Roadblock or Accelerator? The Effect of Electric Vehicle Subsidy Elimination

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Abstract

Federal and state governments in many countries subsidize the early adopters of electric vehicles (EVs) to promote green technology. These programs often use quotas or deadlines, to phase out the subsidies, which can create dynamic incentives for car manufacturers. Most papers in the literature study the effect of subsidy introduction on market outcomes in static settings, but there is little work that addresses the dynamic effects of subsidy-capping designs. This paper explores these effects in the US electric vehicle market. I develop a structural model of the consumer vehicle choice and manufacturer's pricing decisions in the US automobile industry and estimate it using comprehensive data on new vehicle registrations, prices, characteristics and subsidies in 30 states between 2011-2017. Based on the primitives that are generated from the model, I conduct counterfactual simulations to compare three subsidy-capping designs: a market-wide deadline, a per-manufacturer deadline, and a per-manufacturer quota. Counterfactual simulations show that, given government expenditure, a per-manufacturer quota leads to 26% lower EV sales than the policies with deadlines. Moreover, each subsidy capping 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 have become a successful means to promote electric vehicles (EV) in several countries such as the United States, Canada, China, Japan, and Norway (Beresteanu and S. Li, 2011; Chandra, Gulati, and Kandlikar, 2010; Jenn, Azevedoa, and Ferreira, 2013). Policymakers typically use provisions like quotas and deadlines to cap these subsidies. Despite the wide use of such provisions, there is little work to understand their effect on market outcomes. This paper extends the literature by considering the dynamic effects of subsidy-capping provisions. I show that different provisions have different effects that can reinforce the intended policy objectives or create unintended consequences that undo the benefits of the subsidy.

Policymakers subsidize plug-in EV purchases to address various externalities: EV adoption has a positive environmental externality due to zero (or low) emissions of greenhouse gases and criteria air pollutants.[1] It enhances national energy security by not relying on gasoline. It has information spillovers to the extent that EV consumers help spread information about the new technology. It also makes entry attractive for charging stations, which is crucial for developing a charging network and further encouraging demand. In addition to addressing these externalities, a policy goal may be to integrate EVs into the automobile industry by overcoming the most significant barrier to their adoption – i.e., high upfront cost – by making EVs price competitive with conventional vehicles.

The traditional Pigouvian solution to correct externalities is to subsidize the externality-generating activity equivalent to the marginal external benefit at the optimal quantity. In principle, governments could subsidize EVs forever; in practice, they allow these subsidies to end after a certain amount of time. There may be several reasons for doing so. First, subsidizing EVs can be prohibitively expensive as EV sales surge due to high administrative costs or other political reasons. Second, marginal gains from informational spillovers are likely to fade as EVs integrate into the auto industry. Finally, the marginal cost, hence the price, is likely to come down with time as EV makers find cheaper ways to produce the battery.

Policymakers worldwide use different strategies to cap the subsidies for EVs and other green technologies, like limiting the total expenditure, imposing a deadline, or combining both. For instance, Norway's EV tax incentive and VAT exemption program (2012) imposed a deadline of 2017 for all manufacturers together with a market-wide target of 50,000 EVs. China's new energy vehicle (NEV) subsidy program (2009) cut the subsidies progressively between 2020 and 2022, with complete expiry in 2022. In the US, before the Inflation Reduction Act (IRA) of August 2022, the federal tax-credit program capped the incentives by giving each EV manufacturer a quota of 200,000 vehicles, following which the credit phased out for that manufacturer. IRA replaced this per-manufacturer cap with a single deadline for their EV purchase subsidies. Each manufacturer, including those that met the quota before 2022, is eligible for subsidy till 2032 (provided the final assembly of their vehicle

[1] Questions have been raised in the literature on the environmental benefits of driving electric vehicles (see Babaee, Nagpure, and DeCarolis (2014), Archsmith, Kendall, and Rapson (2015), Holland et al. (2016), and Buekers et al. (2014), among others) since charging the battery increases pollution at the power plant. The total emissions associated with driving EVs are less than gasoline cars if the electricity is generated from renewable energy sources, and there may be long-term environmental gains if electric vehicle adoption is complemented with renewable electricity generation.

occurred in North America). Are these designs equally effective in raising EV penetration? What are their implications for market outcomes like 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 non-refundable income tax credits of up to $7500 to EV consumers. Before the Inflation Reduction Act (IRA), the program combined a per-manufacturer quota and a per-manufacturer deadline to cap these credits. Each EV manufacturer received a quota of 200,000 vehicles, following which the credit phased out over a year as follows: it was unchanged in the quarter in which the manufacturer delivered the 200,000th EV and in the next quarter, and then reduced to half for that manufacturer. It then reduced to one-fourth of the original value following a six-month deadline and then expired following another six-month deadline. In this paper, I separately examine the per-manufacturer quota and the per-manufacturer deadline and compare them with a market-wide deadline, as instituted by the IRA.[2]

First, I use an illustrative model to show that a per-manufacturer quota can create an incentive to delay EV sales and thereby undermine the effect of subsidy. The incentive results from the timing component in the design. Specifically, by staying below the quota, a manufacturer qualifies for the subsidy for an additional period. Moreover, this incentive is reinforced by the oligopoly structure of the automobile industry, as staying below the quota protects EV manufacturers from fierce competition from others below the quota. In contrast, capping the subsidy using a deadline does not create this incentive because manufacturers can not 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. The model allows consumers to care about the number of EVs previously sold in their local geographic area (network effect) to capture information gains from early adopters and mobility gains from the development of a charging network in the nascent EV market (Kalish and Lilien, 1983; Heutel and Muehlegger, 2015; Springel, 2021; S. Li et al., 2017). In contrast, the supply side is an oligopoly with product differentiation where car manufacturers compete in prices, and the first-order conditions of profit-maximizing firms characterize the equilibrium. The key feature of the model is that, in addition to current profits, it allows vehicle manufacturers to care about the following year's profits while 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. In the presence of a per-manufacturer quota, the network-effect-induced incentives work opposite to the quota-induced incentives; the overall effect is apriori ambiguous and depends on market parameters like own- and cross-price elasticities and network effect. I estimate these demand parameters using product-level data on vehicle registrations, characteristics, and federal and state-level subsidies in 30 states between 2011-2017. Based on the estimated demand parameters and

[2]In addition to replacing the previous phaseout design with a market-wide deadline, the IRA also introduced a final assembly requirement, whereby a tax credit is only available for electric vehicles that were assembled in North America. Because the focus here is to understand the effect of the subsidy elimination designs, I ignore the final assembly requirements instituted by the IRA.

the first-order conditions of the manufacturers' profit functions, I then recover the vehicle markups and marginal costs in 2017 – the last year in my sample. Finally, based on these primitives, I recompute pricing equilibria under three subsidy-capping designs – (1) a market-wide deadline where all manufacturers face the same deadline, (2) a per-manufacturer deadline where manufacturers face separate deadlines, and (3) a per-manufacturer quota where manufacturers face separate quotas. I compare these designs with a counterfactual with no subsidy.

Counterfactual simulations show that subsidy-capping designs have a consequential impact on market outcomes. First, given government expenditure, even though all subsidy designs boost the EV market penetration, a per-manufacturer quota leads to 26% lower EV sales than the designs with deadlines. Two factors drive the reduction in sales: (1) Staying below the quota in any period allows EV manufacturers to qualify for subsidies in the next period, and (2) Because the subsidy is eliminated only for the EV-makers who exhaust the quota, staying below the quota protects the manufacturers from fierce competition from other EV-makers below the quota. As a result, subsidy programs that impose a deadline are more cost-effective in increasing EV market penetration than a per-manufacturer quota. Moreover, subsidy-capping designs may have spillovers on conventional vehicles' sales and, therefore, indirectly affect consumer surplus, manufacturers' profits, and liquid fuel consumption.

Finally, the subsidy capping designs affect profit distribution across the manufacturers. Compared to a market-wide deadline, a per-manufacturer deadline disproportionately shifts profits away from the manufacturers that face the deadline. In contrast, a per-manufacturer quota does not necessarily shift profits away from manufacturers facing a quota because it allows them to control when the subsidy expires. This finding sheds light on the argument made by the dominant EV manufacturers like Tesla, General Motors (GM), and Nissan, who 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 the per-EV manufacturer cap; the dominant EV-makers and other EV supporters formed an EV-drive Coalition and argued (among other reforms) to remove the cap. After the original design survived the tax reform of 2017, the top EV makers who initially lobbied to preserve these incentives even started favoring their removal altogether (Lambert, 2018). Replacing the per-manufacturer cap with a market-wide deadline in the IRA is likely to affect the profits for these EV manufacturers.

The paper adds to multiple strands of the literature. First and foremost, it contributes to the emerging literature investigating the role of government in promoting green technology. Some papers like Chandra, Gulati, and Kandlikar (2010), Gallagher and Muehlegger (2011), and Jenn, Azevedoa, and Ferreira (2013) take a reduced-form approach to quantifying the effect of government support programs. For instance, Jenn, Azevedoa, and Ferreira (2013) use a spatial-autoregressive model and find that the federal tax credits for hybrid EVs, on average, led to a 3-20% increase in hybrid market share in the US. Others like A. Van Benthem, K. Gillingham, and Sweeney (2008), Beresteanu and S. Li (2011), Acemoglu et al. (2012), and Aghion et al. (2016) take a structural approach. For instance, Beresteanu and S. 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% of the hybrid vehicle sales in the US in 2006. Most papers in this group study the effect of subsidy introduction on prices and welfare in a static equilibrium while ignoring the dynamics of subsidy elimination. This paper adds to the literature by explicitly modeling the responses of forward-looking producers to subsidy-capping designs in a micro-founded model. Comparing the market outcomes under different subsidy designs allows systematic policy-making – one based on arraying alternative designs and comparing the advantages and disadvantages of each. The analysis is relevant for other eco-friendly products where policymakers use similar subsidy-capping designs. Examples include fuel cell vehicles, solar panels, small wind turbines, and geothermal heat pumps.

In addition, this paper adds to the literature on the incidence effects of subsidy programs. Some papers on the US clean energy subsidies include Sallee (2011), Borenstein and Davis (2016), Gulati, McAusland, and Sallee (2017), and Pless and A. A. Van Benthem (2019). Examples from other contexts include Cabral, Geruso, and Mahoney (2018) on health insurance subsidies, Polyakova and Ryan (2019) on Affordable Care Act subsidies, and Fan and Zhang (2022) on cellphone subsidies. This paper adds to the incidence literature by highlighting that, for a given value of the subsidy, the incidence depends on the design of the subsidy program. Unlike most papers that study observed changes in the market outcomes surrounding the changes in subsidies, this paper takes a structural approach that allows for a detailed analysis of mediating factors and a simulation of market outcomes under counterfactual subsidy-capping designs. Sallee (2011) is closely related to the paper. He studies the incidence of hybrid vehicle tax credits enacted through the Energy Policy Act (2005) and finds that the subsidy-exclusive transaction prices of Toyota Prius did not increase in response to these tax credits. Sallee argues that Toyota did not increase prices because it believed that raising prices could lower future demand for hybrids. Such expectation may also be relevant for the nascent plug-in EV industry and rationalizes the modeling of network effect in this paper.

