Three Essays on the Effects of Government Policies

by

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A dissertation submitted in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
(Economics)
in the University of Michigan
2022

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To Shadab

Acknowledgments

I am deeply indebted to my chair, Ying Fan, and my advisors, Joel Slemrod, Catherine Hausman, and Zach Brown, for their invaluable advice and continued guidance throughout the research process. It has been a privilege to work with such brilliant and kind economists.

I gratefully acknowledge the financial support for my dissertation from the Ryoichi Sasakawa Young Leaders Fellowship Fund, the Alfred P. Sloan Foundation Pre-doctoral Fellowship on Energy Economics, the Rackham Graduate Student Research Grant, and the Graduate Research Award by the Department of Economics at the University of Michigan. In addition, the economics department staff, including Hiba Baghdadi, Mary Ceccanese, Laura Flak, Julie Heintz, Mary Mangum, and Lauren Pulay, have been more than helpful during different stages of the program and I am grateful to them for everything they do.

Fellow Michigan students have been incredible sources of support and ideas. Mos Bunyada Laoprapassorn, Michelle Lam, and Barthélémy Bonadio have been my constant companions throughout my time at Michigan, and I will fondly remember our countless conversations, celebrations, and Ann Arbor explorations. Bhanu Gupta and Wenting Song have been my sources of strength and inspiration, especially during the job market; they have my most profound appreciation. Finally, Xing Guo, Obeid Ur Rehman, Xuan Teng, and Andrew Usher have often given me excellent Ph.D. and life advice, for which I'm grateful.

I am also grateful to my undergraduate advisors, Tanika Chakraborty and Arshad Rahman, for inspiring me to pursue a Ph.D. and for being my trusted mentors through all these years, and to my dear old friends, Arushi Jain, Munira Attaar, Pushp Toshniwal, Kanika Dev, Mariyam Patanwala, and Rashida Nagdawala for being my steady sources of joy.

Most of all, I am grateful to my parents, Zarina and Zoaib Ali Lohawala, my parents-in-law, Nelofer and Burhanuddin Bohra, and my husband, Shadab Azeem, for being my constant champions. Their encouragement, love, and support are my most beautiful blessings.

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Abstract

This dissertation studies the role of government policies on environmental and safety externalities generated by the transportation sector. The first two chapters focus on the automobile industry in the United States, which is subject to a series of government-imposed environmental regulations. The third chapter focuses on the alcohol regulations in India, which affect traffic-related safety externalities.

Chapter 1 analyzes the effect of provisions such as deadlines and quotas that policymakers typically use to phase out subsidies for electric vehicles. Such provisions 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 chapter 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, subsidies, and demographics in 30 states between 2011-2017. Based on the primitives 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 32% 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.

Chapter 2, joint with Ying Fan, studies the effects of separating passenger cars and light-duty trucks in the US Corporate Average Fuel Economy standards. The lower standard for light trucks creates a perverse incentive for manufacturers to redesign large vehicles as light-duty trucks instead of passenger cars to achieve compliance. We exploit a historical change in the car-truck definitions to provide evidence that manufacturers change vehicle characteristics to qualify for favorable regulatory treatment. To quantify the welfare effect of such regulation gaming behavior, we develop and estimate a structural model of the US automobile industry using data between 2001-2016 and conduct a counterfactual simulation

where we change “marginal” truck SUVs to passenger cars for CAFE purposes. We find that designing SUVs as light-duty trucks instead of passenger cars results in higher manufacturer profits, higher consumer surplus, and higher fuel consumption.

Chapter 3 analyzes the effect of alcohol regulations on road traffic accidents, injuries, and fatalities in India. Alcohol-related regulations in India are subject to intense scrutiny, but there is little documentation on the effects of these policies on road safety. In this chapter, I use state-level data on road accidents and the changes in alcohol regulations across states and road types between 2004-2019 to identify the impact of two regulations on road traffic accidents: (1) regulation of demographic access to alcohol through state-wide alcohol ban and minimum legal drinking age and (2) regulation of location where alcohol is sold through sales ban near highways. The results show that a state that moves from an alcohol prohibition to a legal drinking age of 16 experiences roughly ten additional accidents per 10,000 vehicles, on average, compared to other states. Moreover, the roads affected by the highway alcohol ban experience six fewer accidents per 10,000 vehicles compared to other roads. Finally, there is evidence of spillovers of neighboring states’ drinking age policies on a state’s road safety.

Chapter 1

Roadblock or Accelerator? The Effect of Electric Vehicle Subsidy Elimination

Nafisa Lohawala

1.1 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 Li, 2011; Chandra et al., 2010; Jenn et al., 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.

Several reasons may justify subsidizing plug-in EV purchases as part of optimal energy and tax policy. First, EV adoption likely 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

[1] Questions have been raised in the literature on the environmental benefits of driving electric vehicles (see Babaee et al. (2014); Archsmith et al. (2015); Holland et al. (2016); 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.

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, the US federal tax-credit program caps the incentives by giving each EV manufacturer a quota of 200,000 vehicles, following which the credit phases out for that manufacturer. In contrast, Norway's initial EV tax incentive and VAT exemption program 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 plans to cut the subsidies progressively between 2020 and 2022, with complete expiry in 2022, while Germany has instituted a single deadline for their EV purchase subsidies and plans to cut them after December 2025. 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 up to $7500 to EV consumers. The program combines a per-manufacturer quota and a per-manufacturer deadline to cap these credits. Each EV manufacturer gets a quota of 200,000 vehicles, following which the credit phases out over a year as follows: it is unchanged in the quarter in which the manufacturer delivers the 200,000th EV and in the next quarter, and then reduces to half for that manufacturer. It then reduces to one-fourth of the original value following a six-month deadline and then expires 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 popular alternative – i.e., a market-wide deadline, where all manufacturers face a single deadline.

I first contrast the effects of different subsidy-capping provisions in an illustrative model and 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 in any period, 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 key feature of this model is that consumers care about the number of EVs previously sold in their local geographic area (network effect). As previously modeled by papers like Kalish and Lilien (1983), Heutel and Muehlegger (2015), Springel (2021), Li et al. (2017), and Li (2018), such a network effect is relevant to the EV industry due to information gains from early adopters and mobility gains from the development of a charging network. 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 supply model is that, in addition to current profits, vehicle manufacturers care about the following year's profits while choosing the 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 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 32% 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 claim that the current US subsidy-capping design puts 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). With the Biden administration's recent proposal of extending the federal EV subsidies (GREEN Act, 2021), subsidy capping is now a policy issue again.

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 et al. (2010); Gallagher and Muehlegger (2011); Jenn et al. (2013) take a reduced-form approach to quantifying the effect of government support programs. For instance, Jenn et al. (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 Van Benthem et al. (2008); Beresteanu and Li (2011); Acemoglu et al. (2012); Aghion et al. (2016) take a structural approach. For instance, Beresteanu and Li (2011) build an equilibrium model of the new car market and estimate that federal income-tax credits for hybrid vehicles accounted for about 20% 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 (2011a), Borenstein and Davis (2016), Gulati et al. (2017), and Pless and Van Benthem (2019). Examples from other contexts include Cabral et al. (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 (2011a) 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 Li et al. (2017); Li (2018); Gillingham (2022); Springel (2021).

The rest of the paper is organized as follows. Section 1.2 provides a brief background of the US plug-in EV industry. Section 1.3 describes an illustrative example to provide economic intuition and identifies the key parameters governing manufacturers' responses to subsidy capping designs. Section 1.4 outlines the utility specification and the supply-side problem. Section 1.5 reports data and summary statistics. Section 1.6 discusses identification, estimating algorithm, and results. Section 1.7 discusses the counterfactual experiments. Section 1.8 summarizes the findings and concludes.

1.2 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.

1.2.1 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.[2]

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 offers non-refundable tax credits for PHEV and BEV purchases made after 31st December 2009 (IRS, 2009). The credit varies 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.[3] BEVs qualify for a higher credit than PHEVs due to their larger battery capacity. Popular BEVs such as all Tesla models and Chevrolet Bolt qualify for the full \$7,500 subsidy.

The US federal tax-credit program uses a unique phaseout provision. As summarized in Figure 1.1, the phaseout is triggered for a manufacturer once it sells 200,000 subsidy-qualifying cars for use in the United States after 31st December 2009. The credit is unchanged in the quarter in which the manufacturer delivers the 200,000th subsidy-qualifying vehicle

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

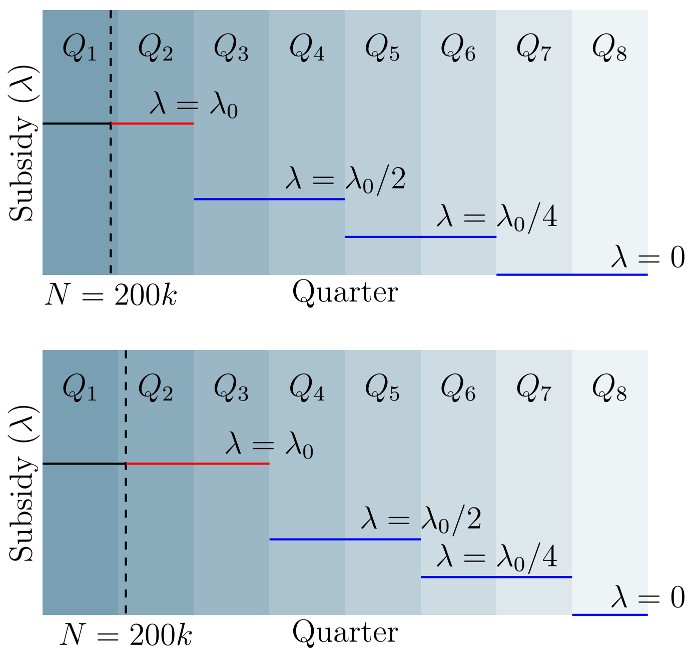
[3]A consumer's purchase must meet specific requirements in order to be eligible for the tax credit. See Internal Revenue Code Section 30D for details.

and in the next quarter. It reduces 50 percent of the original value for the next two quarters, 25 percent for the other two quarters, and then expires. All eligible plug-in vehicles sold during the phaseout period qualify for the credit.

This program 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; 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). As of 2021, no other manufacturer has crossed 200,000 deliveries. Nissan is next in line, while others are trailing far behind.

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.1 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 1.1: 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.

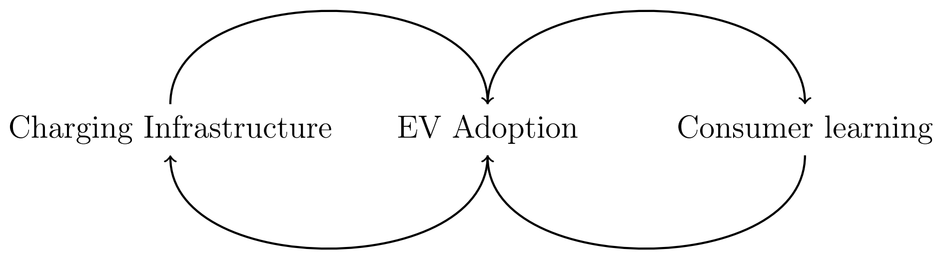
1.2.2 Key Features of the Federal Subsidy Design

The current subsidy capping design 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 follow the quota create no such incentive because manufacturers cannot control when the subsidy expires.

An EV maker's response to the per-manufacturer quota may 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 1.2 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 face 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 is theoretically ambiguous and depends on the relative strengths of the two channels. I discuss this mechanism further in Section 1.3, 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.

Figure 1.2: 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.

1.2.3 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.

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 1.4 and incorporate it into my model by including the value of ZEV credits in the firms' profit functions.

1.3 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 1.4 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 1.2, 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.

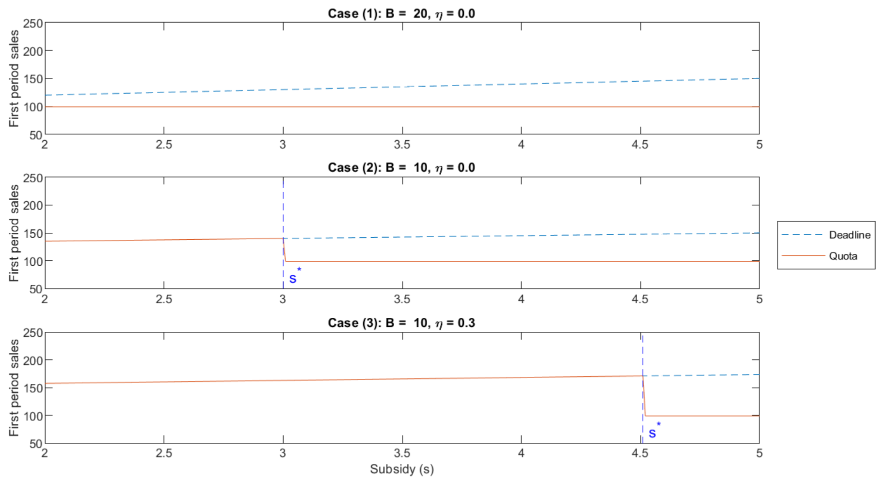
$$\lambda_t = \begin{cases} s, & \text{if } t = 1 \\ s\mathbf{I}[Q_1(p_1 - s) < \Gamma], & \text{if } t = 2 \end{cases}$$

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 1.3 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 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

Figure 1.3: 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).

can answer how subsidy-capping designs affect market penetration, gasoline consumption, consumer surplus, and firms' profits.

1.4 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 et al. (1995)

and Petrin (2002), where consumers choose a single vehicle from all available fuel types. Including all the fuel types allows me to simulate 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 1.3 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.

1.4.1 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:

$$U_{ijmt} = \alpha_i p_{jmt} + x_{jt}\beta_i + N_{jmt}\eta + \xi_{jmt} + \epsilon_{ijmt} \tag{1.1}$$

where p_{jmt} represents the price faced by the consumer, given by 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 1.1, 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, and β_i is a $K \times 1$ vector of taste coefficients. 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 allows for consumer heterogeneity in preferences by interacting car attributes with household characteristics D_{imt} and unobserved preferences V_{imt}. Specifically,

$$\begin{pmatrix} \alpha_i \\ \beta_i \end{pmatrix} = \begin{pmatrix} \alpha \\ \beta \end{pmatrix} + \Pi D_{imt} + \Sigma V_{imt}.$$

where Π is a $(K+1) \times d$ matrix of parameters, and D_{imt} is $d \times 1$ vector of household characteristics (including the number of children in the household and the age of the household head). The distribution of D_{imt} comes from the Current Population Survey. For computational reasons, I restrict many elements of Π to equal zero. I include an interaction between the number of children and vehicle size and interaction between the age of household head and vehicle performance. These parameters are identified by the variation in the distribution of demographics across different markets. Similarly, Σ is a $(K+1)\times(K+1)$ diagonal matrix of parameters, and V_{imt} is a $(K+1) \times 1$ vector assumed to be standard normal. I allow for heterogeneity in price sensitivity and tastes for driving cost and vehicle types (i.e., van, SUV, and pickup). These parameters are identified by the variation in choice sets across different markets. The parameters (Π, Σ) break the independence of relevant alternatives (IIA) property of standard logit models by ensuring that a price increase for a vehicle model will divert disproportionately more consumers to other similar vehicles. As such, they play a valuable role in identifying cross-price elasticities.

The specification also 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. 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. It also reflects 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 1.5.2, 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 a mixed logit:

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

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

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

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

1.4.2 Supply

I model the vehicle market as served by a multi-firm, differentiated-product industry where firms engage in Bertrand price competition and seek individually to maximize their profits across all their products. Each firm f prices all vehicles in its portfolio to maximize profits from the 30 US markets while taking the product mix as given. 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.

A multi-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. Multi-period pricing 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 should allow 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. Since a multi-period pricing model is computationally challenging to estimate, I use the following strategy: I recover the marginal costs in 2017 under the assumption of static Nash-Bertrand equilibrium and use a two-stage pricing assumption only in the counterfactual analyses. Static pricing assumption may be reasonable in 2017 because firms were still far from exhausting the subsidy, and the dynamics of subsidy elimination were not relevant. In the absence of network effect, both specifications will lead to similar estimates. This is not true in the presence of network effect because firms maximizing static profits do not internalize network effect. Although this simplification affects marginal cost estimates, it is not restrictive for the counterfactual analysis because it does not affect the elimination-induced incentives. I elaborate firms' profit-maximization problem under the static Nash-Bertrand assumption in this section, and postpone the discussion of the two-stage game to Section 1.7.

In the static game, each firm f maximizes its current profit. 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. Given the demand system, the profit for the firm f in year t is

$$\Pi_{ft} = \sum_{m} \sum_{j \in \mathcal{J}_{ft}} \left[p_{jt} - c_{jt} + h_{jmt} \right] Q_{jmt}, \tag{1.2}$$

where 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 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 recharge time of less 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.

Given the firms' profit in equation 1.2, the optimal price for product j satisfies the following first order condition:

$$\sum_{m} \left[Q_{jmt} + \sum_{k \in \mathcal{J}_{ft}} \left((p_{kt} - c_{kt} + h_{kmt}) \frac{\partial Q_{kmt}}{\partial p_{jt}} \right) \right] = 0.$$

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

$$\frac{\partial Q_{kmt}}{\partial p_{jt}} = H_{mt} \frac{\partial s_{kmt}}{\partial p_{jt}} = \begin{cases} H_{mt} \int s_{ijmt}(1 - s_{ijmt}) \alpha_i dP(D), & \text{if } j = k \\ -H_{mt} \int s_{ijmt} s_{ikmt} \alpha_i dP(D), & \text{otherwise.} \end{cases} \tag{1.3}$$

Suppose there are J models available in period t. Then the first order conditions define a system of J simultaneous equations that are linear in marginal cost and must hold exactly at equilibrium:

$$p_{.t} = c_{.t} + \Delta_{Q,t}^{-1}\left(Q_{.t} + \Delta_{H,t}\mathbf{1}_{J\times 1}\right),$$

where $p_{.t}$, $c_{.t}$ and $Q_{.t}$ are vector of of prices, marginal costs, and sales. $\Delta_{Q,t}$ is defined as

$$\Delta_{Q,t}(j,k) = \begin{cases} -\sum_m \frac{\partial Q_{kmt}}{\partial p_{jt}}, & \text{if } j \text{ and } k \text{ are produced by the same firm,} \\ 0 & \text{otherwise,} \end{cases} \tag{1.4}$$

$\Delta_{H,t}$ is defined as

$$\Delta_{H,t}(j,k) = \begin{cases} -\sum_m h_{jmt}\frac{\partial Q_{kmt}}{\partial p_{jt}}, & \text{if } j \text{ and } k \text{ are produced by the same firm,} \\ 0 & \text{otherwise,} \end{cases} \tag{1.5}$$

and $\Delta_{Q,t}^{-1}\left(Q_{.t} + \Delta_{H,t}\mathbf{1}_{J\times 1}\right)$ is the vector of markups that depends on the parameters of the demand system and the observed price vector. I use this system of equations 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 1.7. 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 for 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.

1.5 Data

1.5.1 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 market with 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 captures this market from the outset. A vehicle is a unique model year, make, model, and fuel type. I use the 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 1st January of such calendar year. If the manufacturer has no annual production period, the term model year represents the calendar year. Model years typically run 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 a given 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 for vehicle shares over 30 states between 2012-2017.

Second, vehicle-level characteristics come from the WARDS Intelligence Data Center, Environmental Protection Agency, and publicly available database www.edmunds.com. Additionally, market segmentation data comes 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: vehicle's fuel economy and market-level fuel prices. Thus, a high gas price in a state raises the cost of driving all gasoline vehicles in that state. 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 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. The federal subsidies take the form of non-refundable tax credits, so in practice, the amount of subsidy depends on the taxpayer's income tax liability. For simplicity, I assume that all customers can claim the full amount of the 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.

In addition to the sales and product characteristics, I use the March Current Population Survey (CPS) data to approximate each market's empirical joint distribution of demographics. Specifically, I sample the age of the household head and the number of children in the household. Finally, I obtain the list of makes for each manufacturer from the annual EPA Auto trend reports. Different brands under the same manufacturer classify as a single firm as consistent with the regulatory definitions. For example, Buick, Cadillac, Chevrolet, GMC, Hummer, and Saturn are all part of General Motors.

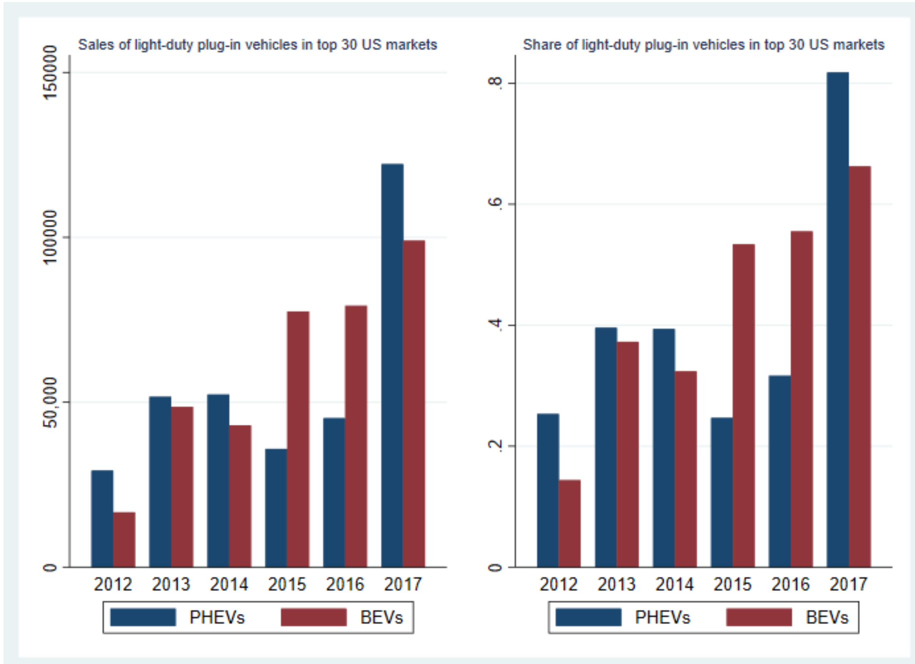
1.5.2 Summary Statistics

Table 1.1 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$\times$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 1.4 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 1.5 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 1.2 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 1.3 summarizes the plug-in EV sales, plug-in EV regulations, and demographics 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 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%).

Figure 1.4: 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.

