two rows show the interactions between EV indicators and cumulative EV sales in the state by manufacturer. These terms have positive signs, indicating that consumers gain more utility from BEVs and PHEVs as the manufacturer's network develops. The next two rows show the interactions between EV indicators and cumulative sales of all EVs that use a compatible Level 3 charger in the state. Both coefficients are negative, possibly because the vehicle sales from competing manufacturers induce consumers to buy those vehicles instead, thus shifting the vehicle's demand leftward. The subsequent rows show the estimates of six random coefficients that measure the dispersion in households' tastes.

Table 5 presents a sample of own and cross-price elasticities, markups (i.e., $p_{jt} - c_{jt}$), and marginal costs implied by the demand estimates and the firms' first-order conditions. Each row corresponds to a different vehicle; the first four rows are the top four plug-in EV cars by sale in 2016, the following three rows are the top conventional cars, and the bottom three rows are the top pickup trucks. Each entry gives the percentage change in demand of the row vehicle associated with a 1 percent increase in the price of the column vehicle. Price elasticities differ across markets for each product, but marginal costs are identical. Rather than presenting elasticities for a particular market, I present the average across all markets in 2017. The cross-price elasticities are larger among similar products. For instance, an increase in the price of the Chevrolet Silverado (pickup) shifts consumers disproportionately to the Ford F-150 (pickup) compared to the Chevrolet Volt (car). Moreover, the less elastic the demand is to the vehicle's own price, the larger the ratio of the markup to price.

12. Appendix B provides the details of the first-stage estimation. The first-stage F-statistic for the excluded instruments is 494.99.

Table 4: Demand Estimates

Variable	Coef	SE
Mean Parameters α and β		
Price (0000 USD)	0.282	0.235
Constant	-12.663***	0.728
Size (0000 in^2)	6.580***	0.754
Performance (Hp/10 lb)	5.976***	0.528
Fuel Cost ($/mile)	-33.734***	8.090
Battery Range (10 miles)	0.009	0.022
BEV	-1.826***	0.665
PHEV	2.823***	0.744
Network Effects		
BEV × log(1+ Manufacturer EV Sales)	0.500***	0.062
PHEV × log(1+Manufacturer EV Sales)	0.529***	0.079
BEV × log(1+ Same-Charger EV Sales)	-0.339***	0.067
PHEV × log(1+Same-Charger EV Sales)	-0.580***	0.117
Std. Dev. Parameters σ_α and σ_β		
Price (0000 USD)	0.414***	0.141
Fuel Cost ($/mile)	4.560	11.550
Car	1.608	1.420
Van	0.013	26.081
Pickup	0.159	15.037
SUV	7.523***	1.057
Fixed Effects		
State FE	Yes	
Time FE	Yes	
Segment FE	Yes	
Obs	62186	

Notes: This table shows the estimates from the flexible logit model. A unit of observation is a vehicle-state-year. Size is wheelbase×width (in thousands of in^2), performance is horsepower by curb weight (in Hp/10 lb), driving cost is fuel cost (in dollars per mile), and battery range is the all-electric range (in 10 miles) for electric vehicles (EVs). The variable "Manufacturer EV Sales" shows cumulative EVs sold by the vehicle's manufacturer in the geographic market until the previous year. The variable "Same-Charger EV Sales" shows cumulative EV sales by all manufacturers with the same Level 3 charging standard in the geographic market until previous year.

Table 5: A Sample of Own and Cross-Price Elasticities

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	Price (USD)	Markup (USD)	Marginal Cost (USD)
(1)	Ford Fusion (PHEV)	-2.951	0.003	0.006	0.003	0.033	0.028	0.026	0.013	0.016	0.011	34,797	9,441	26,155
(2)	Chevrolet Volt (PHEV)	0.001	-2.693	0.005	0.003	0.033	0.029	0.027	0.012	0.015	0.010	34,342	8,199	27,303
(3)	Tesla Model S (BEV)	0.001	0.003	-5.321	0.002	0.029	0.022	0.022	0.019	0.023	0.014	85,133	10,682	75,118
(4)	Toyota Prius Prime (PHEV)	0.001	0.003	0.005	-2.462	0.032	0.029	0.026	0.011	0.013	0.010	28,204	8,842	20,539
(5)	Honda Accord (Gas)	0.001	0.003	0.006	0.003	-2.752	0.030	0.028	0.014	0.016	0.012	27,952	9,825	18,127
(6)	Honda Civic (Gas)	0.001	0.003	0.005	0.003	0.033	-2.359	0.028	0.012	0.014	0.010	22,465	9,184	13,282
(7)	Toyota Camry (Gas)	0.001	0.003	0.005	0.003	0.035	0.030	-2.602	0.013	0.016	0.011	25,725	9,753	15,973
(8)	Ford F (Gas)	0.000	0.001	0.003	0.001	0.010	0.008	0.008	-3.111	0.028	0.019	35,786	11,415	24,372
(9)	Chevrolet Silverado (Gas)	0.000	0.001	0.003	0.001	0.010	0.008	0.008	0.024	-3.271	0.020	38,653	11,808	26,846
(10)	Toyota Tacoma (Gas)	0.000	0.001	0.003	0.001	0.010	0.008	0.008	0.022	0.026	-2.871	31,704	10,786	20,918

Notes: Columns (1)–(10) report average cross-price elasticities for 10 vehicles across all sample states in 2017, calculated from the demand estimates in Table 4. Each entry (i, j), where i is the row and j is the column, refers to the average percentage change in demand for model j when the price of model i changes by 1 percent in the markets where both products are available. Columns (11), (12), and (13) report the prices, markups and marginal costs, respectively.

Table 6 summarizes the estimated elasticities, markups, and marginal costs for all 382 models observed in 2017. Panel (a) summarizes these for all vehicles. The average own-price elasticity is -3.97, which is within the range of the estimates in the literature (Berry, Levinsohn, and Pakes 1995; Li 2018).[13] The marginal costs range from $19,372 at the 25th percentile to $42,246 at the 75th percentile. Panels (b) and (c) break the sample into plug-in EVs and conventional vehicles. The average prices of plug-in EVs are higher, but the estimated average elasticities and markups are similar.

Table 6: Marginal Cost Estimates

Variable	Mean	25%	Median	75%	Std Dev	Obs
Panel (a): All vehicles						
Price before subsidy (USD)	45,984	28,204	38,061	54,086	270,679	382
Own-price elasticity	-3.97	-4.66	-3.64	-2.94	1.46	382
Markup (USD)	10,584	9,004	10,470	11,798	2,521	382
Marginal cost (USD)	35,552	19,372	28,133	42,246	25,078	382
Panel (b): Plug-in EVs						
Price before subsidy (USD)	51,990	31,527	38,886	73,496	294,074	34
Own-price elasticity	-3.86	-5.32	-3.08	-2.54	1.76	34
Markup (USD)	9,061	7,088	8,940	10,838	3,732	34
Marginal cost (USD)	44,624	26,506	34,070	60,815	26,664	34
Panel (c): Conventional vehicles						
Price before subsidy (USD)	45,397	27,473	37,800	53,307	268,019	348
Own-price elasticity	-3.98	-4.64	-3.71	-3.05	1.43	348
Markup (USD)	10,732	9,189	10,554	11,805	2,325	348
Marginal cost (USD)	34,666	18,646	27,715	41,695	24,781	348

Notes: This table summarizes the price elasticities, markups, and vehicle marginal costs calculated from the demand estimates in Table 4 and the first-order conditions of firms' profit maximization.

