Cross-State Spillovers of Regulation Under National Pricing Strategies: Evidence from Electric Vehicles *

Sarah Armitage[†] Frank Pinter[‡]

September 30, 2025

Abstract

When policies differ across regions but prices are not set independently across regions, the equivalency between demand- and supply-side policy instruments breaks down. Drawing on price discrimination theory, we show that regional demand-side tools such as consumer subsidies generate effective price variation across regions for a product, while producer subsidies do not, creating different incentives for firms and ultimately different policy responses. We study the interaction between firms' pricing strategies and the state-level Zero-Emission Vehicle (ZEV) policy that gives automobile manufacturers incentives to sell electric vehicles in California and nine other states. Focusing on 2012–17, we build and estimate a structural model of the market for new passenger vehicles, examining the impacts of the ZEV program in the regulated region and spillovers to other states. We compare the ZEV policy to counterfactual demand-side subsidy and tax programs of similar stringency. Under the assumption that Tesla sets national prices, our estimates imply that a demand-side subsidy and tax, holding incentives per vehicle in ZEV states fixed, would increase electric vehicle sales in the US by 13%.

JEL keywords: L10, L62, Q58

*The views expressed in this paper are those of the authors and do not necessarily reflect those of the Federal Trade Commission or any individual Commissioner. This paper replaces an earlier paper titled "Regulatory Mandates and Electric Vehicle Product Variety." We thank Ariel Pakes, Robin Lee, Dennis Yao, Joseph Aldy, Edward Glaeser, and James Stock for support and guidance. We also thank Jeff Gortmaker, Myrto Kalouptsidi, Stephanie Kestelman, Jing Li, Erica Moszkowski, Charles Murry, Elie Tamer, Stephanie Weber, Ron Yang, Anthony Yu, and participants at the Harvard Environmental Economics Seminar, IIOC, LSE Environment Week, and SITE for helpful comments; Joshua Linn and Benjamin Leard for generously sharing data; and four industry experts for useful insights. We acknowledge support from the Lab for Economic Applications and Policy and Harvard Business School. Armitage gratefully acknowledges financial support from the NBER Pre-Doctoral Fellowship in Energy Economics and the Joseph Crump Fellowship at Harvard University.

[†]Boston University.

[‡]Federal Trade Commission. Contact: frankpinter.com.

1 Introduction

In the United States, environmental policy is often made in a bifurcated policy landscape. For automobiles and other products, some states have adopted generous subsidies and stringent standards, while other states have adopted few or no environmental interventions. When a state-level policy affects products that are sold in national product markets, policy impacts may encompass not only direct effects within the regulated state's borders, but also spillovers to other states not directly covered by the policy.[1] We study how state-level environmental policy creates inter-state pricing spillovers in the market for new light-duty passenger vehicles, using the Zero Emissions Vehicle (ZEV) mandate as a case study.

Standard economic theory predicts that supply-side and demand-side policy instruments are equivalent when the policy covers the entire market. However, when policies differ across regions but prices cannot adjust freely across regions, the equivalency breaks down. As we demonstrate in this paper, state-level demand-side tools such as consumer subsidies generate effective price variation across regions, while state-level supply-side tools such as producer subsidies do not. As a result, the two tools create different incentives for firms, producing different markups over marginal cost and ultimately different policy responses. The effects on consumer, producer, and total surplus will then differ, as will the policy's overall effectiveness at achieving policymakers' stated goals.

We study these effects in the context of the Zero Emissions Vehicle (ZEV) mandate, a prominent state-level policy shaping the electric vehicle industry, between 2012 and 2017. Adopted by California and nine other US states, the mandate required the largest automakers to sell electric vehicles in the state, or buy credits from other automakers, to meet a specified quota (0.4–1.5% of their sales in covered states). The goal of the mandate was to induce sales of electric vehicles to reach mass-market quantities. We investigate the consequences of policymakers' choice to use a supply-side mandate rather than rely on demand-side policies,

[1] See, e.g., Eyer and Kahn (2017). Analogous spillovers may exist for national environmental policies influencing products sold internationally.

simulating policy impacts under alternative national and regional pricing regimes. As a major supply-side policy in an important environmental product market, the ZEV mandate is well suited for studying the impact of regional policy incidence on spillovers in broader markets.

To build economic intuition, we first construct an analytical model of monopoly pricing where products are subsidized regionally but prices are constrained to be uniform across broader markets. Our approach extends insights from the literature on third-degree price discrimination, in which only demand varies across regional markets (Schmalensee 1981; Aguirre, Cowan, and Vickers 2010), to a setting where regional policies also differ. Under mild conditions, we show that the share of the product sold in the regulated region is increasing in the amount of the subsidy provided to consumers rather than producers. By contrast, the effect of increasing the consumer subsidy on the total quantity sold across both regions is ambiguous and depends on the relative curvature of demand in the two regions. This result is closely related to the effect of third-degree price discrimination on total output, given the effective price discrimination induced by the regional consumer subsidy. We also show that the impact on total welfare is ambiguous, but a necessary condition for overall welfare to increase in the amount of the subsidy provided to consumers is that total quantity increases. The effects on regional welfare depend on assumptions about how producer surplus and emissions externalities are distributed across regions.

While our theoretical model helps to build intuition for the relationship between regional policy design and price discrimination, in a multi-product oligopoly setting such as the U.S. passenger vehicle market, we also have to consider differential substitution patterns and exposure to the policy across products. To understand empirically the incentives facing manufacturers and analyze social welfare, we build and estimate a model of consumer demand and producer price-setting in the market for new passenger vehicles in the United States from 2012 to 2017. We adopt a Berry, Levinsohn, and Pakes (1995)-style model of discrete choice demand, with differentiated products and heterogeneous consumer tastes. Firm prices are set by Bertrand competition among multiproduct firms. We explicitly incorporate state-level heterogeneity in environmental regulation. The estimated model parameters deliver estimates of markups over marginal cost and consumer surplus.

To inform our empirical model, we use evidence from a survey of new vehicle buyers to test alternative pricing regimes. Reported transaction prices vary idiosyncratically, even within a product and region. Nonetheless, we find a systematic pattern: non-Tesla electric vehicle prices are about $1,500 lower in regulated states than elsewhere, controlling for vehicle characteristics and consumer demographics and accounting for state-level tax and subsidy policy. We interpret this finding to mean that automakers may use flexible pricing to sell more electric vehicles in regulated states, except for Tesla, which is constrained by its strategy of publicly posting national prices.

Finally, we use counterfactual simulations to evaluate the impact of the supply-side ZEV policy relative to a demand-side policy of comparable stringency. We examine how policy design affects pricing in covered and non-covered states, both in our baseline specification where Tesla is the only automaker to employ national pricing and in alternative market structures where all automakers are constrained to price nationally.[2] We then examine how policy spillovers — the total quantity of EVs sold and changes in welfare in non-regulated states — differ under alternative policy and pricing regimes. When replacing the ZEV program with a dollar-equivalent consumer subsidy on EVs and consumer tax on conventional vehicles, we find that EV sales would increase by 13% nationwide, driven by a large increase in EV sales in ZEV states that is only partly offset by a decrease in "spillover" sales to non-ZEV states. Alternatively, we find that the ZEV program's quantity target could be met with a lower consumer subsidy for EVs and tax on conventional vehicles, resulting in welfare gains but fewer spillover sales in non-ZEV states.

This paper highlights a new mechanism by which regional environmental policies may affect market outcomes in other regions. Prior literature has largely focused on leakage

[2]Because Tesla represented a substantial portion (41%) of all EV sales during the study period, its pricing strategy has first-order effects on overall policy outcomes.

effects, as emitting activity moves from stricter to laxer jurisdictions (Fowlie, Reguant, and Ryan 2016); on binding national regulations, under which stricter state-level policies induce reallocation while leaving national emissions constant (Williams 2012; Goulder, Jacobsen, and van Benthem 2012; Linn and McConnell 2017; Leard and McConnell 2021); and on trade in energy inputs (Kotchen and Maggi 2025; Abuin 2025). We highlight the potential for pricing spillovers across regions, depending on the incidence of regional policies.

Our study also adds to the literature on conditions under which the equivalent economic incidence of demand- and supply-side policies breaks down. Conditions explored in previous literature include salience (Chetty, Looney, and Kroft 2009), evasion (Kopczuk, Marion, Muehlegger, and Slemrod 2016), and discontinuous tax schedules (Hargaden and Roantree 2020). In a similar setting to this paper, Sallee (2011) documents differential effects of national demand-side and supply-side subsidies for the second-generation Toyota Prius, attributing them to dynamics in consumer perceptions. We consider an additional reason why demand- and supply-side policies may have different effects: the interaction between regional policies and broader product markets.