Table 1.1: New Vehicle Sales and Characteristics in the Sample States

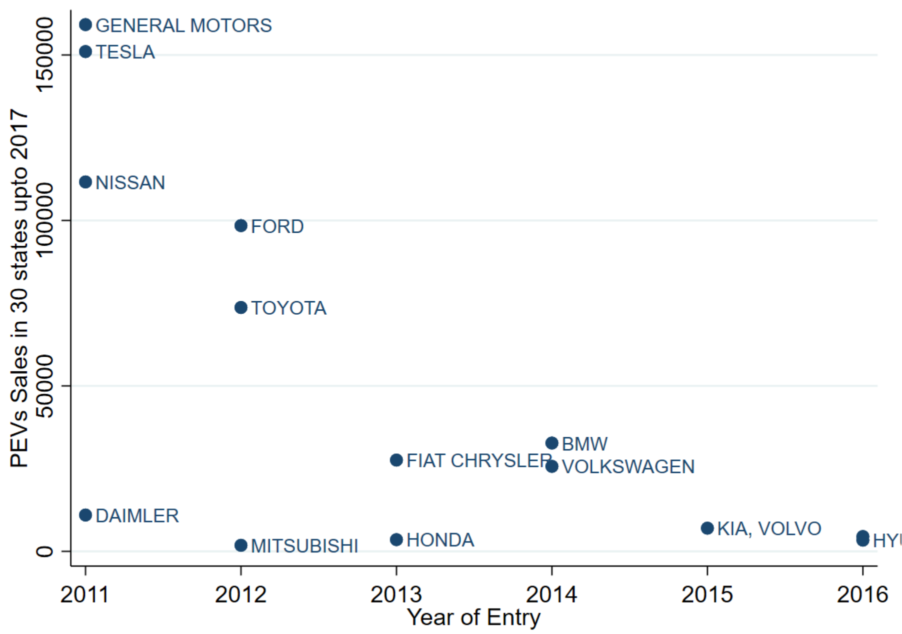
Year	Models		MSRP ($'000)		Sales ('000)		Size ('0000 in ^{2})		Performance (Hp/lb)		Driving Cost ($/10 miles)		Battery Range (miles)	
	EV	Other	EV	Other	EV	Other	EV	Other	EV	Other	EV	Other	EV	Other
2012	6	331	37.66	25.00	45	11523	0.74	0.80	0.36	0.58	0.05	0.16	53.26	0.00
2013	10	351	38.99	25.78	100	12957	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.

1.6 Estimation and Results

The next step is to estimate the structural model described in Section 1.4. 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

Figure 1.5: 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 1.2: 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.

Table 1.3: 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.

the demand estimation does not rely on the supply-side conduct. Section 1.6.1 describes the estimation and identification of the demand parameters, and Section 1.6.2 reports the results from estimating the structural model.

1.6.1 Estimation and Identification

The basic issue that motivates the demand estimation is 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, the 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, which are unobserved, 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 1.1. Both cases result in price endogeneity.

Identification requires a set of exogenous instruments. Vehicle characteristics other than price are valid instruments for themselves as they are 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 et al. (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:

$$z_{jmt}^{k} = (x_{jt}^{k}, \sum_{r\neq j, r\in\mathcal{J}_{fmt}} x_{rt}^{k}, \sum_{r\neq j, r\notin\mathcal{J}_{fmt}} x_{rt}^{k}) \tag{1.6}$$

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.

The demand estimation follows Berry et al. (1995) and Nevo (2000). I decompose the indirect utility as

$$U_{ijmt} = \delta_{jmt}(p_{jmt}, x_{jt}, N_{jmt}, \xi_{jmt}; \theta_1) + \mu_{ijmt}(p_{jmt}, x_{jt}, D_{imt}, V_{imt}; \theta_2) + \epsilon_{ijmt} \tag{1.7}$$

where

$$\delta_{jmt} = \alpha p_{jmt} + x_{jt}\beta + N_{jmt}\eta + \xi_{jmt}$$

and

$$\mu_{ijmt} = \begin{bmatrix} p_{jmt} & x_{jt} \end{bmatrix} \times \left[\Pi D_{imt} + \Sigma V_{imt}\right].$$

Here, δ_{jmt} represents the mean consumer valuation of the vehicle j in region m and period t, and μ_{ijmt} captures the consumer-specific deviations. $\theta_1 = (\alpha, \beta, \eta)$ includes linear parameters capturing mean consumer valuation, and $\theta_2 = (\Pi, \Sigma)$ includes non-linear parameters capturing variation in preferences across consumers.

I estimate demand parameters using simulated Generalized Method of Moments using the population moment condition that is a product of instrumental variables Z and 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.

1.6.2 Results

Table 1.4 shows the results from the estimating demand derived from the indirect utility specification in equation 1.1.[4] 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 sales that measure the network effect. These terms have positive signs, indicating that consumers gain more utility from BEVs and PHEVs as the network develops. 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. The final two rows show the interactions of performance with age and vehicle size with the number of children. Both interactions are imprecisely estimated.

Table 1.5 presents a sample of own and cross-price elasticities, markups, and marginal costs implied by the demand estimates. 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 1.6 summarizes the elasticities, markups, and marginal costs for all vehicle models in 2017. The average own-price elasticity is -3.06. Among the 397 models, the marginal costs range from about $12,000 at the 25th percentile to about $38,000 at the 75th percentile.

1.7 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

[4] Appendix A.2 provides the details of the first stage estimation. The first-stage F-statistic for the excluded instruments is 345.001.

Table 1.4: Demand Estimates

Variable	Coef	SE
Mean Valuations		
p_{jmt}	-0.886***	0.107
Constant	-11.020***	2.485
Vehicle Size	4.161***	0.722
Performance (Hp/wt)	1.113	2.262
Driving Cost	-2.701	7.073
Battery Range	0.009***	0.001
BEV	-2.801***	0.287
PHEV	-0.936***	0.342
Network Effects		
BEV × Cumulative EV Sales	0.092***	0.025
PHEV × Cumulative EV Sales	0.116**	0.046
Random Coefficients		
Price	0.211***	0.054
Driving Cost	2.993	10.457
Van	0.518	1.200
Pickup	0.279	11.171
SUV	4.339**	2.024
Demographic Interactions		
Age × Performance	0.059	0.429
Nchild × Size	-0.127	0.133
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 available model, 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 1.5: 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)	TESLA MODEL X (BEV)	-4.304	0.000	0.000	0.000	0.000	0.001	0.003	0.001	0.005	0.005	79,773	11,288	68,485
(2)	CHEVROLET VOLT (PHEV)	0.001	-1.882	0.000	0.000	0.000	0.000	0.002	0.001	0.004	0.004	31,155	10,544	20,611
(3)	NISSAN LEAF (BEV)	0.001	0.000	-1.514	0.000	0.000	0.000	0.002	0.001	0.004	0.004	26,080	9,796	16,284
(4)	HYUNDAI IONIQ (BEV)	0.003	0.003	0.000	-1.649	0.000	0.000	0.003	0.002	0.004	0.003	29,390	7,705	21,686
(5)	CADILLAC CT6 (PHEV)	0.002	0.001	0.000	0.000	-4.237	0.001	0.003	0.000	0.004	0.004	72,311	14,276	58,035
(6)	CADILLAC CT6 (GAS)	0.001	0.000	0.000	0.000	0.000	-3.530	0.002	0.001	0.004	0.004	51,715	14,649	37,066
(7)	ACURA MDX (GAS)	0.001	0.000	0.000	0.000	0.000	0.000	-3.067	0.001	0.005	0.006	42,594	13,433	29,161
(8)	TOYOTA TUNDRA (GAS)	0.000	0.000	0.000	0.000	0.000	0.000	0.001	-2.221	0.146	0.162	27,529	12,364	15,165
(9)	CHEVROLET SILVERADO (GAS)	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.030	-2.047	0.163	26,673	13,356	13,317
(10)	FORD F (GAS)	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.030	0.147	-1.996	26,214	12,833	13,381

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 1.4. 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 1.6: Marginal Cost Estimates

Variable	Mean	25%	Median	75%	Std Dev	Obs
Price (before subsidy, $1000)	51,009	23,992	33,040	52,313	582,553	397
Own-price elasticity	-3.06	-3.57	-2.49	-1.86	2.11	397
Markup, ($1000)	13,436	12,016	12,728	13,949	2,670	397
Marginal cost, ($1000)	37,572	11,938	21,295	38,213	56,008	397

Notes: This table summarizes the price elasticities, markups and vehicle marginal costs calculated from the demand estimates in Table 1.4 and the first order conditions of firms' profit maximization.

quota. In each case, I use the parameter estimates from Section 1.6 to recompute the pricing equilibria under the two-stage game described in Section 1.7.2, and calculate the market outcomes of interest, assuming that product offerings, marginal costs, demographics, and state-level subsidies stay at the observed 2017 levels.

1.7.1 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

Table 1.7: Features of Counterfactual Subsidy-Elimination Designs

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

between 2011-2017. The subsidy evolves as follows:

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

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 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 1.7 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.

1.7.2 Computing Equilibrium in the Two-Stage Game

To account for the dynamics of subsidy elimination, I allow firms to maximize the sum of profits in the current and the following year, assuming that subsidies, once eliminated, will not be reinstated in the future. I assume that firms' product portfolios, demand shocks, and marginal costs remain the same in both years and that firms do not discount the future. The two-stage assumption is guided by computational simplicity. The assumption 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 total two-year profit is

$$\Pi_{ft} = \sum_{m} \sum_{j \in \mathcal{J}_{ft}} \left[(p_{jt} - c_{jt} + h_{jmt}) Q_{jmt} + \ (p_{j,t+1} - c_{jt} + h_{jmt}) Q_{jm,t+1} \right]. \tag{1.8}$$

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.

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:

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

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

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

Solving for the optimal price vector $p^*_{.t}$ introduces important computational challenges because $\Pi^*_{f,t+1}(p_{.t})$ is not necessarily differentiable in $p_{.t}$. Differentiability holds under a market-wide deadline and a per-manufacturer deadline, where firms cannot control the status of the subsidies in period $t+1$. However, differentiability does not hold under a per-manufacturer quota where the federal subsidy in period $t+1$ depends on firms' actions in period t.

If $\Pi^*_{f,t+1}(p_{.t})$ is differentiable in $p_{.t}$, the necessary optimality condition in period t with respect to price of product j is

$$Q_{jt} + \sum_{m} \sum_{k \in \mathcal{J}_{ft}} (p_{kt} - c_{kt} + h_{kmt}) \frac{\partial Q_{kmt}}{\partial p_{jt}} + \frac{\partial \Pi^*_{f,t+1}(p_{.t})}{\partial p_{jt}} = 0. \tag{1.9}$$

In this case, I use a fixed point of equation 1.9 to compute the new pricing equilibrium, calculating the partial derivative $\frac{\partial Q_{kt}}{\partial p_{jt}}$ using equation 1.3 and $\frac{\partial \Pi^*_{f,t+1}(p_{.t})}{\partial p_{jt}}$ numerically.

If $\Pi^*_{f,t+1}(p_{.t})$ is not differentiable in $p_{.t}$, I use the following strategy to compute the equilibrium[5]: First, based on the observation that manufacturers other than Tesla and GM

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

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 $t+1$ 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 1.9. The final equilibrium under the per-manufacturer quota is the Nash equilibrium in this 2×2 game.

1.7.3 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

$$\Delta CS_{imt} = \frac{1}{\alpha_i} \left[\left(ln \sum_{j=1}^{J} exp(\delta^{(c)}_j + \mu^{(c)}_{ij}) \right) - \left(ln \sum_{j=1}^{J} exp(\delta^0_j + \mu^0_{ij}) \right) \right], \tag{1.10}$$

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 1.2. Finally, the total gasoline consumption from the vehicles sold in period t under counterfactual c is $\sum_j \frac{1}{mpg_j} \times Q_{jt}^{(c)} \times VMT_j$ where $Q_{jt}^{(c)}$ 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.

1.7.4 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 1.6 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 150,000.[6] 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 150,000 vehicles to ensure the subsidy in 2018. Note that although these manufacturers get a quota of 150,000, their EV sales in equilibrium are strictly lower than 150,000 because of strategic responses by other manufacturers. As shown in Table 1.8, 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 (2)), Tesla raises the price of Model X by 10% under a per-manufacturer quota (Column (3)). Similarly, GM raises the prices of the Cadillac CT6 (PHEV) by 6% and lowers the prices of the comparable gasoline version of Cadillac CT6 by 5.6%. Such effect on prices is a consequence of the assumption that firms control the sales of their vehicles only through prices and not any other mechanisms. In practice, manufacturers can also delay EV sales by creating an artificial shortage, but such mechanisms are challenging to model due to data limitations. Although the rise in EV prices is an outcome of model specification and

[6] Appendix table A.3 reports the EV sales separately for all manufacturers.

cannot be taken at face value, it demonstrates the strong incentive to delay EV sales that is robust to the specification. Two factors drive this incentive: (1) Staying below the quota in any period allows manufacturers to qualify for the subsidy 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.

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 1.6 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 A.3 shows that Tesla's EV sales rise by 86% 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 1.9 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.[7] 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; GM additionally lowers the prices of conventional vehicle alternatives. Because of these efforts, the subsidy-induced EV sales are around 70% lower compared to the deadline designs. Moreover, the sales of conventional vehicles rise as consumers substitute from EVs towards GM's low-cost conventional alternatives. Due to the reduction in GM's conventional-vehicle prices, the incidence changes under the per manufacturer quotas compared to either deadline; the subsidy-induced consumer surplus rises by 137%, the aggregate manufacturer profits reduce by 42%, and the government expenditure is 34% 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

[7] 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 1.3.

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.

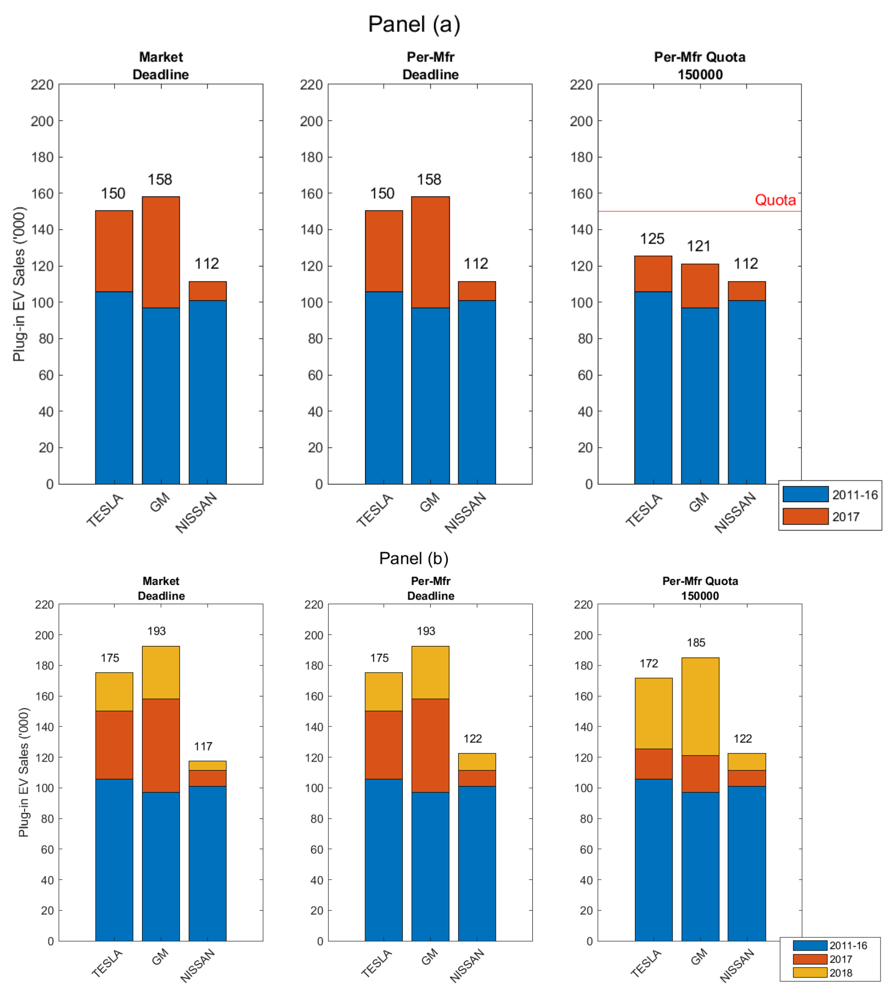
Panel (c) shows these market outcomes summed over the two years. The market-wide deadline is the least expensive and results in the lowest EV sales, consumer surplus, and manufacturer profits. The per-manufacturer deadline is more expensive and results in the highest EV sales and lowest conventional 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 69 more EVs and 11 fewer conventional vehicles than the counterfactual with no subsidy. The program results in 0.8 million gallons lower fuel consumption, \$0.54 million higher consumer surplus, and \$0.58 million higher manufacturer profits. Similarly, EV subsidies with a per-manufacturer deadline sell around 69 more EVs and 11 fewer conventional vehicles than the counterfactual with no subsidy. The program results in 0.8 million gallons lower fuel consumption, \$0.53 million higher consumer surplus, and \$0.60 million higher manufacturer profits. Finally, EV subsidies with a per-manufacturer quota sell 53 more EVs and 63 more conventional vehicles than the counterfactual with no subsidy. The program results in 5.7 million gallons higher fuel consumption, \$1.41 million higher consumer surplus, and \$0.53 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 1.10 decomposes the profits across manufacturers under different counterfactuals. Tesla earns at least \$221 million (or 45%), GM earns at least \$244 million (0.4%), and Nissan earns at \$23 million 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. Among the three counterfactuals with EV subsidies, Tesla and GM earn higher profits under the per-manufacturer quota than the deadline designs because they qualify for the 2018 subsidies under the per-manufacturer quota but not under the deadlines. For instance, Tesla's profits rise by 20% compared to the per-manufacturer deadline. In contrast, other EV manufacturers like Nissan, Toyota, BMW, and Volkswagen earn the highest profits under the per-manufacturer deadline because they qualify for subsidies in 2018 and face less competition from Tesla and GM. These manufacturers earn lower profits under the market-wide deadline as they do not qualify for the 2018 subsidies, and lower profits under the per-manufacturer deadline as they face more competition from Tesla and GM.

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 1.3. 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 32% 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.

Figure 1.6: Effect of Elimination Designs on EV Sales



Notes: This figure shows the cumulative plug-in EV sales 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 1.8: Effect of Elimination Designs on Vehicle Prices and Sales in 2017

Vehicle	Outcome	No Subsidy	Market Deadline	Per-Mfr Deadline	Per-Mfr Quota (150000)
TESLA MODEL X (BEV)	Price (USD)	80,002	79,987	79,987	88,212
	Sales	8,514	16,159	16,161	7,786
CHEVROLET VOLT (PHEV)	Price (USD)	31,435	31,392	31,392	40,387
	Sales	18,582	35,377	35,380	15,942
NISSAN LEAF (BEV)	Price (USD)	26,161	26,155	26,221	26,218
	Sales	5,643	10,712	10,650	10,652
HYUNDAI IONIQ (BEV)	Price (USD)	30,087	29,934	30,259	30,258
	Sales	257	493	479	480
CADILLAC CT6 (PHEV)	Price (USD)	72,627	72,583	72,583	76,956
	Sales	138	262	262	177
CADILLAC CT6 (GAS)	Price (USD)	51,715	51,715	51,716	48,839
	Sales	10,208	10,196	10,196	13,111
ACURA MDX (GAS)	Price (USD)	42,597	42,594	42,594	42,587
	Sales	63,596	63,516	63,518	63,414
TOYOTA TUNDRA (GAS)	Price (USD)	27,528	27,529	27,529	27,519
	Sales	49,145	49,100	49,102	48,993
CHEVROLET SILVERADO (GAS)	Price (USD)	26,672	26,673	26,673	26,441
	Sales	341,218	341,028	341,031	346,713
FORD F (GAS)	Price (USD)	26,214	26,214	26,214	26,202
	Sales	367,706	367,554	367,558	366,422

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 1.7.

Table 1.9: Effect of Elimination Designs on Aggregate Outcomes

Outcome	Market Deadline	Per-Mfr Deadline	Per-Mfr Quota (150000)
Panel (a): 2017 Outcomes			
Δ EV Sales	89,810	87,628	26,017
Δ Conv Sales	-14,223	-13,872	158,567
Δ Gas Consumption (Million Gallons)	-1,039.98	-1,014.25	14,163.85
Δ Consumer Surplus (Million USD)	693.32	676.15	1,605.11
Δ Total Profits (Million USD)	749.13	751.5	433.35
Govt Expenditure (Million USD)	1,328.6	1,316.97	870.19
Panel (b): 2018 Outcomes			
Δ EV Sales	2,489	45,874	96,230
Δ Conv Sales	-398	-7,315	-15,259
Δ Gas Consumption (Million Gallons)	-29.2	-532.81	-1,116.1
Δ Consumer Surplus (Million USD)	30.25	360.67	1,631.53
Δ Total Profits (Million USD)	21.3	413.37	787.9
Govt Expenditure (Million USD)	0	623.46	1,420.16
Panel (c): Total			
Δ EV Sales	92,299	133,501	122,248
Δ Conv Sales	-14,621	-21,187	143,308
Δ Gas Consumption (Million Gallons)	-1,069.18	-1,547.06	13,047.75
Δ Consumer Surplus (Million USD)	723.57	1,036.82	3,236.64
Δ Total Profits (Million USD)	770.42	1,164.86	1,221.25
Govt Expenditure (Million USD)	1,328.6	1,940.44	2,290.36
Panel (d): Total (Normalized)			
Δ EV Sales	69	69	53
Δ Conv Sales	-11	-11	63
Δ Gas Consumption (Million Gallons)	-0.8	-0.8	5.7
Δ Consumer Surplus (Million USD)	0.54	0.53	1.41
Δ Total Profits (Million USD)	0.58	0.6	0.53

Notes: This table shows the change in aggregate market outcomes under the counterfactual simulations discussed in section 1.7 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 1.10: Effect of Elimination Designs on Profit Distribution

Manufacturer	No Subsidy	Market Deadline	Per-Mfr Deadline	Per-Mfr Quota (150000)
ASTON MARTIN	32	32	32	32
BMW	7,869	7,943	8,024	8,013
DAIMLER	6,872	6,873	6,878	6,868
FERRARI	40	40	40	39
FIAT CHRYSLER	42,397	42,427	42,471	42,392
FORD	47,832	47,901	47,981	47,899
GENERAL MOTORS	61,737	61,991	61,981	62,335
HONDA	35,193	35,170	35,160	35,120
HYUNDAI	19,588	19,587	19,592	19,565
JAGUAR LAND ROVER	3,094	3,091	3,090	3,085
KIA	12,432	12,441	12,454	12,439
MAZDA	5,523	5,520	5,518	5,512
MITSUBISHI	2,370	2,369	2,369	2,366
NISSAN	36,072	36,106	36,150	36,095
ROLLS-ROYCE	48	48	48	48
SUBARU	14,537	14,529	14,525	14,509
TESLA	491	712	712	857
TOYOTA	55,208	55,297	55,409	55,336
VOLKSWAGEN	15,253	15,272	15,298	15,279
VOLVO	1,889	1,900	1,912	1,908

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

1.8 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 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.