Finally, the paper is a part of the broad empirical literature on automobile industry regulation. In some papers, firms face certain constraints when choosing prices for their products. For instance, in Goldberg (1995), firms are constrained by export quotas, while in Jacobsen (2013), firms are constrained by the US corporate average fuel economy standards. In this paper, firms face similar constraints in choosing product prices when facing per-manufacturer quotas on the EV subsidies. This paper also complements recent papers focusing on the EV segment, including S. Li et al. (2017), J. Li (2018), K. T. Gillingham (2022), and Springel (2021).

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 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, estimating algorithm, and results. Section 7 discusses the counterfactual experiments. Section 8 summarizes the findings and concludes.

2 Industrial Background

This section begins with a brief description of the US plug-in EV market and the federal EV 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 the development of EVs.

2.1 Plug-in EV Market and Federal Tax Credits

Plug-in electric vehicles are road vehicles powered by batteries that can be recharged by plugging into the electric grid. They come in two varieties: (i) battery electric vehicles (BEVs), which are powered exclusively through electricity, and (ii) plug-in hybrid electric vehicles (PHEVs), which use an electric motor as the primary power source, and the internal combustion engine as a backup. BEVs and PHEVs differ from fuel-cell electric vehicles (FCEVs) like Honda Clarity and conventional hybrids (HEVs) like the Toyota Prius, both of which cannot be plugged into an electric grid.

The plug-in EV market in the US mostly developed after Nissan introduced Leaf in late 2010. Since then, with fuel efficiency and environmental regulations becoming increasingly stringent, most vehicle manufacturers in the US have added plug-in technology to their portfolios. The early entrants include Tesla, GM, Nissan-Mitsubishi, Ford, and Fisker Automotive. The relatively new entrants include BMW, Daimler, Fiat Chrysler, Volkswagen, Honda, and (more recently) Hyundai, Kia, and Volvo. As of writing this paper in 2021, Tesla is the highest-selling EV maker, followed by GM and Nissan-Mitsubishi.[3]

The US federal government started a tax credit program for PHEV and BEV purchases under the Energy Improvement and Extension Act of 2008. The program offered non-refundable tax credits for PHEV and BEV purchases made after 31st December 2009 (IRS, 2009). The credit varied by car model and is worth $2,500 plus $417 for each kilowatt-hour of battery capacity over 4 kWh and capped at $7,500.[4] 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.

Before IRA, the US federal tax-credit 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 use in the United States after 31st December 2009. The credit was unchanged in the quarter in which the manufacturer delivers the 200,000th subsidy-qualifying vehicle and in the next quarter. It reduced 50 percent of the original value for the next two quarters, 25 percent for the other two quarters, and then expired. All eligible plug-in vehicles sold during the phaseout period qualify for the credit. This design followed suit of the tax credit program for conventional hybrid vehicles (Energy Policy Act, 2005), allegedly designed to prevent dominant foreign manufacturers like Toyota and Honda from benefiting more than domestic manufacturers over the program's life (Lazzari, 2006;

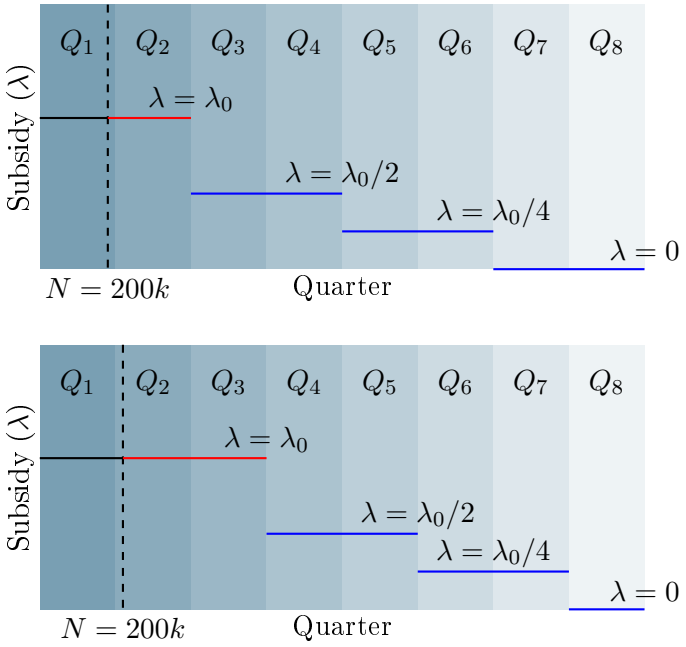
[3] Nissan and Mitsubishi were independent entities during the sample period (2011-2017) and are treated as such in the analysis.

[4] A consumer's purchase must meet specific requirements in order to be eligible for the tax credit. See Internal Revenue Code Section 30D for details.

Leonhardt, 2006). Interestingly, the first two manufacturers who hit the threshold (Tesla and GM) in the EV market are American. Tesla delivered the 200,000th qualifying vehicle in July 2018. Correspondingly, Tesla cars qualified for $7500 credit between July-December 2018, $3750 between January-June 2019, and $1875 between July-December 2019 (IRS, 2018). General Motors delivered the 200,000th qualifying vehicle in Nov 2018 and faced the subsidy expiration in April 2020 (IRS, 2019).

Because only two manufacturers have faced subsidy elimination in the US, I rely on structural methods in this paper 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 the consumers' and manufacturers' decisions, and use the estimated market parameters to simulate pricing equilibrium under counterfactual designs and compare market outcomes. 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, the conventional hybrid tax credit program has better data availability during and after the subsidy elimination because the program expired in 2010. Nonetheless, this paper focuses on the plug-in EV tax credit program for two reasons. First, in contrast to the plug-in EVs, conventional hybrids compared better than the dominant alternatives by combining the benefits of gasoline engines and electric motors. As a result, hybrid vehicles were already in high demand before the tax credits started. Second, in contrast to the EV tax-credit program that offers benefits up to $7500 and a 200,000 per-manufacturer cap, the hybrid tax-credit program offered tax credits only up to $3150 with a much lower per-manufacturer cap of 60,000. Toyota exhausted the quota within a few months of the program (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.

Figure 1: Subsidy Capping Design Adopted in the US



Notes: This figure explains the subsidy phaseout, which triggers in the second quarter after the EV manufacturer delivers the 200,000th subsidy-qualifying vehicle. In the first six months of the phaseout, any consumer who purchases a qualifying vehicle from that manufacturer receives 50 percent of the original subsidy. In the second six months, the subsidy further reduces to 25 percent and is completely eliminated thereafter. There is no limit to the number of vehicles that can receive subsidies during the phaseout period. Panels (a) and (b) show the subsidy evolution if the manufacturer exhausts the 200,000 threshold at the end of quarter $Q1$ versus at the beginning of quarter $Q2$, respectively. A quick look indicates that there substantial incentive to delay car 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 subsidy capping design in Figure 1 is a combination of a per-manufacturer quota of 200,000 vehicles and three per-manufacturer deadlines. The first two deadlines reduce the value of the credit, while the final deadline eliminates it. Compared to the per-manufacturer deadline, the per-manufacturer quota creates incentives to delay 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 the 200,000th vehicle to the next quarter (e.g., in July instead of June) can push the subsidy reduction ahead by three months. Second, the subsidy is eliminated only for the EV makers who exhaust the quota. As such, exhausting quota before others exposes an EV maker to fierce competition because others continue to benefit from the subsidy. By delaying the sales of subsidy-qualifying vehicles, EV-makers 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.

An EV maker'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 consumer learning and charging infrastructure development. Figure 2 demonstrates both these mechanisms. Consumer learning creates a feedback effect on demand: potential consumers experientially infer the quality of plug-in EVs as their exposure increases. This mechanism is vital for the infant EV industry because, in the absence of information about the quality of EVs, car drivers may be unwilling to purchase a technology different from the dominant designs. Marketing literature extensively focuses on "word of mouth" effects that consider uncertainty in product quality (Kalish and Lilien, 1983; Heutel and Muehlegger, 2015). Charging infrastructure creates a similar feedback effect: more charging stations allow more consumers to purchase an EV, and more EVs make entry more appealing for the charging stations. The role of charging infrastructure may not seem obvious, considering that consumers can charge EVs by plugging into an ordinary electric outlet. However, the ordinary outlets are very slow and not viable for traveling long distances exceeding the vehicle's battery capacity. The presence of fast charging infrastructure is crucial to ensure the vehicle's mobility, especially for BEVs since 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).

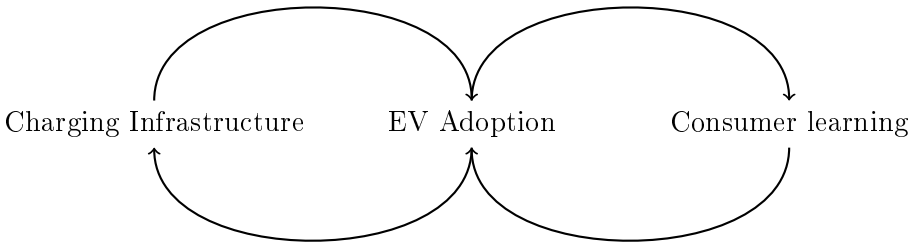
In the presence of such gains, EV makers facing a per-manufacturer quota faces two conflicting forces. On the one hand, surpassing the quota means forgoing future subsidies. On the other hand, staying below the quota means forgoing the network gains from additional sales. As a result, EV makers' response to a per-manufacturer quota depends 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 consumers' utility to depend on the cumulative EV sales by the manufacturer. For simplicity, I do not model the supply-side gains separately.

2.3 State-level Subsidies and ZEV Mandates

In addition to the federal subsidies, some state and local governments offer monetary or non-monetary incentives for EV purchases. Monetary incentives, on top of the federal tax credits, range from \$250 to \$7,500. The combined benefits can add up to \$13,000 or more per consumer in states like California. Examples of non-monetary incentives include access to carpool lanes and free meter parking.

California's zero-emission vehicle (ZEV) program has also significantly influenced the development of the plug-in EV market. Designed by the California Air Resources Board (CARB) 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.

Figure 2: Network Effect



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

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 either use credits accumulated in other years or buy credits from other manufacturers. Conversely, manufacturers that exceed their credit requirements can bank excess credits for use in later years or sell them to other manufacturers. For instance, Tesla and Nissan sold relatively higher BEV volumes than other manufacturers starting in 2012 and gathered 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 effect of subsidy-capping designs. Section 4 generalizes the example to the full oligopoly model that 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 price faced by the consumers:

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

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. Higher the value of η, the more valuable the early adopters. As described in the section 2, such network effect may be relevant for new technologies such as EVs due to consumer learning or charging network development.

Let λ_t denote the purchase subsidy in period t. The price faced by the consumers 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:

$$\underset{p_1,p_2}{max}(p_1 - c)Q_1(p_1 - \lambda_1) + (p_2 - c)Q_2(p_1 - \lambda_1, p_2 - \lambda_2)$$

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.