7 Counterfactual Experiments

The next step is to compare market outcomes under the different subsidy-capping designs. I examine three designs: (1) a market-wide deadline where all manufacturers face the same deadline, (2) a per-manufacturer deadline where each manufacturer faces a separate deadline, and (3) a per-manufacturer quota where each manufacturer faces a separate quota on the number of subsidy-eligible vehicles. In the last design, as in the actual US design, if the manufacturer sells fewer EVs than its quota in any period, then all EVs it sells in the next period also qualify for the subsidy.

In each case, I use the parameter estimates from Section 6 to recompute the pricing equilibria under the two-stage game from Section 7.2 and calculate the market outcomes of interest, assuming that product offerings, marginal costs, state-level subsidies, and demand shocks stay at the 2017

13. Berry, Levinsohn, and Pakes 1995 estimate elasticities for the conventional vehicles in the range −3 to −6. Li 2018 finds average price elasticity of -2.7 for EVs.

levels.

7.1 Counterfactual Subsidy-Capping Designs

1. **Marketwide deadline:** This design institutes a single deadline for all firms. Consumers who purchase EVs up to the end of 2017 qualify for the subsidy:

$$\lambda^{(1)}_{jt} = \lambda^0_j \mathbf{1}(t \leq 2017),$$

where λ^0_j is the initial federal subsidy for vehicle j as observed in the data.

2. **Per-manufacturer deadline:** This design institutes a deadline for Tesla and GM. Consumers who purchase up to the end of 2017 qualify. Consumers who buy other brands qualify in both 2017 and 2018. I discuss the rationale for this design below. The subsidy evolves as follows:

$$\lambda^{(2)}_{jt} = \begin{cases} \lambda^0_j \mathbf{1}(t \leq 2017) & \text{if } f \in \{\text{Tesla, GM}\} \\ \lambda^0_j & \text{otherwise.} \end{cases}$$

3. **Per-manufacturer quota:** This design gives each manufacturer a quota κ. All consumers qualify in 2017. Consumers who purchase a vehicle in 2018 qualify if the manufacturer sells fewer than κ subsidy-eligible vehicles between 2011 and 2017. The subsidy evolves as follows:

$$\lambda^{(3)}_{jt} = \lambda^0_j \big[\sum_{\tau=2011}^{t-1} \sum_{j \in \mathcal{J}_{f\tau} \cap \mathcal{J}_{EV}} Q^{(3)}_{j\tau} \leq \kappa \big],$$

where $\mathcal{J}_{EV}$ is the set of all EVs and $\sum_{\tau=2011}^{t-1} \sum_{j \in \mathcal{J}_{f\tau} \cap \mathcal{J}_{EV}} Q^{(3)}_{j\tau}$ is the manufacturer's nationwide cumulative EV sales between 2011 and $t-1$.

Because I only observe annual vehicle sales, I allow counterfactual designs to affect the per-vehicle subsidies yearly. In practice, the US phaseout design affected them quarterly. The per-manufacturer deadline and quota are inspired by the US design, which combines both of these. The choice of Tesla and GM for a per-manufacturer deadline is because these manufacturers had the highest cumulative EV sales up to 2017, which allows for convenient comparison with the quota—a design that only affects Tesla and GM in the simulations. In practice, policymakers could base the per-manufacturer deadlines on year of entry, which can help raise market penetration by reducing the barriers to entry and ensuring multiple suppliers in the new industry.

My analysis focuses on the short-term dynamic implications of the subsidy-capping designs on the market outcomes. In the long term, these designs could affect market penetration differently if they affect manufacturers' entry. I do not model entry into the EV market because most major manufacturers already had EVs in their portfolio by the time the subsidy began to phase out.

Table 7 summarizes the features of each design. Under a marketwide deadline, the subsidy is eliminated for all manufacturers simultaneously; no incentive to reduce EV sales exists in 2017 because firms' actions do not affect whether they qualify for a subsidy in 2018. Under a per-manufacturer deadline, the subsidy is eliminated for manufacturers according to their separate deadlines. As before, no incentive exists to reduce EV sales. Finally, under the quota, the subsidy is eliminated for manufacturers based on when they exhaust it, creating an incentive to reduce sales in 2017.

Table 7: Features of Counterfactual Subsidy-Elimination Designs

Feature	Marketwide Deadline	Per-Manufacturer Deadline	Per-Manufacturer Quota
Differential elimination	✗	✓	✓
Incentive to reduce EV sales	✗	✗	✓

7.2 Computing Equilibrium Under a Per-Manufacturer Quota

Solving for the optimal price vector $p^*_{\cdot t}$ under the quota introduces important computational challenges because $\Pi^*_{f,t+1}(p_{\cdot t})$ is not differentiable in $p_{\cdot t}$. This is because the subsidy in period $t+1$ depends on firms' actions in period t. I address this challenge using the following strategy to compute the equilibrium.[14] First, based on the observation that manufacturers other than Tesla and GM sold very few EVs up to 2016, I conjecture that these manufacturers stay within the quota in 2017 in the equilibrium. I then consider four scenarios, depending on Tesla and GM's choice of crossing the quota in 2017 (discussed next). Finally, I confirm my conjecture by verifying that cumulative sales by other manufacturers stay below the quota. The conjecture holds in the counterfactual analysis.

When the conjecture holds, the original game can be reformulated as a two-player game represented in the normal form by the following payoff matrix:

Tesla/ GM	Cross	Don't Cross
Cross	$(\Pi^{Tesla}_{CC}, \Pi^{GM}_{CC})$	$(\Pi^{Tesla}_{CD}, \Pi^{GM}_{CD})$
Don't Cross	$(\Pi^{Tesla}_{DC}, \Pi^{GM}_{DC})$	$(\Pi^{Tesla}_{DD}, \Pi^{GM}_{DD})$

The payoff vector in each cell represents the sum of profits in periods t and $t+1$ for Tesla and GM. In each case, Tesla and GM solve a constrained maximization problem in 2017. For instance, when Tesla plays "Don't Cross," it chooses prices to maximize the two-period profits subject to the constraint that its cumulative EV sales stay below the quota in 2017.

$$\max_{p_{jt}, j\in\mathcal{J}_{Tesla,t}} \sum_m \sum_{j\in\mathcal{J}_{Tesla,t}} [p_{jt} - c_{jt} + h_{jmt}]Q_{jmt} + \Pi^*_{Tesla,t+1}(p_{\cdot t})$$

$$\text{s.t.} \sum_{\tau=2011}^{2017} \sum_{j\in\mathcal{J}_{Tesla,t}} Q_{j\tau} \leq \kappa.$$

14. An alternative solution is to use grid-search algorithms. However, these algorithms tend to be very slow.

In contrast, all other manufacturers solve for prices using Equation 3. The final equilibrium under the per-manufacturer quota is the Nash equilibrium in this 2×2 game.