Chapter 2

Differential Regulation and Firm Responses: A Study of the CAFE Standard

Ying Fan and Nafisa Lohawala

2.1 Introduction

Major auto-industry regulations in the United States, such as Corporate Average Fuel Economy (CAFE) standards by the National Highway Traffic Safety Administration (NHTSA), impose separate restrictions on passenger cars and light-duty trucks. Created in the 1970s, CAFE regulations imposed less stringent targets for light-duty trucks as they were primarily used for commercial and agricultural work and comprised less than 25% of the new vehicle sales. Although light-duty trucks are now increasingly used as personal vehicles and account for more than 50% of new vehicle sales, such differential treatment remains intact. The favorable treatment of light trucks creates a perverse incentive for manufacturers to redesign large vehicles as light-duty trucks instead of passenger cars to achieve compliance. In doing so, manufacturers can increase the average fuel economy for both fleets since a redesigned vehicle that would have fallen short of the car standard may exceed the truck standard. This substitution can harm the efficacy of these regulations in reducing gasoline use.

What are the likely implications of these efforts on market outcomes? Should regulators continue to treat cars and trucks separately? In this paper, we take a step towards answering these questions by examining the gaming opportunity that arises due to separate fuel economy regulations for passenger cars and light-duty trucks and quantifying its welfare and environmental effects.

We start with exploiting a historical change in the car-truck definitions to examine whether and to what extent manufacturers change product characteristics to qualify for favorable regulatory treatment. Before 2011, the NHTSA generally classified pickup trucks, vans, minivans, and SUVs as trucks for CAFE purposes, while sedans, coupes, and wagons as cars. In 2011, the NHTSA reclassified all two-wheel-drive SUVs under 6,000 lb gross vehicle weight as cars, reducing the total truck share by approximately 10%. This reclassification, combined with the favorable treatment of light-duty trucks in CAFE standards, creates an incentive to make heavier SUVs and equip them with four-wheel drive to classify them as trucks. Our empirical strategy is to compare the change in the proportion of light-weight SUVs equipped with a four-wheel drive after the policy change to that for non-SUVs to examine whether the drivetrain of SUVs changed disproportionately following the policy change. We find that controlling for the year fixed effects and vehicle-type-specific linear time trends, the probability of a light-weight SUV being equipped with four-wheel drive increased by 9.4 percentage points more than non-SUVs.

To quantify the welfare effects of the car-truck differential treatment, we develop and estimate a structural model of the US automobile industry. The demand side is captured by a discrete-choice model. The supply side is an oligopoly with product differentiation where car manufacturers compete in prices. We estimate the model parameters using product-level data on vehicle characteristics and sales.

Based on the estimated model, we quantify the welfare effect of the gaming behavior by changing some "marginal" trucks to become cars, recomputing the pricing equilibrium, and calculating changes in welfare measures as well as environmental measures. We find lower consumer surplus, lower manufacturer profits, and lower fuel consumption in the counterfactual scenario. Put it differently, the gaming behavior increases both consumer and producer surplus at an environmental cost.

The paper adds to multiple strands of literature. First and foremost, it adds to the growing literature on the impact of regulatory policies on transportation-related pollution and greenhouse gas emissions, examples of which include Greene (1991); Goldberg (1998); Kleit (2004); Klier and Linn (2012); Jacobsen (2013); Bento et al. (2017); Whitefoot et al. (2017); Bento et al. (2018); Ito and Sallee (2018). Several studies describe CAFE as a distortionary and costly way to conserve fuel as manufacturers can use a variety of loopholes to relax the stringency of the standards, leading to lower fuel efficiency and higher emissions. Multiple papers allude to the possibility that the car-truck loophole may have contributed to the shift in the mix of vehicles on the road (Sallee, 2011b; Anderson et al., 2011). This paper adds to the debate by providing evidence of such gaming and examining its welfare impact.

Second, it contributes to the literature documenting tax-driven product innovation, examples of which include Sallee and Slemrod (2012); Slemrod (2013); Gillitzer et al. (2017); Ito and Sallee (2018). Sallee and Slemrod (2012), for example, find that vehicle manufacturers respond to mandatory fuel economy labels by precisely manipulating fuel economy ratings to qualify for favorable treatment. This paper examines producer responses to a similar characteristic notch and quantifies the welfare effects.

Finally, the paper contributes to the literature on endogenous product choice, examples of which include Fan (2013); Eizenberg (2014); Wollmann (2018); Chaves (2019); Fan and Yang (2020). Chaves (2019) is closely related to our paper. He analyzes the impact of a discontinuous tax schedule on product variety in the Brazilian automobile industry. We add to this literature by studying how a regulatory differential treatment of products of different categories affects manufacturers' product choice and the welfare consequences.

The rest of the paper is organized as follows. Section 2.2 provides the institutional background. Section 2.3 describes the data and provides evidence of firms' gaming behavior. Section 2.4 describes the demand and supply model. Section 2.5 explains estimation and presents the estimation results. Section 2.6 explains the counterfactual design and reports the results. Section 2.7 concludes.

2.2 Background

The fuel economy is regulated because the consumption of gasoline generates three distinct externalities. First, greater demand for gasoline may threaten energy security, which can have political consequences and increase economic volatility. Second, gasoline consumption releases carbon dioxide into the atmosphere, contributing to climate change. The United States is one of the largest greenhouse emitters, and vehicle emission counts for 27% of its total emission[1]. Third, gasoline consumption releases local air pollutants that have environmental and health implications. Fuel economy standards address the nation's energy security, climate change, and air pollution.[2]

In this section, we describe the Corporate Average Fuel Economy (CAFE). We also describe two other policies regarding vehicle fuel economy: Gas Guzzler Tax (GGT) and Greenhouse Gas Emission (GHG) standards. In this paper, we focus on manufacturers' responses to CAFE because it is the oldest and most central to the US policy. Moreover, GGT applies only to a few cars, while GHG regulations are analogous to CAFE.

[1] See https://www.epa.gov/ghgemissions/inventory-us-greenhouse-gas-emissions-and-sinks

[2] A gasoline tax could be more cost-effective at reducing gasoline consumption than fuel economy standards. However, a high gasoline tax tends to be politically unpopular.

2.2.1 Corporate Average Fuel Economy Standards

Legislated in 1975 through the Energy Policy and Conservation Act (EPCA), CAFE standards are targeted toward reducing gasoline consumption. The standards are set by the National Highway Traffic Safety Administration (NHTSA) every model year and impose a limit on the average fuel economy of the vehicles sold by each manufacturer each year, with separate limits for passenger cars and light-duty trucks.

To determine manufacturers' compliance with CAFE standards, fuel economy values are measured by the Environmental Protection Agency (EPA) through the "2-cycle" tests, which comprise a "city" test that emulates the driving conditions in a city and a "highway" test imitating highway travel. The final fuel economy rating mpg_j (in miles per gallon) is computed as a weighted harmonic average of the city (C_j) and highway (H_j) test ratings: $mpg_j = \frac{1}{\frac{0.55}{C_j}+\frac{0.45}{H_j}}$. Alternative fuel vehicles such as battery-electric, fuel cell, hybrid, and flex-fuel vehicles earn a higher fuel economy rating.[3]

Individual vehicles need not meet their target exactly. Instead, a manufacturer's compliance is determined by how its average fleet fuel economy compares to the average targets of the manufactured vehicles. Manufacturers must individually meet the requirements in three separate fleets: domestic passenger cars, import passenger cars, and light trucks. The average fuel economy performance for manufacturer f in the fleet k is calculated by the following harmonically weighted formula:

$$CAFE_f^{(k)} = \frac{\sum\limits_{j \in \mathcal{J}_f^{(k)}} q_j}{\sum\limits_{j \in \mathcal{J}_f^{(k)}} q_j / mpg_j}, \tag{2.1}$$

where q_j denotes the production volume of vehicle j and $\mathcal{J}_f^{(k)}$ denotes set of vehicles produced by manufacturer f in the fleet k. Manufacturer's required fuel economy level for the fleet i is calculated using a similar formula:

$$d_f^{(k)} = \frac{\sum\limits_{j \in \mathcal{J}_f^{(k)}} q_j}{\sum\limits_{j \in \mathcal{J}_f^{(k)}} q_j / T_j}, \tag{2.2}$$

where T_j is the target value for vehicle j.

CAFE first came into effect in 1978 for passenger cars and 1979 for light-duty trucks. The

[3] For example, the fuel economy of a dedicated E85 vehicle for CAFE compliance purposes is adjusted by dividing its actual fuel economy rating by 0.15 (equivalent to multiplying by 6.67).

target value for trucks has always been below the passenger car standards. This distinction was made because when these regulations were enacted in the 1970s, the light-duty trucks were mainly used for commercial and agricultural work and accounted for less than 25 percent of total new car sales. Today, they account for more than 50 percent of all automobile sales in the US and are increasingly used as personal vehicles. As such, the share of total fuel consumption and emissions attributable to these vehicles steadily increased. Despite this shift, the regulatory distinction between passenger cars and light-duty trucks remained intact.

Manufacturers comply with the standards by reporting to the EPA and the NHTSA annually with information regarding their model year fleet production and sales numbers, fleet characteristics, and the fuel economy results from the EPA-approved test cycles. The NHTSA compares each fleet's mpg performance against the applicable standard. If manufacturers exceed CAFE requirements in a given year, they earn CAFE credits which may be used to offset deficiencies three years before or the five years after the year in which they are earned. Manufacturers with a shortfall pay a civil penalty, which is currently \$5.5 per 0.1 mpg below the standard multiplied by the manufacturer's total volume in the US domestic market:

$$(\sum_{j \in \mathcal{J}_f^{(k)}} q_j) \cdot 55 \cdot (d_f^{(k)} - CAFE_f^{(k)}) \tag{2.3}$$

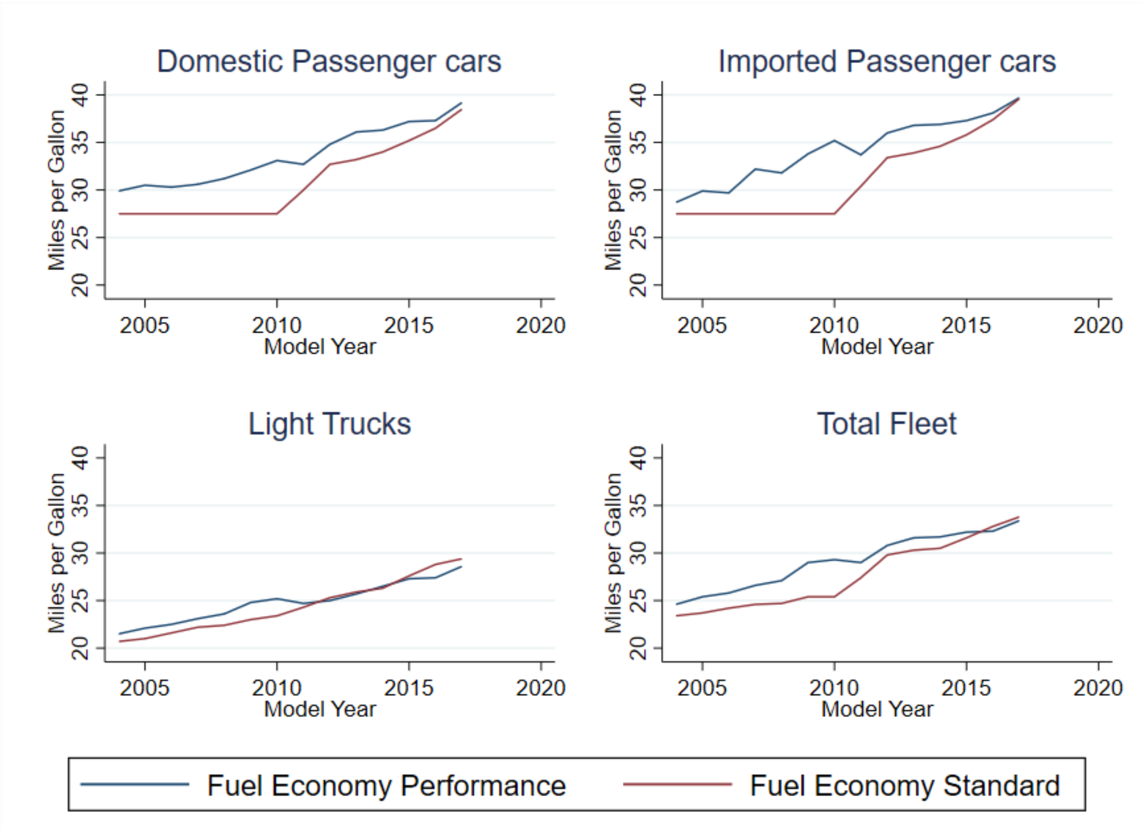
Following the Energy Independence and Security Act (EISA) of 2007, the NHTSA also allows a manufacturer with a shortfall to comply by transferring credits from one of its fleets (cars or light-duty trucks) to the fleet with the shortfall or trading for credits (purchasing credits) from another manufacturer starting from the model year 2011.[4]

Figure 2.1 plots the fleet-wide average fuel economy targets and performance during 2004-2017 separately for domestic passenger cars, imported passenger cars, and light-duty trucks. Before 2011, the NHTSA set a single target for all vehicles in a fleet. The target for both passenger car fleets was 27.5 mpg, while that for light-duty trucks increased from 20.7 in 2004 to 23.4 in 2010. After 2011, the EISA (2007) introduced targets based on vehicles' footprint ($wheelbase \times trackwidth$), with less stringent targets for larger vehicles. Although targets for passenger cars and light-duty trucks are determined by a similar formula, they are more stringent for passenger cars than light-duty trucks regardless of footprint.[5] Figure 2.1 shows that the actual fuel economy for new vehicles has closely tracked the CAFE standard

[4]In addition to the footprint-based CAFE standard as explained above, each manufacturer must meet a minimum standard of the higher of either 27.5 mpg for domestic passenger automobiles or 92% of the projected average for all manufacturers. Traded or transferred credits cannot be used to meet this requirement. However, all manufacturers meet this latter reqruiement in our sample.

[5]Appendix B.2 summarizes the target formulas for passenger cars and light-duty trucks after 2011.

Figure 2.1: Fuel Economy Performance v/s Standard

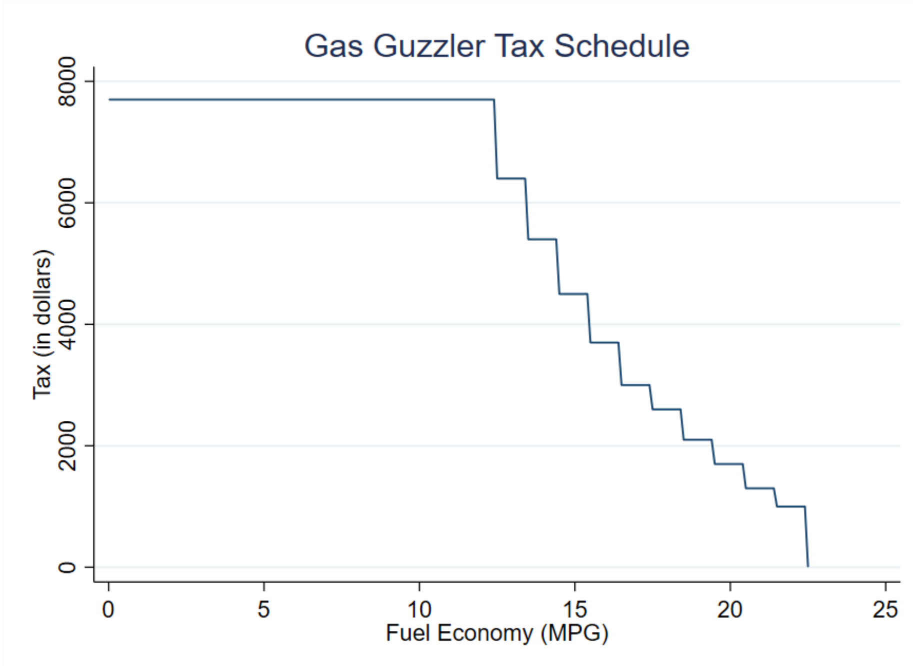


Source: NHTSA's CAFE Public Information Center

for all the fleets. However, the fuel economy standards and performance have evolved quite differently for cars and trucks. For example, between 2010 and 2017, the average fuel economy standard for the light truck fleet increased by 26%, and the average fuel economy performance increased by 13%. In contrast, the average fuel economy standard for the domestic passenger car fleet increased by 40%, and the average fuel economy performance increased by 18%.

The fleet designation of a vehicle is determined by its characteristics. To be considered a light-duty truck, a vehicle's characteristics must meet certain criteria that enable off-road driving, such as drivetrain, vehicle weight, as well as minor characteristics like approach and break-over angle. Vehicles that do not meet these criteria are classified as passenger cars. There was a change in the criteria in 2011, which we exploit in Section 2.3.3. Appendix B.1 documents the regulatory definitions of a passenger car and a light-duty truck used by the NHTSA after 2011.

Figure 2.2: Gas Guzzler Tax Schedule



2.2.2 Other Fuel Economy Policies

In 2009, the Obama administration introduced a national program for greenhouse gas emissions (GHG) and fuel economy, requiring manufacturers to reduce tailpipe GHG emissions and simultaneously increase the fuel economy of their vehicles starting from 2012. Like CAFE standards, compliance with the GHG standards is assessed separately for car and truck fleets at the end of each model year and uses the same harmonically weighted average as in (2.1) and (2.2) where fuel economy measures is replaced by emissions. Again similar to CAFE standards, the emission performance is measured through the 2-cycle test procedure, and the target is based on the vehicle footprint so that larger vehicles receive a higher CO_2-equivalent emissions target. GHG standards have a separate credit program and credit market than the CAFE standards. This program defines credits in terms of emissions (denoted in terms of the megagrams of CO_2) reduced relative to the emissions allowed by the standard. Manufacturers are allowed to bank, transfer credits across fleets, and trade credits with other manufacturers. Overall, the CAFE and GHG regulations are similar in design. Moreover, low fuel economy typically leads to high greenhouse gas emissions. Therefore, in our model, we do not consider GHG as a separate constraint.

In addition to the fuel economy regulations, a federal excise tax, i.e., Gas Guzzler Tax (GGT), is levied on individual passenger car models with especially low EPA-estimated fuel-economy ratings. The tax was enacted in 1978 as part of the Energy Tax Act to reduce negative externalities associated with fuel consumption. GGT does not cover pickup trucks, minivans, and sport utility vehicles (SUVs) because these vehicle types were not widely available in 1978 and were rarely used for non-commercial purposes. The tax was phased in between 1980 and 1991. The schedule has not changed since then. However, because the tax is not adjusted for inflation, its real value has gradually fallen over time. The tax schedule is a step function in fuel economy. Vehicles with a fuel economy rating of at least 21.5 mpg are exempt from the tax. For vehicles with a fuel economy rating below 21.5 mpg, the tax ranges from $1000 to $7700 (Figure 2.2), with higher values for lower mileages. The vehicle's manufacturer remits the tax to the IRS at the end of the model year based on the total number of gas guzzler vehicles they sold that year. The tax is visible to consumers as a line item on the window stickers of the new cars. Most mainstream cars are efficient enough to avoid the tax. Roughly 60 vehicles were affected by the tax in 2017. These cars tend to be high-priced and high-performance and include many Ferrari, Lamborghini, Maserati, and Rolls-Royce models. We take the GGT into account in our model.

2.3 Data

2.3.1 Data Sources

We combine data from several sources. Vehicle sales come from Wards Intelligence. A vehicle is defined by make/ model/ fuel type/ year. A market is a calendar year.[6] Market size is estimated by the US Census Bureau's state-level annual estimates of total households, and the market shares are calculated by dividing the total sales volume by the number of households in a state in a year. We divide vehicles into four types: sedan/ wagons, vans, pickup trucks, and SUVs. We further divide the sedan/ wagon type into small, middle, large, and luxury segments and the SUV type into crossovers and SUV segments. In each year, the sample includes all vehicles with more than 5000 sales in the US.

We also obtain vehicle characteristics from WARDS Intelligence and fill in missing values based on the information from Edmunds. We collect data on the manufacturer's suggested retail price (MSRP), horsepower, curb weight, drivetrain (2WD or 4WD), vehicle size (footprint), and fuel type. To estimate the prices faced by consumers and manufacturers, we also collect information on manufacturer discounts from the Autonews data center and federal subsidies for alternative energy vehicles from the Department of Energy. We complement

[6]CAFE regulations are based on model year production instead of calendar year sales. A model-year refers to the production cycle, which typically lasts one year and begins in August or September of the previous calendar year. However, calendar-year sales closely follow model-year sales and still provide a good approximation of CAFE requirements.

these data with the EPA's classification of vehicle trims into cars and trucks for CAFE compliance and EPA's fuel economy ratings.

Consumers care about the price, cost of driving, and other vehicle characteristics. We measure the price faced by consumers as the difference between MSRP and all the purchase incentives, including the federal subsidies and the average discounts provided by the manufacturer in that year. We measure size by length$\times$width and cost of driving (dollars per 10 miles) as the price of fuel per gallon divided by fuel economy.[7] Fuel prices come from the US Energy Information Administration.[8]

Firms care about their profits, which includes GGT and CAFE liabilities. The price that enters the profit function is the difference between MSRP and the average discounts provided by the manufacturer in that year. We obtain the historical CAFE targets from the annual reports published by the NHTSA and the GGT schedule from 26 US Code § 4064.

EPA calculates two types of fuel economy values from the city and highway test results: the unadjusted CAFE values and the adjusted on-road values that reflect in-use performance. CAFE values are used to determine manufacturers' compliance with the applicable average fuel economy standards and Gas Guzzler ratings. The adjusted on-road values are used in the fuel economy guide and on new vehicle labels to enable consumers to make more informed choices regarding fuel efficiency when purchasing a new vehicle. The two types of values are generated in different ways and are not directly comparable, although, generally, unadjusted CAFE values are higher than the adjusted on-road values. Therefore, we use the adjusted on-road values to determine consumers' cost of driving and the unadjusted CAFE values to determine manufacturers' CAFE compliance and Gas Guzzler Tax.

Although we observe vehicle characteristics at the trim level, the vehicle sales data are at the make-model-fuel level. Therefore, we match the two datasets by taking the characteristics of the cheapest trim for each vehicle. Note that different trims of a single model may classify as either a passenger car or light-duty truck for CAFE compliance, depending on its characteristics. For instance, the two-wheel-drive Honda CR-V qualifies as a passenger car, and the four-wheel-drive CR-V qualifies as a light-duty truck. In our demand model, we drive the demand for each vehicle-drivetrain, sum over different drivetrains within the same vehicle to match the sales at the vehicle/year level.[9]

[7] We approximate the cost of driving for a dual fuel vehicle (e.g., PHEV) using a 50/50 arithmetic average of the cost of driving under each fuel.

[8] EPA does not report fuel economy for larger vehicles exempt from fuel economy regulations. In such cases, we use empirical data on fuel efficiency performance from a website www.fuelly.com used by drivers to track their fuel usage.