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

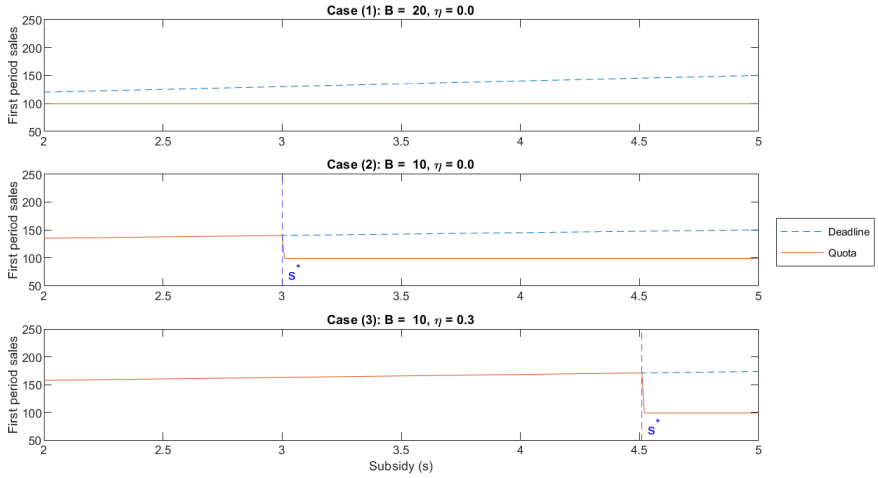
In contrast, the second design introduces a cap Γ on the number of subsidy-qualifying sales. All first-period buyers are eligible for the subsidy. Second-period buyers qualify for the subsidy only if first-period sales fail to exceed the quota.

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

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 differ under the two designs. Figure 3 illustrates this by comparing the optimal first-period sales under the deadline and quota ($\Gamma = 100$) designs as a function of the subsidy s. Panel (1) uses parameter values $A = 300$, $B = 20$, $c = 5$, and $\eta = 0$. A quick look at the figure indicates that, in this situation, the first-period sales vary substantially under quota and deadline. When facing a quota, the firm sells only Γ cars in the first period to secure subsidy in the second period. When facing a deadline, the firm makes no such attempt as the second-period subsidy does not depend on its actions.

The privately optimal prices and sales depend on the underlying parameters like price elasticity and the network effect. Panels (2) and (3) demonstrate this by varying parameters 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). In this situation, the gains from the subsidy are lower as compared to panel (1). As a result, the firm facing a quota stays below the quota when the subsidy exceeds a threshold s^*. When the subsidy is lower than s^*, the loss from selling fewer EVs in the first period offsets the gains from the subsidy in the second period. As a result, the firm behaves as if facing a deadline, and the two designs are equivalent. In panel (3), I increase the network effect η to 0.3 while keeping the price sensitivity as in panel (2). The firm facing a quota now faces a nontrivial dilemma: on the one

Figure 3: Deadline vs Quota in a Monopoly



Notes: This figure shows the first period sales as a function of the subsidy s in three different situations. Each panel fixes $c = 5$ and $A = 300$, but changes either the price coefficient B or the network effect η.

Case (1): The price coefficient $B = 20$ and the network effect $\eta = 0$. Then, if subsidy is below s^*, the firm sells fewer cars in presence of a quota as compared to a deadline to secure future subsidy.

Case (2): The network effect is as in case (1) but the price coefficient is lowered to $B = 10$. In this situation, s^* is higher than before; the firm reduces the first-period sales only when the subsidy is high.

Case (3): The price coefficient remains as in case (2) but network effect is raised to $\eta = 0.3$. In this situation, s^* is higher than in case (2).

hand, exhausting the quota shrinks the future demand; on the other hand, attracting early adopters encourages the future demand. In this situation, s^* is even higher than case (2), implying that the firm stays below the quota only when the subsidy is substantial.

Several lessons emerge from this simple analysis. First, a per-manufacturer quota can create incentives to delay EV sales. In the monopoly example, this incentive results from the timing component in the subsidy design – staying below the quota in any period allows the firm to qualify for the subsidy in the next period. In an oligopoly, this incentive will be reinforced because staying below the quota also protects the firm from fierce competition from others below the quota. Second, the effect of subsidy-capping designs depends on market parameters. In the monopoly example, it depends on the value of the subsidy, own-price elasticity, and network effect. In an oligopoly, market outcomes like profit distribution will also depend on the cross-price elasticities. By recovering the key market parameters, we can answer how subsidy-capping designs affect market penetration, gasoline consumption, consumer surplus, and firms' profits.

4 Full Model

I now describe the complete model with the consumer and manufacturers' decision problems in the 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. I focus only on the new vehicle market since used car sales are not relevant for manufacturers' profit maximization.

The demand specification follows the discrete-choice framework of Berry, Levinsohn, and Pakes (1995) and Petrin (2002), where consumers choose a single vehicle from all available fuel types. Including all the fuel types allows simulating what happens to the entire market of automobiles under counterfactual scenarios. To ease computation, I assume that consumers are myopic in that they do not consider the future evolution of prices or infrastructure while deciding and only purchase if the vehicle serves their present driving needs. In contrast, the supply side is an oligopoly with product differentiation where car manufacturers choose prices for all vehicles in their portfolio. I first use the estimated demand elasticities to recover the marginal costs in 2017 and then investigate what would have happened if the elimination occurred in 2017 under different subsidy-capping designs. In practice, subsidy elimination began in the US in 2018. However, as discussed below, I avoid this year in the estimation to ensure that the demand elasticities are not influenced by intertemporal substitution. While the 2017 data is imperfect to inform the effect of actual subsidy design directly, it allows examining the dynamic tradeoffs highlighted in Section 3 and predict the effect that different subsidy-capping designs would have had during 2017. I elaborate on the consumer demand and the car manufacturers' decision problems below.

4.1 Demand

Each period, the consumers arrive at the market to purchase a car. 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 characteristics as well as 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 price faced by the consumer 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 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 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 $t-1$. 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. Such attributes may include unobserved 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 consumers' utility from an EV to depend on the cumulative EV sales from the same manufacturer, as well as the cumulative EV sales from all manufacturers using the same type of charger. The rationale is that previous EV adoption from the same manufacturer in a geographic area mitigates the uncertainty in quality in that area, as early adopters help spread information about the quality of the products among the consumer pool. Moreover, the cumulative EV sales from all manufacturers using the same type of charger accounts for the available charging infrastructure network vital to guarantee EV drivers' mobility. The rich dataset used in the study includes car registrations since the recent development of the plug-in EV market in the US and allows calculating the cumulative EV sales in each geographic market precisely.

Modeling the vehicle purchase decisions as static is reasonable for buyers of conventional gasoline-powered vehicles as these vehicles do not evolve substantially over time. However, buyers of EVs may also care about the timing of their purchases to take advantage of better prices. For instance, if consumers believe that subsidies will expire, they may advance their EV purchases. To ensure that the demand parameters reflect actual purchase choices and not an intertemporal substitution, I estimate the demand model using data unaffected by the subsidy changes (i.e., 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, subsidy-induced timing effects are unlikely to be relevant, and the elasticities will likely reflect the actual changes in the vehicle choice. Although subsidy elimination may induce changes in the purchase timing, it is unlikely to affect the vehicle choice behavior. As a result, I can later 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 over time. The static assumption imposes that consumers' car purchase behavior is governed by their present driving needs, which is reasonable because they 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 the consumers would have to wait for a long time to get significant improvements in the

battery range.

Consumers make a vehicle purchasing decision by maximizing their utilities across all vehicle models with the outside option of non-purchase or purchase of a used vehicle. Since the consumers are myopic, the outside good does not include the option value of making the vehicle purchase decision in the future. The utility from 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

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

Since ϵ follows iid logit, the choice probability is:

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

The individual choices can be aggregated into a market-level demand system by integrating the choice probability over the distribution of demographics in the population. The share of vehicle j in the market mt is

$$s_{jmt} = \int \frac{exp(\alpha_i p_{jmt} + x_{jt}\beta_i + N_{jmt}\eta + \xi_{jmt})}{1 + \sum_{j' \in \mathcal{J}_{mt}} exp(\alpha_i p_{j'mt} + x_{j't}\beta_i + N_{j'mt}\eta + \xi_{j'mt})} dP(V).$$

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

4.2 Supply

I model the vehicle market as served by a multi-firm, differentiated-product industry where firms engage in Bertrand price competition. Given the market primitives, each firm f seeks to maximize the sum of profits in the current and the following year across all its products in all the geographic markets while taking the product mix as given. The profit for firm f is:

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

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 zero. 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-electric vehicles, plug-in hybrids, and hydrogen fuel cell vehicles earned ZEV credits depending on their battery charge time and range. Vehicles with a range of fewer than 50 miles earned one credit, while vehicles 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 Honda Civic and Toyota Prius (AT-PZEV) earned up to 0.8 of a ZEV credit, and gasoline vehicles with lower emissions (PZEV) than federal standards earned up to 0.2 of a ZEV 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 2218.

A two-period pricing model is vital to examine how firms respond when the dynamics of elimination become relevant. For instance, firms facing a per-manufacturer quota on subsidies may increase EV prices to delay exhausting the quota. A static model will fail to capture such adjustments. The two-period pricing 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 demand. For instance, the model allows the firms facing a per-manufacturer quota to keep the prices low and surpass the quota if they believe that raising current 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 higher discount factor.

The prices chosen in year t affect the profits in year $t+1$ by influencing only a set of commonly observed state variables, i.e., the value of EV subsidies and the 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

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

In 2017, all the EV manufacturers in the US were way behind the quota of 200,000 vehicles. As a result, their profit maximization problems in 2017 are not constrained by the quota, ensuring

that $\Pi^*_{f,t+t}(p_{.t})$ is differentiable in $p_{.t}$. Therefore, the necessary optimality condition in period t with respect to 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:

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

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.

Some caveats of the model are noteworthy. First, firms control sales only through short-run price changes. Vehicle characteristics other than the price evolve exogenously, which is reasonable because manufacturers typically make product decisions over a longer horizon than pricing decisions. In practice, firms facing a per-manufacturer quota could also delay sales by creating an artificial shortage. I do not model this mechanism in the absence of such data. While such simplification does not affect the model estimation, it affects how firms respond to counterfactual subsidy-capping designs. I discuss the implications of this assumption further in Section 7. Second, throughout the analysis, I abstract from entry and exit decisions. In practice, subsidy capping designs may also affect firms' entry into the EV market. While this concern was important when the subsidy was enacted in 2009, it is less relevant today because most major manufacturers in the US already have some EVs in their portfolio.

Finally, other overlapping regulations imposed on vehicle manufacturers, like federal corporate average fuel economy (CAFE) and greenhouse gas (GHG) standards, also create incentives to increase EV sales. CAFE and GHG standards influence the market on the supply side by imposing limits on the average fuel economy and greenhouse emissions of the vehicles that a manufacturer sells each year. Both regulations grant extra credits to EVs and, hence, create incentives for manufacturers to sell more EVs. For simplicity, I ignore the incentives created by both these regulations. 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, ignoring the quota-induced incentive to delay sales. 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 like banking credits from over-compliance in one year 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 and 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 comes from various sources. First, the vehicle sales data purchased from IHS markit contains new light-duty vehicle registrations in 30 states during the calendar years 2011-2017. The selected states capture the highest EV market share in 2016. I use these states to define a geographic market. Since the EV market mostly developed after 2010, the data capture this market from the outset. A vehicle is a unique model year, make, model, and fuel type. I use vehicle registrations for all fuel types to account for substitution between all fuel types. For each market, I estimate the market 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 one and the sum of inside goods market shares. I exclude the models with very low 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 the 1st January of the calendar year. It typically runs from October to September of the next year (e.g., 2016 models were released in 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. Since I do not observe the 2011 models sold in the 2010 calendar year, I only use 2011 data to calculate cumulative EV sales in each market but not in the demand estimation. In total, there are 62,588 observations of vehicle shares over 30 states between 2012-2017.