Unlike per-manufacturer quota, $\Pi^*_{f,t+1}(p_{.t})$ is still differentiable in $p_{.t}$ under the marketwide and per-manufacturer deadlines because firms' actions in period t do not affect the subsidies in period $t+1$. In these cases, I use a fixed point of Equation 3 to compute the new pricing equilibrium, calculating the partial derivative $\frac{\partial Q_{kt}}{\partial p_{jt}}$ using Equation 4 and $\frac{\partial \Pi^*_{f,t+1}(p_{.t})}{\partial p_{jt}}$ numerically.

7.3 Outcomes of Interest

The relevant market outcomes include government expenditure, consumer surplus, firm profits, sales of electric and conventional vehicles, and total gasoline consumption.[15] Government expenditure in period t under the counterfactual c is $\sum_j \lambda^{(c)}_{jt} Q^{(c)}_{jt}$. As it changes across the experiments, I report it to facilitate direct comparison between different elimination designs.[16] Consumer surplus represents compensating variation (McFadden et al. 1973; Small and Rosen 1981). For household i, the compensating variation in any counterfactual scenario (c) from a comparison scenario is given by

$$\Delta CS_{imt} = \frac{1}{-\alpha_i}\left[\left(ln \sum_{j \in \mathcal{J}_{mt}} exp(\delta^{(c)}_{jmt} + \mu^{(c)}_{ijmt})\right) - \left(ln \sum_{j \in \mathcal{J}_{mt}} exp(\delta^{0}_{jmt} + \mu^{0}_{ijmt})\right)\right], \tag{6}$$

where α_i is household's marginal utility of income. Given the compensating variation for a specific household, the change in average surplus in market m is $\int_i \Delta CS_{imt} dF(\alpha_i, \beta_i)$. The total change in consumer surplus is the sum of changes in all markets $\sum_m \int_i \Delta CS_{imt} ddF(\alpha_i, \beta_i)$. Profits are calculated using Equation 2. Finally, the total gasoline consumption from the vehicles sold in period t under the counterfactual c is $\sum_j \frac{1}{mpg_j} \times Q^{(c)}_{jt} \times VMT_j$ where $Q^{(c)}_{jt}$ is the total sales of vehicle j and VMT_j is the miles traveled during its lifetime. I assume that vehicles travel 12,000 miles per year and have a life of 15 years.

7.4 Counterfactual Results

This section reports the market outcomes from simulating the alternative designs. Overall, the results show that each design has different implications for market penetration, environmental impact, and distribution of gains across consumers and manufacturers. I elaborate on the results next.

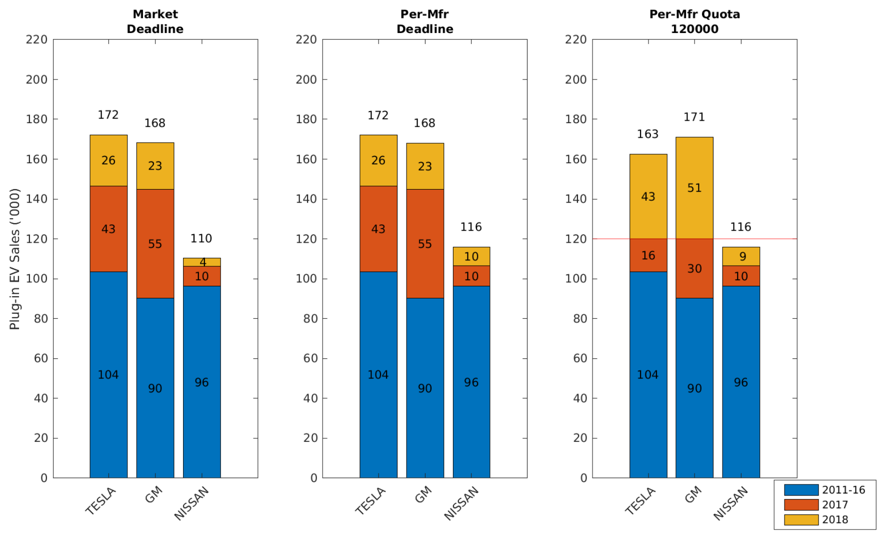
15. The sum of consumer surplus and manufacturer profits does not reflect welfare for two reasons. First, economic agents do not internalize the environmental effects of EVs. Second, elimination designs are likely to have different long-term impacts due to the network effect, which are not captured by aggregating the two-period outcomes.

16. Alternative strategies to compare the designs include fixing the government expenditure across the experiments by changing the amount or duration of the subsidy. Both approaches have limitations. Changing the amount affects consumer prices and, hence, purchase behavior, making it difficult to disentangle the effect of subsidy elimination. Changing the duration requires modeling more than two periods, which complicates computation.

7.4.1 EV Prices and Sales

Figure 6 shows the cumulative EV sales for Tesla, GM, and Nissan under a marketwide deadline, a per-manufacturer deadline, and a per-manufacturer quota of 120,000.[17],[18] The blue bars indicate total sales between 2011 and 2016, as observed in the data, and the orange and yellow bars indicate sales in 2017 and 2018, respectively, under the recomputed equilibria.

Figure 6: Effect of Subsidy-Capping Designs on EV Sales



Notes: This figure shows the cumulative plug-in electric vehicle sales (in thousands) under different subsidy-capping designs for the three dominant manufacturers. The blue bars indicate total sales 2011–2016, as observed in the data, and the orange and yellow bars indicate sales in 2017 and 2018, respectively, under the recomputed equilibria.

For Tesla and GM, sales in 2017 remain the same under the marketwide and the per-manufacturer deadlines because they cannot control the status of subsidies in 2018. In contrast, the quota acts as a binding constraint for both manufacturers, and they remain below it to ensure the subsidy in 2018. Table 8 illustrates the mechanism behind this finding, showing that when facing the quota, Tesla and GM lower EV sales in 2017 by raising the prices of EVs in 2017. For instance, compared to the counterfactual with no subsidy (Column (1)), GM raises the price of the Chevrolet Volt by $4,924 (Column (4)). Notably, for Tesla Model S, the increase in price is $13,500, which is even higher than the actual subsidy of $7,500, implying a negative pass-through to consumers in 2017.