[9] Accounting for the drivetrain almost perfectly predicts the regulatory fleet of a trim. For a few vehicle-drivetrain combinations that classify as a passenger car or light-duty truck based on other characteristics, we calculate manufacturers' fleet-specific CAFE performances by approximating a vehicle's car and truck

Finally, we obtain the data on makes produced by each company from EPA. Consistent with the regulatory definitions, we 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.

2.3.2 Summary Statistics

Table 1.1 summarizes the sales and characteristics separately for cars and trucks (as classified by NHTSA) for each year in the sample. There are 5,523 observations comprising 3,767 unique models/ year/ fuel type combinations, 1,756 of which have both two-wheel drive (2WD) and four-wheel drive (4WD) variants. The first two columns report the model year and sales, and the subsequent columns show the total vehicle-drivetrain combinations that classify as car or truck,as well as the sales-weighted average of real price, size (length$\times$width), cost of driving (in dollars per ten miles), and the ratio of horsepower by weight (in hp/10lb) — separately for light-duty trucks and passenger cars. Between 2001-2016, the total sales in the sample rose from 16.7 million to 17.1 million. The number of trucks rose from 125 to 171 and passenger cars rose from 160 to 214. The average cost of driving varied across years depending on the fuel prices, but was higher for light-duty trucks than passenger cars across all years. The average vehicle size increased from 14.3 to 15.2 thousand in^2 for trucks, and from 12.9 to 13.2 thousand in^2 for passenger cars. The average vehicle performance increased from 0.48 to 0.59 hp/10lb for light-duty trucks, and from 0.56 to 0.62 hp/10lb for passenger cars. The vehicle size was higher and average vehicle performance was lower for light-duty trucks than passenger cars across all years.

Table 2.2 shows manufacturer compositions and CAFE performance in 2016 based on NHTSA's public information center. In 2016, Tesla had a much higher performance compared to other manufacturers because it specializes exclusively in electric vehicles that garner extra credits under CAFE. Fiat Chrysler paid a civil penalty of 77.3 million dollars due to the CAFE shortfall. The remaining manufacturers with a shortfall complied by either banking credits, trading with other manufacturers, or transfering across fleets.

2.3.3 Evidence on Vehicle Redesigning

The definition of light-duty trucks was revised by the NHTSA in 2011, which allows us to examine firms' responses to the favorable regulatory treatment of light-duty trucks through vehicle redesigning. Before 2011, pickup trucks, vans, minivans, and SUVs were generally classified as trucks under the regulatory definitions, while sedans, coupes, and wagons were

sales based on the fraction of this vehicle's trims that qualify as a truck in a given year.

Table 2.1: New Vehicle Sales and Characteristics

Year	Sales ('000s)	Vehicle Counts		Avg MSRP ($'000)		Avg $/10 miles		Avg Size ('0000 in ^{2})		Avg Horsepower/Weight (Hp/10lb)	
		Truck	Car	Truck	Car	Truck	Car	Truck	Car	Truck	Car
2001	16679	125	160	34.48	34.04	0.12	0.09	1.43	1.29	0.48	0.56
2002	17216	133	162	35.28	33.81	0.11	0.08	1.43	1.28	0.48	0.66
2003	16418	148	161	36.83	34.54	0.12	0.09	1.44	1.29	0.50	0.57
2004	16583	157	172	36.68	34.33	0.14	0.11	1.46	1.31	0.51	0.56
2005	17233	166	181	36.71	34.96	0.18	0.14	1.48	1.31	0.51	0.58
2006	16298	164	187	36.16	33.88	0.17	0.13	1.48	1.31	0.52	0.59
2007	16014	181	185	33.69	32.57	0.18	0.14	1.49	1.32	0.53	0.60
2008	14708	183	190	33.44	32.47	0.22	0.18	1.50	1.32	0.54	0.61
2009	10290	182	184	34.48	32.70	0.14	0.11	1.49	1.32	0.54	0.60
2010	10791	169	173	35.04	33.90	0.17	0.13	1.49	1.33	0.54	0.61
2011	12162	168	185	34.33	32.56	0.20	0.16	1.50	1.33	0.56	0.61
2012	13804	159	199	35.30	33.20	0.21	0.16	1.52	1.32	0.57	0.62
2013	15187	159	208	36.04	34.36	0.19	0.15	1.52	1.32	0.57	0.62
2014	15795	153	213	35.69	34.43	0.19	0.14	1.52	1.32	0.59	0.64
2015	16622	162	224	36.54	33.81	0.13	0.10	1.51	1.32	0.59	0.62
2016	17185	171	214	37.19	33.18	0.11	0.08	1.52	1.32	0.59	0.62

Notes: This table shows the evolution of key variables between 2001-2016, using vehicle sales and characteristics data from Wards, EPA, and Edmunds. From left to right, we report the total sales, numbers of truck and car vehicles, and sales-weighted average vehicle characteristics. Size is length$\times$ width (in '0000 in^2), performance is horsepower by curb weight (in 10 lb), and cost of driving is fuel cost (in dollars) per ten miles. Vehicle counts show the total model-fuel-drivetrain combinations that are classified as cars or trucks. Moreover, for the purpose of calculating the sales-weighted averages, we approximate the number of car and truck sales based on the fraction of vehicle-drivetrain combinations that qualify as a car or truck in the EPA data.

Table 2.2: Manufacturer Composition in 2016

Manufacturer	Makes	Outcome	Passenger Car		Light Truck
			Domestic	Import	
BMW	BMW, MINI	Performance	0	34.1	28.8
		Standard	0	36.3	29.9
		Sales	0	289036	99451
DAIMLER	MERCEDES-BENZ, SMART	Performance	36.2	32.6	26.9
		Standard	35.9	35.6	29.5
		Sales	73807	146394	109864
FIAT CHRYSLER	CHRYSLER, DODGE , FIAT , JEEP , RAM	Performance	31.8	32.4	26.4
		Standard	35.7	38.1	29.0
		Sales	577051	55808	1365868
FORD	FORD, LINCOLN	Performance	36.2	30.7	25.9
		Standard	36.5	37.7	27.2
		Sales	977210	1290	1126877
GENERAL MOTORS	BUICK, CADILLAC , GMC	Performance	34.6	38.8	25.2
		Standard	36.1	39.9	26.9
		Sales	1081698	141219	1354255
HONDA	ACURA, HONDA	Performance	41.8	48.2	31.2
		Standard	37.3	40.8	30.4
		Sales	999276	72256	731659
HYUNDAI	HYUNDAI	Performance	0	38.2	26.4
		Standard	0	36.9	30.5
		Sales	0	697914	19889
JAGUAR LAND ROVER	JAGUAR, LAND-ROVER	Performance	0	27.7	24.9
		Standard	0	34.2	29.7
		Sales	0	16903	97650
KIA	KIA	Performance	0	36.6	27.2
		Standard	0	37.1	29.7
		Sales	0	562133	157956
MAZDA	MAZDA	Performance	0	42.1	34.2
		Standard	0	37.3	31.4
		Sales	0	305635	153192
MITSUBISHI	MITSUBISHI	Performance	0	36.8	34.9
		Standard	0	38.7	32.8
		Sales	0	26172	49097
NISSAN	CHEVROLET, INFINITI , NISSAN	Performance	41.8	37.1	30.1
		Standard	37.3	36.9	30.1
		Sales	706573	236761	409137
SUBARU	SUBARU	Performance	0	36.9	36.5
		Standard	0	38.0	32.5
		Sales	0	153926	402071
TESLA	TESLA	Performance	319.9	0	0
		Standard	34.7	0	0
		Sales	46058	0	0
TOYOTA	LEXUS, SCION , TOYOTA	Performance	36.5	41.7	26.7
		Standard	36.3	38.0	29.3
		Sales	437646	917366	1022967
VOLKSWAGEN	AUDI, PORSCHE , VOLKSWAGEN	Performance	0	0	0
		Standard	0	0	0
		Sales	0	0	0
VOLVO	VOLVO	Performance	0	35.9	29.6
		Standard	0	35.9	29.6
		Sales	0	32207	57283

Notes: This table shows each manufacturer's makes and CAFE performances in 2016 based on NHTSA's public information center.

Table 2.3: SUV Car vs Truck Classification After 2011

GVWR	2WD	4WD
$\geq$ 6000 lb	Truck	Truck
$<$ 6000 lb	Car	Truck

Notes: This table summarizes EPA and NHTSA's criteria for classifying SUVs into passenger cars and light-duty trucks after 2011. In addition to drivetrain and GVWR, the classification also includes characteristics like approach and breakover angle that enable off-road driving. However, car or truck classification almost always comes down to weight and drivetrain configurations.

classified as cars. In 2011, the NHTSA reclassified all 2WD SUVs under 6,000 lb GVWR as cars. SUVs must now have a 4WD or GVWR above 6,000 lb to be classified as trucks (see Table 2.3). The 2011 reclassification did not affect passenger cars, pickups, and vans. The reclassification of SUVs, combined with the favorable treatment of trucks in CAFE standards, creates an incentive for firms to use a 4WD in light-weight SUVs to classify them as trucks. Figure 2.3 shows the number of SUV and sedan/ wagon trims with inertia weight less than 4500 lb that were equipped with a 4WD.[10] Panel (a) shows that the number of SUV trims equipped with 4WD increased by a bigger margin than SUVs equipped with 2WD. In contrast, panel (b) shows that this was not the case with sedans.[11]

We also estimate the following linear probability model:

$$Y_{ht} = \lambda \times Treat_{ht} + \delta_{type(h)} + \delta_t + \kappa_{type(h)} t + \epsilon_{ht}, \tag{2.4}$$

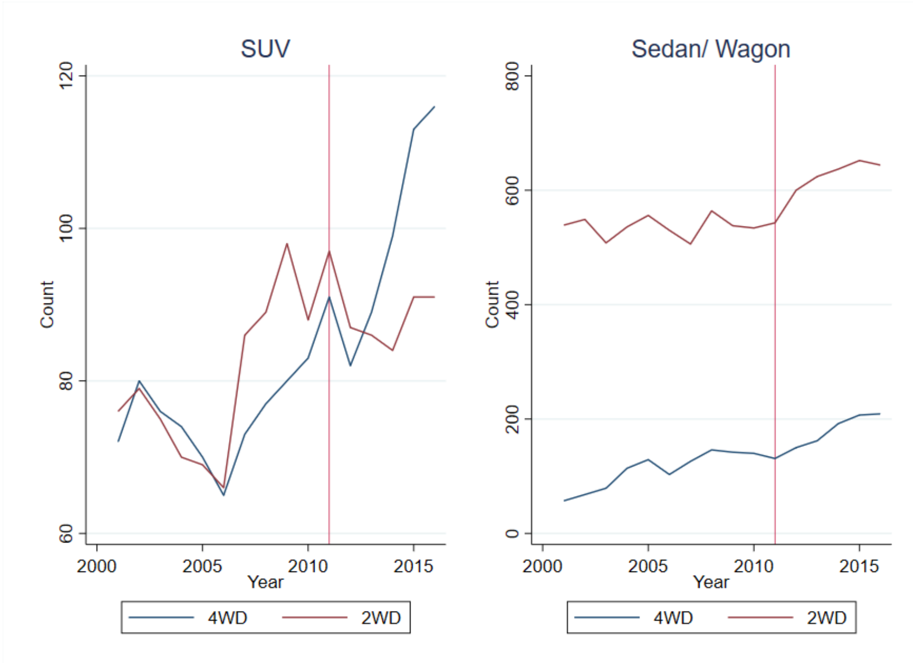
where h is a vehicle/trim, $type(h)$ indicates whether vehicle/trim h is a sedan/wagon, pickup, SUV, or van, and t is the index of year. In the regression, Y_{ht} takes value one if vehicle/trim h is equipped with a 4WD, and zero otherwise. $Treat_{ht}$ is an indicator that takes value one for SUVs after the year 2011 and zero otherwise. $\delta_{type(h)}$ are vehicle-type fixed effects to control for the inherent differences in vehicle categories that affect firms' drivetrain choice and δ_t are time fixed effects that control for year-specific differences in drivetrain preferences. In addition, we allow for a vehicle-type-specific time trend as captured by $\kappa_{type(h)} t$.

Table 2.4 reports the estimates from this regression. Controlling for year fixed effects and a vehicle-type-specific linear time trend, the probability of a light-weight SUV being equipped with 4WD increased by 10.7 percentage points more than that of non-SUVs. This result suggests that firms redesign some SUVs to classify them into the favored light truck

[10] The Wards data on vehicle GVWR contain many missing values. Moreover, the regulatory agencies do not record it. However, EPA records vehicles' inertia weight (i.e., the weight of the empty vehicle + 300 lb), and roughly anything over 4500 lb inertia weight is above 6,000 lb GVWR.

[11] Similarly, there is an incentive to bunch above GVWR of 6000 lb. EPA does not record vehicle GVWR, so we are unable to check that.

Figure 2.3: SUVs and Sedans by Drivetrain



Source: EPA

Notes: Sample consists of all vehicles with inertia weight $\geq$ 4500 lb.

fleet.

Note that there was another change in CAFE regulation in 2011, i.e., starting from 2011, firms were allowed to transfer CAFE credit across fleets. This change leads to less incentives for firms to game and thus should bias against our finding.

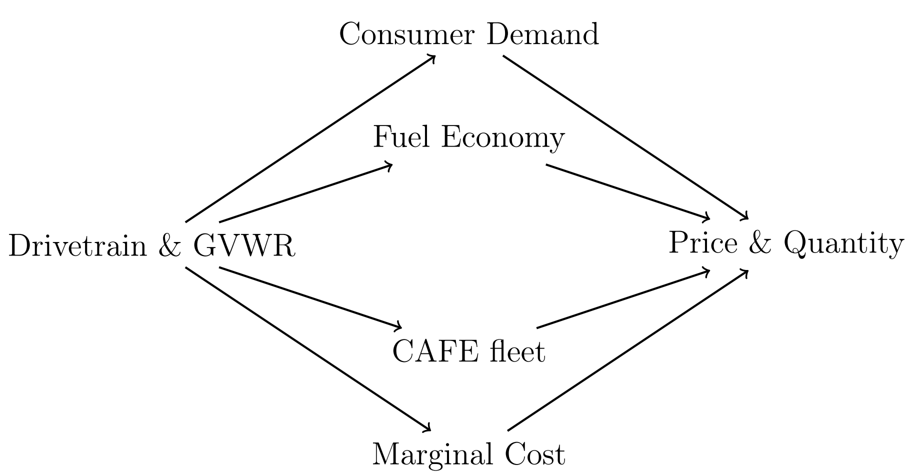
Designing large vehicles as light-duty trucks instead of passenger cars affect market outcomes through several channels. Figure 2.4 describes these mechanisms. On the demand side, the change in vehicle drivetrain would affect consumer utility directly, as well as indirectly through their effect on the cost of driving (4WD vehicles consume more fuel and are costlier to drive). On the supply side, the changes in vehicle drivetrain would affect the vehicle's CAFE mpg rating, CAFE fleet classification (i.e., car or truck), gas guzzler tax (since trucks are exempt), and marginal cost. Together, the demand- and supply-side factors would determine the price and sales in the equilibrium. To quantify the welfare effects of vehicle redesigning, we next describe the structural model that incorporates these mechanisms.

Table 2.4: Evidence of Regulation Gaming

VARIABLE	4WD
Treat	0.094***
	(0.002)
Observations	14,576
R-squared	0.079
Vehicle Type FE	Yes
Year FE	Yes
Vehicle-Type Time Trend	Yes

Notes: This table reports the outcome from estimating equation (2.4). Sample consists of all vehicle/trims with inertia weight ≤ 4500 lb. The dependent variable is an indicator taking value one if the trim is equipped with 4WD. *Treat* is an indicator taking value one for SUVs after 2011 and zero otherwise. Standard errors clustered by vehicle type (sedan/wagon, pickup, SUV, and van) are presented in the parenthesis. *** indicates 99% level of significance. ** indicates 95% level of significance. * indicates 90% level of significance.

Figure 2.4: How Redesigning Drivetrain and Weight Affect Market Outcomes



2.4 Model

To quantify the effects of firms' gaming behavior, we set up a demand and supply model of the US auto market. Section 1.4.1 describes the demand side, in which consumers choose a vehicle among all available vehicles in a year. Next, Section 1.4.2 describes the supply side, in which firms choose prices to maximize their profits given consumer demand and fuel economy policies. Finally, Section 2.4.3 describes the relationship between a vehicle's drivetrain and fuel economy, which indirectly affects consumers' and firms' decisions, as described in Figure 2.4.

2.4.1 Demand

Consumer i's utility from choosing vehicle j and drivetrain d in time t is

$$u_{ijdt} = x_{jdt}\beta_i - p_{jdt}\alpha_i + \xi_{jt} + \epsilon_{ijdt}, \tag{2.5}$$

where x_{jdt} is a $K \times 1$ vector of vehicle characteristics such as horsepower per weight and cost of driving. Price p_{jdt} is MSRP less manufacturer discounts and federal tax credits. ξ_{jt} represents the part of mean utility that is unobservable to the researcher but known to consumers and producers. ϵ_{ijdt} represents idiosyncratic tastes assumed to be i.i.d. and follow type I extreme value distribution. The outside option represents the alternative of non-purchase or purchase of a used vehicle. The utility from this choice is normalized to $U_{i0t} = \epsilon_{i0t}$.

The price coefficient α_i is 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. The random coefficients for product characteristics are assumed to follow a normal distribution with parameters β and $\sigma_{\beta l}$ for the l^{th} dimension of β_i.

Although we allow characteristics such as price and cost of driving to differ across the drivetrains, we only observe sales at the model level. We, therefore, aggregate the predicted shares across different drivetrains of a model and match them with the observed model share in the data. The market share of product j in the market t is the sum of shares across different drivetrains:

$$s_{jt} = \int \sum_d \frac{exp(x_{jdt}\beta_i - p_{jdt}\alpha_i)}{1 + \sum_{j'd' \in \mathcal{J}_t} exp(x_{j'd't}\beta_i - p_{j'd't}\alpha_i)} dF(\alpha_i, \beta_i),$$

where $\mathcal{J}_t$ is the set of vehicle/drivetrain combinations available in market t. The aggregate demand for vehicle j is $q_{jt} = M_t s_{jt}$ where M_t is market size in period t.

2.4.2 Supply

Firms observe the demand and marginal cost shocks and simultaneously choose prices, which are the difference between MSRP and retail discounts. Note that the price in the demand model is this price minus the federal tax credit. With an abuse of notation, we use the same p_{jdt} to represent both the price on the demand and the supply sides. Following (Jacobsen, 2013), we model two types of fleets: passenger car and light-duty truck.[12] Firms choose prices to solve

$$\max_{p_{jdt}, jd \in \mathcal{J}_{ft}} \sum_{jd \in \mathcal{J}_{ft}} (p_{jdt} - mc_{jdt} - GGT_{jd}) q_{jdt}(p_t) + 5.5 \sum_{k \in C,T} Credit^{(k)}(\overrightarrow{q}_{ft}^{(k)}(p_t)), \tag{2.6}$$

where $Credit^{(k)}(\overrightarrow{q}_{ft}^{(k)})$ is equal to the difference, in tenths of a mile per gallon, between the manufacturer's achieved and required CAFE levels, multiplied by the number of vehicles in the relevant fleet, i.e.,

$$Credit^{(k)}(\overrightarrow{q}_{ft}^{(k)}) = \left[CAFE^{(k)}(\overrightarrow{q}_{ft}^{(k)}) - d^{(k)}(\overrightarrow{q}_{ft}^{(k)}) \right] \times (\sum_{j \in \mathcal{J}_{ft}^{(k)}} q_{jt}) \times 10,$$

and $CAFE^{(k)}(\overrightarrow{q}_{ft}^{(k)})$ and $d^{(k)}(\overrightarrow{q}_{ft}^{(k)})$ are as defined in equations 2.1 and 2.2, respectively.[13] As explained in Section 2.2, the CAFE program allows manufacturers to trade credits with others and transfer credits across their fleets. Therefore, the profit function in (1.2) includes the second term. When a manufacturer fails to meet the standard, it pays \$5.5 for each credit shortage, i.e., the penalty rate set by the NHTSA. Conversely, when a manufacturer

[12] In practice, the regulation subdivides the passenger car fleet into domestic and import fleets. A vehicle is considered as part of the domestic fleet if 75% or more of it is produced domestically; else it is a part of the import fleet. While this division may have had some impact initially, firms have since been able to equalize the fuel economy of the two groups of passenger cars without major structural changes (National Research Council, 2002).

[13] We use several approximations in calculating the CAFE performance. (1) While the EPA uses annual production volume to compute CAFE, we use calendar year sales instead in the absence of actual production data. (2) In practice, the Alternative Motor Fuels Act (AMFA) allows manufacturers to increase their fleet fuel economy performance by producing dual-fueled or flex-fueled vehicles (FFV). We do not observe the sales of advanced technology vehicles separately and, hence, ignore this flexibility. (3) The demand model predicts sales at the model-drivetrain level, but different trims within a model-drivetrain combination may still have different fuel economies. We average the fuel economy across all trims within a model-drivetrain combination. Similarly, different trims within a model-drivetrain combination may classify as either passenger cars or light-duty trucks, depending on other characteristics. In such cases, we approximate the number of car and truck sales based on the fraction of trims that qualify as a truck as observed in the EPA data. (4) In practice, the regulation subdivides the passenger car fleet into domestic and import fleets. Here, we treat them as a single fleet.

exceeds the standard, we assume it earns \$5.5 for each surplus credit. We do not have the data for the credit market. While not perfect, this assumption approximates the actual credit market when markets are efficient so that manufacturers with surplus CAFE credits can sell their credits to others at a price equal to the penalty rate set by the NHTSA.

The formulation in (1.2) reasonably represents CAFE standards after 2011. However, before 2011, firms could not trade credits with others or transfer them across fleets, even though they could save credits for future use. As a result, a firm that consistently exceeds its fuel economy target had no use for its CAFE credits and, therefore, would not take into account the second term in (1.2). In the later counterfactual analysis, we focus on the last year of our sample, i.e., 2016. We only recover marginal costs for 2011 – 2016 based on the first-order conditions that correspond to (1.2) as shown in Appendix B.3 and estimate the marginal cost parameters using this reduced sample.

We parametrize marginal cost as $mc_{jt} = w_j\gamma + \omega_{jt}$ where w_j includes vehicle characteristics such as fuel economy as well a time trend.