Second, 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, the vehicle registration data is at the make-model-fuel level. Hence, I match the total vehicle registrations to the characteristics of the base model. Vehicle characteristics include the MSRP, horsepower, curb weight, wheelbase, size-related measures (length and width), fuel type, and fuel efficiency. The demand model allows consumers' utility to depend on the size, performance, cost of driving, and battery range (for EVs). I measure size by the product of length and width, performance by the ratio of horsepower and curb weight, and cost of driving by the state-level fuel price per gallon divided by the vehicle's fuel economy. The cost of driving varies with two sources: the vehicle's fuel economy and the market-level fuel prices. Thus, a high gas price in a state raises the cost of driving all gasoline vehicles in that state. State-level fuel prices come from the US Energy Information Administration (EIA).

Although average transaction prices are preferred in demand estimation, such data are not readily available. Instead, I collect manufacturers' retail discount discounts from Automotive News and federal and state-level subsidies from the US Department of Energy to approximate the prices faced by consumers and firms. Federal and state-level subsidies vary across models and time. In the

presence of purchase subsidies, the price that enters the firms' profit function is different from the price faced by the consumer. The price that enters the profit function is the difference between MSRP and the average discounts provided by the manufacturer in that year. The price faced by consumers is the difference between MSRP and all the purchase incentives, including manufacturer discounts, federal subsidies, and state-level subsidies. Federal subsidies take the form of non-refundable tax credits, so in practice, the subsidy amount depends on the taxpayer's income tax liability. For simplicity, I assume that all customers can claim the full tax credit. The justification, here, 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 US dollars.

Finally, I obtain the list of makes for each manufacturer from the annual EPA Auto trend reports. Consistent with the regulatory definitions, I assume that different makes of the same parent manufacturer classify as a single firm. For example, Buick, Cadillac, Chevrolet, GMC, Hummer, and Saturn are all part of General Motors.

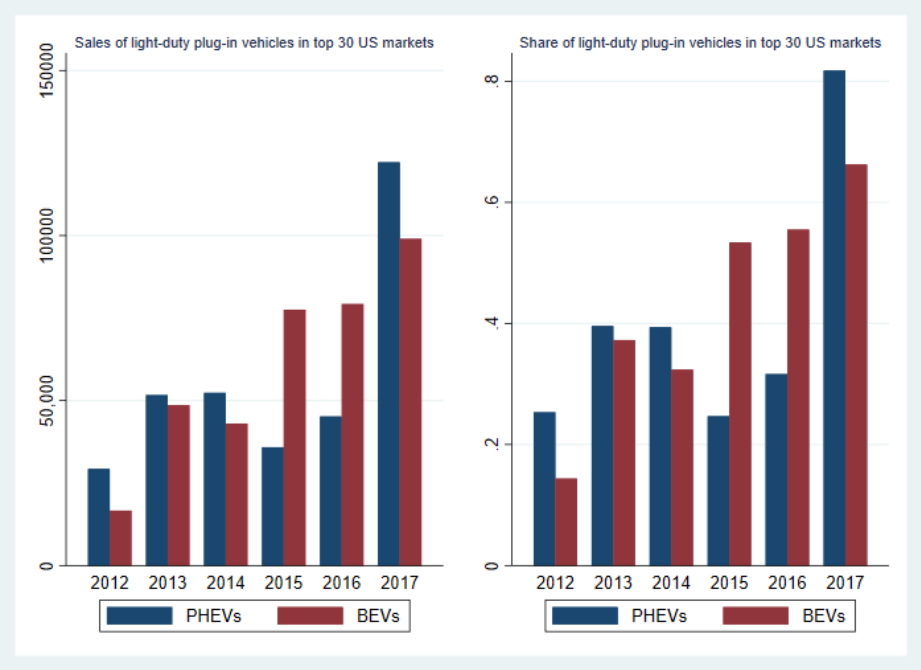
5.2 Summary Statistics

Table 1 summarizes the sales and the 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, total sales, size (length×width), performance (in HP per 10 lb), cost of driving (in dollars per ten miles), and battery range (in miles) separately for plug-in EVs and other fuel-type vehicles. The available EV models rose from 7 in 2012 to 32 in 2017; their total sales in the sample states rose from 46 thousand in 2012 to 221 thousand in 2017. Models of other fuel types rose from 331 in 2012 to 365 in 2017; their total sales in the sample states rose from 11.5 million in 2012 to 14.7 million in 2017. The average vehicle size remained fairly stable across both types. The average vehicle performance for EVs increased from 0.36 Hp/10 lbs in 2012 to 0.47 Hp/10 lbs in 2017, while that of other fuel types remained stable at around 0.58 Hp/10 lbs. The average cost of driving for EVs remained stable at around \$0.05 per ten miles, while 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 53.26 miles in 2012 to 116.14 miles in 2017. Figure 4 shows the annual share of both varieties of plug-in EVs in the sample states between 2011-2017. The sales and share of both BEVs and PHEVs went up in the sample states. Together, they represented 1.5% of the domestic automobile sales by 2017.

Figure 5 shows all the EV makers in the industry with their year of entry on the horizontal axis and the total vehicles sold in the sample states of the US on the vertical axis. Table 2 summarizes the plug-in EV models and the nominal value of federal EV subsidies for each manufacturer in 2017. The subsidy ranged from \$3793 for BMW I8 (PHEV) to \$7500 for pure BEVs. The subsidy remained unchanged for all models in the sample period.

Table 3 summarizes the plug-in EV sales and regulations in all 30 markets for 2017. Columns (1)-(4) summarize the total number and percentage of plug-in EV sales and the presence of purchase

Figure 4: Sales and Fraction of Light-duty Plug-ins in the Sample States



Notes: The figure shows the evolution of the plug-in EV industry in US in the first eight years. The horizontal axis in each panel shows the model years. The left and the right panels show the total plug-in sales and the fraction of plug-ins in the sample states.

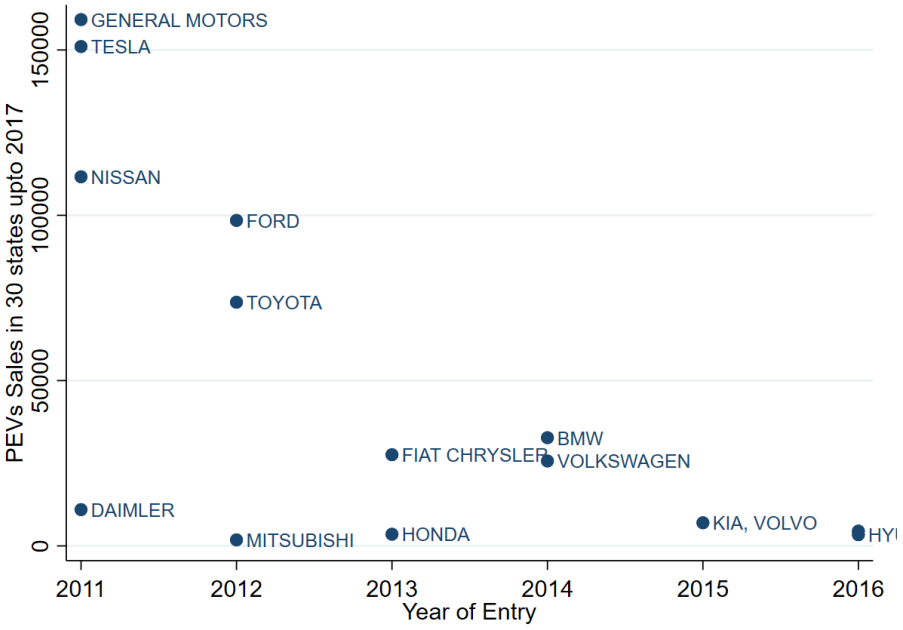
incentives and ZEV mandates. The subsequent columns show the average demographics in these states from the March CPS. Six of the 30 states provide some subsidies for plug-in EVs, and eight have the ZEV requirement. A quick look shows that states with subsidies or ZEV mandates have higher plug-in EV sales. The percentage of plug-in EV sales is highest in California (3.88%) and lowest in Oklahoma (0.09%).

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

Year	Models		MSRP ($'000)		Sales ('000)		Size ('0000 in ^{2})		Performance (Hp/lb)		Driving Cost ($/10 miles)		Battery Range (miles)	
	EV	Other	EV	Other	EV	Other	EV	Other	EV	Other	EV	Other	EV	Other
2012	6	331	37.66	25.00	45	11523	0.74	0.80	0.36	0.58	0.05	0.16	53.26	0.00
2013	10	351	38.99	25.78	100	12957	0.76	0.81	0.42	0.58	0.05	0.15	83.52	0.00
2014	17	369	40.79	25.96	94	13202	0.76	0.82	0.42	0.58	0.05	0.14	83.80	0.00
2015	19	374	43.85	26.66	113	14420	0.76	0.81	0.48	0.58	0.04	0.10	102.36	0.00
2016	25	357	49.76	26.49	124	14159	0.82	0.82	0.56	0.58	0.04	0.09	133.12	0.00
2017	32	365	41.76	26.69	221	14725	0.79	0.82	0.47	0.58	0.04	0.10	116.14	0.00

Notes: This table shows the evolution of key variables in the sample states between 2012-2017, using vehicle registration data from IHS Markit and vehicle characteristics data from Wards, EPA and Edmunds. Columns (6)-(9) show the sales-weighted average vehicle characteristics. Size is length× width (in '0000 in^2), performance is Horsepower by curb weight (in 10 lb), driving cost is fuel cost (in dollars) per ten miles, and battery range is the all electric range (in miles) for EVs.

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



Notes: This figure shows the major plug-in EV manufacturers in the US based on vehicle registration data from IHS Markit. For each manufacturer, the x-coordinate shows the year in which their first plug-in EV sale appears in the sample. The y-coordinate shows the total plug-in sales between 2011-2017.

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 EV models and federal consumer subsidies in 2017 for each manufacturer.

6 Estimation and Results

The next step is to estimate the structural model described in Section 4. I first estimate the demand system and then recover marginal cost assuming that the data are generated by static 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, smoothness of the ride, and expected resale value, cannot be measured directly. However, the price will likely reflect these unobserved characteristics if they are costly for the vehicle manufacturer or affect the demand for the vehicle. Similarly, the advertisement efforts of the manufacturer are unobserved but may be correlated with the pricing discounts. Second, I do not observe the average vehicle transaction price and instead approximate the price using MSRP minus purchase incentives. As a result, variations in the retail price across markets enter $\Delta\xi_{jmt}$ in equation 1. Both cases result in price endogeneity.