Such a striking effect of the quota on prices is partly a consequence of the modeling assumption that firms control sales through price alone. In practice, manufacturers can also create an artificial shortage of qualifying vehicles by lowering production and may not drastically increase prices. However, data limitations do not allow examining this mechanism. Even though the model specification leads to an unconvincingly large increase in EV prices under the quota, it is valuable because it high-

17. Appendix Table 13 reports EV sales separately for all manufacturers.

18. I explore other values of the per-manufacturer quota in Appendix D.

lights the strong incentive to reduce EV sales under this design that is robust to the specification. Two factors drive this incentive: (1) staying below the quota in any period allows manufacturers to qualify for the subsidy on all EVs in the next period, and (2) as the subsidy is eliminated only for manufacturers that exhaust the quota, staying below it prevents exposure to increased competition from manufacturers below it.

Unlike Tesla and GM, Nissan's EV sales in 2017 remain unaffected because it is far below the per-manufacturer quota in 2017. Although Nissan had comparable sales during 2011–2016, it sells much less than Tesla and GM in 2017 under each counterfactual. This is because Tesla and GM introduced new models, such as the Chevrolet Bolt and Tesla Model 3, in 2017, which gained popularity since their introduction. In contrast, Nissan only sold a single model (the Leaf) in 2017.

Table 8: Effect of Subsidy-Capping Designs on Vehicle Prices and Sales in 2017

Vehicle	Outcome	No Subsidy	Market Deadline	Per-Mfr Deadline	Per-Mfr Quota (120,000)
Chevrolet Bolt (BEV)	Price (USD)	40,157	39,041	39,026	44,905
	Sales	8,208	21,594	21,634	10,826
Chevrolet Volt (PHEV)	Price (USD)	35,774	35,006	34,992	40,698
	Sales	15,300	32,864	32,897	18,929
Tesla Model S (BEV)	Price (USD)	85,869	85,410	85,412	99,369
	Sales	14,801	24,651	24,639	9,854
Toyota Prius Prime (PHEV)	Price (USD)	29,050	28,656	28,202	28,215
	Sales	18,775	30,205	31,661	31,714
Honda Accord (Gas)	Price (USD)	27,959	27,952	27,952	27,958
	Sales	330,695	329,571	329,491	329,994
Honda Civic (Gas)	Price (USD)	22,474	22,466	22,466	22,471
	Sales	341,661	340,506	340,423	340,911
Toyota Camry (Gas)	Price (USD)	25,726	25,725	25,725	25,730
	Sales	270,928	270,025	269,961	270,301
Ford F (Gas)	Price (USD)	35,788	35,787	35,786	35,788
	Sales	277,994	277,768	277,755	277,888
Chevrolet Silverado (Gas)	Price (USD)	38,653	38,653	38,653	38,653
	Sales	305,132	304,825	304,809	305,018
Toyota Tacoma (Gas)	Price (USD)	31,707	31,705	31,705	31,708
	Sales	220,559	220,273	220,253	220,391

Notes: This table shows the equilibrium prices (before subsidy) and sales across the 30 sample states in 2017 for a sample of vehicles using counterfactual simulations described in Section 7.

Next, consider the effect of subsidy-capping designs on EV sales in 2018. As Tesla and GM do not qualify under the marketwide or per-manufacturer deadlines, they sell almost the same number of EVs under both. In contrast, they qualify in 2018 under the quota. As a result, they sell more EVs in 2018 than under either of the deadlines, which partly offsets their low sales in 2017. For instance, Tesla's EV sales rise by 65 percent under the quota compared to the per-manufacturer deadline. Nissan sells more EVs in 2018 under a per-manufacturer deadline and the quota than under a marketwide deadline because it qualifies in the first two cases but not in the last.

7.4.2 Aggregate Market Outcomes

As market outcomes differ by manufacturer and over time, I report the aggregate market-level outcomes in Table 9 using no subsidy as the benchmark counterfactual. As the total government expenditure changes across these designs, I also report it for each design.

Panel (a) shows the aggregate market outcomes in 2017. Both the marketwide and per-manufacturer deadlines lead to a similar boost in EV sales, as expected. Moreover, all other market outcomes look similar under the two designs. In contrast, the outcomes under the quota are governed by Tesla and GM trying to stay below it by charging higher prices. Because of these efforts, the subsidy-induced EV sales are around 54 percent lower than the per-manufacturer deadline. Moreover, the reduction in conventional vehicle sales is lower as consumers substitute from the high-priced EVs toward lower-cost conventional alternatives in 2017. The subsidy-induced consumer surplus reduces by 62 percent, the aggregate manufacturer profits increase by 23.5 percent, and the government expenditure reduces by 29.4 percent.

Panel (b) shows the aggregate market outcomes in 2018. Those under the marketwide deadline are close to the counterfactual with no subsidy because the subsidy expires for everyone in 2018. However, EV sales are higher than in the counterfactual with no subsidy because of the network-effect gains from the 2017 subsidies. This outcome shows that in the presence of network effect, EV subsidies can have a long-term impact on market penetration. Specifically, by reducing the up-front cost of EVs, purchase subsidies raise EV sales in 2017. And, because EV consumers care about previous EV adoption, the demand for EVs shifts right in 2018. Compared to the marketwide deadline, the subsidy-induced EV sales are substantially higher under a per-manufacturer deadline because all manufacturers other than Tesla and GM qualify in 2018. Moreover, subsidy-induced EV sales are even higher under the quota because all manufacturers, including Tesla and GM, qualify in 2018.

Panel (c) shows the market outcomes summed over the two years. By construction, the marketwide deadline design only disburses subsidies in 2017. As a result, it requires the least government expenditure and results in the lowest EV sales, consumer surplus, and manufacturer profits. The per-manufacturer deadline requires additional government expenditure, as it also pays out in 2018. It results in the greatest boost in EV sales and highest reduction in conventional vehicle sales and gasoline consumption. Finally, the quota requires the highest government expenditure but results in the least reduction in conventional vehicle sales, lowest consumer surplus, and highest manufacturer profits.

Table 9: Effect of Subsidy-Capping Designs on Aggregate Outcomes

Outcome	Market Deadline	Per-Mfr Deadline	Per-Mfr Quota (120,000)
Panel (a): 2017 Outcomes			
Δ EV Sales	89,007	94,551	43,856
Δ Conv Sales	-34,478	-35,974	-12,427
Δ Gas Consumption (Million Gallons)	-2,546.11	-2,651.85	-853.45
Δ Consumer Surplus (Million USD)	1,066.84	1,135.19	428.01
Δ Total Profits (Million USD)	461.24	432.16	534.07
Govt Expenditure (Million USD)	1,219.41	1,250.22	881.56
Panel (b): 2018 Outcomes			
Δ EV Sales	1,904	43,161	89,807
Δ Conv Sales	-833	-12,464	-34,283
Δ Gas Consumption (Million Gallons)	-64.4	-878.96	-2,535.68
Δ Consumer Surplus (Million USD)	35.93	560.97	1,109.05
Δ Total Profits (Million USD)	12.54	280.7	525.41
Govt Expenditure (Million USD)	0	511.75	1,200.88
Panel (c): Total			
Δ EV Sales	90,911	137,712	133,663
Δ Conv Sales	-35,311	-48,438	-46,710
Δ Gas Consumption (Million Gallons)	-2,610.51	-3,530.8	-3,389.13
Δ Consumer Surplus (Million USD)	1,102.78	1,696.16	1,537.06
Δ Total Profits (Million USD)	473.78	712.86	1,059.48
Govt Expenditure (Million USD)	1,219.41	1,761.97	2,082.43
Panel (d): Total (Normalized)			
Δ EV Sales	75	78	64
Δ Conv Sales	-29	-27	-22
Δ Gas Consumption (Million Gallons)	-2.14	-2	-1.63
Δ Consumer Surplus (Million USD)	0.9	0.96	0.74
Δ Total Profits (Million USD)	0.39	0.4	0.51