2.4.3 Fuel Economy

In addition to directly affecting consumers' utility and vehicle's marginal cost, the vehicles' drivetrain and weight are likely to affect consumers' cost of driving and vehicles' CAFE mpg rating. Consumers' cost of driving, in turn, also affects consumers' utility, while CAFE mpg rating, in turn, affects vehicle manufacturers' CAFE compliance. We need to pin down the relationship between fuel economy and vehicle characteristics such as drivetrain and weight. To this end, we regress vehicles' cost of driving and CAFE mpg on vehicle characteristics, including an indicator for 4WD, vehicle size, horsepower, curb weight (10 lb), indicators for electric and hybrid vehicles, vehicle-segment fixed-effects, and year fixed-effects.[14]

2.5 Estimation and Results

2.5.1 Demand

To deal with the potential endogeneity issue regarding the price, we use the sum over all the firm's other vehicles' characteristics and the sum over all the competing vehicles' characteristics as instruments for price. Vehicle characteristics include vehicle size, horsepower per

[14] Consumers' cost of driving as the price of fuel per gallon divided by the EPA's adjusted on-road mpg values. CAFE mpg ratings are EPA's unadjusted mpg values that do not necessarily reflect real-world driving. As mentioned in Section 1.5.1, the unadjusted and adjusted mpg values are generated in different ways and are not directly comparable. Therefore, we regress vehicles' cost of driving and CAFE mpg rating separately.

weight, cost of driving, and indicators for 4WD, EV and hybrid vehicles. Following Berry et al. (1995), we estimate the demand paramters using the Generalized Method of Moments where the moments are constructed based on the instrumental variables mentioned above.

Table 2.5 reports the demand estimation results. The first panel shows the estimates of the mean parameters α and β. Most coefficients are precisely estimated and have expected signs. While the estimate of the coefficient for 4WD is only marginally significant, the interaction between SUV and 4WD has a positive and statistically significant coefficient, indicating that consumers like 4WD on SUVs. 4WD provides more traction and steering control, which is valuable in snowy and rainy climates and also for rough roads and other off-roading scenarios. That probably explains why consumers value it on SUVs. Vehicle size and 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 second panel shows the estimates of the random coefficients that measure the dispersion in households' tastes. These coefficients are the standard deviations of the tastes for the vehicle characteristics.

Table 2.6 shows a sample of own and cross price elasticities in the year 2016. Each row in this table corresponds to a different vehicle; the first five rows correspond to the top five passenger cars by sale, and bottom five rows correspond to the top five SUVs. Each entry gives the percentage change in demand of the row vehicle associated with a 1% increase in the price of the column vehicle. The cross-price elasticities are larger among similar products. For instance, increase in price of Honda Accord shifts the consumers disproportionately to Nissan Altima compared to Nissan Rogue. Table 2.7 summarizes the own price elasticities for products between 2001-2016. The average own-price elasticity is -2.03, and ranges from -2.37 at the 25th percentile to about -1.93 at the 75th percentile. The average marginal cost is USD 16,852 and ranges from USD 7,926 at the 25th percentile to USD 21,743 at the 75th percentile.

2.5.2 Marginal Cost

We back out mc_{jt} based on the first-order conditions and then regress the marginal cost on covariates w_{jt}. The second rwo of Table 2.7summarizes the recovered marginal costs between 2011 and 2016. The average marginal cost is USD 16,852 and ranges from USD 7,926 at the 25th percentile to USD 21,743 at the 75th percentile.

Table 2.8 summarizes the marginal cost parameters. The coefficients on vehicle size, horsepower per weight, 4WD, curb weight, and the indicator for alternative energy vehicle are positive and significantly different from zero, indicating that producing these features

Table 2.5: Demand Estimates

Coefficients	Est	SE
Mean Parameters α and β		
Price ('0000 USD)	-0.230	0.476
Four Wheel Drive	-3.353	2.812
SUV x Four Wheel Drive	1.994***	0.533
Dollar per 10 miles	-7.112*	3.956
Vehicle Size ('0000 in^2)	2.727***	0.464
Horsepower/weight (Hp/10lb)	0.490	0.502
Electric	-1.370***	0.297
Hybrid	-0.980***	0.130
Trend	-0.056***	0.010
Std. Dev. parameters σ_α and σ_β		
Price ('0000 USD)	0.458	0.458
Four Wheel Drive	2.354	1.995
Dollar per 10 miles	5.144	4.612
Car	1.814*	1.050
Pickup	2.450*	1.403
SUV	0.237	2.367
Van	4.095*	2.358
Fixed Effects		
Vehicle Manufacturer FE	Yes	
Vehicle Segment FE	Yes	
Obs	5523	

Notes: This table shows the estimates of the demand parameters. *** indicates 99% level of significance. ** indicates 95% level of significance. * indicates 90% level of significance.

Table 2.6: Own and Cross Price Elasticities

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1)	HONDA CIVIC (2WD CAR)	-1.289	0.027	0.025	0.001	0.001	0.001	0.001	0.000	0.001	0.000
(2)	TOYOTA CAMRY (2WD CAR)	0.031	-1.497	0.031	0.001	0.001	0.001	0.001	0.001	0.001	0.001
(3)	TOYOTA COROLLA (2WD CAR)	0.024	0.025	-1.218	0.001	0.001	0.001	0.001	0.000	0.001	0.000
(4)	FORD ESCAPE (4WD SUV*)	0.002	0.002	0.002	-1.622	0.017	0.015	0.016	0.010	0.013	0.008
(5)	HONDA CR-V (4WD SUV*)	0.002	0.002	0.002	0.014	-1.574	0.015	0.015	0.010	0.013	0.008
(6)	NISSAN ROGUE (4WD SUV*)	0.002	0.002	0.002	0.013	0.015	-1.502	0.014	0.009	0.012	0.007
(7)	TOYOTA RAV4 (4WD SUV*)	0.002	0.002	0.002	0.014	0.016	0.014	-1.545	0.009	0.012	0.008
(8)	JEEP GRAND-CHEROKEE (4WD SUV)	0.002	0.003	0.002	0.020	0.023	0.020	0.021	-1.885	0.019	0.012
(9)	FORD EXPLORER (4WD SUV)	0.002	0.003	0.002	0.019	0.022	0.019	0.020	0.014	-1.848	0.011
(10)	TOYOTA HIGHLANDER (4WD SUV)	0.002	0.003	0.002	0.019	0.022	0.020	0.020	0.014	0.018	-1.863

Notes: Columns (1)-(10) report average cross-price elasticities for the top 3 cars, the top 4 marginal trucks SUVs (i.e., SUVs with 4WD and inertia weight $\leq$ 4500 lb, marked wth a *), and the top 3 non-marginal truck SUVs (i.e., SUVs with 4WD and inertia weight $>$ 4500 lb) in 2016, calculated from the demand estimates in Table 2.5. Each entry (i, j), where i is the row and j is the column, refers to the percentage change in demand for vehicle-drivetrain j when the price of vehicle-drivetrain i changes by 1%.

Table 2.7: Own-price elasticities and Marginal Cost

Variable	Mean	25%	Median	75%	Std Dev	Obs
Own-price elasticity (%)	-2.03	-2.37	-1.93	-1.57	0.65	5523
Marginal cost (USD)	16,852	7,926	13,387	21,743	13,435	2180

Notes: This table summarizes the own-price elasticities and marginal costs calculated from the demand estimates in Table 2.5 on data between 2001-2016 and the first order conditions of firms' profit maximization on data between 2011-2016.

Table 2.8: Marginal Cost Estimates

Variable	Coef	SE
Vehicle Size (0000 in^2)	-6.614**	3.281
Horsepower	0.004*	0.003
Curb Weight	0.001***	0.000
Four Wheel Drive	0.132***	0.046
Electric	2.429***	0.413
Hybrid	0.293	0.199
Time Trend	0.021**	0.010
Obs	2180	

Notes: This table summarizes the marginal cost parameters. Heteroskedasticity robust standard errors are presented in the parenthesis. *** indicates 99% level of significance. ** indicates 95% level of significance. * indicates 90% level of significance.

is costly for manufacturers. Controlling for the other covariates, the inclusion of 4WD is estimated to raise the marginal cost per vehicle by around $1320 in the sample.

2.5.3 Vehicle Characteristics and Fuel Economy Rating

Table 2.9 summarizes the regression results governing the relationship between vehicle fuel and other vehicle characteristics. Features such as 4WD, curb weight, and vehicle size reduce a vehicle's fuel economy rating and increase the cost of driving, ceteris paribus. Column (1) shows that controlling for the other covariates, the inclusion of 4WD is estimated to reduce the CAFE mpg rating of a vehicle by around 1.116. This estimate allows us to capture the effect of drivetrain on manufacturers' CAFE liability. Moreover, column (2) shows that controlling for the other covariates, the inclusion of 4WD increases the cost of driving by $4 per ten thousand miles. This estimate allows us to capture the indirect effect of drivetrain on consumers' utility through cost of driving.

Table 2.9: Fuel Economy and Cost of Driving Parameters

	CAFE MPG Rating		Dollar per 10 miles	
Variable	Coef	SE	Coef	SE
4WD	-1.116***	0.128	0.004***	0.000
Vehicle Size (0000 in^2)	-6.207***	0.782	0.001	0.003
Horsepower	-0.017***	0.001	0.000***	0.000
Curb Weight (10 lb)	-0.201***	0.021	0.002***	0.000
Electric	318.536***	1.038	-0.111***	0.004
Hybrid	19.678***	0.326	-0.052***	0.001
Year FE	Yes		Yes	
Vehicle Segment FE	Yes		Yes	
Obs	5523		5523	

Notes: This table summarizes the fuel economy parameters. Standard errors are presented in the parenthesis. *** indicates 99% level of significance. ** indicates 95% level of significance. * indicates 90% level of significance.

2.6 Counterfactual Experiments

2.6.1 Counterfactual Design

We quantify the effect of the regulation gaming by changing some "marginal" light-duty trucks to passenger cars, recomputing the pricing equilibrium, and calculating the change in market outcomes such as consumer surplus, manufacturers' profits and fuel economy performances, and vehicles' liquid fuel consumption. We do so for the year 2016, the last year of our sample.

As shown in Table 2.3, the NHTSA classifies 2WD SUVs with GVWR less than 6000 lb as cars. Based on this definition, we define "marginal" light-duty trucks as SUVs with 4WD and inertia weight less than 4500 lb. Table 2.10 shows the number of marginal trucks and the fraction of vehicles in the light-duty truck fleet that are classifies as marginal trucks for each manufacturer.

Changing marginal trucks to cars by changing their drivtrain to 2WD affects the market outcomes through six channels. First, changing 4WD to 2WD affects demand directly. Second, this change affects consumers' cost of driving; we compute the cost of driving for each redesigned vehicle using estimates from Table 2.9. Third, because the redesigned vehicles classify as cars, they may also be subject to the gas guzzler tax; we compute the tax for each redesigned vehicle using the gas guzzler schedule in Figure 2.2. Fourth, changing the drivetrain affects the marginal cost; we compute the new marginal costs for the redesigned vehicles based on the estimates of marginal cost parameters. Fifth, the change in vehicle's fuel economy affects its CAFE mpg rating; we compute the new CAFE fuel economy rating from Table 2.9. Lastly, having 2WD changes the compliance fleet from truck to car.

In our counterfactual simulation where we change the drivetrain of the marginal trucks from 4WD to 2WD, we allow for all six channels and recompute the new price equilibrium. The comparison of the outcomes in the data and those in this counterfactual scenario informs us about the effects of the firms' gaming behavior. In addition to prices and quantities, we also report changes in consumer surplus, manufacturer profits, and fuel consumption. We compute the total gasoline consumption as $\sum_{jd} \frac{1}{mpg_{jd}} \times Q_{jd} \times VMT_j$ where mpg_{jd} is calculated by dividing fuel price by dpm_{jd} from Table 2.9. Q_{jdt} is the total sales of vehicle j drivetrain d and VMT_j is the miles travelled during its lifetime. We assume that vehicles travel 12,000 miles per year and have a life of 15 years.[15]

Table 2.10: Marginal Trucks for Each Manufacturer

Manufacturer	Marginal Trucks	
	Total	Fraction
BMW	2	0.3
DAIMLER	2	0.3
FIAT CHRYSLER	7	0.3
FORD	3	0.2
GENERAL MOTORS	3	0.1
HONDA	4	0.4
HYUNDAI	1	0.5
JAGUAR LAND ROVER	2	0.4
KIA	2	0.5
MAZDA	2	0.7
MITSUBISHI	2	0.7
NISSAN	4	0.1
SUBARU	3	1.0
TESLA	0	0.0
TOYOTA	4	0.2
VOLKSWAGEN	3	0.6
VOLVO	2	0.4

Notes: This table shows the number of marginal trucks and the fraction of vehicles in the light-duty truck fleet that are classify as marginal trucks for each manufacturer.

[15]Fuel economy regulations can create a "rebound effect" (Greene et al., 1999), where consumers increase driving as a result of lower fuel costs caused by tighter standards. Here, we ignore such effects.

2.6.2 Results

Table 2.11 shows the prices and sales for the top 3 cars, the top 4 marginal trucks SUVs (i.e., SUVs with 4WD and inertia weight $\leq$ 4500 lb, marked with a *), and the top 3 non-marginal truck SUVs (i.e., SUVs with 4WD and inertia weight $>$ 4500 lb) in the data and the counterfactual. Comparing the prices and quantities in the data (Column (1)) to those in the counterfactual simulation (Column (2)), we can see that the prices of popular cars remain almost unchanged in the counterfactual, and the corresponding sales increase. In contrast, the prices of redesigned light-weight SUVs increase while the sales decrease. These changes result from a combination of several changes. On the demand side, removing 4WD from the light-weight SUVs has a negative effect on consumer utility, ceteris paribus. However, removing 4WD also reduces the cost of driving, which has an indirect positive effect on the mean utility, ceteris paribus. On the supply side, removing 4WD reduces a vehicle's marginal cost. As for the CAFE standards, the redesigned SUVs have higher CAFE ratings and are now counted as passenger cars with a less-favorable treatment in the CAFE standards. To decompose the overall effects into those due to the traditional demand and supply considerations, due to the change in CAFE ratings in the CAFE standards, and due to the change of fleet in the CAFE standards, we conduct two additional counterfactual simulations, where firms completely ignore CAFE credits in their profit function in one counterfactual simulation (Column (3)) and firms ignore the fleet change but take into account the CAFE rating changes (as well as the demand and supply changes) in the other (Column (4)). Based on the comparison between the data and Column (3), we can see that under the traditional demand-supply considerations, the prices and sales of the redesigned light-weight SUVs decrease. This is because demand for these products shifts to the left, and their marginal costs decrease. Comparison between Columns (3) and (4) shows the effect of firms' consideration of changes in CAFE ratings. Because the redesigned SUVs earn higher CAFE ratings, firms should have incentives to sell more of them to meet CAFE standards. Indeed, we find lower prices for redesigned SUVs in Column (4) than in Column (3). Similarly, comparing Columns (4) and (2) gives the effect of firms' consideration of the fleet change. Because these redesigned SUVs are now counted as passenger cars with a less-favorable treatment in the CAFE standard, firms have an incentive to raise their prices and sell fewer of them. We indeed find that the prices of redesigned SUVs in Column (2) are higher than those in Column (4). As for the heavy-weight 4WD SUVs in the last three rows of Table 2.11, we find that their prices and sales increase as consumers substitute to these vehicles.

Table 2.12 shows each manufacturer's CAFE performance for the passenger car and light-duty truck fleets based in the data and equilibrium in the counterfactual scenario. Note that manufacturers' compliance based on the sales in the data closely follows the NHTSA's records

Table 2.11: Counterfactual Vehicle Prices and Sales in 2016

Original Vehicle-Drivetrain	Outcome	(1) Data	(2) Counterfactual	(3) Decomposition: Ignore Rating & Fleet Changes	(4) Decomposition: Ignore Fleet Changes
HONDA CIVIC (2WD CAR)	Price (USD)	18,408	18,423	18,404	18,404
	Sales	367,042	367,614	368,037	368,019
TOYOTA CAMRY (2WD CAR)	Price (USD)	22,282	22,275	22,284	22,284
	Sales	380,610	381,855	381,555	381,526
TOYOTA COROLLA (2WD CAR)	Price (USD)	17,093	17,098	17,089	17,089
	Sales	355,877	356,677	356,846	356,841
FORD ESCAPE (4WD SUV*)	Price (USD)	26,615	23,391	23,152	23,106
	Sales	202,138	104,208	105,909	106,238
HONDA CR-V (4WD SUV*)	Price (USD)	25,622	22,586	22,336	22,274
	Sales	237,682	122,342	124,440	124,969
NISSAN ROGUE (4WD SUV*)	Price (USD)	23,901	20,520	20,469	20,433
	Sales	214,639	114,644	115,025	115,310
TOYOTA RAV4 (4WD SUV*)	Price (USD)	24,818	21,644	21,449	21,390
	Sales	215,043	112,015	113,527	113,991
JEEP GRAND-CHEROKEE (4WD SUV)	Price (USD)	32,875	33,919	33,934	33,938
	Sales	129,665	165,049	164,889	164,846
FORD EXPLORER (4WD SUV)	Price (USD)	32,042	33,563	33,569	33,569
	Sales	170,612	210,233	210,135	210,122
TOYOTA HIGHLANDER (4WD SUV)	Price (USD)	32,317	33,735	33,734	33,734
	Sales	108,116	133,756	133,744	133,739

Notes: This table shows the equilibrium prices and sales for a sample of vehicles in the data as well as in the counterfactual scenario.

in Table 2.2. The differences in calculations arise from the different approximations made in the model.[16] The performance of the passenger car fleet reduces for most manufacturers because SUVs, which are now a part of the passenger car fleet, are generally less fuel-efficient than other passenger cars (i.e., sedans and wagons). Moreover, passenger car sales rise because SUVs now count as passenger cars. Again because the light-weight SUVs are a part of the passenger car fleet, the performance of light-duty truck fleet also reduces for most manufacturers because the remaining vehicles (i.e., pickups, vans, and heavy-weight trucks) in the light-duty truck fleet tend to be less fuel-efficient than light-weight SUVs.

Finally, Table 2.13 shows the aggregate outcomes and welfare measures. The total passenger car sales rise by 1559 thousand, the light-duty truck (and the overall) sales fall by 2574 thousand, and the overall sales fall by 1016 thousand compared to the data. The aggregate manufacturer profits falls by 16,283 million dollars, aggregate consumer surplus falls by 21,519 million dollars, and gas consumption falls by 7,057 million gallons during the lifetime of newly sold vehicles. In other words, firms' gaming behavior due to the differential treatment of cars and trucks in the CAFE standards leads to an increase in both consumer and producer surpluses, however, at an environmental costs.

[16]See Footnote 13

Table 2.12: Manufacturer Fuel Economy Performance for Passenger Cars and Light-Duty Trucks

Manufacturer	Outcome	Passenger Cars		Light Trucks	
		Data	Counterfactual	Data	Counterfactual
BMW	Performance	35	34.7	27.1	25.1
	Standard	36.4	36.4	29.9	29.3
	Sales	284,225	311,175	79,865	58,642
DAIMLER	Performance	31.9	32.1	26.1	23.3
	Standard	35.7	35.7	29.5	28.8
	Sales	199,148	224,482	125,343	106,962
FIAT CHRYSLER	Performance	30.1	29.5	26.5	26
	Standard	35.6	36.3	28.8	27.1
	Sales	577,918	917,807	1,672,089	1,094,621
FORD	Performance	35.8	35	25.8	24.9
	Standard	36.4	36.3	26.9	26.1
	Sales	904,009	1,070,231	1,664,072	1,430,976
GENERAL MOTORS	Performance	29.4	29.8	24	23
	Standard	36.1	36.3	26.9	26.3
	Sales	290,745	332,768	631,069	597,942
HONDA	Performance	40	38.9	31.6	29.2
	Standard	37.3	37.2	30.5	28.4
	Sales	1,021,807	1,236,127	590,564	191,073
HYUNDAI	Performance	36.3	36.3	27.1	28.3
	Standard	36.7	36.7	30.9	30.9
	Sales	699,408	713,451	59,638	16,535
JAGUAR LAND ROVER	Performance	30.7	30.9	24.9	22.6
	Standard	33.7	35.2	29.9	29.1
	Sales	6,645	19,173	71,067	62,525
KIA	Performance	35.2	35	27.8	27.1
	Standard	37	37	30.1	28.3
	Sales	485,118	512,904	154,446	64,359
MAZDA	Performance	41.7	40.6	34.3	32.5
	Standard	37.3	37.2	31.5	29.3
	Sales	214,355	257,945	86,510	5,867
MITSUBISHI	Performance	41.8	39.3	34	36.5
	Standard	39.7	39.3	32.8	32.8
	Sales	47,933	68,833	48,778	8,640
NISSAN	Performance	37.7	37.4	25.6	23.9
	Standard	36.9	36.9	27.3	26.4
	Sales	1,890,203	2,090,546	1,667,450	1,380,209
SUBARU	Performance	35.4	35.7	34.9	0
	Standard	38	38	32.5	0
	Sales	160,128	399,552	429,786	0
TESLA	Performance	314.2	314.5	0	0
	Standard	32.2	32.2	0	0
	Sales	18,263	18,697	0	0
TOYOTA	Performance	39.8	39.2	26.7	25
	Standard	37.3	37.3	29.3	28.5
	Sales	1,397,399	1,522,127	1,042,356	822,594
VOLKSWAGEN	Performance	36.3	35.4	28	27.2
	Standard	38	37.8	30.5	28.9
	Sales	379,598	430,591	130,485	50,336
VOLVO	Performance	37.3	34.9	30.2	31.5
	Standard	35.9	35.8	29.7	29
	Sales	27,403	36,491	52,112	40,176

Notes: This table shows manufacturers' fuel economy performances for passenger cars and light-duty trucks in 2016 in the data as well as in the counterfactual scenario.

Table 2.13: Counterfactual Aggregate Outcomes

Δ Sales (000s)	-1,016
Δ Car Sales (000s)	1,559
Δ Truck Sales (000s)	-2,574
Δ Gas Consumption (Million Gallons)	-7,057
Δ Consumer Surplus (Million USD)	-21,519
Δ Total Profits (Million USD)	-16,283

Notes: This table shows the change in aggregate market outcomes in 2016 under the counterfactual scenario compared to the data.

2.7 Conclusion

This paper examines the gaming opportunity that arises due to separate fuel economy regulations for passenger cars and light-duty trucks in the US Corporate Average Fuel Economy CAFE standards. The favorable treatment of light trucks creates a perverse incentive for manufacturers to redesign large cars as trucks to achieve compliance. Thus, part of manufacturers' compliance strategy could be to tweak the characteristics of existing vehicles so that they qualify as light-duty trucks instead of passenger cars. This strategy requires little effort on the part of manufacturers, and potentially worsens the vehicle's fuel economy.

We first exploit the 2011 changes in the car-truck definitions to provide suggestive evidence that firms change product characteristics to classify their vehicles as light-duty trucks instead of passenger cars under the CAFE regulations. Next, we develop and estimate a structural model of the US automobile industry to quantify the welfare and environmental effects of regulation gaming. We find that designing SUVs as light-duty trucks instead of passenger cars results in higher manufacturer profits, higher consumer surplus, and higher fuel consumption. In this study, we quantify the equilibrium effects of changing "marginal" trucks back to cars, while holding other vehicles in the market fixed. We plan to quantify how the separate fuel economy regulations affect firms' product choice as well prices in future work.