Table 3: State-Level EV Sales, Incentives and Demographics

Market	Plug-in sales	Percent of Total sales	Plug-in Incentives	ZEV State	Age	Nchild
ARIZONA	17,368	0.77	-	-	47.7	1.1
CALIFORNIA	483,996	3.86	Yes	Yes	47.3	1.1
COLORADO	19,173	1.12	Yes	-	49.0	1.0
CONNECTICUT	10,641	0.92	Yes	Yes	50.0	0.9
FLORIDA	38,977	0.47	-	-	46.9	1.1
GEORGIA	33,682	1.07	-	-	52.1	0.9
HAWAII	9,155	1.76	-	-	47.8	1.1
ILLINOIS	22,209	0.52	-	-	47.6	1.1
INDIANA	5,916	0.37	-	-	49.0	1.0
MARYLAND	17,457	0.81	Yes	Yes	48.9	1.0
MASSACHUSETTS	22,147	0.95	Yes	Yes	49.0	1.0
MICHIGAN	23,507	0.58	-	-	47.4	1.1
MINNESOTA	8,537	0.52	-	-	47.8	1.1
MISSOURI	6,590	0.35	-	-	47.1	1.1
NEVADA	6,100	0.68	-	-	50.0	1.0
NEW HAMPSHIRE	3,302	0.55	-	-	48.9	1.0
NEW JERSEY	25,418	0.67	-	Yes	48.8	1.0
NEW YORK	45,861	0.70	Yes	Yes	47.9	1.0
NORTH CAROLINA	12,618	0.45	-	-	48.4	1.1
OHIO	12,598	0.32	-	-	47.5	1.1
OKLAHOMA	4,574	0.09	-	-	48.5	1.0
OREGON	20,653	1.95	-	Yes	49.4	1.0
PENNSYLVANIA	17,805	0.42	-	-	47.7	1.0
TENNESSEE	7,461	0.41	-	-	46.5	1.1
TEXAS	32,472	0.34	-	-	44.8	1.5
UTAH	6,548	0.82	-	-	50.0	1.0
VERMONT	3,294	1.22	-	Yes	47.8	1.1
VIRGINIA	15,995	0.62	-	-	48.2	1.1
WASHINGTON	39,549	2.19	-	-	48.7	1.0

Notes: Columns (1) and (2) shows the total plug-in EV sales and percent of plug-in EV sales as a percentage of total new car sales during 2011-2017 based on IHS 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. The subsequent columns show the mean demographics in 2017 based on March CPS. Age is the age of the household head. Nchild is the number of children in the household.

Identification requires a set of exogenous instruments. Vehicle characteristics other than price are valid instruments for themselves as they are a 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 all the firm's other vehicles' characteristics and the sum over all the competing brands' characteristics 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:

$$z_{jmt}^k = (x_{jt}^k, \sum_{r \neq j, r \in \mathcal{J}_{fmt}} x_{rt}^k, \sum_{r \neq j, r \notin \mathcal{J}_{fmt}} x_{rt}^k) \tag{5}$$

Overall, there are ten excluded instruments.

These instruments vary over vehicle models in each market and across time. They are relevant as 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 vehicles to be different from the substitution with other firms' vehicles. For instance, consumers who will switch away to another of the same firm's vehicles following a price increase do not represent as much of a loss as the consumers who switch to other firms' vehicles. 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, if demand unobservables are serially correlated, then the estimated network-effect parameters are inconsistent. Here, I maintain the assumption that the demand unobservables are not serially correlated conditional on the market and year fixed-effects.

Following Berry, Levinsohn, and Pakes (1995) and Nevo (2000), I estimate the demand parameters using simulated Generalized Method of Moments using the population moment condition that is a product of instrumental variables described above with the unobservable demand shocks $\Delta\xi_{jmt}$. At each trial value of θ_2, I first obtain the constants δ_{jmt} by equating predicted shares to the observed market shares and use them to solve for $\Delta\xi_{jmt}$. The GMM objective function is $M(\theta_1, \theta_2)\Omega M(\theta_1, \theta_2)'$ where $M(\theta_1, \theta_2)$ denotes the empirical moment conditions and the Ω denotes the weighing matrix. The demand estimation proceeds in two steps. In the first step, I set $\Omega = \frac{1}{n}(Z'Z)^{-1}$ to obtain initial consistent parameter estimates. In the second step, I recompute the optimal weighting matrix based on the first-step estimates and re-estimate the model. Finally, I compute the markups and marginal cost of vehicles implied by the demand estimates and the first-order conditions of the firms' profit functions.

6.2 Results

Table 4 shows the results from the estimating demand derived from the indirect utility specification in equation 1.[5] The first eight rows show the coefficients measuring the mean valuations. Most coefficients are precisely estimated and have expected signs. Price enters with a negative coefficient indicating that consumers dislike high prices, all else held equal. The size of the vehicle and the horsepower to weight ratio have positive coefficients, indicating that consumers value size and power. The negative coefficient on the cost of driving per mile implies that consumers prefer high fuel efficiency, which reduces the cost per mile. The signs on the BEV and PHEV indicators are negative, indicating that in the absence of a network (i.e., zero cumulative EV sales) and ceteris paribus, plug-in EVs are less preferred to the conventional models. In addition, comparing the magnitudes of BEV and PHEV indicators suggests that BEVs are less preferred to PHEVs, possibly because they do not have a gasoline backup. The next two rows show the interactions between EV indicators and cumulative EV sales in the state by the vehicle's manufacturer. These terms have positive signs, indicating that consumers gain more utility from BEVs and PHEVs as the vehicle manufacturer's network develops. The next two rows show the interactions between EV indicators and cumulative sales of all the EVs with the same charger type in the state. Both coeffcients are negative, possibly reflecting competition from other EV manufacturers. The subsequent rows show the estimates of five random coefficients that measure the dispersion in households' tastes. These coefficients are the standard deviations of the tastes for the vehicle characteristics.

Table 5 presents a sample of own and cross-price elasticities, markups, and marginal costs implied by the demand estimates. Each row in this table corresponds to a different vehicle; the first four rows correspond to the top four plug-in EVs by sale in 2016, the next three rows correspond to the top conventional cars, and bottom three rows correspond to the top pickup trucks. Each entry gives the percentage change in demand of the row vehicle associated with a 1% increase in the price of the column vehicle. Price elasticities differ across markets for each product. In contrast, marginal costs are identical across the markets for each product. 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 Chevrolet Silverado (pickup) shifts the consumers disproportionately to Ford F-series (pickup). Table 6 summarizes the elasticities, markups, and marginal costs for all vehicle models in 2017. The average own-price elasticity is -3.17. Among the 397 models, the marginal costs range from $12,384 at the 25th percentile to $37,639 at the 75th percentile.

7 Counterfactual Experiments

The next step is to compare market outcomes under different subsidy-capping designs. I examine three designs: a market deadline, per-manufacturer deadline, and per-manufacturer quota. In each

[5] Appendix B provides the details of the first stage estimation. The first-stage F-statistic for the excluded instruments is 345.001.

Table 4: Demand Estimates

Variable	Coef	SE
Mean Valuations		
Price	0.040	0.216
Constant	-11.090***	1.009
Vehicle Size	3.944***	0.469
Performance (Hp/wt)	1.307***	0.165
Driving Cost	-0.181	3.203
Battery Range	0.080***	0.011
BEV	-1.590***	0.347
PHEV	-0.248	0.397
Network Effects		
BEV × log(1+ MFr Cumulative EV Sales)	0.170***	0.031
PHEV × log(1+MFr Cumulative EV Sales)	0.123**	0.058
BEV × log(1+ Same-Charger EV Sales)	-0.187***	0.036
PHEV × log(1+Same-Charger EV Sales)	-0.085	0.078
Random Coefficients		
Price	0.372***	0.117
Vehicle Size	1.660	6.507
Driving Cost	1.575***	0.390
Van	0.143	12.785
Pickup	3.438**	1.584
SUV	0.056	1.939
Fixed Effects		
State FE	Yes	
Time FE	Yes	
Segment FE	Yes	
Obs	62588	

Notes: This table shows the estimates from the flexible logit model. A unit of observation is a vehicle-state-year. Size is length× width (in '0000 in^2), performance is Horsepower by curb weight (in 10 lb), driving cost is fuel cost (in dollars) per ten miles, and battery range is the all electric range (in miles) for EVs. Cumulative EV Sales shows total EVs sold by the manufacturer 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)	CHEVROLET BOLT (BEV)	-2.213	0.002	0.004	0.002	0.017	0.015	0.017	0.005	0.005	0.003	35,168	6,583	29,033
(2)	CHEVROLET VOLT (PHEV)	0.001	-1.962	0.003	0.002	0.017	0.016	0.017	0.005	0.005	0.003	31,155	9,804	21,773
(3)	TESLA MODEL S (BEV)	0.001	0.002	-3.783	0.001	0.016	0.014	0.015	0.005	0.004	0.003	65,752	10,611	55,065
(4)	TOYOTA PRIUS PRIME (PHEV)	0.001	0.002	0.003	-1.759	0.017	0.016	0.017	0.005	0.005	0.003	25,157	10,468	15,097
(5)	HONDA ACCORD (GAS)	0.001	0.002	0.003	0.002	-1.821	0.016	0.017	0.005	0.005	0.003	21,616	11,156	10,460
(6)	HONDA CIVIC (GAS)	0.001	0.002	0.003	0.002	0.017	-1.577	0.017	0.005	0.005	0.003	18,121	10,813	7,308
(7)	TOYOTA CAMRY (GAS)	0.001	0.002	0.003	0.002	0.017	0.016	-1.678	0.005	0.005	0.003	19,561	11,367	8,194
(8)	FORD F (GAS)	0.000	0.000	0.001	0.000	0.003	0.003	0.003	-2.206	0.161	0.103	26,214	11,777	14,437
(9)	CHEVROLET SILVERADO (GAS)	0.000	0.000	0.001	0.000	0.003	0.003	0.003	0.166	-2.243	0.103	26,673	12,312	14,361
(10)	TOYOTA TACOMA (GAS)	0.000	0.000	0.001	0.000	0.003	0.003	0.003	0.170	0.165	-2.062	23,400	11,095	12,305

Notes: Columns (1)-(10) report average cross-price elasticities for ten 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% in the markets where both products are available. Columns (11),(12), and (13) report the prices, markups and marginal costs, respectively.

Table 6: Marginal Cost Estimates

Variable	Mean	25%	Median	75%	Std Dev	Obs
Price before subsidy (USD)	51,009	23,992	33,040	52,313	582,553	397
Own-price elasticity	-3.17	-3.46	-2.51	-1.94	2.38	397
Markup, (USD)	13,241	11,529	12,454	14,361	2,939	397
Marginal cost, (USD)	37,812	12,384	21,726	37,639	55,859	397

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.

case, I use the parameter estimates from Section 6 to recompute the pricing equilibria under the two-stage game described in Section 7.2, and calculate the market outcomes of interest, assuming that product offerings, marginal costs, demographics, and state-level subsidies stay at the observed 2017 levels.

7.1 Counterfactual Subsidy-Capping Designs

I examine three counterfactual designs.