Our analysis of how pricing flexibility influences policy outcomes is particularly important given changes in pricing models due to the rise of e-commerce. Existing literature has shown that competition with online retailers, which are more likely to use nationally standardized prices, leads traditional retailers to use more standardized prices as well (Cavallo 2018).[3] Our results shed light on how this technological shift may affect outcomes from regional policies; we analyze a setting in which traditional dealers (legacy automakers) compete with online retailers (Tesla). We also contribute to the literature on pricing flexibility in the automotive sector, which has focused on dealer-customer bargaining (Busse, Silva-Risso, and Zettelmeyer 2006; Langer and Miller 2013; Chandra, Gulati, and Sallee 2017; D'Haultfœuille, Durrmeyer, and Février 2019; Sagl 2024), by considering the role of regional policies in pricing variation.

[3] Our analysis of national prices also connects to a literature on standardized pricing across regions, which has largely examined retail chains. This literature has shown that standardized pricing can increase profits under oligopoly (Adams and Williams 2019), and alters the equilibrium effects of local shocks and policies (DellaVigna and Gentzkow 2019; Leung 2021).

To our knowledge, few other papers conduct systematic welfare analyses of state-level ZEV mandates, despite their emphasis by industry observers.[4] Independently, Linn (2022) and Linn (2023) have examined the effects of ZEV mandates within structural models of the new vehicle market, emphasizing interactions with other policies. Prior literature on the design and effects of the mandate from other perspectives, which has informed our modeling and our discussion of institutional features, includes Dixon, Porche, and Kulick (2002), Bedsworth and Taylor (2007), Vergis and Mehta (2012), Greene, Park, and Liu (2014), Linn and McConnell (2017), and McConnell and Leard (2021). In the context of China, Kwon (2023) uses a structural model to contrast a credit-based policy (resembling the ZEV mandate) with a regime of subsidies when the market for regulatory credits is imperfectly competitive. In a forward-looking analysis, Holland, Mansur, and Yates (2021) evaluates a hypothetical cap-and-trade system to limit sales of gasoline vehicles over a long horizon (analogous to the ZEV mandate with tradeable credits).

More generally, the literature on pro-electric vehicle policies (reviewed most recently in Rapson and Muehlegger (2023)) has quantified the effects of purchase subsidies (Tal and Nicholas 2016; Jenn, Springel, and Gopal 2018; Muehlegger and Rapson 2022; Muehlegger and Rapson 2023; Xing, Leard, and Li 2021; Archsmith, Muehlegger, and Rapson 2022); public and private investment in complementary infrastructure, particularly charging stations (Li 2023); and a combination of both (Li, Tong, Xing, and Zhou 2017; Zhou and Li 2018; Springel 2021; Remmy 2025). Our study of the ZEV mandate also broadens an extensive literature on the effects of supply-side environmental policies in the automobile industry, which has focused primarily on fuel economy standards like the Corporate Average Fuel Economy (CAFE) and state and federal greenhouse gas standards.[5] Within this

[4]See "Automakers question Calif. zero-emission mandate as feds reassess mpg rules" (Eric Kulisch, Automotive News, 12/12/17).

[5]The fuel economy literature has documented effects of standards on vehicle characteristics (Knittel 2011; Klier and Linn 2012; Whitefoot, Fowlie, and Skerlos 2017; Ito and Sallee 2018; Reynaert 2021) and equilibrium prices and quantities (Goldberg 1998; Goulder, Jacobsen, and van Benthem 2012; Jacobsen 2013; Davis and Knittel 2018), and estimated the costs of compliance (Anderson and Sallee 2011). This literature has typically contrasted standards with intensity-based policies like fuel taxes (Knittel 2012; Anderson and Sallee 2016).

literature, Durrmeyer and Samano (2018) contrast supply-side standards with demand-side taxes and subsidies within a structural model of demand and supply. They highlight that a supply-side standard that operates firm-by-firm, like CAFE before 2011, induces a different shadow cost of regulation at each firm, while a competitive credit trading market or a program of demand-side subsidies and taxes instead equalize shadow costs across firms.

The rest of the paper proceeds as follows. Section 2 provides institutional background about the early electric vehicle market and the ZEV mandate. Section 3 provides a theoretical analysis of pricing spillovers from regional policies. Section 4 describes our empirical model of automobile demand and pricing, and Section 5 describes our data. Section 6 provides a reduced form analysis of pricing heterogeneity across regulated and non-regulated states. Section 7 describes our structural estimation and results, and Section 8 describes our counterfactual simulations. Section 9 concludes.

2 Institutional background

The first generation of mass-market electric vehicles (EVs) in the US was introduced starting in 2010–11. Most major automakers in the US introduced an electric vehicle in the years that followed, but models varied widely in engineering characteristics and in sales levels.

In this paper, we define electric vehicles to include only battery electric vehicles (BEVs), which have no internal combustion engine and rely solely on an electric motor and battery. We contrast BEVs with gasoline-powered vehicles, which include conventional internal combustion engine vehicles, hybrids, and plug-in hybrids (PHEVs).[6] Our framing reflects both the design of the policy we study and our focus on Tesla, which only produced battery electric vehicles.

Electric vehicles grew in popularity throughout the US during our study period (2012-17), both in sales and as a share of the new passenger vehicle market (see Appendix Figure A.1).

[6]Some observers instead define "electric vehicle" more broadly to include plug-in hybrids and, sometimes, hybrids.

Table 1 shows selected data for the electric vehicle models available in the US in our study period, including the timing of product introduction, total sales, manufacturer suggested retail price (MSRP), and battery range.

Table 1: Battery electric vehicles sold in the US, 2012–17

Model	First Year	Sales	MSRP	Range (mi)
Tesla Model S	2012	117,000	$57,400–$135,000	139–335
Nissan LEAF	2011	106,000	$28,800–$37,250	73–107
Tesla Model X	2016	35,000	$74,000–$145,000	200–295
Chevrolet Bolt EV	2017	27,000	$36,620–$40,905	238
Fiat 500e	2013	25,000	$31,800–$32,995	84–87
Volkswagen e-Golf	2015	13,000	$28,955–$36,995	83–125
Ford Focus	2012	9,000	$29,120–$39,200	76–115
BMW i3	2014	9,000	$41,350–$44,450	81–114
Chevrolet Spark	2014	7,000	$25,120–$27,010	82
smart fortwo	2013	6,000	$23,800–$29,000	57–68
Kia Soul	2015	5,000	$31,950–$35,950	93
Mercedes-Benz B-Class	2014	4,000	$39,900–$41,450	87
Tesla Model 3	2017	3,000	$35,000	310
Toyota RAV4	2012	3,000	$49,800	103
Mitsubishi i-MiEV	2012	2,000	$22,995–$31,125	59–62
Honda Clarity	2017	1,000	$36,620	89
Honda Fit	2013	1,000	$36,625	82
Hyundai Ioniq	2017	<1,000	$29,500–$32,500	124

Note: Compiled from data from MSN Autos, FuelEconomy.gov, and IHS. Includes all battery electric vehicles (excludes plug-in hybrids). All years are model years. Columns are: make and model; model year of introduction; sales in model years 2012–17 (rounded); MSRPs across trims (nominal dollars); and EPA battery range in miles.

2.1 Policy of interest: ZEV mandate

The Zero Emission Vehicle (ZEV) mandate, adopted by California and nine other states during our study period,[7] was intended to induce sales of "zero-emission" vehicles to reach mass-market quantities. The program required large automakers to meet a quota of credits, which any automaker could earn by selling battery electric vehicles in those states.[8] Each

[7] New York, Massachusetts, Vermont, Maine, Connecticut, Rhode Island, Oregon, New Jersey, and Maryland. In model years 2012–17, California accounted for 11% of new vehicle sales, and the other nine states together accounted for 16%. Additional states joined after 2017.

[8] Hydrogen fuel cell vehicles also counted generously toward the quota, but few were sold in this period.

manufacturer's quota was based on its sales of non-electric vehicles, so that larger manufacturers of non-electric vehicles faced a larger quota. The number of credits earned for selling each battery electric vehicle was a function of the vehicle's range on a full battery charge. Manufacturers could trade credits with each other and bank credits for later use, effectively creating a producer subsidy for selling electric vehicles and a tax for large manufacturers selling non-electric vehicles. According to data from state regulators, credit trades were common, and Tesla was the predominant seller of credits.[9]

In our study period, six large automakers faced the ZEV quota: Chrysler, Ford, GM, Honda, Nissan, and Toyota. Other manufacturers could earn credits for selling electric vehicles, and then sell the credits to regulated automakers, but they faced no credit obligation of their own. Figure A.4 shows the annual compliance obligations for each of the large manufacturers. To give one example: in California in model year 2017, Nissan faced a quota of 3,800 credits (3% of its California sales volume of 127,800 vehicles). Because Nissan earned three credits for each Leaf electric vehicle sold, it could meet its quota by selling 1,300 Leaf vehicles. Nissan well exceeded this quota, selling 4,600 Leaf vehicles in California and 1,100 in the other nine states. (If its sales had fallen short, Nissan could have drawn on its bank of 50,800 credits or purchased credits from another manufacturer.)