Chapter 3

Alcohol Regulations and Road Traffic Accidents in India

Nafisa Lohawala

3.1 Introduction

The motor vehicle population in India is growing faster than economic and population growth. The surge in motorization and road network development has brought the challenge of addressing road accidents. Between 1970-2019, the reported road traffic accidents increased from 114 thousand to 449 thousand, road injuries increased from 70 to 451 thousand, and fatalities increased from 15 to 151 thousand (TRW, 2019). India ranks first in the number of road accident deaths across the 199 countries reported in the World Road Statistics (2018), accounting for almost 11% of the global accident-related deaths. Traffic-related injuries significantly burden the health sector in pre-hospital and acute care and rehabilitation. UNESCAP (2020) estimates India's economic cost from road crashes at approximately $58 billion. Another study by the Fumagalli et al. (2017) suggests that India could improve its GDP by 16.3% by reducing road accident deaths over the next 24 years.

In the past decade, a primary goal of public policy has been to reduce road traffic accidents and fatalities (TRW, 2019). Can alcohol regulations help? Driving under the influence of alcohol is a leading cause of road traffic accidents worldwide (McLean et al., 1987; Fabbri et al., 2002; Martin et al., 2017). In India, an average of nearly 12,000 drunk driving accidents are recorded every year (TRW, 2019) – and this may be a gross underestimate because police often lack the manpower and technology to measure drivers' alcohol levels (Banerjee et al., 2019). In addition, alcohol consumption in India has surged drastically over the past years. Per-capita alcohol consumption increased from 2.4 liters of alcohol in 2005 to 4.3 liters in 2010 and further to 5.7 liters in 2016 (WHO, 2019). If drunk driving is an important cause of road traffic accidents, then reducing alcohol availability may reduce the accidents. However, the effect of alcohol restrictions is not obvious because the target population can substitute to the black market and low-quality products in the presence of weak law enforcement. Moreover, because alcohol laws are nonuniform across states, people in the neighborhood of states with more liberal alcohol policies can cross the border to buy and consume alcohol. In that case, restricting alcohol could increase road-traffic accidents by raising the travel distance required to obtain alcohol.

Despite these concerns, alcohol regulation as a strategy for reducing road traffic accidents is worth examining because alcohol use is widely associated with road traffic accidents, and there is wide latitude for changing such regulations. Additionally, these regulations come with a nontrivial tradeoff because they affect state governments' tax revenue and the tourism industry. India provides an interesting context because of two reasons. First, drinking age regulations are legislated at the state level, and there is no consensus among states about the appropriate drinking age. Moreover, alcohol regulations are constantly evolving. For example, in 2021 alone, Delhi and Haryana lowered the legal drinking age, and the Bihar government is contemplating a relaxation of the ban it imposed in 2016 (Kumar, 2022). As a result, state government regulations provide a large-scale policy experiment with substantial variation across states and time. Second, although alcohol regulation is a subject of intense scrutiny in India, there is little documentation of the effect of these regulations on road traffic accidents.

This paper adds to the discussion by documenting the effects of two regulations on road traffic accidents: (1) regulation of demographic access to alcohol through state-wide alcohol ban and minimum legal drinking age and (2) regulation of location where alcohol is sold through sales ban near highways. I combine the data on state-level alcohol regulations with road traffic accidents, injuries, and fatalities in 27 states between 2004-2019 and take advantage of two sources of variation: (1) differences in the timing of prohibition and age-based alcohol regulation across states and (2) a nationwide alcohol sales ban near highways that affected certain roads in non-prohibition states. The analysis rests on a fixed-effects model using state-road type-level panel data from India stretching over almost fifteen years. In some specifications, I also allow for spillovers of neighboring states' drinking age policies on a state's road safety. Finally, because fixed effects regressions may be biased in settings combining multiple treatment timings and treatment effect heterogeneity (De Chaisemartin and D'Haultfoeuille, ming), I conduct additional robustness analysis to avoid comparing treatment units to inappropriate controls.

Overall, the results suggest that both regulations affect road safety. The most conservative estimates show that a state that moves from alcohol prohibition to legal drinking age of 16 experiences roughly ten additional accidents per 10,000 vehicles, on average, compared to other states. Moreover, the roads affected by the highway alcohol ban experience six fewer accidents per 10,000 vehicles compared to other roads. The highway ban possibly works by reducing distractions on the roads, suggesting that it can be an effective policy tool to prevent road traffic accidents. Given that a highway ban is much less disruptive than other regulations like total prohibition, the policy can also be promising in other countries. Finally, there is evidence of spillovers of neighboring states' drinking age policies on a state's road safety, suggesting potential gains from equalizing the legal drinking age across states.

This paper adds to the literature in two ways. First, it contributes to the literature examining the effect of alcohol regulations on road safety and public health. Some papers on road safety include Chaloupka et al. 1993; Miron and Tetelbaum 2009; Lovenheim and Slemrod 2010; Lovenheim and Steefel 2011; Marcus and Siedler 2015. Papers on other outcomes include Carpenter and Dobkin (2011) on public health, Luca et al. (2015) on violence against women, and Carpenter and Dobkin (2010); Chaudhuri et al. (2018) on crimes. Most papers in the literature study regulations in developed countries. This paper focuses on a developing country instead, where weaker institutions warrant the need for a closer examination. Second, the paper adds to the literature on road safety in India, examples of which include Kanchan et al. (2012), Farooqui et al. (2013), Singh (2017), Luca et al. (2019), and Banerjee et al. (2019). Most work on road safety in India is descriptive, and not much written on combating drunk driving. This paper is closely related to Luca et al. (2019), who provide suggestive evidence that stricter alcohol control is associated with lower rates of motorbike accidents, and Banerjee et al. (2019), who study the efficient deployment of police resources to combat drunk driving.

The rest of the paper is organized as follows. Section 3.2 gives a background on the cultural context and alcohol policies adopted in India. Section 3.3 describes the data. Section 3.4 describes the empirical strategy, identification and results. Section 3.5 concludes.

3.2 Background

Alcohol consumption leads to a loss of driving ability due to several reasons. Physiological effects include impairments in coordination, concentration, reflexes, reaction time, depth perception, and peripheral vision. Excessive doses of alcohol may also lead to sedation. Psychological effects include an increase in aggression. In addition to the above, the use of safety devices is known to be negatively associated with alcohol use (Kweon and Kockelman, 2003).

Alcohol regulation policies are typically justified on externality grounds: alcohol consumption can compromise others directly (e.g., in the case of crime or traffic accidents) or indirectly (e.g., through higher costs for the health care system). In general, regulation can take several forms: (i) regulating demographic access (e.g., minimum legal drinking age), (ii) regulating the location of alcohol sale, (iii) regulating temporal access (e.g., hours and days of sale); and (iv) regulating economic access (e.g., alcohol taxes). India implemented some versions of each in the past years, at state or national levels. This section summarizes the implemented regulations.

3.2.1 State-wide Alcohol Ban and Legal Drinking Age Policies

The Indian constitution grants each state legislature the power to draft rules governing the sale and consumption of alcohol in the state. As a result, every state has different laws, including minimum legal drinking age and excise policy. Some states impose a blanket prohibition, while others fix a minimum legal drinking age (MLDA) ranging between 18 to 25. Figure 3.1 shows the distribution of the legal drinking age across states in 2019. While Bihar, Gujarat, Manipur, Mizoram, and Nagaland banned alcohol, Goa, Himachal Pradesh, Karnataka, and Sikkim, imposed a legal drinking age of 18, Kerala imposed 23, and Haryana, Maharashtra, Meghalaya, and Punjab imposed 25.[1] The remaining states imposed a drinking age of 21 years.

Motivations for alcohol prohibition and legal drinking age typically include curbing domestic violence and road accidents, cultural attitudes, and health issues linked with excessive drinking. While blanket prohibition restricts all age groups, the minimum legal drinking age limits underage drinking, which is typically linked with long-lasting adverse consequences on adolescents, such as crimes (Carpenter and Dobkin, 2010), teenage pregnancy (Carpenter, 2005), alcohol dependence (Guttmannova et al., 2011), neural abnormalities (Squeglia et al., 2014), academic performance (Lindo et al., 2013) and risky driving (Zakrajsek and Shope, 2006). From the perspective of road safety, restricting underage drinking can be helpful because adolescents are more likely to binge drink, i.e., consume a large amount of alcohol in a short time, making them more dangerous drivers. In India, 22% percent of the road-accident deaths in 2019 involved drivers in the age-group 18-25 (TRW, 2019).

However, the effect of these policies on road safety is ambiguous. From a restricted individual's perspective, alcohol ban and legal drinking age increase the search costs of obtaining alcohol, including time, transportation cost, and the risk associated with obtaining alcohol. Therefore, the effectiveness of alcohol regulation depends on the increase in search costs associated with the regulation. A regulation will work if it increases the search cost significantly among the target age group; else not. For instance, it may be ineffective if

[1]Manipur imposed a prohibition in almost half of its districts. Maharashtra imposed a prohibition in 3 out of 36 districts.

the target population can easily substitute to the black market, lower quality alternatives, or other liberal states. Substitution to black markets is possible in the presence of weak law enforcement because state borders are porous, and alcohol can be smuggled. For instance, alcohol prohibition has proven ineffective in Manipur because of alcohol smuggling and thriving black markets (Kamei, 2014). Substitution to low-quality alternatives such as indigenous alcohol is similarly possible. For instance, the dry state of Gujarat has witnessed several occasions of alcohol poisoning. Finally, substitution to other states with liberal alcohol laws is possible for people residing in proximity to other states with liberal alcohol laws as they may start driving to those states to consume alcohol. This substitution can make alcohol-related accidents more likely.

More generally, alcohol ban and legal drinking age policies present a nontrivial tradeoff for the states as they prevent states from collecting tax revenue on alcohol sales. The revenue losses can be significant. For example, just before the ban, in 2014-15, Bihar made over Rs 3,100 crore from excise duty on alcohol sales, according to the Economic Survey of 2016. Moreover, black marketing in the absence of proper enforcement leads to further social issues as well—for instance, the media has reported a rising involvement of Bihar's unemployed youth in bootlegging and school children in alcohol smuggling (Parth, 2017). Several states that implemented a ban later revoked it, claiming that smuggling rendered the ban ineffective; examples include Andhra Pradesh, Haryana, and Manipur.

Despite nontrivial law evasion, legal drinking age policies have been shown to significantly affect the likelihood of alcohol consumption. Luca et al. (2019) find that men of the legal drinking age are almost 30% more likely to drink alcohol. In addition, alcohol prohibition has been shown to reduce violence against women (Luca et al., 2015). So it is possible that such regulations may reduce road traffic accidents as well.

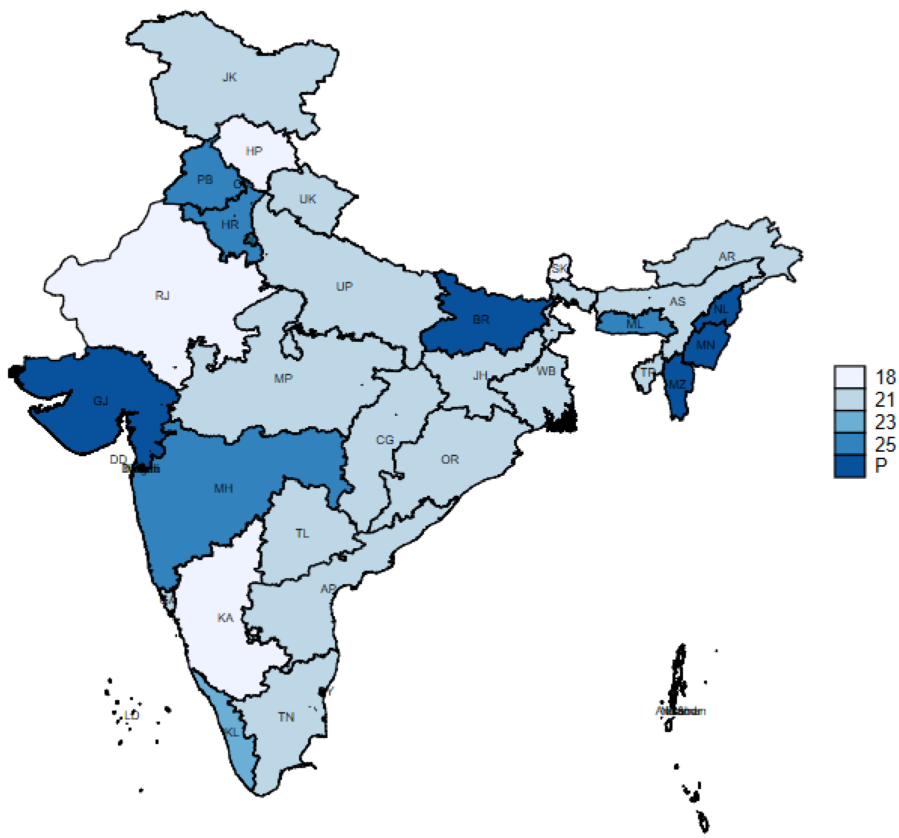
3.2.2 Alcohol Ban near Highways

Highways comprise about 5% of the total road network but witness 52% of the accidents (TRW, 2019). Prompted by the high number of deaths caused due to drunken driving, the Supreme court banned the sale of alcohol within 500 meters of national and state highways, effective April 1, 2017. The ban did not hold for highways within city limits. The court also banned all signages indicating the presence of alcohol vends on national and state highways, arguing that they distracted the drivers.[2]

Like other policies related to alcohol, the effect of highway bans is ambiguous. On the

[2]The orders have been gradually relaxed for some states based on the appeals by the respective state governments (Ananthakrishnan, 2018). For example, the distance in Himachal Pradesh, Meghalaya, and Sikkim was reduced to 220 meters instead of 500 meters due to their unique geography.

Figure 3.1: Legal Drinking Age Policies across States in 2019



Notes: The figure shows the state-wise minimum legal drinking age in 2019. Darker shades indicate higher values. P indicates the states that prohibited alcohol in 2019.

one hand, the ban (if enforced properly) may work if the visual cues from the alcohol shops and signage distract drivers and induce impulsive drunk driving. On the other hand, it may have little impact on highway road safety since people can easily evade the ban by buying alcohol before starting their journey. Moreover, limiting alcohol availability near highways will induce people to substitute to buying and consuming alcohol within city limits. Even if accidents decrease on highways, accidents on other roads may increase. However, since city roads have lower speed limits, fatalities may be lower. Finally, black markets and weak law enforcement may render the regulation ineffective. Even if licensed shops shut down, branded alcohol may still be available on highways through informal channels without proper law enforcement.

Like other regulations, highway bans have received public scrutiny. Food and beverage businesses that made investments across the highways opposed the ban because it affected their livelihoods. The ban was also unwelcome by several state governments because they lost excise revenue. For example, the ban majorly impacted Mahe (Puducherry), which closed 64 alcohol shops that contributed Rs 67 crore in 2015 (Harigovind, 2016).

3.2.3 Other Regulations

Apart from the two policies mentioned above, states also put alcohol excise taxes, which raise the consumer-facing price of alcohol, reduce alcohol consumption by the law of demand, and reduce drunk driving. Some states also regulate the hours and days of sales. Due to data limitations, I exclude these regulations from this analysis. I discuss the implications of excluding alcohol taxes in Section 3.4.

Numerous national-level policies have also been implemented over the years. For instance, Cable Television Network Regulation (Amendment) Bill (2000) banned the advertising of alcoholic beverages across India. Alcohol companies still advertise using surrogate means like selling the brand name for soda or water or music. Similarly, section 185 in the Motor Vehicles Act, 1988 makes driving under the influence a criminal offense in India. In 2019, an amendment to the Motor Vehicle Act (among other reforms) raised the fine for drunk driving from INR 2,000 to INR 10,000 and imprisonment from six months to four years. Penalties are assessed based on the blood alcohol content at the time of the offense. I exclude these policies since the changes affected the entire nation simultaneously.

3.3 Data

The data on road traffic accidents comes from the "Road Accidents in India" publications by the Transport Research Wing (TRW) of the Ministry of Road Transport and Highways, which include road accidents broken by road type in all states between 2004-2019. I match the accident data with the legal drinking age policies from state-specific excise records. I also match the total registered motor vehicles for each state from the TRW Road Transport Yearbook.[3] I obtain state-level lengths of different types of roads and state-level GDP for the years 2004-2019 from the Reserve Bank of India's handbook of statistics on Indian states. Finally, I obtain the age-wise district-level population from the 2001 census of India and the state-level population from the 2001 and 2011 censuses.

Four states changed the demographic regulation of alcohol during the sample period. Bihar banned alcohol in 2016. Mizoram repealed its 17-year-old alcohol ban in 2014 and banned alcohol again in 2019. Kerala banned alcohol in 2014 but lifted it in 2017, raising the minimum legal drinking age from 18 to 23 in 2017. Finally, Maharashtra lowered its MLDA (for hard liquor) to 21 from 25 for one year (2005). The highway ban only affected the states that legalized alcohol when the ban was implemented but did not affect the states that already banned alcohol.

I make three simplifications in the analysis. First, I exclude Manipur in the absence of reliable data on the legal drinking age. Manipur imposed a blanket prohibition before 2002 but lifted it in half of its districts through Manipur Liquor Prohibition (amendment) bill (2002). However, I was unable to find reliable data on the legal drinking age in the districts that legalize alcohol. Moreover, for 2014-2019, I aggregate the accidents in Telangana state with Andhra Pradesh, as the two states split in 2014 but retained the same drinking age policies. Finally, I assume the legal drinking age in Karnataka to be 18. In practice, there was a lack of clarity within the state regarding the minimum drinking purchase age. The legal drinking age is 21 as per Karnataka Excise Department (1967) and 18 as per the Karnataka Excise Act (1965). Some bars serve those above 18, while others refuse service to anyone below 21 (Yadav, 2016; The Hindu, 2016).

[3] When vehicle registrations are unavailable, I linear-interpolate them from the adjacent years.

3.4 Empirical Model and Results

3.4.1 Empirical Model

I begin by estimating the following specification using accident data broken by road classification and incorporating different alcohol policies as regressors.

$$RTA_{rst} = \beta_0 + \beta_1 Drink_{st} + \beta_3 HwyBan_{rst} + \beta_4 X_{rst} + \delta_r + \delta_s + \delta_t + \delta_{st} + \epsilon_{rst} \tag{3.1}$$

where RTA_{st} denotes accident rate defined as

$$RTA_{rst} = \frac{\text{Accidents of road type } r \text{ in state } s \text{ in year } t}{\text{vehicle registration in state } s \text{ in year } t} \times 1000. \tag{3.2}$$

Because accidents increase with total vehicles on road, accident rate is a better indicator to assess road safety when compared to accidents. This model specification captures alcohol regulations through a combination of variables. First, $Drink_{st}$ captures the effect of alcohol age restrictions and equals the fraction of drivers in the age group 18-45 that are legally eligible to drink:

$$Drink_{st} = \frac{\text{Population in state } s \text{ with age} \in [MLDA, 45]}{\text{Population in state } s \text{ with age} \in [16, 45]}. \tag{3.3}$$

I approximate $Drink_{st}$ using age-wise 2001 census population. This variable takes a value of zero for states with a drinking age of 45 and above, including the prohibition states. It would take a value of one if a state (hypothetically) imposed a drinking age of 16. Thus, a change in $Drink_{st}$ from 0 to 1 is equivalent to moving from alcohol prohibition to a legal drinking age of 16. This variable varies across states due to differences in legal drinking age and demographic composition. However, because the population is only approximated using the 2001 census, the variation within a state across time is entirely driven by changes in the drinking age of alcohol. I use the age group 16-45 because 16 is the legal driving age in India, and drivers below 45 years are the most susceptible to accidents. In 2019, 81% of the drivers killed in road accidents were younger than 45 years (TRW, 2019), even though the age group 16-45 comprised only 46% of the total population in the 2011 census. For a state s, $Drink_{st}$ increases when the state reduces its legal drinking age. The coefficient β_1 indicates the effect of a state's demographic regulations and can be interpreted as the change in the state's accident rate associated with moving from alcohol prohibition to a legal drinking age of 16, conditional on other covariates.

The presence of liberal alcohol regulations just across the state border can compromise the impact of the state's policies for two reasons. First, residents living close to states with liberal alcohol policies can drive to these states to consume alcohol. Such effects have been found in developed countries (Lovenheim and Slemrod, 2010). Second, because state borders are porous, variations in alcohol policies can create grey markets where smuggled alcohol is readily available to the population. To capture this effect, replace $Drink_{st}$ in some specifications with the fraction of the state population within the age group 16-45 that can legally obtain alcohol in their own or nearby district. Specifically, let $\mathcal{S}$ denote the set of districts in a state s, and $\mathcal{N}_d$ denote the set of districts bordering a district d. Then,

$$DrinkN_{st} = \frac{\sum_{d \in \mathcal{S}} (\text{Population in district } d \text{ with age } \in [min\{MLDA_{d'}\}_{d' \in d \cup \mathcal{N}_d}, 45])}{\text{Population in state } s \text{ with age} \in [16{,}45]}. \tag{3.4}$$

Like $Drink_{st}$, this variable also varies across states and time. However, the variation comes from two sources: $DrinkN_{st}$ increases when the state s reduces its legal drinking age or when a state bordering s reduces its legal drinking age. For example, when Kerala banned alcohol in 2014, $DrinkN_{st}$ reduced in Tamil Nadu because it shares a border with Kerala and had a higher drinking age than Kerala in 2014. The coefficient β_2 indicates the effect of the own and neighboring state's demographic regulations and can be interpreted as the change in the accident rate associated with the change in the own or neighboring district's legal drinking age from 45 to 16, conditional on other covariates.

Finally, $HwyBan_{rst}$ takes value one for highways in non-ban states after 2016 and zero otherwise. The effect of the highway alcohol ban depends on the alcohol prohibition laws and the road type. For instance, the ban did not affect Gujarat because it already prohibited alcohol throughout the state. Among the states that legalize alcohol, only the roads that classify as highways are affected. The coefficient β_3 indicates the effect of the highway ban and can be interpreted as the change in the accident rate from being affected by the highway ban, conditional on other covariates.