Notes: This table shows the change in aggregate market outcomes under the counterfactual simulations discussed in section 7 compared to the counterfactual with no subsidies. Panel (a) shows the market outcomes in 2017, Panel (b) shows the outcomes for 2018, Panel (c) shows the aggregate outcomes over the two years, and Panel (d) shows aggregate two-period outcomes normalized by government expenditure. All simulations assume that the subsidy elimination began after 2017.

Panel (d) shows the aggregate two-period outcomes, normalizing the government expenditure at \$1 million. Because government expenditure is not held constant across different experiments, such normalization is required to compare the cost-effectiveness of different designs. Panel (d) shows that subsidies with a marketwide deadline sell around 75 more EVs and 29 fewer conventional vehicles than the counterfactual with no subsidy. The program results in 2.14 million gallons of lower fuel consumption, \$0.9 million higher consumer surplus, and \$0.39 million higher manufacturer profits. Similarly, subsidies with a per-manufacturer deadline sell around 78 more EVs and 27 fewer conventional vehicles than the counterfactual with no subsidy. The program results in 2 million gallons lower fuel consumption, \$0.96 million higher consumer surplus, and \$0.4 million higher manufacturer profits. Finally, subsidies with a quota sell 64 more EVs and 22 fewer conventional vehicles than the counterfactual with no subsidy. The program results in 1.63 million gallons higher fuel consumption, \$0.74 million higher consumer surplus, and \$0.51 million higher manufacturer profits.

In each case, consumers and manufacturers share the benefits unequally. However, the benefits accrued to consumers are the lowest under the quota, indicating a substantial leakage of benefits to manufacturers. This outcome is a result of Tesla and GM raising the prices of their EVs in 2017 to stay below the quota. As noted, the effect of the quota on prices is partly a consequence of the model specification, whereby firms control EV sales only through prices. In practice, manufacturers can also stay below the quota by lowering EV production. However, doing so would also lower the consumer surplus compared to the deadline designs.

Overall, the results show that for a given government expenditure, a marketwide or per-manufacturer deadline are almost equally effective at raising EV penetration in the short term and result in similar benefits for consumers. Moreover, the quota is less effective at raising EV penetration compared to the deadlines and results in the lowest benefits for consumers.

7.4.3 Profit Distribution Across Manufacturers

Table 10 decomposes the profits across manufacturers under different counterfactuals. Tesla earns at least \$237 million (or 32.6 percent), GM earns at least \$208 million (0.5 percent), and Nissan earns at least \$17 million (0.08 percent) more profits from EV subsidies than the counterfactual with no subsidy. Note that compared to GM and Nissan, EV subsidies have a much higher impact on Tesla (as a percent of total profits) because it focuses exclusively on EVs.

Tesla and GM earn the lowest profits under the per-manufacturer deadline because they do not qualify for subsidies in 2018, whereas others still do. They earn slightly higher profits under a marketwide deadline when no manufacturer qualifies in 2018. They earn the highest profits under the quota, as they qualify in 2018. For instance, Tesla's profits rise by 9.6 percent compared to the per-manufacturer deadline.

In contrast, other EV manufacturers, such as Nissan and Toyota, earn the least profits under the marketwide deadline when they do not qualify for subsidies in 2018. They earn slightly higher profits under a per-manufacturer deadline when they qualify in 2018, which allows them to have a competitive advantage over Tesla and GM in 2018. Like Tesla and GM, they also earn the highest profits under the quota. This is likely because they have a competitive advantage over Tesla and GM in 2017, both of which must limit their EV sales in 2017 to qualify in 2018.

7.4.4 Discussion

Overall, the results show a substantial incentive for manufacturers to reduce EV sales under a per-manufacturer quota when it acts as a binding constraint, which can decrease the effectiveness of the subsidy. This observation confirms the intuition from the monopoly example in Section 3. Although the rise in EV sales in 2018 partially offsets the sales reduction in 2017, the combined normalized sales over the two years are 18 and 14 percent lower compared to the per-manufacturer and marketwide deadlines, respectively. This observation shows that deadlines are likely to be more cost-effective in aiding EV market penetration compared to a binding per-manufacturer quota. Moreover, because EV manufacturers are multiproduct oligopolists, the designs may also affect the prices and sales of conventional vehicles. On aggregate, these designs affect consumer surplus, manufacturer profits, and liquid fuel consumption. Finally, each design affects the profit distribution across manufacturers differently. Compared to a marketwide deadline, a per-manufacturer deadline shifts profits away from the manufacturers facing it. Thus, if the deadline is based on the year of entry, this would imply more support for newer manufacturers. In contrast, a per-manufacturer quota does not necessarily shift profits away from manufacturers facing it because it allows them to control when the subsidy expires.

Before IRA, the EV subsidies were eliminated using a combination of a per-manufacturer quota and per-manufacturer deadlines (see Figure 1). IRA replaced that design with a marketwide deadline. The results from the analysis indicate that a marketwide deadline is almost as cost-effective as a per-manufacturer deadline. It is also at least as cost-effective as a per-manufacturer quota when the quota acts as a binding constraint. Thus, all else equal, replacing the earlier design is likely to positively affect EV market penetration and create a higher reduction in the liquid fuel consumption closer to 2032, when the dynamics of subsidy elimination become relevant. Moreover, the pass-through to consumers is also likely to be higher compared to the earlier design. However, as the per-manufacturer quota and deadline have different implications for profit distribution, the effect of replacing the subsidy-capping design on the profit distribution across EV manufacturers is ambiguous.