In our study period, the ZEV quota did not strictly apply state-by-state. Instead, under a rule called the travel provision, each state's quota could be met with vehicles sold in other ZEV states. For example, automakers could meet their requirements in all ten states by selling electric vehicles in California. According to industry observers, some automakers focused their electric vehicle efforts on California, which had the largest population by far of the participating states and generous government subsidies to consumers.[10]

In addition to the mandate on "zero-emission" vehicles, the ZEV program established a

[9]As described in Section 5.4.2, Tesla and state regulators provided data during our study period that allow us to estimate credit prices.

[10]See, e.g., "Kia: Soul EV Not a Compliance Car" (Christie Schweinsberg, WardsAuto, 10/27/14). As Appendix Figure A.1 shows, EVs made up a much higher share of new vehicle sales in California than in the other ZEV states.

mandate on low-emissions gasoline vehicles, hybrids, and plug-in hybrids, collectively dubbed Partial Zero Emission Vehicles (PZEVs). The mandate applied to automakers that faced the ZEV mandate and an additional group of mid-sized automakers.[11] Although excess ZEV credits could count toward the PZEV credit requirement, but not vice versa, each manufacturer's sales of hybrids and low-emissions gasoline vehicles each year was well over PZEV requirements, and there was little trading of PZEV credits among manufacturers. As a result, we assume in this paper that the PZEV mandate was not a binding constraint on any automaker, and we focus on the ZEV mandate in the analysis that follows.

Appendix A.2 describes the rules and goals of the ZEV mandate in greater detail.

2.2 Other policies

The ZEV mandate did not exist in isolation but was part of a patchwork of state and federal automobile regulations and programs during this period. At the federal level, the Corporate Average Fuel Economy (CAFE) program and the Greenhouse Gas (GHG) program regulated fleetwide fuel economy; during the study period, these regulations took the form of tradeable credit programs.[12] The federal government subsidized plug-in hybrids and electric vehicles for consumers through the IRC 30D income tax credit of up to $7,500 for electric vehicles. At the state level, many different incentives were available for consumers of electric vehicles, plug-in hybrids, and hybrids, which we describe in greater detail in Appendix Section C.3. Other relevant state and local policies included support for EV charging infrastructure and access to high-occupancy vehicle (HOV) lanes for EV drivers.

In this paper, we seek to understand the impact of the ZEV mandate under alternative policy designs, but our empirical model explicitly incorporates federal incentives, state

[11] Between 2009 and 2017, this group consisted of BMW, Daimler, Hyundai, Jaguar Land Rover, Kia, Mazda, Mitsubishi (2009 only), Subaru, Volkswagen, and Volvo (2009–11 only).

[12] The CAFE program, administered by the US National Highway Traffic Safety Administration (NHTSA), and the GHG program, administered by the US Environmental Protection Agency (EPA), were intended to be harmonized, though some differences remained. See Appendix Section A.3 for additional discussion of the federal GHG program. California also operated a GHG program, but California and federal rules were harmonized during our study period.

incentives, and the federal GHG program for accuracy.

3 Theory of inter-region spillovers

In this section, we use a stylized model to illustrate the potential for inter-region spillovers from regional policies due to cross-region pricing constraints. We consider impacts on four outcomes of interest: the total quantity sold across the regulated and non-regulated jurisdictions, the share of total quantity sold in the regulated jurisdiction, total welfare, and welfare in each of the regulated and non-regulated jurisdictions. Specifically, we fix a total subsidy amount and examine marginal changes in the outcomes of interest from providing more as a consumer subsidy rather than a producer subsidy. Our analysis draws heavily from the literature on third-degree price discrimination (Schmalensee 1981; Aguirre, Cowan, and Vickers 2010), which examine the effects of incrementally relaxing constraints against price discrimination across markets, adapted to our setting of differential policies across regions within a broader product market.[13]

Consider a monopolist who sells one product in two regions, Z (for ZEV, or regulated) and N (for non-ZEV, or unregulated). Demand is given by $q_Z(p_Z)$ and $q_N(p_N)$, respectively, where demand is decreasing in price and twice differentiable. The monopolist faces a constant marginal cost mc in both regions. Following Schmalensee (1981) and Aguirre, Cowan, and Vickers (2010), an important assumption in the analysis that follows is that profits in each region are strictly concave in price. This condition holds whenever demand in each region is concave. If demand is convex, we require that it is not too convex. See Appendix Section B.1 for additional discussion.

The regulator in region Z devotes a fixed amount sub to subsidizing the product.[14] Of

[13]There is a long literature on the impacts of third-degree price discrimination on total output, welfare, and other outcomes. See, for example, Varian (1985) for impacts of price discrimination on welfare; Holmes (1989) for a model of price discrimination under duopoly; Varian (1989) for a literature review; Cowan (2012) for impacts on consumer surplus; and Miravete (2024) for empirical analysis of the impacts of price discrimination using grocery store scanner data.

[14]While the ZEV mandate was not technically a subsidy program, the provision for credit trading created

that total amount, t is provided as a consumer subsidy, while $sub-t$ is provided as a producer subsidy. There is no subsidy available in region N. Of course, if the monopolist could set prices separately in the regulated and unregulated regions, then the statutory incidence of the subsidy would not affect its economic incidence; that is, outcomes would not depend on the magnitude of t. However, we instead assume that the monopolist is constrained to charge a single standardized price across the two regions, even though there are policy incentives to support the product in one region but not the other. Letting p denote the single price charged by the firm, the monopolist's profits are given by:

$$\pi = \pi_Z + \pi_N = (p + sub - t - mc) \cdot q_Z(p - t) + (p - mc) \cdot q_N(p) \tag{1}$$

Notice that producer margins in the regulated region depend on the magnitude of the producer subsidy $sub-t$, while demand in the regulated region depends on the magnitude of the consumer subsidy t. We assume that the monopolist serves both regions under all possible values of $t \in [0, sub]$.[15]

First, let's consider the impact of the policy design on the total quantity sold in both regions. Total quantity is given by:

$$Q = q_Z(p - t) + q_N(p) \tag{2}$$

Totally differentiating this expression with respect to t and substituting the firm's first-order condition with respect to p gives:

$$\frac{dQ}{dt} = \Big(\frac{-q'_N(p) \cdot q'_Z(p-t)}{\pi''_Z + \pi''_N}\Big)\Big(\frac{(p - mc) \cdot q''_N(p)}{q'_N(p)} - \frac{(p + sub - t - mc) \cdot q''_Z(p-t)}{q'_Z(p-t)}\Big) \tag{3}$$

an *implicit* subsidy for electric vehicles (and tax on conventional fuel vehicles), consistent with the long economic literature on tradeable credit programs (e.g., Durrmeyer and Samano (2018).)

[15] In general, relaxing constraints on price discrimination may yield additional output expansion from entry into new regions. In our setting, the effective price discrimination enabled by a consumer subsidy may have a similar effect.

See Appendix B.2 for the full derivation.

Proposition 1: Whether total quantity Q increases with a higher consumer subsidy t, holding fixed the total subsidy amount sub, depends on the relative curvature of demand in the regulated versus unregulated regions. Given our concavity assumption for the profit functions, the first term in parentheses in equation 3 is positive, and the overall sign depends on the second term in parentheses. We can sign this term under various conditions:

1. If demand in region N is concave ($q_N'' < 0$) while demand in region Z is convex ($q_Z'' > 0$), then $\frac{dQ}{dt} > 0$.

2. Conversely, if demand in region N is convex ($q_N'' > 0$) while demand in region Z is concave ($q_Z'' < 0$), then $\frac{dQ}{dt} < 0$.

3. If demand is linear in both regions ($q_Z'' = 0$ and $q_N'' = 0$), then $\frac{dQ}{dt} = 0$. In this case, Q depends only on the total subsidy amount sub.[16]

4. If demand in both regions are concave, or both are convex, then the sign of $\frac{dQ}{dt}$ depends on the relative curvature of the demand functions and the relative markups across regions. All else equal, more concave demand in region N and less concave demand in region Z means total output is more likely to increase with greater consumer subsidy.

Proof: See Appendix B.2.

These results extend the literature on the output effects of third-degree price discrimination to our analysis of regional demand- and supply-side subsidies. For non-marginal changes in policy design, if the sign of $\frac{dQ}{dt}$ remains constant across the relevant range of Δt, then we can immediately sign ΔQ; otherwise, we integrate over $\frac{dQ}{dt}$. Of course, in our empirical setting with oligopolistic multi-product firms, we must also consider differences in cross-price elasticities across regions, as well as the relative exposure of different products

[16] This result for linear demand has a direct analogy to Pigou's 1920 result that third-degree price discrimination does not affect a monopolist's total output when demand is linear in all regions (and the monopolist serves all regions) (Pigou 1920).

to regional policies. We return to these issues in our discussion of counterfactual results in Section 8.