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

$$\lambda_{jt}^{(1)} = \lambda_j^0 \mathbf{1}(t \leq 2017)$$

   where λ_j^0 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 EVs manufactured by Tesla or GM up to the end of 2017 qualify for a subsidy. Consumers who buy other brands qualify in both 2017 and 2018. The subsidy evolves as follows:

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

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

$$\lambda_{jt}^{(3)} = \lambda_j^0 \Big[\sum_{\tau=2011}^{t-1} \sum_{j \in \mathcal{J}_{f\tau}, j \in \mathcal{J}_{\mathcal{EV}}} Q_{j\tau}^{(3)} \leq \kappa \Big]$$

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

Because I only observe annual vehicle sales, I allow counterfactual designs to affect the federal

Table 7: Features of Counterfactual Subsidy-Elimination Designs

Feature	Market-wide Deadline	Per-Manufacturer Deadline	Per-Manufacturer Quota
Differential elimination	×	✓	✓
Incentive to delay	×	×	✓

subsidies at a yearly level. In practice, the US phaseout design affects the subsidies at a quarterly level. The per-manufacturer deadline and per-manufacturer quota are inspired by the US phaseout design, which is a combination of both these designs. The choice of Tesla and GM for a per-manufacturer deadline is guided by the fact that these manufacturers had the highest cumulative EV sales up to 2017, which allows for convenient comparison with the per-manufacturer quota – a design that only affects Tesla and GM in the simulations. In practice, per-manufacturer deadlines may also depend on the year of entry. Table 7 summarizes the features of each subsidy-capping design. Under a market-wide deadline, the elimination coincides for all manufacturers. In addition, there is no incentive to delay EV sales in 2017 because firms' actions do not affect whether they qualify for a subsidy in 2018. Under a per-manufacturer deadline, the elimination occurs for manufacturers according to their individual deadlines. As before, there is no incentive to delay EV sales. Finally, under a per-manufacturer quota, the elimination occurs for manufacturers based on when they exhaust the quota. As a result, there is an incentive to delay EV sales in 2017.

7.2 Computing Equilibrium under a Per-Manufacturer Quota

Solving for the optimal price vector $p^*_{.t}$ under a per-manufacturer quota introduces important computational challenges because $\Pi^*_{f,t+1}(p_{.t})$ is not differentiable in $p_{.t}$. 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[6]: First, based on the observation that manufacturers other than Tesla and GM sold very few EVs up to 2016, I conjecture that these manufacturers do not cross the quota in the equilibrium. I then consider four scenarios, depending on Tesla and GM's choice of whether to cross the quota in 2017 (discussed below). 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	(π^T_{CC}, π^G_{CC})	(π^T_{CD}, π^G_{CD})
Don't Cross	(π^T_{DC}, π^G_{DC})	(π^T_{DD}, π^G_{DD})

The payoff vector in each cell of the matrix represents the sum of profits in periods t and $t+1$

[6] Alternative solution is to use grid-search algorithms. However, these algorithms tend to be very slow.

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 profits, subject to the constraint that its cumulative EV sales stay below the quota.

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

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

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 market-wide deadline and the per-manufacturer deadline because firms cannot control 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. Government expenditure in period t under counterfactual c is $\sum_j \lambda^{(c)}_{jt} Q^{(c)}_{jt}$. Since expenditure changes across the experiments, I report it to facilitate direct comparison between different elimination designs. 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

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

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 $\int_i \Delta CS_{imt} dP(D)$. The total change in consumer surplus is the sum of changes in all markets $\sum_m \int_i \Delta CS_{imt} dP(D)$. Profits are calculated using equation 2. Finally, the total gasoline consumption from the vehicles sold in period t under 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 travelled 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 alternative subsidy-capping designs. Overall, the results show that each elimination design has different implications for the EV market penetration, environmental impact, and the distribution of gains across consumers and manufacturers.

I elaborate on the results below.

Figure 6 shows the cumulative EV sales for Tesla, GM, and Nissan under a market-wide deadline, a per-manufacturer deadline, and a per-manufacturer quota of 120,000.[7] Panel (a) shows the cumulative EV sales between 2011-2017. The blue bars indicate the total EV sales between 2011-2016, as observed in the data, and the orange bars indicate the EV sales in 2017 under the recomputed equilibria. Panel (b) adds yellow bars showing EV sales in 2018 under the recomputed equilibria.

The 2017 outcomes remain the same under the market-wide and the per-manufacturer deadlines because, in either case, the manufacturers cannot control the status of subsidies in 2018. In contrast, when facing a per-manufacturer quota, Tesla and GM stay below the quota of 120,000 vehicles to ensure the subsidy in 2018. As shown in Table 8, these manufacturers lower EV sales in 2017 by raising the prices of and lowering the prices of conventional vehicles in 2017. For instance, compared to the per-manufacturer deadline (Column (3)), GM raises the price of Chevrolet Bolt by $11,987 under a per-manufacturer quota (Column (4)). Two factors drive this incentive: (1) Staying below the quota in any period allows manufacturers to qualify for the subsidy in the next period, and (2) As the subsidy is eliminated only for the EV makers who exhaust the quota, staying below the quota protects the EV-maker from fierce competition from other manufacturers below the quota.

The effect on EV sales in 2018 depends on who qualifies for subsidies in 2018. No manufacturer qualifies for the subsidy under a market-wide deadline; all manufacturers except Tesla and GM qualify under a per-manufacturer deadline. Figure 6 shows that, as a result, Tesla and GM sell fewer EVs under a per-manufacturer deadline than under a market-wide deadline. Meanwhile, other EV-makers like Nissan charge higher prices and sell more EVs. In contrast to the first two designs, Tesla and GM qualify for subsidies in 2018 under the per-manufacturer quota. As a result, they sell more EVs in 2018 than under either of the deadlines. For instance, Appendix 13 shows that Tesla's EV sales rise by 67.5% under a per-manufacturer quota compared to the per-manufacturer deadline. As a result, the higher EV sales in 2018 offset the low sales in 2017.

As market outcomes differ among manufacturers and over time, I report the aggregate market-level outcomes in Table 9 using no subsidy as the benchmark counterfactual. Since the total government expenditure changes across these designs, I also report the total government expenditure for each design.[8] Panel (a) shows the aggregate market outcomes in the year 2017. The outcomes under the market-wide deadline and the per-manufacturer deadline are similar, as expected. In contrast, the outcomes under the per-manufacturer quota are governed by Tesla and GM trying to stay below the quota. Both manufacturers charge higher prices for their plug-in EVs. Because of these efforts, the subsidy-induced EV sales are 76.2% lower compared to the deadline designs. Moreover, the reduction in conventional vehicle sales is lower as consumers substitute from the high-priced EVs towards lower-cost conventional alternatives. The subsidy-induced consumer surplus reduces by 240%, the aggregate manufacturer profits reduce by 17.2%, and the government expenditure is

[7] Appendix table 13 reports the EV sales separately for all manufacturers.

[8] Alternative strategies to compare the designs include fixing the government expenditure across the experiments by changing subsidy duration or subsidy amount. Both approaches have limitations. Changing the duration complicates equilibrium computation, and changing the subsidy amount changes firms' decisions under a per-manufacturer quota, as shown in Figure 3.

36.9% lower. The outcomes under a per-manufacturer quota are striking because even though the subsidies are meant to encourage EV sales, manufacturers' efforts to delay the subsidy elimination result in lower prices and higher sales of conventional vehicles. Again, this outcome is partly driven by the modeling assumption that firms control the sales of their EVs only through prices. As a result, GM lowers the prices of conventional vehicles and raises the prices of EVs in effort to stay below the quota. In practice, if manufacturers delay EV sales by creating an artificial shortage of EVs, the conventional vehicle sales and consumer surplus may not rise as much. Nonetheless, the results demonstrate the possible spillovers on the other products in an oligopoly with product differentiation.

Panel (b) shows the aggregate market outcomes in the year 2018. The outcomes under the market-wide deadline are close to the no-subsidy counterfactual. Although the government expenditure in 2018 is zero, the EV sales are higher than the no-subsidy counterfactual because of network effect gains from the 2017 subsidies. This outcome shows the long-term impact of the EV subsidies. Specifically, by reducing the upfront cost of EVs, purchase subsidies raise the sales of EVs in 2017. Because EV consumers care about the previous EV adoption, the demand shifts right in 2018. Compared to the market-wide deadline, the subsidy-induced EV sales, consumer surplus, and aggregate manufacturer profits are substantially higher under a per-manufacturer deadline because all manufacturers other than Tesla and GM continue to qualify for the 2018 subsidies. Similarly, compared to the per-manufacturer deadline, the subsidy-induced EV sales, consumer surplus, and manufacturer profits are substantially higher under a per-manufacturer quota because, in addition to other manufacturers, Tesla and GM qualify for the 2018 subsidies.

Panel (c) shows these market outcomes summed over the two years. The market-wide deadline is the least expensive and results in the lowest EV sales, consumer surplus, and manufacturer profits. The per-manufacturer deadline is more expensive and results in the highest EV sales and lowest conventional vehicle sales and gasoline consumption. Finally, the per-manufacturer quota is the most expensive and results in the highest conventional vehicle sales, consumer surplus, and manufacturer profits due to the possible spillovers on conventional vehicles. Moreover, consumers experience three-fourths of the gains due to these spillovers.

Panel (d) shows the aggregate two-period outcomes normalized by the government expenditure. 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 for a government expenditure of \$1 million, EV subsidies with a market-wide deadline sell around 66 more EVs and 18 fewer conventional vehicles than the counterfactual with no subsidy. The program results in 1.21 million gallons lower fuel consumption, \$0.04 million higher consumer surplus, and \$0.54 million higher manufacturer profits. Similarly, EV subsidies with a per-manufacturer deadline sell around 68 more EVs and 18 fewer conventional vehicles than the counterfactual with no subsidy. The program results in 1.25 million gallons lower fuel consumption, \$0.03 million higher consumer surplus, and \$0.55 million higher manufacturer profits. Finally, EV subsidies with a per-manufacturer quota sell 50 more EVs and 14 fewer conventional vehicles than the counterfactual with

no subsidy. The program results in 0.92 million gallons higher fuel consumption, $0.02 million lower consumer surplus, and $0.61 million higher manufacturer profits. Note that the sum of consumer surplus and manufacturer profits does not reflect welfare because of 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.