Table 10: Effect of Subsidy-Capping Designs on Profit Distribution

Manufacturer	No Subsidy	Market Deadline	Per-Mfr Deadline	Per-Mfr Quota (120,000)
BMW	6,185	6,232	6,292	6,300
Daimler	6,073	6,064	6,066	6,069
Fiat Chrysler	24,814	24,821	24,861	24,867
Ford	29,028	29,046	29,088	29,099
General Motors	41,368	41,594	41,576	41,775
Honda	27,787	27,730	27,705	27,709
Hyundai	11,016	11,005	11,004	11,006
Jaguar Land Rover	2,417	2,410	2,408	2,410
Kia	7,398	7,398	7,409	7,410
Mazda	3,725	3,718	3,715	3,715
Mitsubishi	1,357	1,356	1,355	1,355
Nissan	20,052	20,069	20,105	20,108
Subaru	9,950	9,930	9,924	9,925
Tesla	726	964	963	1,056
Toyota	41,405	41,437	41,522	41,528
Volkswagen	11,784	11,781	11,794	11,800
Volvo	1,222	1,226	1,232	1,234

Notes: This table shows manufacturer-level profits (in million USD) during 2017–2018 from sales in the 30 sample states under the counterfactual simulations.

8 Conclusion

This paper demonstrates the implications of the subsidy-capping provisions in purchase-subsidy programs designed to promote infant green technologies. I focus on the US plug-in EV market, which is important to understand given its potentially enormous environmental benefits. Using a monopoly example, I first show that the provisions may aid or hinder the EV market penetration, and the magnitude of the effect depends on structural primitives such as own- and cross-price demand elasticities and the network effect. Next, to compare alternative provisions, I develop a structural model of the automobile industry, where consumers choose vehicles to purchase among all fuel types by maximizing utility, and firms choose prices for vehicles to maximize their profits. Then, I estimate the demand-side parameters using product-level data on the newly registered vehicles, prices, characteristics, and subsidies across 30 states in the initial years of the EV market that were unaffected by eliminating subsidies. Using the demand parameters, I recover vehicle markups under the assumption of static Nash-Bertrand equilibrium. Finally, I use the market primitives and a two-stage pricing model to predict firms' responses when they face three counterfactual subsidy-capping designs: a marketwide deadline, a per-manufacturer deadline, and a per-manufacturer quota.

Overall, the results show that, all else equal, the quota, when binding, incentivizes manufacturers to reduce EV sales compared to the deadline designs. Two factors drive this incentive: (1) staying below the quota in any period allows manufacturers to qualify for the subsidy on all EVs in the next period, and (2) as the subsidy is eliminated only for those that exhaust the quota, staying below it protects them from competition from other manufacturers below it. As a result, given government expenditure, deadlines can be more cost-effective in increasing EV market penetration than the quota. Because manufacturers have market power, this can also translate into lower pass-through of subsidies to consumers compared to the deadline designs. In addition, because manufacturers are multiproduct oligopolists, the designs affect the sales of conventional vehicles and, hence, the consumer surplus, manufacturer profits, and liquid fuel consumption; they also affect the distribution of profits across manufacturers.

These findings facilitate a deeper understanding of the role of policy in influencing technology change in three ways. First, they elucidate the effect of the subsidy design on market penetration in a theoretically motivated analysis. Because EVs offer a viable solution to fuel efficiency and energy security, policymakers are eager to increase adoption. The US market share of EVs has remained limited despite several incentive programs. Careful design is therefore crucial, especially considering that EV tax incentives cost billions of dollars and receive much scrutiny. Second, the paper sheds light on the impact of the subsidy design on consumer surplus and the distribution of profits across manufacturers, which is helpful for targeting. For instance, compared to a marketwide deadline, a per-manufacturer deadline shifts profits away from the manufacturers facing it. Despite the penalty on dominant manufacturers, a per-manufacturer deadline may be justified if significant barriers to manufacturers' entry exist, because positive externalities from the entry appear in the form of environmental benefits, innovation spillovers, and higher national energy security. Finally, the implications from the plug-in EV market may also hold for other countries and sustainable technologies, such as solar panels and wind energy.

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Appendix

A EV Manufacturers and Buyers Respond to Subsidy-Capping Designs

This section offers evidence that EV manufacturers and buyers respond to the subsidy-capping designs based on Tesla and GM's experiences. Tesla and GM surpassed 200,000 plug-in sales in July and November 2018, respectively.

Figure 7 compares the monthly nationwide sales of Tesla's most affordable model (Model 3) with GM's most popular plug-in hybrid (Chevrolet Volt) during March 2018–June 2019. Three observations are worth noting. First, the subsidy affects consumers' purchase decisions, as evident from the intertemporal bunching surrounding changes in the federal tax credit. The credit available for Model 3 in January was half as generous compared to December, and January sales correspondingly plummeted to 50 percent of the December sales volume. Such bunching does not appear for Chevrolet Volt, which did not face a reduction in tax credits in January 2019, pointing to the possibility that the changes in federal subsidy affected consumers' buying decisions. This bunching conflates the changes in purchase choice and purchase timing because some consumers aware of the looming change may have bought earlier to take advantage of the more generous subsidy. Such timing effects pose a challenge in estimating demand elasticities, which I discuss in Section 4. Second, deadlines are effective in inducing car sales. Once Tesla exhausted the threshold, it faced a six-month deadline: all vehicles delivered by December 2018 qualified for a \$7,500 subsidy. Between July and December, Tesla set new production and delivery records. Third, manufacturers likely respond to a quota by reducing EV sales, as evident by the 130 percent spike in Model 3 sales in July 2018. If Tesla reached the threshold in June instead of July, its subsidy would have reduced to half in October 2018 instead of January 2019. The low sales volume in June is consistent with the incentive to push the delivery of the 200,000th vehicle to July. Comparing the sales of the Chevrolet Volt shows that seasonality in demand is not enough to explain the difference between the June and July sales volumes.

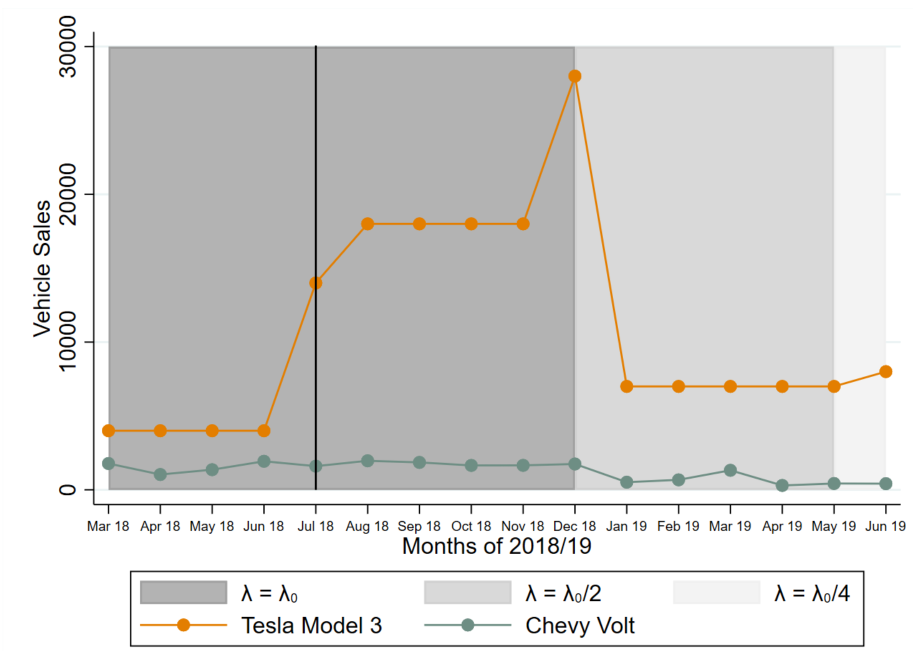
To quantify the effect of quota and deadlines on the quarterly sales volume, I also estimate the following regression:

$$Sales_{jft} = \beta_0 + \beta_1.t + \beta_2.I^D_{ft} + \beta_3.I^Q_{ft} + \delta_j + \delta_{qtr} + \epsilon_{jft}$$

where I^D_{ft} takes value 1 if firm f faces a deadline within next two quarters; I^Q_{ft} is 1 if firm f has sold less than 200,000 vehicles up to quarter t and is restricted by the quota. $\delta_j$and δ_{qtr} indicate product and quarter fixed effects. The coefficient β_2 indicates the effect of deadline, and β_3 indicates the effect of quota on EV sales. The variation comes only from Tesla and GM because no other firm has exhausted the quota yet. Controlling for product and quarter fixed effects, these firms, on average, sell 3,000 more EVs under the two-quarter deadline and 3,000 fewer EVs under the quota of 200,000.

Although these findings inform us of the importance of the subsidy-capping designs, they do not explain what happens with a marketwide deadline. Moreover, the variation is only driven by Tesla

Figure 7: Tesla Model 3 and GM Chevrolet Volt Sales, 2017–2018



Notes: This figure plots the total nationwide sales of the Model 3 and Volt between March 2018 and June 2019 based on the monthly sales estimates by Automotive News Data Center. The black vertical line indicates July 2018—when Tesla delivered the 200,000th qualifying vehicle. GM reached this threshold in Nov 2018. The shades of grey indicate the value of Tesla's federal subsidy; darker shades indicate higher values. Tesla's phaseout began in January 2019, and the subsidy for all its models was reduced from \$7,500 to \$3,750. GM's subsidy was reduced in April 2019.

Table 11: Evidence: EV Sales Depend on the Subsidy-Capping Design

VARIABLES	(1) Sales (1,000s)	(2) Sales (1,000s)	(3) log(Sales)	(4) log(Sales)
Approaching Deadline	2.797***	5.171***	0.432	0.593
	(0.926)	(1.011)	(0.477)	(0.498)
Quota Constrained	-3.076***	0.649	-0.240	-0.580
	(0.876)	(1.478)	(0.451)	(0.728)
trend	0.004		-0.007	
	(0.020)		(0.010)	
Constant	4.323***	0.813	6.213***	6.430***
	(0.973)	(1.410)	(0.501)	(0.694)
Observations	836	836	836	836
R-squared	0.376	0.425	0.266	0.380
Product FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Firm-level trend		Yes		Yes

Source: WardsAuto US Light Vehicle Quarterly Sales
Notes: Standard errors are in parentheses. *** indicates 99 percent level of significance. ** indicates 95 percent level of significance. * indicates 90 percent level of significance.

and GM, as the subsidy was not eliminated for any other manufacturer. Therefore, to compare the different subsidy-capping designs, I rely on structural methods in the paper.

B First-Stage Regression Results

Table 12 reports the results of the first-stage regression. IVs 1–5 are the sum over the characteristics of firm's other vehicles. IVs 6–10 are sums over the characteristics of competing vehicles. Vehicle characteristics used to construct the excluded instruments include a constant, vehicle size, performance, driving cost, and battery range.

Table 12: First-Stage Regression Results

Dependent Variable: Price ($'0000)			
	Variable	Coef	SE
Included IV			
	Constant	-8.447***	1.447
	Size (0000 in^2)	6.439***	0.143
	Performance (Hp/10lb)	9.026***	0.065
	Fuel Cost ($/mile)	6.797***	0.484
	Battery Range (10 miles)	-0.038***	0.009
	BEV	2.778***	0.250
	PHEV	2.927***	0.252
	BEV × log(1+Manufacturer EV Sales)	-0.000	0.028
	PHEV × log(1+Manufacturer EV Sales)	-0.187***	0.022
	BEV × log(1+ Same-Charger EV Sales)	-0.274***	0.036
	PHEV × log(1+Same-Charger EV Sales)	0.036	0.037
Excluded IV			
	IV_1	0.149***	0.034
	IV_2	-0.323***	0.037
	IV_3	0.165***	0.014
	IV_4	0.168***	0.020
	IV_5	0.009***	0.002
	IV_6	-0.035	0.033
	IV_7	0.042	0.036
	IV_8	0.003	0.013
	IV_9	-0.032***	0.010
	IV_{10}	-0.000	0.002
Obs	62186		
R-squared	0.583		
F test			
F(66, 62119)	1,317.700		
F test of excluded IV			
F(10, 62119)	494.992		

Notes: Size is wheelbase× width (in thousands of in^2), performance is horsepower by curb weight (in 10 lb), driving cost is fuel cost (in dollars per mile), and battery range is the all-electric range (in miles) for electric vehicles (EVs). The variable "Manufacturer EV Sales" shows the total EVs sold by the manufacturer in the geographic market until the previous year. The variable "Same-Charger EV Sales" shows cumulative EV sales by all manufacturers with the same Level 3 charging standard in the geographic market until the previous year. IVs 1–5 are the sum over the characteristics of firm's other vehicles. IVs 6–10 are sums over the characteristics of competing vehicles. Vehicle characteristics used to construct the excluded instruments include a constant, vehicle size, performance, driving cost, and battery range. *** indicates 99 percent level of significance. ** indicates 95 percent level of significance. * indicates 90 percent level of significance.