Next let's consider the impact of policy design on the share of total quantity purchased in region Z. The region Z share is given by:

$$s_Z = \frac{q_Z(p-t)}{q_Z(p-t) + q_N(p)} \tag{4}$$

We then totally differentiate equation 4 with respect to t and use the fact that strict concavity of the profit function guarantees $p'(t) \in (0, 1)$.

Proposition 2: The share of the product purchased in the regulated region is increasing in the amount of the consumer subsidy:

$$\frac{ds_Z}{dt} = \frac{(q_Z'(p-t) \cdot (p'(t) - 1) \cdot q_N(p)) - (q_N'(p) \cdot p'(t) \cdot q_Z(p-t))}{(q_Z(p-t) + q_N(p))^2} > 0 \tag{5}$$

Proof: See appendix.

Finally, let's consider the impact of the policy design on welfare. We assume that consumption of the product generates a positive externality e, thereby motivating the regulator's subsidy. Total welfare is given by:

$$\begin{aligned} W = & \int_{p-t}^{\infty} q_Z(x)dx + (p + sub - t - mc + e) \cdot q_Z(p-t) \\ & + \int_{p}^{\infty} q_N(x)dx + (p - mc + e) \cdot q_N(p) - sub \cdot q_Z(p-t) \end{aligned} \tag{6}$$

We again differentiate with respect to t. We rewrite the result in terms of $p_{t=0}$, the manufacturer's price when the entire subsidy is provided as a producer subsidy (i.e., $t = 0$). Following Schmalensee (1981), we can then express the marginal impact on welfare in terms of an "output effect" and a "misallocation effect," using the terminology of the price discrimination literature:

$$\frac{dW}{dt} = \underbrace{(p_{t=0} - mc + e)\frac{dQ}{dt}}_{\text{Output effect, incl. externality}} + \underbrace{(p - t - p_{t=0})q_Z'(p-t)(p'(t)-1) + (p - p_{t=0})q_N'(p)p'(t)}_{\text{Misallocation effect}} \tag{7}$$

The output effect represents the marginal benefits of overall output expansion, or the marginal costs of output contraction. The sign of the output effect depends on the sign of $\frac{dQ}{dt}$. As an extension of the standard price discrimination literature, this term is now weighted by the externality benefits e in addition to private surplus.

The misallocation effect represents the market distortion from introducing effective price discrimination through the consumer subsidy. The interpretation is consistent with the standard price discrimination literature: marginal willingness-to-pay is no longer equated across regions. The misallocation effect is negative for all $t > 0$; to see this result, note that $p - t < p_{t=0} < p$ (derivation in appendix). Recall also that the misallocation effect does not capture overall distortions from a subsidy that deviates from the Pigouvian first-best, as our thought experiment is not to compare the regulator's subsidy regime to a first-best (or no) subsidy regime. Rather we evaluate the welfare effects of a demand-side subsidy relative to a supply-side subsidy, given the interactions between regulated and non-regulated regions in the overall product market.

Proposition 3: The marginal welfare impact of increasing the consumer subsidy t, holding constant the overall subsidy sub, may be positive or negative. A necessary but not sufficient condition for $\frac{dW}{dt} > 0$ is that overall output expands, i.e., $\frac{dQ}{dt} > 0$.[17]

Proof: See appendix.

We can also evaluate the impact of the consumer subsidy on regional welfare. To do so, we must take a stand on how consumer surplus, producer surplus, and the externality affect

[17] Aguirre, Cowan, and Vickers (2010) derive a set of sufficient conditions, relevant to a wide range of demand functions, under which welfare is everywhere increasing in t, everywhere decreasing in t, or increasing and then decreasing in t. These results could also be extended to our application of regional policy design.

welfare in different regions.[18] For ease of exposition, we assume here that regional welfare consists of consumer surplus, producer surplus and the externality from products sold in that region. However, for our empirical analysis in Section 8, we explore alternative assumptions about the relative weight that regulators place on various components of welfare.

Under these assumptions, let W_Z represent welfare in region Z. Totally differentiating W_Z with respect to t gives:

$$\frac{dW_Z}{dt} = (p - t - mc + e) \cdot q'_Z(p - t) \cdot (p'(t) - 1) \tag{8}$$

An analogous result holds for W_N:

$$\frac{dW_N}{dt} = (p - mc + e) \cdot q'_N(p) \cdot p'(t) \tag{9}$$

Proposition 4: As long as the consumer subsidy is not too large relative to the externality (i.e., $t \leq e$), then welfare in region Z is increasing in the consumer subsidy ($\frac{dW_Z}{dt} > 0$), and welfare in region N is decreasing in the consumer subsidy ($\frac{dW_N}{dt} < 0$).

Proof: See appendix.

As with the impact of the consumer subsidy on output, welfare outcomes in our empirical setting also depend on substitution patterns in a multiproduct oligopoly. To understand the impact of consumer or producer subsidies in the context of the ZEV program, we must turn to our empirical model. Nonetheless, this stylized analytical model helps to illuminate tradeoffs in subsidy design, which depend on how the regulator values deployment in its own region relative to spillovers in other regions. We return to these tradeoffs in Section 8.

[18] For consumer surplus, it is straightforward to assume that consumption in region Z contributes to welfare only in region Z and vice versa. By contrast, the impact of producer surplus on regional welfare is context-dependent – for example, depending on how profits are domiciled. Likewise, the externality may have local or global welfare impacts.

4 Empirical model of demand and pricing

To simulate the effects of policy changes on the automobile market, we build and estimate a model of manufacturer pricing and consumer choice. Conditional on the set of products (new vehicles) available in each model year, firms set prices and consumers choose which products to purchase. The demand model predicts the degree of consumer substitution across products when prices or consumer subsidies change. The pricing model is needed to estimate marginal costs, and predicts the price effects of changes in policy.

Our analysis is built on a discrete choice model of demand for new vehicles in the vein of Berry, Levinsohn, and Pakes (1995). In each region and model year, there is a population of consumers who each choose one product: either one of the gasoline vehicles, electric vehicles, and hybrids available in that region and model year, or an outside good, which captures the choice not to buy a new vehicle.

Let the set of geographical regions be $\mathcal{M}$ and index regions by $m \in \mathcal{M}$. The periods are model years, indexed by $t = 1, \ldots, T$. Let the set of products available in region m and year t be $\mathcal{C}_{mt}$, and index products by j. Firms are indexed by f, and the set of products offered by firm f in period t is $\mathcal{J}_{ft}$.

Demand. Indirect utility for consumer i in region m and model year t from purchasing product j is

$$u_{ijmt} = \alpha(p_{jmt} - \text{subsidy}_{jmt}) + x'_{jmt}\beta_i + \xi_{jmt} + \varepsilon_{ijmt}.$$

Observed characteristics enter the consumer's utility through p_{jmt}, the price of product j in region m; subsidy_{jmt}, the total federal and state consumer subsidy for j in region m; and x_{jmt}, a vector of other observed characteristics (see Section 5.1). In addition, ξ_{jmt} is a quality shock unobserved by the econometrician and ε_{itmj} is a Type 1 Extreme Value shock distributed independently across consumers, alternatives, and regions. Indirect utility from purchasing the outside good, $j = 0$, is $u_{i0mt} = \varepsilon_{i0mt}$.

We parameterize tastes using α and β_i. Heterogeneous tastes for characteristic k are captured by $\beta_{ik} = \beta_k + \sigma_{ik}\nu_{ik}$, where $\nu_{ik} \sim N(0,1)$ is a vector of individual taste differences unobserved by the econometrician (independent across consumers and independent of all observed variables), and σ_k is a parameter to be estimated.

Market shares in region m and year t are then given by

$$s_{jmt} = \int \frac{\exp(\alpha(p_{jmt} - \text{subsidy}_{jmt}) + x_{jmt}\beta_i + \xi_{jmt})}{1 + \sum_{k \in \mathcal{C}_{mt}} (\alpha(p_{kmt} - \text{subsidy}_{kmt}) + x_{kmt}\beta_i + \xi_{kmt})} \, dF_{\theta,mt}(\beta_i), \tag{10}$$

where $F_{\theta,mt}$ is the joint distribution of β_i over the population of consumers in region m and model year t, indexed by the parameter vector $\theta = (\alpha, \beta, \Pi, \Sigma)$.

By modeling utility as a function of the post-subsidy price, we assume that consumers value a \$1 government subsidy and a \$1 reduction in price equally. (This requires that consumers both know about subsidies and believe at the time of purchase that they will be able to take advantage of them.)

Like the majority of existing literature on automobile demand, we abstract away from the strategic timing of vehicle purchases and the effect of owning multiple vehicles. We assume that consumers do not respond to beliefs about future product availability or future changes to product characteristics or prices. We do not model dependence across time periods: every consumer enters the market every period, and preferences do not depend on the vehicles the consumer already owns.