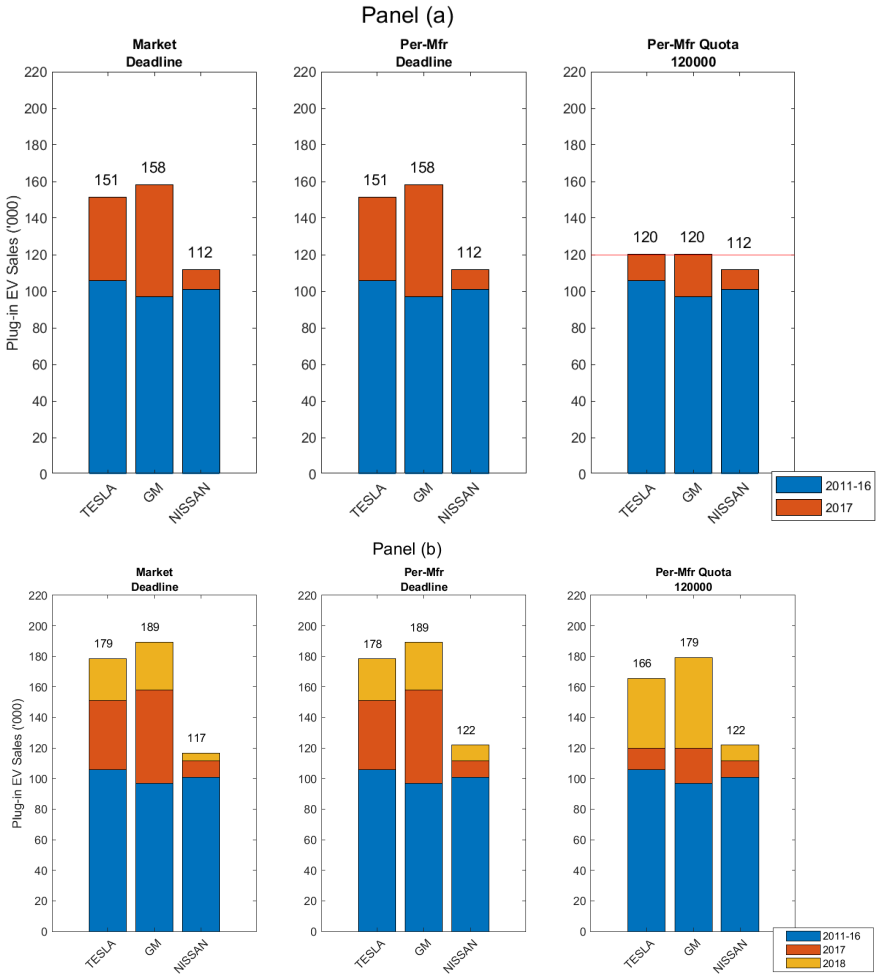
Table 10 decomposes the profits across manufacturers under different counterfactuals. Tesla earns at least $255 million (or 29%), GM earns at least $279 million (0.4%), and Nissan earns at least $71 million (0.2%) more profits from EV subsidies than the no-subsidy. EV subsidies have a much higher impact on Tesla (as a percent of total profits) because it focuses exclusively on EVs. Compared to a market-wide deadline, a per-manufacturer deadline disproportionately shifts profits away from Tesla and GM, because they do not qualify for subsidies in 2018 while others continue to qulaify. Among the three subsidy designs, Tesla and GM earn higher profits under the per-manufacturer quota than the deadlines because they qualify for subsidies in 2018. For instance, Tesla's profits rise by 4.2% compared to the per-manufacturer deadline. Other EV manufacturers like Nissan and Toyota also earn the highest profits under the per-manufacturer quota because they qualify for subsidies in 2018 and face less competition from Tesla and GM in 2017. These manufacturers earn lowest profits under the market-wide deadline when they do not qualify for subsidies in 2018.

Overall, the results show that there is a substantial incentive for manufacturers to delay EV sales under a per-manufacturer quota, 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 reduction in EV sales in 2017, the combined normalized sales over the two years are 26% lower when compared to either deadline design. This observation shows that deadlines are more cost-effective in aiding EV market penetration. Moreover, because EV manufacturers are multi-product oligopolists, the designs may also affect the sales of conventional vehicles. As a result, these designs affect consumer surplus, manufacturer profits, and liquid fuel consumption. Finally, each subsidy elimination design affects the profit distribution across manufacturers differently. Compared to a market-wide deadline, a per-manufacturer deadline disproportionately shifts profits away from the manufacturers that face the deadline. In contrast, a per-manufacturer quota does not necessarily shift profits away from manufacturers facing a quota because it allows them to control when the subsidy expires.

8 Conclusion

This paper demonstrates the implications of subsidy-capping provisions in purchase-subsidy programs designed to promote infant green technologies. I focus on the US plug-in EV market, an important market to understand considering its potentially enormous environmental benefits. Using a monopoly example, I first show that the subsidy-capping provisions may aid or hinder the EV market penetration, and the magnitude of the effect depends on structural primitives like own- and

Figure 6: Effect of Elimination Designs on EV Sales



Notes: This figure shows the cumulative plug-in EV sales (in thousands) under different elimination designs for the three dominant EV-makers. Panel (a) shows the cumulative EV sales between 2011-2017. The blue bars indicate the total EV sales between 2011-2016, as observed in the data, and the orange bars indicate the EV sales in 2017 under the recomputed equilibria. Panel (b) adds yellow bars showing EV sales in 2018 under the recomputed equilibria.

Table 8: Effect of Elimination Designs on Vehicle Prices and Sales in 2017

Vehicle	Outcome	No Subsidy	Market Deadline	Per-Mfr Deadline	Per-Mfr Quota (110000)
CHEVROLET BOLT (BEV)	Price (USD)	36,200	35,393	35,391	47,378
	Sales	13,117	25,307	25,308	9,628
CHEVROLET VOLT (PHEV)	Price (USD)	32,121	31,365	31,363	43,290
	Sales	18,116	35,476	35,479	13,194
TESLA MODEL S (BEV)	Price (USD)	66,515	65,720	65,720	84,504
	Sales	15,529	26,294	26,292	7,920
TOYOTA PRIUS PRIME (PHEV)	Price (USD)	25,730	25,298	25,156	25,167
	Sales	21,314	32,330	32,740	32,850
HONDA ACCORD (GAS)	Price (USD)	21,620	21,616	21,616	21,621
	Sales	336,369	335,284	335,263	336,056
HONDA CIVIC (GAS)	Price (USD)	18,124	18,121	18,121	18,125
	Sales	348,321	347,174	347,152	347,977
TOYOTA CAMRY (GAS)	Price (USD)	19,559	19,561	19,561	19,565
	Sales	331,464	330,484	330,464	331,090
FORD F (GAS)	Price (USD)	26,214	26,214	26,214	26,215
	Sales	367,695	367,547	367,545	367,656
CHEVROLET SILVERADO (GAS)	Price (USD)	26,672	26,673	26,673	26,672
	Sales	341,201	341,021	341,018	341,188
TOYOTA TACOMA (GAS)	Price (USD)	23,400	23,400	23,400	23,402
	Sales	231,334	231,187	231,184	231,282

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.

Table 9: Effect of Elimination Designs on Aggregate Outcomes

Outcome	Market Deadline	Per-Mfr Deadline	Per-Mfr Quota (120000)
Panel (a): 2017 Outcomes			
Δ EV Sales	88,633	90,332	21,424
Δ Conv Sales	-23,519	-23,942	-6,128
Δ Gas Consumption (Million Gallons)	-1,612.04	-1,640.9	-404.46
Δ Consumer Surplus (Million USD)	41.28	42.22	-59.14
Δ Total Profits (Million USD)	725.72	719.56	595.26
Govt Expenditure (Million USD)	1,346.98	1,356.37	855.76
Panel (b): 2018 Outcomes			
Δ EV Sales	664	42,042	89,039
Δ Conv Sales	-179	-11,349	-23,581
Δ Gas Consumption (Million Gallons)	-12.46	-772.55	-1,617.73
Δ Consumer Surplus (Million USD)	8.74	9.15	6.05
Δ Total Profits (Million USD)	6.19	337.13	745.46
Govt Expenditure (Million USD)	0	577.08	1,339.99
Panel (c): Total			
Δ EV Sales	89,297	132,374	110,463
Δ Conv Sales	-23,698	-35,291	-29,709
Δ Gas Consumption (Million Gallons)	-1,624.5	-2,413.44	-2,022.19
Δ Consumer Surplus (Million USD)	50.02	51.37	-53.1
Δ Total Profits (Million USD)	731.91	1,056.7	1,340.72
Govt Expenditure (Million USD)	1,346.98	1,933.45	2,195.75
Panel (d): Total (Normalized)			
Δ EV Sales	66	68	50
Δ Conv Sales	-18	-18	-14
Δ Gas Consumption (Million Gallons)	-1.21	-1.25	-0.92
Δ Consumer Surplus (Million USD)	0.04	0.03	-0.02
Δ Total Profits (Million USD)	0.54	0.55	0.61

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 the government expenditure. All simulations assume that the subsidy elimination began after 2017.

Table 10: Effect of Elimination Designs on Profit Distribution

Manufacturer	No Subsidy	Market Deadline	Per-Mfr Deadline	Per-Mfr Quota (120000)
ASTON MARTIN	32	32	32	32
BMW	8,316	8,380	8,455	8,461
DAIMLER	7,310	7,307	7,311	7,315
FERRARI	40	40	39	40
FIAT CHRYSLER	41,787	41,817	41,861	41,868
FORD	46,875	46,930	47,000	47,011
GENERAL MOTORS	60,963	61,257	61,242	61,390
HONDA	35,652	35,607	35,587	35,599
HYUNDAI	19,238	19,228	19,229	19,234
JAGUAR LAND ROVER	3,307	3,303	3,302	3,303
KIA	12,204	12,208	12,219	12,222
MAZDA	5,485	5,479	5,476	5,478
MITSUBISHI	2,283	2,281	2,281	2,281
NISSAN	35,962	35,991	36,033	36,041
ROLLS-ROYCE	50	50	50	50
SUBARU	14,640	14,628	14,623	14,626
TESLA	878	1,134	1,133	1,181
TOYOTA	55,475	55,540	55,638	55,654
VOLKSWAGEN	15,598	15,606	15,625	15,632
VOLVO	1,987	1,994	2,003	2,004

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

cross-price demand elasticities and network effect. Next, to compare alternative subsidy-capping provisions, I develop a structural model of the US automobile industry, where consumers choose vehicles to purchase by maximizing utility across all fuel types, 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 geographic markets in the initial years of the EV market that were unaffected by the subsidy elimination. 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 as they face three counterfactual elimination designs: a market-wide deadline, a per-manufacturer deadline, and a per-manufacturer quota.

Overall, the results show that all else being equal, per-manufacturer quotas create an incentive to delay 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 in the next period, and (2) As the subsidy is eliminated only for the EV makers who exhaust the quota, staying below the quota protects the EV-maker from fierce competition from others below the quota. As a result, given government expenditure, subsidies with deadlines are more cost-effective in increasing EV market penetration than subsidies with a per-manufacturer quota. In addition, because EV manufacturers are multi-product oligopolists, elimination designs also affect the sales of conventional vehicles and, hence, affect the consumer surplus, manufacturer profits, and liquid fuel consumption. Finally, the results show that subsidy-capping designs 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, it elucidates the effect of 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 EV adoption. In the US, the market share of EVs has remained limited despite several incentive programs; even the consumers who buy EVs tend to use them as their secondary vehicle. 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 distributional impact of subsidy design on manufacturers' profits, which is helpful for subsidy targeting. For instance, compared to a market-wide deadline, a per-manufacturer deadline disproportionately shifts profits away from the manufacturers facing the deadline. Despite the penalty on dominant manufacturers, a per-manufacturer deadline (rather than a market-wide deadline) may be justified if there are significant barriers to manufacturers' entry because there are positive externalities from the entry in the form of environmental benefits, innovation spillovers, and enhanced national energy security. Finally, the implications from the plug-in EV market may also hold for other sustainable technologies such as solar panels and wind energy.