C Counterfactuals

Table 13: Effect of Subsidy-Capping Designs on EV Sales

Manufacturer	Year	No Subsidy	Market Deadline	Per-Mfr Deadline	Per-Mfr Quota (120,000)
BMW	2011–2016	31,261	31,261	31,261	31,261
	2017	9,592	16,304	17,298	17,436
	2018	8,779	8,688	15,070	15,630
DAIMLER	2011–2016	8,485	8,485	8,485	8,485
	2017	1,546	2,387	2,467	2,489
	2018	1,401	1,348	2,119	2,179
FIAT CHRYSLER	2011–2016	18,031	18,031	18,031	18,031
	2017	3,692	7,603	8,626	8,739
	2018	4,009	4,264	9,518	9,856
FORD	2011–2016	68,414	68,414	68,414	68,414
	2017	12,431	19,178	19,706	19,806
	2018	11,309	10,756	16,681	17,323
GENERAL MOTORS	2011–2016	90,090	90,090	90,090	90,090
	2017	23,642	54,687	54,761	29,910
	2018	22,253	23,427	23,254	51,116
HONDA	2011–2016	857	857	857	857
	2017	2	2	2	2
	2018	2	2	2	2
HYUNDAI	2011–2016	1,320	1,320	1,320	1,320
	2017	1,012	1,689	1,913	1,942
	2018	958	1,004	1,810	1,882
KIA	2011–2016	3,571	3,571	3,571	3,571
	2017	1,640	2,896	3,371	3,376
	2018	1,679	1,850	3,603	3,595
MITSUBISHI	2011–2016	1,652	1,652	1,652	1,652
	2017	4	11	11	11
	2018	4	4	10	10
NISSAN	2011–2016	96,165	96,165	96,165	96,165
	2017	4,430	9,966	10,212	10,237
	2018	4,225	4,230	9,514	9,490
TESLA	2011–2016	103,550	103,550	103,550	103,550
	2017	25,158	42,900	42,880	16,450
	2018	25,197	25,721	25,647	42,567
TOYOTA	2011–2016	42,144	42,144	42,144	42,144
	2017	18,775	30,205	31,661	31,714
	2018	18,715	19,264	31,636	31,572
VOLKSWAGEN	2011–2016	18,084	18,084	18,084	18,084
	2017	3,913	6,437	6,743	6,806
	2018	3,537	3,430	5,740	5,944
VOLVO	2011–2016	1,979	1,979	1,979	1,979
	2017	1,480	2,060	2,220	2,255
	2018	1,400	1,382	2,025	2,109

Notes: This table shows the electric vehicle sales for each manufacturer. Sales in 2011–2016 are reported as observed in the data. Sales in 2017 and 2018 are computed under the counterfactual policy simulations discussed in Section 7.

Table 14: Effect of Subsidy-Capping Designs on Vehicle Prices and Sales, 2018

Vehicle	Outcome	No Subsidy	Market Deadline	Per-Mfr Deadline	Per-Mfr Quota (120,000)
Chevrolet Bolt (BEV)	Price (USD)	41,074	41,045	41,043	39,740
	Sales	7,856	8,474	8,441	20,778
Chevrolet Volt (PHEV)	Price (USD)	36,604	36,588	36,590	35,644
	Sales	14,270	14,822	14,682	30,124
Tesla Model S (BEV)	Price (USD)	86,362	86,363	86,372	85,850
	Sales	14,853	15,164	15,111	24,510
Toyota Prius Prime (PHEV)	Price (USD)	30,243	30,267	29,667	29,660
	Sales	18,715	19,264	31,636	31,572
Honda Accord (Gas)	Price (USD)	27,960	27,960	27,957	27,952
	Sales	330,769	330,755	330,124	329,657
Honda Civic (Gas)	Price (USD)	22,474	22,474	22,471	22,466
	Sales	341,737	341,724	341,066	340,602
Toyota Camry (Gas)	Price (USD)	25,726	25,726	25,730	25,726
	Sales	270,967	270,949	270,359	270,043
Ford F (Gas)	Price (USD)	35,788	35,787	35,787	35,786
	Sales	277,998	277,994	277,872	277,758
Chevrolet Silverado (Gas)	Price (USD)	38,653	38,653	38,652	38,653
	Sales	305,136	305,127	304,998	304,816
Toyota Tacoma (Gas)	Price (USD)	31,707	31,707	31,708	31,705
	Sales	220,568	220,560	220,387	220,268

Notes: This table shows the equilibrium prices (before subsidy) and sales across the 30 sample states in 2018 for a sample of vehicles using counterfactual simulations described in Section 7.

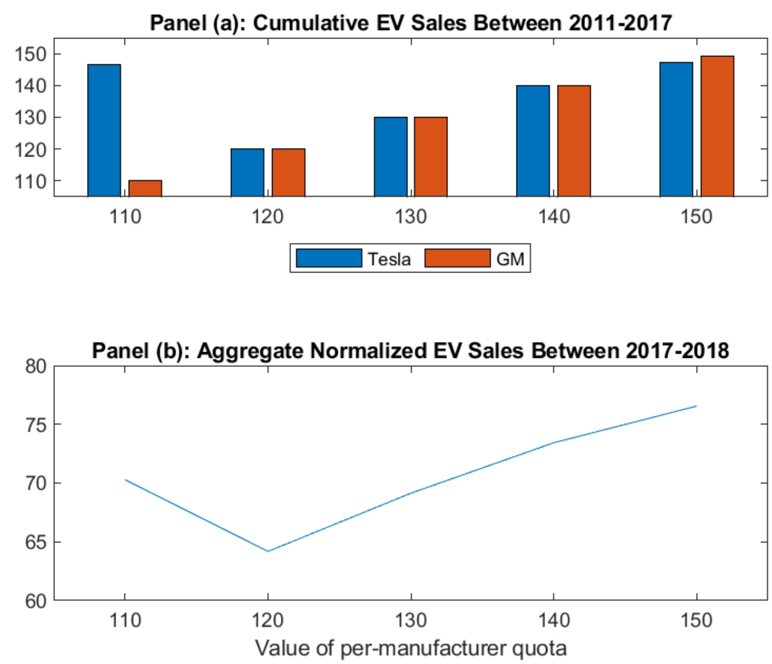
D Other Values of the Per-Manufacturer Quota

This section explores the effect of EV subsidies on the market outcomes under different values of the per-manufacturer quota. Using the parameter estimates from Section 6, I recompute the equilibrium for five different values of the quota and plot the resulting outcomes in Figure 8. In each case, I fix the total EV sales between 2011 and 2016 as observed in the data.

Panel (a) shows the total EVs sold by Tesla and GM between 2011 and 2017. When the quota is 110,000, Tesla chooses to exceed it in 2017, even if that sacrifices eligibility in 2018. When the quota is between 120,000 and 140,000, both Tesla and GM choose to stay below the quota to ensure subsidies in 2018. When the quota is 150,000, it is not binding for either manufacturer. In that case, both manufacturers respond similarly compared to when they face a deadline.

Panel (b) shows the aggregate boost in EV sales across all manufacturers during 2017 and 2018 compared to the counterfactual with no subsidy, fixing the government expenditure at $1 million. Although each policy increases EV sales, the boost depends on the value of the quota. The farther the quota is from manufacturers' privately optimal sales, the more they are incentivized to reduce EV sales and the fewer EVs may be sold for the same level of expenditure. However, when the quota is too small, some manufacturers may find it more beneficial to exceed it, even if it makes them ineligible for future subsidies. Finally, when the quota is not binding, the outcomes are similar to when manufacturers face a deadline.

Figure 8: Effect of EV Subsidies on EV Sales Under Different Values of the Per-Manufacturer Quota



Notes: Panel (a) shows the cumulative electric vehicle (EV) sales (in thousands) by Tesla and GM between 2011 and 2017 under the different values of a per-manufacturer quota. In each case, I fix the sales between 2011 and 2016 as in the data and recompute the equilibrium in 2017. Panel (b) shows the aggregate boost in EV sales due to subsidy between 2017 and 2018 compared to the counterfactual with no subsidy, fixing the government expenditure at $1 million.