The discrete choice model we use also rules out capacity constraints, which would induce unobserved variation in consumer choice sets as not all products are available to all consumers. Our method is thus imperfect for Tesla, which used waitlists to manage bottlenecks as it introduced and ramped up production of new models during this period.[19] Our estimates implicitly subsume any waitlists in the unobserved characteristic.

[19] See, e.g., "Tesla Q4 2017 Vehicle Production and Deliveries" (press release, 1/3/18). In the 2000s, the Toyota Prius used a similar strategy (Sallee 2011).

Pricing. We classify firms into national-pricing and flexible-pricing firms based on industry knowledge and the empirical analysis of transaction prices in Section 6. National-pricing firms set one price per product, while flexible-pricing firms set separate prices for each region and product. Prices then form a Nash equilibrium of a Bertrand game among these firms. By explicitly incorporating state regulations into firm profits, we allow for potentially complex cross-state pricing spillovers. A national-pricing firm may respond to state policy by changing its national price, which affects consumers in other states. In turn, firms with flexible pricing may alter their prices in other states to respond to this price change.

A firm with a national pricing strategy sets product prices to maximize firm profit across regions, taking rivals' prices as given. We assume that national pricing firms' marginal costs are the same across regions, so that the profit from a selling a vehicle only varies geographically due to differences in regulation.[20] Consider a national pricing firm f with product set $\mathcal{J}_{ft}$ in model year t. For each product $j \in \mathcal{J}_{ft}$, the firm observes marginal cost mc_{jt} and the value of regulatory credits in each region v_{jmt}, then chooses its price p_{jt}. (We define v_{jmt} in the next section.) Let p_{mt} be the vector of all prices in region m and year t. The firm's problem is

$$\max_{\{p_{jt}\}_{j \in J_{ft}}} \sum_{j \in \mathcal{J}_{ft}} \sum_{m \in \mathcal{M}} (p_{jt} + v_{jmt} - mc_{jt}) s_{jmt}(p_{mt}) M_{mt}, \tag{11}$$

where M_{mt} is the market size in region m in year t. The firm's first order condition with respect to p_{jt} is

$$0 = \sum_{m \in \mathcal{M}} \left(s_{jmt} + \sum_{k \in \mathcal{J}_{ft}} (p_{kt} + v_{kmt} - mc_{kt}) \frac{\partial s_{kmt}}{\partial p_{jt}} \right) M_{mt}. \tag{12}$$

A firm with a flexible pricing strategy solves the same problem, but is free to choose prices p_{jmt} that differ across regions within a year and possibly has marginal costs mc_{jmt}

[20] We also assume that marginal costs do not depend on quantity, which rules out capacity constraints.

that differ by region. The firm's problem is

$$\max_{\{p_{jmt}\}_{j\in J_{ft}, m\in\mathcal{M}}} \sum_{j\in\mathcal{J}_{ft}} \sum_{m\in\mathcal{M}} (p_{jmt} + v_{jmt} - mc_{jmt}) s_{jmt}(p_{mt}) M_{mt}. \tag{13}$$

The firm's first order condition with respect to p_{jmt} is

$$0 = s_{jmt} + \sum_{k\in\mathcal{J}_{ft}} (p_{kmt} + v_{kmt} - mc_{kmt}) \frac{\partial s_{kmt}}{\partial p_{jmt}}. \tag{14}$$

Under these assumptions, equilibrium prices are the joint solution to all firms' first order conditions.

Supply-side policy. We model supply-side national and state policies using the v_{jmt} term in the profit function. Generally, selling a low-emissions or electric vehicle earns credits, while selling a high-emissions or gasoline vehicle costs credits. These credits include both ZEV credits, which are the focus of our study, and federal GHG credits, which we include in our empirical model for accuracy. When credits have non-zero prices in equilibrium, changes in credit holdings will enter the firm's per-period profit function.

In order to value this credit effect in firm profits, we take advantage of the data on credit prices described in Section 5.4. We treat firms as price takers in the market for regulatory credits, and we assume that accessing this market is costless for all firms. Therefore, in equilibrium, all firms value the marginal credit at its market price.[21] If firms are certain about credit prices when making decisions, the mandate is economically equivalent to a producer subsidy and tax.[22]

We obtain the net change in credits from selling one unit of product j, which we label $c_{jt,GHG}$ and $c_{jmt,ZEV}$ for GHG and ZEV credits, respectively. Now let $r = (r_{t,GHG}, r_{mt,ZEV})$ be the vector of credit prices in the ZEV and GHG credit markets. (In regions m where the

[21] Although Tesla was the largest seller of credits, we do not see evidence it exercised market power in this period. Credits were available from other manufacturers as well, as described in Section A.2.

[22] Under firm uncertainty about credit prices, the results will generally differ, as in Aldy and Armitage (2022). We assume throughout that firms are certain about credit prices.

ZEV regulation does not apply, the price is zero.) Then the net value of regulatory credits earned from selling an additional unit of j in region m and model year t is

$$v_{jmt} \equiv c_{jt,GHG}\, r_{t,GHG} + c_{jmt,ZEV}\, r_{mt,ZEV}\,.$$

5 Data

5.1 Product characteristics and sales

Our dataset consists of gasoline, flex-fuel, electric, and hybrid vehicles classified as cars or light trucks (with a gross vehicle weight rating under 8500 pounds) whose base version has a MSRP under $120,000. We remove products that were only sold to fleet or government buyers. We assume that a product without any sales in a given region and year was not offered.[23] We use model years 2012 through 2017.

We are interested in product differentiation that is technologically significant and relevant to consumers, not small differences between trims of the same model. Therefore, we aggregate products to the level of model year, make, model, technology type (electric, plug-in hybrid, hybrid, gas) and battery size; within each group, we use the characteristics of the trim with the most national sales.[24]

Sales. To measure vehicle sales, we use the universe of US new passenger vehicle registrations in calendar years 2012 through 2018, obtained from S&P Global (formerly R.L. Polk).[25] This dataset contains the count of registrations for each model year, make, model, fuel type, trim, and state. We use state-level data for the ten ZEV states, and aggregate the rest of

[23] This contrasts with Li (2023), who uses more granular regions and thus encounters products that were offered but had zero sales.

[24] When our sales data do not identify the exact trim, we use the lowest-priced plausible match. See Appendix C.1 for details.

[25] Because we are missing sales data before January 2012, we extrapolate the full level of sales in model year 2012 using data from January 2012 onward. See Appendix C.2 for additional details.

the US into one region for our analysis.[26] Our data contain both sales and leases; we treat both as sales.

We define the market size as the number of households in each state and year, from American Community Survey 1-year estimates.

Characteristics. For product characteristics, we combine trim-level data from MSN Autos, the US Environmental Protection Agency's FuelEconomy.gov dataset, and Ward's Automotive Yearbook, and supplement with additional sources as needed. MSN Autos provides MSRP[27] and technical specifications, including size, horsepower, weight, and battery capacity.[28] FuelEconomy.gov provides fuel economy data and the battery range for electric vehicles and plug-in hybrids. Ward's Automotive Yearbook provides each model's production location and additional technical specifications that we use when MSN Autos data are missing.

Selected product characteristics and cost shifters are summarized in Table 2. We generally follow Grieco, Murry, and Yurukoglu (2024) in our choice of characteristics that enter consumer demand, augmenting with additional EV-specific characteristics. Specifically, we use technical characteristics (horsepower), proxies for vehicle size (weight, footprint, and truck/SUV/van indicators), electric capability (electric range, electricity consumption per mile, and EV/PHEV/hybrid indicators), fuel economy (in miles per gallon or miles per gallon equivalent, top-coded at 60), an indicator for the first year a model is available, and the number of trims a model has. In Table 2, we also summarize other variables that do not enter consumer demand, including CO_2 emissions per mile and cost shifters.

[26] We ignore the possibility that the state of the dealer, which is the relevant state for ZEV compliance, differs from the vehicle's state of registration. Traveling across state lines to purchase a new vehicle is often onerous for the consumer and discouraged by the manufacturer, and makes the purchase ineligible for some states' EV and hybrid subsidies.

[27] All dollar-valued inputs to demand estimation (including vehicle prices and subsidies) use nominal dollars.

[28] When MSN does not provide battery capacity, we back it out from the federal IRC 30D subsidy amount or obtain it from news sources.