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Appendix

A EV-makers and Buyers Respond to Elimination

This section offers evidence that EV-makers and buyers respond to subsidy elimination based on Tesla Motors' and General Motors' experiences with subsidy elimination. Tesla and General Motors 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 (i.e., Model 3) with General Motors' most popular plug-in hybrid (i.e., 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 Tesla Model 3 in January was half as generous compared to the credit in December, and correspondingly the car sales in January plummeted to 50% of the December sales volume. Such bunching does not appear for Chevy 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. Note that this bunching conflates the changes in purchase choice and purchase timing since some consumers aware of the looming change may have advanced their purchases 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 $7500 subsidy. Tesla used this opportunity by setting new production and delivery records between July and December. Third, manufacturers likely respond to quota by delaying EV sales, as evident by the 130% spike in Tesla Model-3 sales in July 2018. If Tesla reached the 200,000-threshold in June instead of July, the phaseout would have initiated 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 Chevy Volt sales shows that seasonality in demand is not enough to explain the difference between the June and July sales volumes.

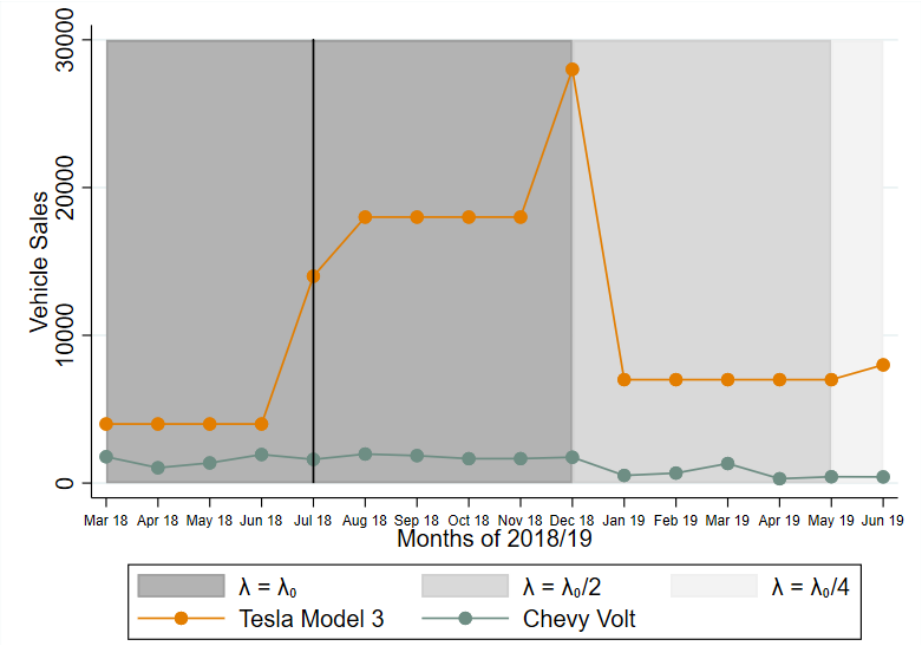
To quantify the effect of quota and deadlines on the quarterly sales volume, I also estimate the following regression:

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

where I^D_{ft} takes value one if firm f faces a deadline within next two quarters, I^Q_{ft} is one if firm f faces the 200,000 quota in quarter t. $\delta_j$and δ_{qtr} indicate product and quarter fixed effects. The coeffcient β_2 indicates the effect of deadline, while β_3 indicates the effect of quota on the EV sales. The variation comes only from Tesla and GM, since no other firm has exhausted the quota yet. Controlling for product and quarter fixed effects, these firms, on average sell 3000 more EVs when facing the two-quarter deadline and 3000 less EVs when facing the 200,000 quota.

While these findings inform us of the importance of subsidy elimination designs, they do not explain what happens in the presence of alternative policies. Moreover, the variation is only driven

Figure 7: Tesla Car Sales in 2017-18



Notes: This figure plots the total nationwide sales of Tesla model 3 and GM Chevrolet Volt between March 2018 - June 2019 based on the monthly sales estimates by Automotive News Data Center. The black vertical line indicates the month July 2018 – the month in which Tesla exhausted the 200,000 quota. GM exhausted the quota in Nov 2018. The shades of grey indicate the value of Tesla's federal subsidy; darker shades indicate higher values. Tesla's subsidy phaseout began in January 2019 and the subsidy for all its models was reduced from \$7500 to \$3750. GM faced the subsidy reduction in April 2019.

Table 11: Evidence: EV Sales Depend on the Type of Elimination

VARIABLES	(1) Sales (1000s)	(2) Sales (1000s)	(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 U.S. Light Vehicle Quarterly Sales
Notes: Standard errors in parentheses. *** indicates 99% level of significance. ** indicates 95% level of significance. * indicates 90% level of significance.

by Tesla and GM, since no other firms faced subsidy elimination in 2018. Therefore, to compare different subsidy-elimination policies, I rely on structural methodology 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 firm's other vehicles' characteristics. IVs 6-10 are sum over all the firms' competing vehicles' characteristics. Vehicle chanaracteristics include a constant, vehicle size, performance, driving cost and battery range, repspectively.

Table 12: First-Stage Regression Results

Dependent Variable: Price (p_{jmt}, in $'0000)			
	Variable	Coef	SE
Included IV			
	Constant	-8.872***	1.452
	Size	6.579***	0.173
	Performance	2.964***	0.048
	Driving Cost	25.498***	0.501
	Battery Range	-0.006	0.011
	BEV	3.685***	0.349
	PHEV	2.172***	0.359
	BEV × Cumulative EV Sales	-0.084**	0.041
	PHEV × Cumulative EV Sales	-0.555***	0.031
Excluded IV			
	IV_1	0.326***	0.037
	IV_2	-0.492***	0.042
	IV_3	0.097***	0.008
	IV_4	0.087***	0.024
	IV_5	0.026***	0.002
	IV_6	-0.073**	0.035
	IV_7	0.095**	0.040
	IV_8	0.008	0.008
	IV_9	-0.076***	0.013
	IV_{10}	-0.002	0.001
Obs	62588		
R-squared	0.676		
F test			
F(67, 62520)	1945.251		
F test of excluded IV			
F(10, 62520)	337.457		

Notes: Size is length× width (in '0000 in^2), performance is Horsepower by curb weight (in 10 lb), driving cost is fuel cost (in dollars) per ten miles, and battery range is the all electric range (in miles) for EVs. Cumulative EV Sales shows total EVs sold by the manufacturer in the geographic market until previous year. Excluded instruments that are assumed uncorrelated with demand error $\Delta\xi_{jmt}$ include the sum of firm's other vehicles' characteristics (constant, size, performance, driving cost, and battery range) and the sum over all the firms' competing brands' characteristics. *** indicates 99% level of significance. ** indicates 95% level of significance. * indicates 90% level of significance.

C Counterfactuals

Table 13: Effect of Elimination Designs on EV Sales

Manufacturer	Year	No Subsidy	Market Deadline	Per-Mfr Deadline	Per-Mfr Quota (120000)
BMW	2011-2016	15,140	15,140	15,140	15,140
	2017	10,995	17,200	17,626	17,702
	2018	10,882	11,029	17,484	17,627
DAIMLER	2011-2016	9,312	9,312	9,312	9,312
	2017	989	1,785	1,805	1,815
	2018	948	935	1,689	1,715
FIAT CHRYSLER	2011-2016	18,115	18,115	18,115	18,115
	2017	4,810	9,207	9,485	9,531
	2018	4,897	4,960	9,621	9,756
FORD	2011-2016	73,611	73,611	73,611	73,611
	2017	16,861	24,653	24,864	24,947
	2018	16,576	16,535	24,253	24,424
GENERAL MOTORS	2011-2016	97,052	97,052	97,052	97,052
	2017	31,394	61,048	61,053	22,948
	2018	30,838	31,205	31,098	59,234
HONDA	2011-2016	2,091	2,091	2,091	2,091
	2017	1,495	1,479	1,479	1,491
	2018	1,459	1,413	1,407	1,432
HYUNDAI	2011-2016	1,350	1,350	1,350	1,350
	2017	1,236	2,003	2,070	2,082
	2018	1,224	1,247	2,061	2,081
KIA	2011-2016	3,664	3,664	3,664	3,664
	2017	1,907	3,262	3,380	3,392
	2018	1,922	1,969	3,440	3,431
MITSUBISHI	2011-2016	1,886	1,886	1,886	1,886
	2017	1	2	2	2
	2018	1	1	2	2
NISSAN	2011-2016	100,875	100,875	100,875	100,875
	2017	5,275	10,735	10,782	10,824
	2018	5,132	5,093	10,386	10,356
TESLA	2011-2016	105,728	105,728	105,728	105,728
	2017	27,332	45,522	45,518	14,272
	2018	27,333	27,273	27,213	45,592
TOYOTA	2011-2016	43,470	43,470	43,470	43,470
	2017	21,314	32,330	32,740	32,850
	2018	21,379	21,599	32,997	32,917
VOLKSWAGEN	2011-2016	18,829	18,829	18,829	18,829
	2017	4,456	6,859	6,941	6,974
	2018	4,342	4,327	6,678	6,741
VOLVO	2011-2016	2,025	2,025	2,025	2,025
	2017	1,796	2,410	2,451	2,457
	2018	1,785	1,795	2,430	2,450

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

Table 14: Effect of Elimination Designs on Vehicle Prices and Sales in 2018

Vehicle	Outcome	No Subsidy	Market Deadline	Per-Mfr Deadline	Per-Mfr Quota (110000)
CHEVROLET BOLT (BEV)	Price (USD)	36,543	36,532	36,536	35,664
	Sales	12,791	12,909	12,860	24,243
CHEVROLET VOLT (PHEV)	Price (USD)	32,446	32,440	32,441	31,618
	Sales	17,887	18,134	18,077	34,731
TESLA MODEL S (BEV)	Price (USD)	66,452	66,452	66,459	65,664
	Sales	15,532	15,497	15,454	26,338
TOYOTA PRIUS PRIME (PHEV)	Price (USD)	26,139	26,145	25,649	25,643
	Sales	21,379	21,599	32,997	32,917
HONDA ACCORD (GAS)	Price (USD)	21,620	21,620	21,619	21,616
	Sales	336,389	336,383	335,866	335,309
HONDA CIVIC (GAS)	Price (USD)	18,124	18,124	18,123	18,120
	Sales	348,344	348,337	347,787	347,202
TOYOTA CAMRY (GAS)	Price (USD)	19,559	19,559	19,563	19,561
	Sales	331,477	331,469	330,932	330,493
FORD F (GAS)	Price (USD)	26,214	26,214	26,214	26,214
	Sales	367,696	367,695	367,620	367,546
CHEVROLET SILVERADO (GAS)	Price (USD)	26,672	26,672	26,672	26,673
	Sales	341,202	341,200	341,139	341,022
TOYOTA TACOMA (GAS)	Price (USD)	23,400	23,400	23,401	23,400
	Sales	231,335	231,334	231,255	231,188

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.