In addition to alcohol policies, I include state-level characteristics X_{rst}, i.e., the state's GDP per capita, vehicle density, road density, and population density, to control for time-variant differences across states that may affect road traffic accidents. GDP per capita is state GDP by population projected from the 2001 and 2011 censuses. Vehicle density is proxied by the total vehicles registered in the state divided by the length of roads in the state. Road density is road length divided by the area of the state (in sq km), and population density is the projected state population divided by the area of the state (in sq km). In addition, I include a road-type indicator δ_r that takes value one for a highway to control for time-invariant differences across road types, such as differences in speed limits. I also include state fixed-effects δ_s to capture the time-invariant differences across states, such as local attitudes towards alcohol and drunk driving. For instance, the Muslim-majority state of Jammu &

Kashmir is likely to have low alcohol consumption, irrespective of the regulation permitting alcohol. State fixed effects ensure that identification is obtained from the policy variation within the states. Finally, I include time fixed-effects δ_t to control for time-varying changes that affect all states and road types. For instance, δ_t captures the effect of the Cable TV advertisement ban and the Motor Vehicle Amendment Act (2019).

These regressions use the total road traffic accidents, including accidents from causes other than drunk driving.[4] The identification assumption is that the change in road traffic accidents following a change in demographic access or highway ban is solely due to the change in drunk driving. The effect of the drinking age is identified by comparing the rate of road traffic accidents in a state before and after the change in the legal drinking age relative to other states. The effect of the highway ban is identified by comparing road traffic accidents on the affected and the unaffected roads after controlling for the state, year, and road-type fixed effects.

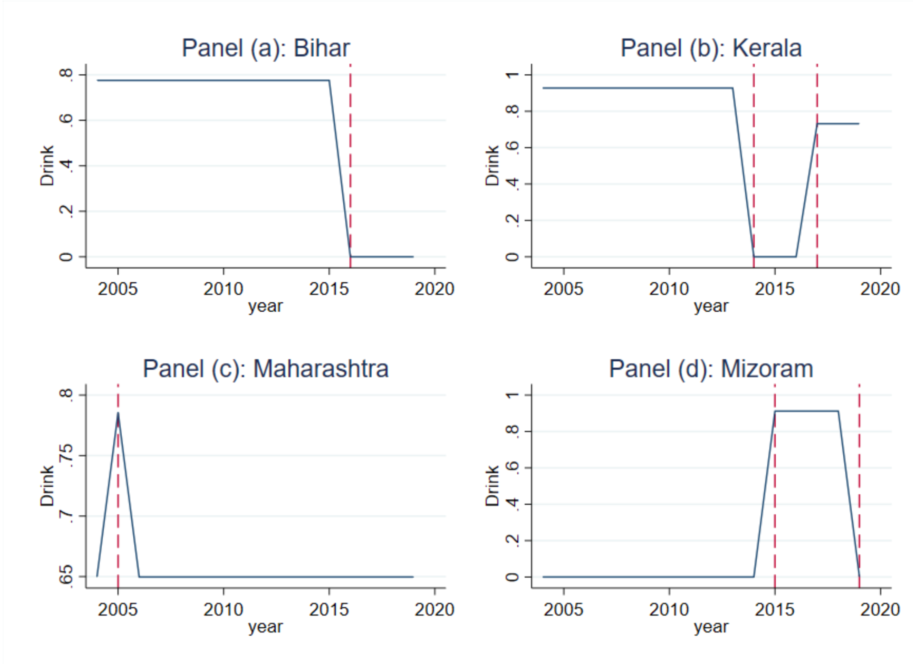
3.4.2 Summary Statistics

Table 3.1 reports the summary statistics of all the variables used in the analysis, broken by road type. There are 864 observations comprising 27 states, 16 years, and two road types. The table also summarizes the variables broken by road type for variables that vary by road type. Panel (a) shows the road-safety outcomes. An average state witnessed 22 accidents, 18 road injuries, and 5 deaths per 10,000 vehicles. Moreover, on average, accident, injury, and death rates are higher on highways than on other roads. The average fraction of the drinking age population ($Drink$) in the age group 16-45 in the sample is 0.7 because most states have a legal drinking age of 21. In contrast, the fraction of the drinking age population accounting for neighboring states' policies ($DrinkN$) is 0.8. The $HwyBan$ indicator takes a value of one for 10% of observations. On highways, it takes a value of one for 20% of observations. On other roads, it is always zero. An average state in the sample has GDP per capita of INR 52 thousand. Moreover, the average vehicle density is 38 vehicles per km of road length, and the average population density is 378 per sq km. Finally, the average road density is 0.8 km per sq km; it is lower for highways than other roads.

Figure 3.2 shows the trend in $Drink$ for the states that changed their legal drinking age or prohibition policy. The dashed lines mark the year of change. Panel (a) shows Bihar, which banned alcohol in 2016. Correspondingly, the fraction of the drinking age population

[4] Although TRW recorded the accidents reported due to driving under the influence of alcohol between 2008-2019, these data are very likely to be underreported for two reasons. (1) Police often lack the manpower and technology to measure blood alcohol levels, and most crashes are not forensically investigated. (2), The role of alcohol is difficult to measure in hit-and-run cases where the offender is missing. In 2019, such cases comprised 15.5% of the total accidents. Because of these reasons, I rely on the total accidents for the analysis.

Figure 3.2: Trends in the Fraction of Drinking-Age Population



Notes: The figure shows fraction of drinking age population in the age-group 16-45 in the states that changed their legal drinking age or prohibition policy. The dashed lines mark the year of policy change.

reduced from 0.76 to 0. Panel (b) shows Kerala, which banned alcohol in 2014 but lifted it in 2017 and raised the minimum legal drinking age from 18 to 23. Panel (c) shows Maharashtra, which lowered MLDA (for hard liquor) to 21 from 25 for one year (2005). Finally, Panel (d) shows Mizoram, which repealed its alcohol ban in 2014 and a legal drinking age of 18. Mizoram banned alcohol again in 2019.

Figure 3.3 shows the histograms of $Drink$, $DrinkN$, and $HwyBan$ in the sample. The distribution of $DrinkN$ is shifted to the right as compared to the distribution of $Drink$ because it accounts for the population living close to states with liberal alcohol policies. Unlike $Drink$ which takes a value of zero for prohibition states, $DrinkN$ is always positive because all prohibition states have some liberal neighbors where residents can legally access alcohol.

3.4.3 Baseline Analysis

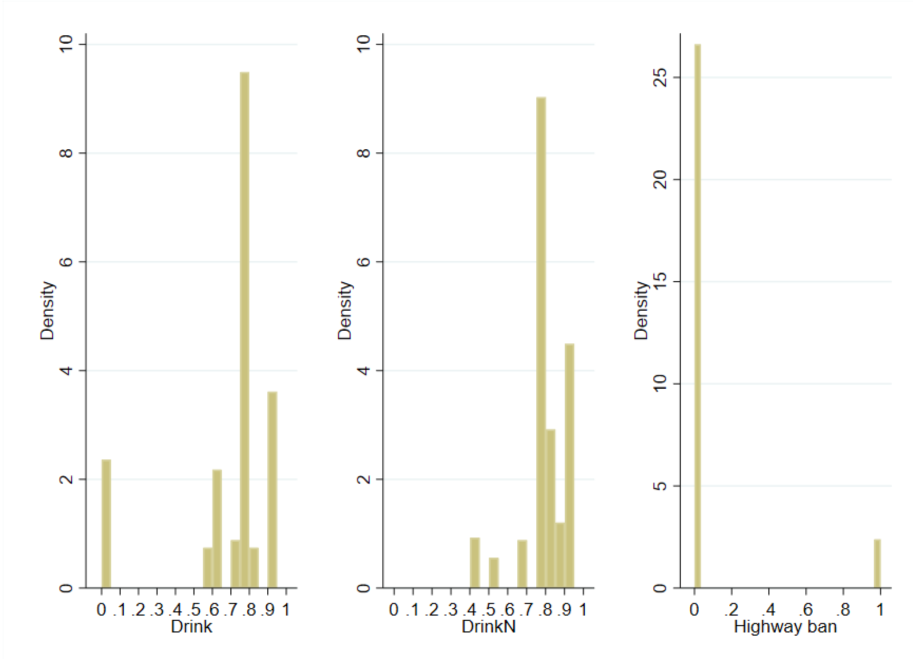
Table 3.2 reports the results from equation 3.1. In each column, the standard errors are clustered at the state level. Column (1) presents the relationship between alcohol policies and road traffic accidents conditional on road type. Column (2) includes additional controls,

Table 3.1: Summary Statistics

	mean	sd	min	max	obs
Panel (a): Outcome Variables					
Accidents per 1000 vehicles	1.8	1.5	0.0	12.8	864
Highways	2.2	1.6	0.1	12.8	432
Other roads	1.4	1.3	0.0	8.9	432
Persons injured per 1000 vehicles	2.1	2.1	0.0	16.9	864
Highways	2.6	2.3	0.1	16.9	432
Other roads	1.7	1.8	0.0	12.8	432
Persons killed per 1000 vehicles	0.5	0.4	0.0	2.8	864
Highways	0.7	0.4	0.0	2.8	432
Other roads	0.4	0.2	0.0	2.0	432
Panel (b): Alcohol regulations					
Drink	0.7	0.3	0.0	0.9	864
DrinkN	0.8	0.1	0.4	0.9	864
Highway Ban	0.1	0.3	0.0	1.0	864
Highways	0.2	0.4	0.0	1.0	432
Other roads	0.0	0.0	0.0	0.0	432
Panel (c): Other covariates					
GDP per capita (INR)	52411.2	31735.9	8566.3	220730.6	864
Vehicles density (per km road)	37.7	33.5	2.3	178.1	864
Population density (per sq km)	378.2	280.7	13.6	1139.4	864
Road length (km) per sq km	0.8	1.1	0.0	6.5	864
Highways	0.1	0.0	0.0	0.2	432
Other roads	1.5	1.2	0.1	6.5	432

Notes: This table summarizes accidents, alcohol policies and other state-level covariates used in the analysis.

Figure 3.3: Histograms of Alcohol Regulations



Notes: The figure shows the histograms of $Drink$, $DrinkN$ and $Hwyban$ variables (as defined in Section 3.4) in the sample.

i.e., GDP per capita, vehicles per km, population density, and road density. $Drink$ has a positive coefficient, meaning that conditional on the covariates, the states with a higher fraction of the drinking age population witness higher road traffic accidents per 1000 km, on average. $HwyBan$ has a negative coefficient, meaning that conditional on the covariates, the roads affected by the highway ban witnessed fewer traffic accidents per 1000 km, on average. Finally, the highway indicator has a positive coefficient, indicating that highways witness more accidents than other roads. Column (3) includes state fixed-effects, ensuring that comparisons identifying the effect of alcohol policies are only made within (and not across) states. Finally, Column (4) includes year fixed-effects. The coefficient for $Drink$ remains positive and significant while that of $HwyBan$ remains negative and significant. The coefficient on $Drink$ in the full specification (i.e., Column (4)) indicates that a state that moves from alcohol prohibition to legal drinking age of 16 experiences roughly one additional accident per 1000 vehicles (or ten accidents per 10,000 vehicles) on average, compared to other states. This finding is in line with Luca et al. (2019), who also find suggestive evidence that stricter alcohol control in India is associated with lower rates of motor vehicle accidents. Moreover, the coefficient on $HwyBan$ in Column (4) indicates that traffic accidents on the roads affected by the highway ban reduced by six per 10,000 vehicles on average, compared to the roads unaffected by the highway ban. Both estimates suggest that regulating alcohol sales can effectively reduce road traffic accidents.

Columns (5)-(8) report analogous regressions replacing $Drink$ with $DrinkN$. In addition to own states' drinking age policies, these specifications also account for the neighboring states' drinking age policies. The results show that the coefficient on $DrinkN$ is almost double the coefficient on $Drink$ across all specifications. The coefficient on $DrinkN$ in the full specification (Column (8)) indicates that the reduction in own or neighboring district's legal drinking age from 45 to 16 is associated with twenty additional accidents per 10,000 vehicles in that state, on average. The coefficients on $HwyBan$ in Columns (4)-(8) are similar to those in Columns (1)-(4). Together, these estimates provide evidence of a significant relationship between alcohol regulations and road safety.

Tables 3.3 and 3.4 replicate the analysis in Table 3.2 for persons injured and killed in road traffic accidents. In both cases, the coefficients on the alcohol policy measures have the same signs as in Table 3.2, lending additional support to the finding that alcohol regulations affect road safety. However, the coefficients on drinking age policies in Table 3.4 are imprecisely estimated, possibly because road fatalities are likely to be noisy indicators of road safety for several reasons. First, a single bus accident may lead to more deaths than ten accidents involving two-wheelers. Second, fatalities may be underreported in the police data because fatalities in which the offender cannot be identified go unreported. Similarly, the deaths in hospitals following a road accident may be unreported if the police and hospital data are not linked. Finally, the accident-related fatalities also depend on the post-accident response systems, such as the availability of ambulances and first-responder training.

It is worth noting that there could be potential biases in these estimates because of uncontrolled factors such as state-level alcohol taxes. However, the direction of the bias is unclear. On the one hand, the decreases in the MLDA may be associated with an increased need for tax revenue (i.e., higher taxes on alcohol). If this were the case, estimates from the panel approach would downward bias the actual effect of the minimum legal drinking age because the estimates would confound the effects of the legal drinking age and alcohol taxation. On the other hand, the increase in MLDA could be associated with the need to reduce alcohol consumption in the state (i.e., higher taxes on alcohol). If this were the case, estimates from the panel approach would upward bias the actual effect of the minimum legal drinking age.

Table 3.2: Road Traffic Accidents

VARIABLES	(1) No Controls	(2) + Controls	(3) + State FE	(4) + Year FE	(5) No Controls	(6) + Controls	(7) + State FE	(8) + Year FE
Drink	2.019***	1.934***	0.988***	1.090***				
	(0.342)	(0.426)	(0.288)	(0.181)				
DrinkN					3.811***	3.706**	1.852**	2.290***
					(1.183)	(1.425)	(0.675)	(0.465)
Highway ban	-1.517***	-1.385***	-0.594***	-0.655***	-1.472***	-1.331***	-0.587***	-0.652***
	(0.156)	(0.169)	(0.155)	(0.191)	(0.167)	(0.185)	(0.156)	(0.189)
Highway	0.990***	1.049***	0.796***	0.838***	0.982***	0.986***	0.794***	0.837***
	(0.191)	(0.271)	(0.246)	(0.245)	(0.192)	(0.261)	(0.246)	(0.246)
GDP per capita (INR)		-0.003	-0.024***	-0.006		-0.003	-0.024***	-0.006
		(0.005)	(0.006)	(0.004)		(0.005)	(0.006)	(0.004)
Vehicles density (per km road)		-0.005	-0.008*	-0.005		-0.007*	-0.008*	-0.006
		(0.003)	(0.004)	(0.004)		(0.004)	(0.005)	(0.004)
Population density (per sq km)		-0.112	-4.458	4.870		0.141	-4.884	4.616
		(0.495)	(2.951)	(3.194)		(0.484)	(3.098)	(3.293)
Road length (km) per sq km		0.058	-0.030	-0.007		0.019	-0.031	-0.008
		(0.206)	(0.179)	(0.180)		(0.188)	(0.179)	(0.180)
Constant	0.058	0.405	4.061***	-0.615	-1.577	-1.180	3.419**	-1.598
	(0.260)	(0.482)	(1.125)	(1.338)	(0.942)	(1.270)	(1.352)	(1.547)
Observations	864	864	864	864	864	864	864	864
R-squared	0.239	0.261	0.651	0.700	0.196	0.226	0.648	0.698
State FE	NO	NO	YES	YES	NO	NO	YES	YES
Year FE	NO	NO	NO	YES	NO	NO	NO	YES

Notes: Sample consists of all states (except Manipur) between 2004-2019. Accidents in Telangana state are aggregated with Andhra Pradesh, as the states split in 2014 but retained the same alcohol policies. Robust standard errors clustered by the state are presented in the parenthesis. *** indicates 99% level of significance. ** indicates 95% level of significance. * indicates 90% level of significance.

Table 3.3: Road Traffic Injuries

VARIABLES	(1) No Controls	(2) + Controls	(3) + State FE	(4) + Year FE	(5) No Controls	(6) + Controls	(7) + State FE	(8) + Year FE
Drink	2.696***	2.587***	1.108**	1.268***				
	(0.602)	(0.676)	(0.419)	(0.259)				
DrinkN					5.462***	5.229**	1.772*	2.437***
					(1.939)	(2.270)	(0.976)	(0.665)
Highway ban	-1.879***	-1.586***	-0.689***	-0.812***	-1.834***	-1.526***	-0.676***	-0.803***
	(0.246)	(0.226)	(0.235)	(0.283)	(0.250)	(0.223)	(0.237)	(0.279)
Highway	1.213***	1.267***	0.906***	0.970***	1.206***	1.181***	0.903***	0.968***
	(0.253)	(0.349)	(0.278)	(0.279)	(0.252)	(0.333)	(0.279)	(0.280)
GDP per capita (INR)		-0.006	-0.038***	-0.011		-0.006	-0.037***	-0.010
		(0.005)	(0.009)	(0.007)		(0.005)	(0.009)	(0.007)
Vehicles density (per km road)		-0.010*	-0.008	-0.005		-0.012**	-0.009	-0.005
		(0.005)	(0.006)	(0.006)		(0.005)	(0.006)	(0.006)
Population density (per sq km)		-1.001	-0.936	13.079***		-0.660	-1.626	12.618***
		(0.710)	(3.700)	(4.340)		(0.676)	(3.873)	(4.433)
Road length (km) per sq km		0.073	-0.080	-0.048		0.019	-0.080	-0.049
		(0.285)	(0.242)	(0.244)		(0.261)	(0.242)	(0.244)
Constant	-0.183	0.857	3.690**	-3.328*	-2.662*	-1.478	3.281*	-4.237**
	(0.405)	(0.625)	(1.402)	(1.776)	(1.515)	(1.881)	(1.690)	(2.031)
Observations	864	864	864	864	864	864	864	864
R-squared	0.195	0.262	0.653	0.706	0.168	0.239	0.651	0.704
State FE	NO	NO	YES	YES	NO	NO	YES	YES
Year FE	NO	NO	NO	YES	NO	NO	NO	YES

Notes: Sample consists of all states (except Manipur) between 2004-2019. Accidents in Telangana state are aggregated with Andhra Pradesh, as the states split in 2014 but retained the same alcohol policies. Robust standard errors clustered by the state are presented in the parenthesis. *** indicates 99% level of significance. ** indicates 95% level of significance. * indicates 90% level of significance.

Table 3.4: Road Traffic Fatalities

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	No Controls	+ Controls	+ State FE	+ Year FE	No Controls	+ Controls	+ State FE	+ Year FE
Drink	0.455***	0.421***	0.101	0.122				
	(0.117)	(0.126)	(0.091)	(0.114)				
DrinkN					0.713**	0.726**	0.239	0.340
					(0.259)	(0.299)	(0.261)	(0.297)
Highway ban	-0.387***	-0.298***	-0.177***	-0.187***	-0.370***	-0.283***	-0.177***	-0.189***
	(0.042)	(0.042)	(0.044)	(0.052)	(0.045)	(0.043)	(0.043)	(0.051)
Highway	0.406***	0.307***	0.350***	0.361***	0.403***	0.293***	0.350***	0.361***
	(0.050)	(0.046)	(0.058)	(0.058)	(0.051)	(0.050)	(0.058)	(0.058)
GDP per capita (INR)		-0.002**	-0.005***	-0.001		-0.002**	-0.005***	-0.001
		(0.001)	(0.002)	(0.002)		(0.001)	(0.002)	(0.002)
Vehicles density (per km road)		-0.002*	-0.002	-0.001		-0.002**	-0.002	-0.001
		(0.001)	(0.001)	(0.002)		(0.001)	(0.001)	(0.002)
Population density (per sq km)		0.056	-0.803	1.537*		0.110	-0.812	1.570*
		(0.111)	(0.678)	(0.795)		(0.125)	(0.659)	(0.773)
Road length (km) per sq km		-0.060*	-0.015	-0.009		-0.068*	-0.015	-0.009
		(0.035)	(0.045)	(0.046)		(0.035)	(0.045)	(0.046)
Constant	0.038	0.326***	0.957***	-0.215	-0.215	0.044	0.841**	-0.412
	(0.078)	(0.095)	(0.260)	(0.297)	(0.198)	(0.235)	(0.323)	(0.369)
Observations	864	864	864	864	864	864	864	864
R-squared	0.350	0.458	0.638	0.686	0.297	0.422	0.638	0.686
State FE	NO	NO	YES	YES	NO	NO	YES	YES
Year FE	NO	NO	NO	YES	NO	NO	NO	YES

Notes: Sample consists of all states (except Manipur) between 2004-2019. Accidents in Telangana state are aggregated with Andhra Pradesh, as the states split in 2014 but retained the same alcohol policies. Robust standard errors clustered by the state are presented in the parenthesis. *** indicates 99% level of significance. ** indicates 95% level of significance. * indicates 90% level of significance.

3.4.4 Robustness

New literature on two-way fixed effects (TWFE) difference-in-differences (DID) shows that estimates obtained through TWFE regressions identify weighted sums of the average treatment effects (ATE) in each group and period, with weights that may be negative (Goodman-Bacon, 2021). DID estimates are unbiased in settings with a single treatment period and settings with homogeneous treatment effects across groups and over time. However, when research settings combine multiple treatment timings and treatment effect heterogeneity (across groups or over time), the TWFE estimates are likely to be biased. Identification is even more nuanced in cases with non-binary treatments, multiple treatments, and treatment spillovers (see De Chaisemartin and D'Haultfoeuille (ming) for a survey of this literature).

The current paper leverages multiple treatment units, multiple periods, and two treatments. The first treatment from legal drinking age and prohibition policies is non-binary, varies at the state level (i.e., sharp design), and has potential spillovers to neighboring states. The second treatment from the highway ban is binary and varies across road types within a state (i.e., fuzzy design). There can be multiple biases in such a setup. (1) When the treatment is non-binary, some DIDs compare accidents in states whose MLDA increases more to states whose MLDA increases less. As a result, the Wald-DID may not estimate a convex combination of effects if the treatment effect is heterogeneous across states (De Chaisemartin and d'Haultfoeuille, 2020a). In the current setup, heterogeneity in treatment effects may arise across states due to differences in law enforcement. For instance, black marketing of alcohol may be easier in some states than in others. Second, in cases with multiple treatments, the coefficient on one treatment may be contaminated by the effect of other treatments (De Chaisemartin and d'Haultfoeuille, 2020b). For example, in the current setup, the coefficient on *Drink* may leverage a DID comparing the road accidents of Mizoram, which was affected by both policies, to the accidents of Madhya Pradesh, which only received the highway-ban treatment. However, if the effects of the highway ban differ in the two groups, they do not cancel each other out and contaminate the coefficient on the *Drink* variable. Finally, because MLDA policies can create spillovers on neighboring states, adding the neighboring states as controls in the sample will downward bias the estimated effect of MLDA on the states that changed their policy.