Table 2: Summary statistics: market and product characteristics

	Min	Max	Weighted mean	Mean	SD
Model year	2012.00	2017.00	2014.64	2014.61	1.70
Products per market	237.00	332.00	303.69	293.49	21.95
Outside good share (%)	81.90	92.23	87.00	87.27	2.21
Product share (%)	0.00	0.83	0.16	0.04	0.08
Trims per model	1.00	76.00	12.17	6.61	6.96
MSRP ($)	10990.00	159200.00	28055.30	40087.75	22267.12
Transaction price ($)	13707.36	137200.67	31507.46	43612.52	23403.79
Govt subsidy ($)	0.00	10500.00	65.33	407.74	1709.60
Footprint (sq. ft.)	26.80	68.70	48.55	48.11	5.56
Horsepower	66.00	762.00	218.77	255.56	100.94
Fuel economy (MPG)	11.78	60.00	25.11	25.53	8.93
New model indicator	0.00	1.00	0.04	0.09	0.29
EV/PHEV/Hybrid indicator	0.00	1.00	0.04	0.15	0.36
EV/PHEV indicator	0.00	1.00	0.01	0.06	0.24
EV indicator	0.00	1.00	0.00	0.03	0.17
Truck indicator	0.00	1.00	0.12	0.04	0.20
SUV indicator	0.00	1.00	0.37	0.34	0.48
Van indicator	0.00	1.00	0.04	0.03	0.18
US brand indicator	0.00	1.00	0.42	0.28	0.45
Weight (lbs)	1808.00	6000.00	3674.66	3823.65	811.85
Electric range (mi)	0.00	315.00	0.74	4.64	25.94
Electricity use (kWh/mi)	0.00	0.44	0.00	0.02	0.06
GHG emissions (gCO2/mi)	98.16	754.61	372.53	380.45	100.28
ZEV net subsidy ($)	-72.00	14520.00	10.78	185.80	1289.22
GHG net subsidy ($)	-4194.24	5368.01	-813.95	-829.89	932.66
Battery pack cost ($)	0.00	32640.00	78.78	499.49	2607.72
Manufacturing wage ($/week)	856.90	1560.00	1116.34	1130.01	82.42
Import indicator	0.00	1.00	0.37	0.64	0.48

Note: Compiled from data from MSN Autos, FuelEconomy.gov, Ward's Automotive Yearbook, IHS, and other sources. Columns are the minimum, maximum, sales-weighted mean, unweighted mean, and unweighted standard deviation across products. Transaction price is derived or imputed from MaritzCX survey data.

Cost shifters. For US-made vehicles, we obtain the state of production from the 2009–17 Ward's Automotive Yearbook at the make-model level.[29] We then match the state to the Quarterly Census of Employment and Wages, from which we obtain the 2009–2017 average weekly wage in the manufacturing sector (NAICS 31-33).[30] We also define an indicator for whether the vehicle was US-made (matched to a US plant in Ward's Automotive Yearbook) or imported.

For vehicles with a lithium ion battery, we also use as a cost shifter a proxy for the cost of the battery. We calculate this proxy by multiplying the battery size (in kilowatt-hours) and BloombergNEF's measure of the industry-wide average battery pack price (in nominal dollars per kilowatt-hour). The battery pack price provides useful variation because the cost of a battery pack of a fixed size fell rapidly each year, totaling 80% (in real terms) from 2011 to 2018.[31] We set this variable to zero for all other vehicles.

Consumer subsidies. We manually compile data on federal and state government incentives to consumers from historical government websites, focusing on point-of-sale rebates, mail-in rebates, and income tax credits.[32] Consumer subsidies are typically deterministic functions of easily observed vehicle characteristics, such as electric range or battery capacity, and sometimes depend on MSRP or purchase price. Additional details about state-level incentives are provided in Appendix Section C.3.

5.2 Transaction prices

Data on region-level transaction prices are sparse, especially for lower-sales vehicle models. The MSRP, commonly used in the literature as a proxy for vehicle price, is set nationally.

[29] Ward's provides these data at the make-model-year-plant level. If a make-model is produced at multiple plants, we use the plant with the highest total 2009–17 production.

[30] For imported vehicles, we set the wage variable to its US average.

[31] See "A Behind the Scenes Take on Lithium-ion Battery Prices" (Logan Goldie-Scot, BloombergNEF, 3/5/19). Estimates from other sources are similar; see Ziegler and Trancik (2021) for comparisons.

[32] We do not observe how often consumers received all the subsidies they were eligible for, and we ignore variation within a model year, which may arise due to changes in funding.

Given our focus on regional differences, our approach requires data on the actual prices paid.

Our starting place is the MaritzCX survey of households that recently purchased or leased a new vehicle. We use survey data from calendar years 2010 through 2017, which we restrict to model year 2012–2017 vehicles.[33] The survey asks recent buyers and lessees of new vehicles to report information on the vehicle (including make, model, and fuel type); household demographics (including state of residence); and purchase, financing, or leasing terms, including the purchase price of the vehicle (for purchases) or the vehicle price used in calculating the lease amount (for leases). Table 3 shows summary statistics for the MaritzCX survey data, including self-reported demographics.[34]

Table 3: MaritzCX survey data summary statistics

Variable	Num. obs.	Min	Max	Mean	SD
ZEV state indicator	581,957	0.00	1.00	0.27	0.44
Model year	581,957	2012.00	2017.00	2014.81	1.61
EV/PHEV/Hybrid indicator	581,957	0.00	1.00	0.08	0.28
EV indicator	581,957	0.00	1.00	0.01	0.10
MSRP ($)	581,636	10990.00	162900.00	30411.78	12728.37
Tax rate (%)	581,957	0.00	7.50	5.70	1.42
Price paid ($)	581,957	10000.00	200000.00	36766.19	15844.18
Price pre-tax ($)	581,957	9302.33	194363.45	34791.55	15002.02
Price pre-tax pre-subsidy ($)	581,957	9302.33	194363.45	34792.55	15002.00
Lease indicator	581,957	0.00	1.00	0.19	0.39
Annual income ($)	444,954	27500.00	450000.00	150019.51	103459.50
Age	540,031	15.00	99.00	53.31	15.15
College degree indicator	581,957	0.00	1.00	0.62	0.49
Household size	581,957	1.00	6.00	2.37	1.20

Note: From MaritzCX survey of new vehicle buyers, model years 2012–17, restricted to responses where the purchase price is between $10,000 and $200,000. MSRP, EV, and hybrid variables are from MSN Autos (merged to survey responses). State tax rate is from Tax Foundation data. Purchase price, state of residence, and demographics are self-reported. Price pre-tax removes state sales tax using Tax Foundation data; price pre-tax pre-subsidy also removes point-of-sale government subsidies. Columns are the minimum, maximum, mean, and standard deviation across responses.

When filling out the survey, buyers are asked to report the transaction price after taxes

[33] The MaritzCX survey data we use is similar to the versions used in Xing, Leard, and Li (2021), Linn (2022), and Linn (2023).

[34] This table only shows responses for which the transaction price was given and fell between $10,000 and $200,000.

and before any trade-ins. Reported transaction prices vary widely, even across buyers of the same model in the same state, due to many factors: dealer-consumer negotiation, manufacturer rebates (Busse, Silva-Risso, and Zettelmeyer 2006; Langer and Miller 2013), dealer fees, trim distinctions not reported in the data, and consumer purchases of add-ons and options. As an illustration, see Appendix Figure D.9 for dispersion in transaction prices of the Nissan LEAF by model year.

In our main specification, we assume that survey respondents accounted for point-of-sale incentives in the reported transaction price, but not post-sale incentives like income tax credits. However, the survey instrument did not provide clear instructions on whether to account for incentives, and consumers may have reported transaction prices inconsistently. In our analysis of differences in transaction prices between ZEV and non-ZEV states in Section 6, we test robustness to alternative assumptions about whether consumers included point-of-sale and post-sale incentives in reported transaction prices.

We also assume survey respondents included state sales tax in their reported prices, as instructed by the survey instrument, and we make no distinction between purchased, financed, and leased vehicles.[35] Unless otherwise noted, we remove the state sales tax from the reported price using Tax Foundation annual data on state sales tax rates. See Appendix C.4 for further details on the survey instrument and our data cleaning approach.

Throughout this paper, we abstract away from within-model-year price variation, including Tesla's (often unexpected) price changes,[36] manufacturers' short-run responses to gasoline price swings (Langer and Miller 2013), and dealers' use of prices to manage inventory within the year (Zettelmeyer, Morton, and Silva-Risso 2006; Murry and Schneider 2016).

[35] Since we do not know the specific location within the state, we do not remove any local sales taxes from the reported price in our preferred specification. However, we also test robustness to removing state-level average local sales taxes in Section 6.

[36] Tesla prices can change multiple times per year. See, e.g., "No more Tesla buyback guarantee as company cuts price of Model X" (Alexandria Sage and Paul Lienert, Reuters, 7/13/16).

5.2.1 Aggregating prices for the demand model

Our demand model uses a single price for each product and region, which requires aggregating from the MaritzCX data. When a product-region combination contains 20 or more survey responses (63% of all entries), we use the mean transaction price as the aggregate price.[37] When the product-region combination contains fewer than 20 survey responses, we may be concerned about outliers and noise in the data. In those cases (12% with 1–20 survey responses, and 25% with zero responses) we use fitted values from the regression described below. For the 6% of entries still missing, we use the MSRP (from MSN Autos) as a fallback. (This only applies to a small number of luxury brands.)