The literature currently lacks an alternative DID estimator that addresses all the above issues. Therefore, I modify the units that can act as effective comparison units to avoid comparing treatment units to inappropriate controls as follows. First, to avoid contaminating the coefficient on one treatment due to the effect of another treatment, I separately evaluate the impact of each treatment. Specifically, because the highway ban only came into effect in 2017, I use data between 2004-2017 to evaluate MLDA policy. Similarly, to assess the highway ban policy, I use data between 2004-2019 and the sample of states that did not experience a change in the drinking age population in the sample. Thus, I exclude Kerala, Mizoram, Maharashtra, Bihar, and their neighbors.

Second, to accommodate heterogeneity in the effect of demographic regulations across states, I run separate regressions for each state that changed its MLDA policy. In each case, the outcome variable is the road accident rate as defined in equation 3.2. The control states are those that did not change their drinking age between 2004-2019. Moreover, to accommodate the spillover effects of demographic regulation, I exclude the neighbors of all states that changed their drinking age from the control group. Table 3.5 shows the results from this analysis. Each column represents a different treatment unit and, hence, a different sample. For example, Column (1) excludes the states that border Bihar (i.e., Jharkhand, Uttar Pradesh, and West Bengal) or experience a change in the fraction of the drinking age population (i.e., Kerala, Maharashtra, Mizoram, and their neighbors). Columns (2), (3), and (4) perform the same analysis for Kerala, Maharashtra, and Mizoram, respectively. Overall, these results reinforce the baseline results. For instance, the coefficient in Column (2) indicates that if Kerala moves from alcohol prohibition to legal drinking age of 16, it would experience roughly fourteen additional accidents per 10,000 vehicles, on average, compared to other states. Moreover, the difference in coefficients across the four columns indicates heterogeneity across states. The insignificant coefficient for Bihar may be due to excessive black marketing of alcohol (Parth, 2017; Kumar, 2022).

Table 3.6 shows the results of evaluating the highway ban policy. Treatment units are highways in the states that legalize alcohol. Control units comprise all roads in the states that banned alcohol between 2004-2019 and non-highway roads in states that legalized alcohol between 2004-2019. Column (1) shows the effect of the highway ban on accident rate conditional on road type. Columns (2), (3), and (4) sequentially include additional covariates, state fixed effects, and year fixed effects. Like Table 3.2, the coefficients on $Hwyban$ are negative and significant. Column (4) indicates that the roads affected by the highway alcohol ban experience roughly six fewer accidents per 10,000 vehicles, on average, compared to other roads.

3.5 Conclusion

This paper is motivated by the alarming trend of road traffic accidents, fatalities, and injuries in India and investigates the role of alcohol regulation on road safety. I document the effects of drinking age regulations and highway alcohol ban using state-level panel data between 2004 and 2019, taking advantage of two sources of variation: (1) differences in the timing of

Table 3.5: Road Traffic Accidents

VARIABLES	(1) BIHAR	(2) KERALA	(3) MAHARASHTRA	(4) MIZORAM
Drink	0.539	1.432***	6.211***	0.823***
	(0.463)	(0.146)	(0.928)	(0.228)
Highway	1.090***	1.046***	0.925**	0.910***
	(0.320)	(0.253)	(0.377)	(0.257)
GDP per capita (INR)	-0.001	-0.003	-0.003	-0.002
	(0.006)	(0.005)	(0.010)	(0.005)
Vehicles density (per km road)	-0.003	-0.006	-0.005	-0.008**
	(0.008)	(0.004)	(0.004)	(0.004)
Population density (per sq km)	3.390	4.250	7.270	5.562
	(3.940)	(4.077)	(4.940)	(3.700)
Road length (km) per sq km	0.319*	0.295**	0.106	0.145
	(0.168)	(0.112)	(0.195)	(0.153)
Constant	0.068	-0.850	-5.403**	-0.585
	(1.430)	(1.507)	(2.032)	(1.370)
Observations	504	560	420	588
R-squared	0.730	0.730	0.672	0.738
State FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Notes: This table shows separate regressions with each state that changed its legal drinking age as the only treatment unit. The control states are those that did not change their drinking age and whose neighbors did not change their drinking age between 2004-2019. Accidents in Telangana state are aggregated with Andhra Pradesh, as the states split in 2014 but retained the same alcohol policies. Robust standard errors clustered by the state are presented in the parenthesis. *** indicates 99% level of significance. ** indicates 95% level of significance. * indicates 90% level of significance.

Table 3.6: Road Traffic Accidents

VARIABLES	(1) No Controls	(2) + Controls	(3) + State FE	(4) + Year FE
Highway ban	-1.231***	-1.183***	-0.631***	-0.592***
	(0.214)	(0.219)	(0.132)	(0.133)
Highway	0.928***	0.735**	0.857***	0.912***
	(0.183)	(0.344)	(0.249)	(0.256)
GDP per capita (INR)		0.001	-0.023***	-0.006
		(0.005)	(0.005)	(0.005)
Vehicles density (per km road)		-0.009**	-0.009*	-0.006
		(0.004)	(0.004)	(0.004)
Population density (per sq km)		-0.213	-2.319	6.281*
		(0.621)	(2.814)	(3.475)
Road length (km) per sq km		-0.170	0.028	0.084
		(0.268)	(0.126)	(0.129)
Constant	1.412***	1.996***	3.712***	-0.213
	(0.218)	(0.564)	(0.903)	(1.252)
Observations	640	640	640	640
R-squared	0.109	0.168	0.670	0.729
State FE	NO	NO	YES	YES
Year FE	NO	NO	NO	YES

Notes: Sample includes that states that did not experience a change in the drinking age population between 2004-2019. Accidents in Telangana state are aggregated with Andhra Pradesh, as the states split in 2014 but retained the same alcohol policies. Robust standard errors clustered by the state are presented in the parenthesis. *** indicates 99% level of significance. ** indicates 95% level of significance. * indicates 90% level of significance.

prohibition and age-based alcohol regulation across states and (2) a nationwide alcohol sales ban near highways that affected certain roads in non-prohibition states.

The results provide evidence of a significant relationship between alcohol regulations and road safety. The most conservative estimates show that a state that moves from alcohol prohibition to legal drinking age of 16 experiences roughly ten additionals accident per 10,000 vehicles, on average, compared to other states. Moreover, the roads affected by the highway alcohol ban experience six fewer accidents per 10,000 vehicles than other roads. Finally, there is evidence of spillovers of neighboring states' drinking age policies on a state's road safety.

As previously noted in the literature, the effect of the legal drinking age suggests significant benefits from restricting underage drinking from the perspective of road safety. The impact of the highway ban noted in this paper also suggests regulating the location of alcohol sales as an effective policy tool to prevent road traffic accidents. The highway ban possibly works by reducing distraction on the roads and appears a promising policy for other countries as well, given that it is much less disruptive than other regulations like state-wide prohibition. Finally, the evidence of spillovers of neighboring states' drinking age policies suggests potential benefits from equalizing the legal drinking age with the neighbors.

Appendix A

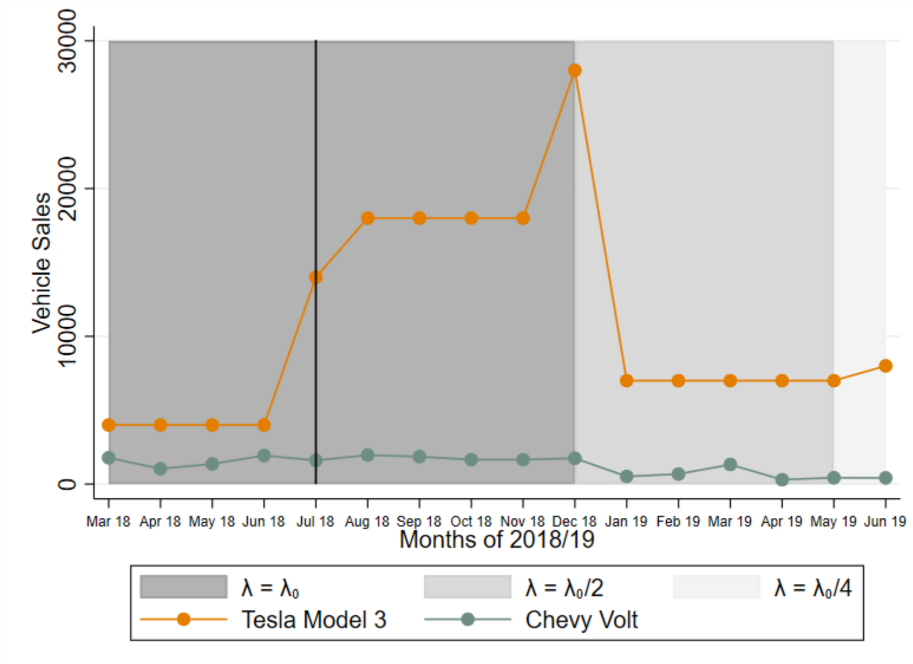
Appendix for Chapter 1

A.1 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 A.1 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 1.4. 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

Figure A.1: 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.

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

Table A.1: 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.

not explain what happens in the presence of alternative policies. Moreover, the variation is only driven 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.

A.2 First-Stage Regression Results

Table A.2 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 A.2: First-Stage Regression Results

Dependent Variable: Price (p_{jmt}, in \$'0000)			
	Variable	Coef	SE
Included IV			
	Constant	-8.995***	1.453
	Size	6.674***	0.172
	Performance	2.977***	0.048
	Driving Cost	25.538***	0.499
	Battery Range	0.002*	0.001
	BEV	2.232***	0.188
	PHEV	4.704***	0.148
	BEV $\times$ Cumulative EV Sales	-0.228***	0.031
	PHEV $\times$ Cumulative EV Sales	-0.440***	0.028
Excluded IV			
	IV_1	0.327***	0.037
	IV_2	-0.493***	0.043
	IV_3	0.099***	0.008
	IV_4	0.079***	0.024
	IV_5	0.003***	0.000
	IV_6	-0.073**	0.035
	IV_7	0.095**	0.040
	IV_8	0.008	0.008
	IV_9	-0.075***	0.013
	IV_{10}	-0.000	0.000
Obs	62588		
R-squared	0.675		
F test			
F(65, 62522)	2000.846		
F test of excluded IV			
F(10, 62522)	345.001		

Notes: Size is length$\times$ 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.

A.3 Counterfactuals

Table A.3: Effect of Elimination Designs on EV Sales

Manufacturer	Year	No Subsidy	Market Deadline	Per-Mfr Deadline	Per-Mfr Quota (150000)
BMW	2011-2016	15,140	15,140	15,140	15,140
	2017	10,018	16,716	16,162	16,165
	2018	11,371	11,693	19,246	19,217
DAIMLER	2011-2016	9,312	9,312	9,312	9,312
	2017	1,000	1,787	1,774	1,775
	2018	1,022	1,030	1,841	1,838
FIAT CHRYSLER	2011-2016	18,115	18,115	18,115	18,115
	2017	4,711	9,137	8,805	8,808
	2018	5,489	5,669	10,723	10,706
FORD	2011-2016	73,611	73,611	73,611	73,611
	2017	16,914	24,220	23,950	23,938
	2018	17,913	18,093	25,851	25,822
GENERAL MOTORS	2011-2016	97,052	97,052	97,052	97,052
	2017	31,973	60,870	60,875	24,164
	2018	33,944	34,739	34,697	63,830
HONDA	2011-2016	2,091	2,091	2,091	2,091
	2017	1,420	1,415	1,415	1,417
	2018	1,577	1,577	1,574	1,571
HYUNDAI	2011-2016	1,350	1,350	1,350	1,350
	2017	1,215	1,969	1,912	1,914
	2018	1,395	1,437	2,295	2,291
KIA	2011-2016	3,664	3,664	3,664	3,664
	2017	1,882	3,241	3,149	3,150
	2018	2,158	2,220	3,758	3,753
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	5,643	10,712	10,650	10,652
	2018	5,729	5,766	10,949	10,937
TESLA	2011-2016	105,728	105,728	105,728	105,728
	2017	23,500	44,614	44,618	19,717
	2018	24,450	24,796	24,761	46,139
TOYOTA	2011-2016	43,470	43,470	43,470	43,470
	2017	21,263	31,413	30,795	30,800
	2018	23,526	23,952	35,144	35,105
VOLKSWAGEN	2011-2016	18,829	18,829	18,829	18,829
	2017	4,257	6,760	6,661	6,662
	2018	4,489	4,541	7,195	7,184
VOLVO	2011-2016	2,025	2,025	2,025	2,025
	2017	1,499	2,253	2,158	2,156
	2018	1,775	1,816	2,680	2,676

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 1.7.

Table A.4: Effect of Elimination Designs on Vehicle Prices and Sales in 2018

Vehicle	Outcome	No Subsidy	Market Deadline	Per-Mfr Deadline	Per-Mfr Quota (150000)
TESLA MODEL X (BEV)	Price (USD)	79,756	79,756	79,758	79,776
	Sales	8,864	8,989	8,976	16,723
CHEVROLET VOLT (PHEV)	Price (USD)	31,137	31,132	31,131	31,148
	Sales	19,764	20,262	20,240	37,155
NISSAN LEAF (BEV)	Price (USD)	26,082	26,084	26,085	26,085
	Sales	5,729	5,766	10,949	10,937
HYUNDAI IONIQ (BEV)	Price (USD)	29,403	29,402	29,401	29,398
	Sales	291	298	565	564
CADILLAC CT6 (PHEV)	Price (USD)	72,291	72,285	72,284	72,304
	Sales	146	150	150	275
CADILLAC CT6 (GAS)	Price (USD)	51,715	51,715	51,714	51,715
	Sales	10,207	10,206	10,202	10,194
ACURA MDX (GAS)	Price (USD)	42,596	42,596	42,595	42,594
	Sales	63,588	63,585	63,548	63,503
TOYOTA TUNDRA (GAS)	Price (USD)	27,528	27,528	27,529	27,529
	Sales	49,140	49,138	49,112	49,092
CHEVROLET SILVERADO (GAS)	Price (USD)	26,672	26,672	26,672	26,673
	Sales	341,200	341,195	341,127	340,997
FORD F (GAS)	Price (USD)	26,214	26,214	26,214	26,214
	Sales	367,688	367,684	367,602	367,525

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 1.7.

Appendix B

Appendix for Chapter 2

B.1 Definitions

Vehicle classifications, as defined at 49 CFR part 523, are below:

1. A **passenger automobile** is any automobile (other than an automobile capable of off-highway operation) manufactured primarily for use in the transportation of not more than 10 individuals.

2. A **non-passenger automobile** means an automobile that is not a passenger automobile or a work truck and includes vehicles described in paragraphs (a) and (b) of this section:

   (a) An automobile designed to perform at least one of the following functions:

      i. Transport more than 10 persons;

      ii. Provide temporary living quarters;

      iii. Transport property on an open bed;

      iv. Provide, as sold to the rst retail purchaser, greater cargo-carrying than passenger-carrying volume, such as in a cargo van; if a vehicle is sold with a second-row seat, its cargo-carrying volume is determined with that seat installed, regardless of whether the manufacturer has described that seat as optional; or

      v. Permit expanded use of the auto- mobile for cargo-carrying purposes or other nonpassenger-carrying purposes through:

         A. For non-passenger automobiles manufactured prior to model year 2012, the removal of seats by means installed for that purpose by the automobile's manufacturer or with simple tools, such as screwdrivers and wrenches, so as to create a at, floor level, surface extending from the forwardmost point of installation of those seats to the rear of the automobile's interior; or

B. For non-passenger automobiles manufactured in model year 2008 and beyond, for vehicles equipped with at least 3 rows of designated seating positions as standard equipment, permit expanded use of the automobile for cargo- carrying purposes or other non-passenger-carrying purposes through the re- moval or stowing of foldable or pivoting seats so as to create a at, leveled cargo surface extending from the forwardmost point of installation of those seats to the rear of the automobile's interior.

(b) An automobile capable of off highway operation, as indicated by the fact that it:

i. Has 4-wheel drive; or is rated at more than 6,000 pounds gross vehicle weight; and

ii. Has at least four of the following characteristics calculated when the automobile is at curb weight, on a level surface, with the front wheels parallel to the automobile's longitudinal center-line, and the tires inflated to the manufacturer's recommended pressure

A. Approach angle of not less than 28 degrees.

B. Breakover angle of not less than 14 degrees.

C. Departure angle of not less than 20 degrees.

D. Running clearance of not less than 20 centimeters.

E. Front and rear axle clearances of not less than 18 centimeters each.

3. **Pickup truck** means a light truck which has a passenger compartment and an open cargo bed.

4. **Minivan** means a light truck which is designed primarily to carry no more than eight passengers, having an integral enclosure fully enclosing the driver, passenger, and load-carrying compartments, and rear seats readily removed, folded, stowed, or pivoted to facilitate cargo carrying. A minivan typically includes one or more sliding doors and a rear liftgate. Minivans typically have less total interior volume or overall height than full sized vans and are commonly advertised and marketed as "minivans".

5. **Sport utility vehicle (SUV)** means a light truck with an extended roof line to increase cargo or passenger capacity, cargo compartment open to the passenger compartment, and one or more rear seats readily removed or folded to facilitate cargo carrying. Generally, 2-wheel drive SUVs equal to or less than 6000 lbs GVWR are

Table B.1: CAFE Targets

Year	Car				Truck			
	a	b	c	d	a	b	c	d
2011	31.2	24	51.41	1.91	27.1	21.1	56.41	4.28
2012	35.95	27.95	.0005308	.0060507	29.82	22.27	.0004546	.0149
2013	36.8	28.46	.0005308	.00541	30.67	22.74	.0004546	.013968
2014	37.75	29.03	.0005308	.004725	31.38	23.13	.0004546	.013225
2015	39.24	29.9	.0005308	.003719	32.72	23.85	.0004546	.01192
2016	41.09	30.96	.0005308	.002573	34.42	24.74	.0004546	.010413

Notes: This table summarizes the parameter values in CAFE targets for years 2011-2016.

passenger cars for CAFE and GHG standards compliance, but continue to be labeled as SUVs.

6. **Station wagon** means cars with an extended roof line to increase cargo or passenger capacity, cargo compartment open to the passenger compartment, a tailgate, and one or more rear seats readily removed or folded to facilitate cargo carrying.

7. **Van** means any light truck having an integral enclosure fully enclosing the driver compartment and load carrying compartment. The distance from the leading edge of the windshield to the foremost body section of vans is typically shorter than that of pickup trucks and SUVs.

B.2 CAFE Target Formulas

The target equation for the passenger car and light trucks for MY 2011 is

$$T_j = \frac{1}{\frac{1}{a} + (\frac{1}{b} - \frac{1}{a})\frac{e^{(footprint_j - c)/d}}{1+e^{(footprint_j - c)/d}}} \tag{B.1}$$

where a, b, c and d are parameters taking different values for passenger car and the light trucks, with less stringent targets for light trucks. The target equation for MYs 2012-2016 is

$$T_j = \frac{1}{min\left\{max\left\{c \times footprint_j + d, 1/a\right\}, 1/b\right\}}. \tag{B.2}$$

The parameter values for each are summarized in table B.1.

B.3 Firms' First-Order Conditions

Given the firms' profit in equation 2.6, the optimal price for product j and drivetrain d satisfies the following first order condition:

$$
\begin{aligned}
&q_{jdt}(p_t) + \sum_{j',d \in \mathcal{J}_{ft}} (p_{j'dt} - mc_{j'dt} - GGT_{j'd}) \frac{\partial q_{j'dt}(p_t)}{\partial p_{jdt}} \\
&-55 \sum_{k=C,T} \left[\frac{\sum_{j',d \in \mathcal{J}_{ft}^{(k)}} \frac{\partial q_{j'dt}(p_t)}{\partial p_{jdt}} / mpg_{j'}}{\left(\sum_{j',d \in \mathcal{J}_{ft}^{(k)}} q_{j'dt}/mpg_{j'd}\right)^2} - \frac{\sum_{j',d \in \mathcal{J}_{ft}^{(k)}} \frac{\partial q_{j'dt}(p_t)}{\partial p_{jdt}} / T_{j'}}{\left(\sum_{j' \in \mathcal{J}_{ft}^{(k)}} q_{j'dt}/T_{j'}\right)^2} \right] \big(\sum_{j,d \in \mathcal{J}_{ft}^{(k)}} q_{jdt} \big)^2 \\
&+110 \sum_{k=C,T} \left[\frac{1}{\left(\sum_{j',d \in \mathcal{J}_{ft}^{(k)}} q_{j'dt}/mpg_{j'd}\right)} - \frac{1}{\left(\sum_{j'd \in \mathcal{J}_{ft}^{(k)}} q_{j'dt}/T_{j'd}\right)} \right] \big(\sum_{j,d \in \mathcal{J}_{ft}^{(k)}} q_{jdt} \big) \left(\sum_{j',d \in \mathcal{J}_{ft}^{(k)}} \frac{\partial q_{j'dt}(p_t)}{\partial p_{jdt}} \right) = 0.
\end{aligned}
\tag{B.3}
$$

B.4 First-Stage Regression

Table B.2 reports the results of the first-stage regression. IVs 1-7 are the sum over firm's other vehicles' characteristics, while IVs 8-14 are the sum over all the firms' competing vehicles' characteristics. Vehicle characteristics include a constant, vehicle size, performance, cost of driving, and indicators for 4WD, hybrid and electric vehicles, respectively.

Table B.2: First-Stage Regression Results

Dependent Variable: Price (p_{jt}, in \$'0000)			
	Variable	Coef	SE
Included IV			
	Four Wheel Drive	0.345***	0.038
	SUV x Four Wheel Drive	-0.020	0.051
	Dollar per 10 miles	12.115***	0.786
	Vehicle Size (0000 in^2)	2.931***	0.111
	Horsepower/weight (Hp/10lb)	2.302***	0.093
	Electric	2.225***	0.317
	Hybrid	1.433***	0.079
	Trend	-0.071**	0.032
Excluded IV			
	IV_1	-0.002	0.031
	IV_2	0.027**	0.011
	IV_3	-0.088***	0.016
	IV_4	0.003	0.021
	IV_5	-0.014	0.014
	IV_6	0.177*	0.092
	IV_7	-0.001	0.014
	IV_8	-0.005	0.022
	IV_9	0.004	0.006
	IV_{10}	-0.031***	0.003
	IV_{11}	0.004	0.014
	IV_{12}	-0.003	0.004
	IV_{13}	0.068	0.043
	IV_{14}	0.008	0.009
Obs	5523		
R-squared	0.716		
F test			
F(48, 5474)	287.929		
F test of excluded IV			
F(14, 5474)	21.617		

Notes: Size is length× width (in '0000 in^2), performance is Horsepower by curb weight (in 10 lb), and cost of driving is fuel cost (in dollars) per ten miles. Excluded instruments that are assumed uncorrelated with demand error $\Delta\xi_{jt}$ include the sum of firm's other vehicles' characteristics (constant, vehicle size, performance, cost of driving, and indicators for 4WD, hybrid and electric vehicles) and the sum over all the firms' competing vehicles' characteristics. *** indicates 99% level of significance. ** indicates 95% level of significance. * indicates 90% level of significance.

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