When the sample size is small or zero, we use the fitted values from a regression of mean transaction price on product-level characteristics and a regional dummy. The regression specification and coefficients, which should be interpreted as predictive rather than causal, are detailed in Appendix C.4.

We still only observe purchase prices, which presents a missing data problem when prices are negotiated rather than posted: we do not observe offers made to consumers who ultimately did not purchase the product. This is a challenge for discrete choice demand estimation, which requires the econometrician to have full information about the characteristics of all products in the choice set. If price discrimination is minimal and prices vary randomly, unobserved offering prices may be higher than the observed prices, due to sales and other idiosyncratically low price offers. But if price discrimination is widespread, the unobserved offering prices may be lower than the observed prices.

[37] For national-pricing firms, we use the national mean. For flexible-pricing firms, we use the mean across ZEV states and the mean across non-ZEV states.

5.3 Consumer second choices

To recover unobserved heterogeneity in consumer tastes, we use consumers' self-reported second choices from the MaritzCX survey of new vehicle buyers for model year 2015.[38] By matching both the reported purchase (first choice) and reported model "most seriously considered" (second choice) to characteristics data from Ward's Automotive Yearbook, we can calculate the covariance of selected product characteristics between purchased products and second choices. (These covariances are shown later in Table 8.)

Due to missing data issues, we drop the buyers of eight vehicle makes, including Tesla, when calculating covariances. These buyers did not receive the survey instrument if they lived in certain states, including California.[39] In addition, the data do not distinguish consumers whose second choice is the outside good from consumers who skipped the question; we also exclude survey respondents whose second choices are missing when calculating the covariances.

5.4 Supply-side regulation

Selling an alternative fuel vehicle may earn the manufacturer credits under supply-side regulations (the federal GHG regulation and the state-level ZEV mandate), while selling a gasoline vehicle may increase the manufacturer's total regulatory requirement.

To estimate the contribution of these supply-side regulations to firm profits, we combine the details of the regulations, which specify the number of credits gained or lost by the manufacturer upon the sale of a given vehicle, with our calculated credit prices. Following the findings of Leard and McConnell (2017) that CAFE standards were not binding on automakers while the GHG regulation was in effect, we set the CAFE credit price to zero.

[38] We start from the same raw data as the transaction price analysis, but use different data restrictions to arrive at the final sample.

[39] The eight makes are BMW, Jaguar, Land Rover, Mercedes-Benz, MINI, Porsche, Smart, and Tesla.

5.4.1 GHG credits and credit prices

To determine the net change in GHG credits $c_{jmt,GHG}$ from selling vehicle j in model year t, we take the difference between the vehicle's statutory emissions and its regulatory target (a year-specific function of vehicle footprint) and multiply by statutory expected vehicle miles traveled and multipliers for electric or plug-in hybrid vehicles.[40] Generally, this quantity is positive for alternative fuel vehicles and efficient gasoline vehicles, and negative for inefficient gasoline vehicles. We assume a constant credit price of $40 per megagram (metric ton) of CO_2, based on estimates summarized in Leard and McConnell (2017).

5.4.2 ZEV credits and credit prices

To determine the net change in ZEV credits $c_{jmt,ZEV}$, we apply separate approaches for electric and non-electric vehicles. For electric vehicles, the number of credits earned is given in public data from the California Air Resources Board and New Jersey Department of Environmental Protection. For non-electric vehicles sold by large manufacturers, the number of credits that must be surrendered per vehicle sold is found in the text of the regulation.[41] For non-electric vehicles sold by small and medium manufacturers, no credits are earned or surrendered.

We estimate average ZEV credit prices by dividing the number of credits Tesla sold to other automakers, as reported to state regulators, by the revenue Tesla earned from those sales, as reported in quarterly filings and shareholder letters.[42] Tesla sales account for a large part of the credit market: during this period, Tesla was the seller for 83% of the credits that were traded overall. We weight credits from different states equally because they were interchangeable under the travel provision. Table 4 shows our estimates of the prices of

[40]Specifically, we apply the computations specified in the text of the regulation to MSN Autos data on footprint, FuelEconomy.gov data on fuel economy and, for PHEVs, FuelEconomy.gov data on utility factor.

[41]In our modeling, we assume the number of ZEV credits the firm surrenders each year is based on its non-EV sales in ZEV states that year. The regulation also allows the firm to use a moving average of non-EV sales in ZEV states in prior years, as detailed in Section A.2.

[42]This method has also been used (independently) by McConnell, Leard, and Kardos (2019). Our estimates are close, but not the same, mainly because we have data from more state regulators than they do.

ZEV credits, along with Tesla's share of total credit sales in the corresponding period. We are unable to observe if the price paid per credit varies across transactions, so we assume a uniform price in each period.

Table 4: Estimated credit prices

Window	Tesla revenue (m)	Tesla credits	Avg credit price	Tesla share
2010Q4—2013Q3	\$166	45,617	\$3,630	67%
2013Q4—2014Q3	\$86	35,869	\$2,400	71%
2014Q4—2015Q3	\$170	87,243	\$1,950	70%
2015Q4—2016Q3	\$204	85,098	\$2,390	92%
2016Q4—2017Q3	\$120	82,584	\$1,460	89%

Note: This table shows the computation of the average price of ZEV credits sold by Tesla in each year. Tesla's revenue from credit sales comes from Tesla's quarterly reports and shareholder letters. The number of credits sold by manufacturer by year was obtained from state regulatory agencies in the ten ZEV states. Prices are nominal and rounded to the nearest ten dollars.

5.5 Emissions externality

The emissions externality of an additional new vehicle is the social cost of the CO_2 emissions the vehicle is expected to emit over its lifetime, relative to the baseline emissions of the outside good. We calculate lifetime emissions as the product of three terms: the social cost of carbon (per unit of emissions), the vehicle's emissions per mile, and the miles driven per vehicle. We set the social cost of carbon to \$175 (in 2017 dollars) following Rennert et al. (2022).

In our main specification, we measure each vehicle's emissions per mile relative to a benchmark representing the outside good, calibrated to 20.9 MPG using 2017 National Household Travel Survey data on model year 2007–2011 non-electric vehicles.[43] In alternative specifications, we instead assume the outside good has no incremental emissions.

Appendix C.6 details how we calculate the externality terms, and Appendix D.3 shows the relationship between emissions externalities and substitution patterns given our estimates

[43]In this specification, the outside good can be understood as continuing to drive existing household vehicles or purchasing a used vehicle. This approach follows Allcott, Kane, Maydanchik, Shapiro, and Tintelnot (2024).

of demand parameters.

6 Analysis of transaction price survey data

In our study period, the US new vehicle market was bifurcated into two groups: Tesla, which posted prices and sold directly to consumers, and the other manufacturers, which used indirect mechanisms to influence the prices customers paid dealers in negotiated transactions. In our baseline specification, we assume that Tesla employs national pricing while other automakers use flexible regional pricing. We also explore the impact of supply-side and demand-side policies under alternative pricing regimes. In this section, we present an analysis of reported transaction prices that justifies this approach.

6.1 Institutional features

A well-publicized part of Tesla's strategy to enter the US vehicle market was its transparent pricing and choice to sell directly to consumers, often online, rather than through dealers.[44] The price for a given model could vary based on trim, add-ons, and the date of purchase, but not from one state to another. For this reason, we constrain Tesla to set prices nationally in the analysis that follows.

In the non-Tesla automobile market, some institutional features push towards a national pricing regime, while other features push towards price variation across space. Automakers set a single nationwide MSRP for each vehicle model-trim, and set dealer invoice prices that vary little across space. The MSRP shapes perceptions of vehicle affordability, which are likely to affect consumers during their search process (even if the ultimate price paid is different). At the same time, manufacturers offer rebates to dealers and to consumers (Busse, Silva-Risso, and Zettelmeyer 2006), which they are free to use to respond to cross-state policy differences subject only to the constraints of their internal systems. Dealers may

[44] See, e.g., "The battle between Tesla and your neighborhood car dealership" (Jacob Bogage, The Washington Post, 9/9/16).

additionally respond to incentives through the negotiation process, which is known to vary based on consumer demographics and consumer information (Murry and Schneider 2016; Chandra, Gulati, and Sallee 2017).[45] Besides differences in the purchase price, automakers may offer region- and model-specific discounts through favorable financing or lease terms, which can be difficult to observe in data.

6.2 Empirical test

To evaluate empirically whether automakers priced electric vehicles differently in ZEV versus non-ZEV states, we examine transaction prices from the MaritzCX consumer survey. As shown in Figure 1, the unconditional data show that non-Tesla EV models systematically sell for lower prices in ZEV states, but Tesla and gasoline vehicles do not.

To address potential confounders, we test for systematic price differences between similar transactions in ZEV and non-ZEV states, conditioning on model, model year, trim, drive type, and body style fixed effects.[46] We also condition on reported demographic characteristics, including household income, age, urbanity, retirement status, marital status, household size, and college attainment. In our preferred specification, we remove state sales tax and point-of-sale incentives from the reported price. Results are presented in Table 5.

We consistently find that the transaction price of EV models is lower in ZEV states – about $1,500 lower for non-Tesla EVs in our preferred specification (column 3 of Table 5) – consistent with automakers using flexible pricing to sell more EV models in regulated states. While we find some difference in prices for plug-in hybrid vehicles, the coefficient is smaller in magnitude and imprecisely estimated. The difference in transaction prices for all other vehicles, captured by the estimated coefficient on ZEV state, is two orders of magnitude smaller and the sign is sensitive to model specification. If consumers in ZEV states consistently purchased lower-tier trims or fewer add-ons, then we would expect this

[45] Manufacturers may also vary consumer prices by manipulating dealer inventory allocations, which would not appear in dealer prices or manufacturer incentives.

[46] Because of the extremely small number of hydrogen fuel cell vehicles sold during the study period, electric vehicles were, in practice, synonymous with ZEV vehicles.

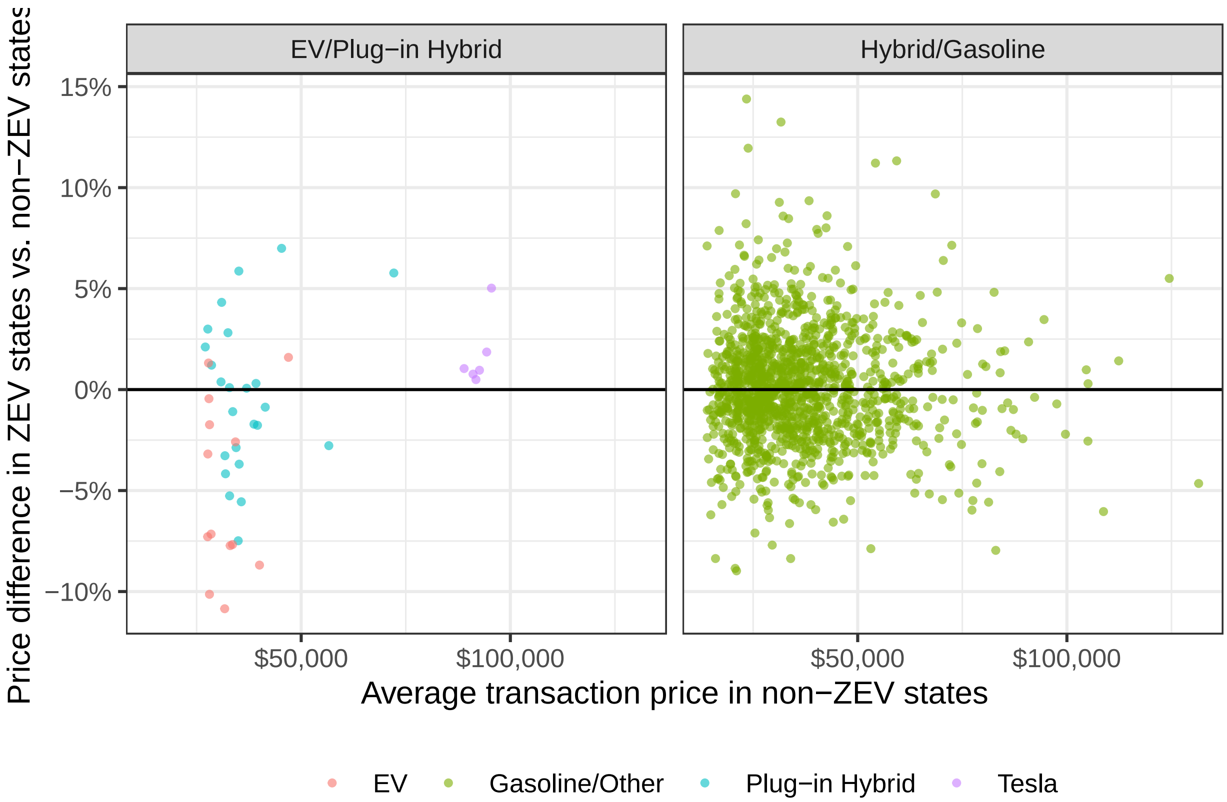

Figure 1: Comparison of transaction prices inside and outside of ZEV states.

Note: Each point represents a model year-make-model-fuel type combination. The horizontal axis is the average price in the non-ZEV-state region; the vertical axis is the average price in the ZEV-state region, as a percentage of the average price in the non-ZEV-state region. Only points representing 20 survey responses in both the ZEV-state and non-ZEV-state regions are included. The transaction price variable removes state sales tax and point-of-sale government incentives.

residual heterogeneity to affect overall differences in price. Based on these results, we do not assume fully constrained national pricing for automakers besides Tesla.[47]

We explore the robustness of these results in Appendix D.1. First, we apply alternative assumptions about how consumers accounted for taxes and incentives in the reported price. In Appendix Table D.7, we consider the full set of possible permutations for how consumers reported the purchase price: including state versus state and average local sales taxes, including average documentation fees versus not, including no incentives versus point-of-sale incentives versus point-of-sale and post-sale incentives. We consistently find that the EV prices are lower for non-Tesla models in ZEV states than non-ZEV states, though the magnitude of the difference varies from $570 to $1,550 depending on the specification. Estimated price differences for plug-in hybrid and all other vehicles are also consistently much smaller. In Appendix Table D.8, we explore the robustness of our preferred specification (reported prices adjusted for state sales taxes and point-of-sale incentives) to alternative modeling approaches. We drop makes with incomplete coverage in the MaritzCX data, specify prices in logs rather than levels, use less granular model-by-model year fixed effects, and used binned rather than continuous household income. We also examine alternative clustering of standard errors. Results are robust to each of these alternative approaches.

7 Estimation

7.1 Estimating the demand model

We estimate demand parameters using a generalized method of moments estimator following Berry, Levinsohn, and Pakes (2004), Grieco, Murry, and Yurukoglu (2024), and Conlon and

[47] Interacting year with ZEV state and electric vehicle (Appendix Table D.6) suggests that this result may be driven by price differences in later years, especially 2017. While the estimated coefficients are negative in all years, they are smaller in magnitude and not statistically significant in earlier years. To some extent, this finding may reflect the larger sample size of EV purchases in later years, but it is also consistent with anecdotal reports that automakers became more sophisticated in their pricing strategies over time. In our demand model, we assume flexible pricing in all years for non-Tesla automakers, but we also explore the impact of alternative pricing strategies in our counterfactual analysis.

Table 5: Transaction prices in ZEV and non-ZEV states

	Reported Price	Reported Price Less Sales Tax	Reported Price Less Sales Tax & POS Rebates
ZEV state	65.626*	-92.893***	-92.830***
	(35.284)	(29.304)	(29.308)
ZEV state × PHEV	-326.239	-534.663	-491.356
	(447.788)	(436.835)	(421.769)
ZEV state × EV	-1223.444***	-1547.133***	-1474.873***
	(437.194)	(448.091)	(425.170)
Model+ Fixed Effects	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes
Observations	443,671	443,671	443,671
R^2	0.88	0.88	0.88

Note: Vehicle fixed effects control for model, model year, trim, drive type, body style, and fuel type. We include additional controls for buyer reported demographics: income, age, metro/suburban/small town/farming area residence, retirement status, marital status, household size, and college attainment. Standard errors are two-way clustered by model-model year and state-make-year. We exclude Tesla vehicles since they were not sold at dealerships and were priced nationally.

Gortmaker (2023). Our estimator relies only on the model of consumer demand, not on the model of pricing. The estimator simultaneously matches model-predicted to observed market shares, matches model-predicted micro-moments to observed survey data, and fits unobserved quality ξ to be uncorrelated with instrumental variables.

The second choice micro-moments recover unobserved heterogeneity in consumer tastes, Σ. Instrumental variables based on cost shifters and government subsidies to consumers identify consumer preference for price, α, in a way that allows for the interdependence of price and unobserved quality ξ. An exogeneity assumption on product characteristics identifies mean consumer preference for characteristics, β.

7.1.1 Implementation

Specifically, we use the second-choice ("micro-BLP") generalized method of moments estimator implemented in PyBLP (Conlon and Gortmaker 2020; Conlon and Gortmaker 2023). This estimator relies on two sets of assumptions: the exogeneity of the instrumental variables and the assumption that the model-predicted micro-moments match empirical values from survey data. We use the same subset of characteristics for random coefficients (Σ) and to generate second choice micro-moments.

We weight moments using the two-stage least squares weight matrix, and we compute share integrals using Halton draws with 500 draws per market. We compute standard errors using the GMM formula, clustering observations at the make-model level to allow for correlation in unobserved quality across regions, across time, and across fuel type and battery size variants.

7.1.2 Exogeneity assumptions

Because prices may be endogenous to product quality, we employ an instrumental variables approach to estimate demand parameters (as in Berry, Levinsohn, and Pakes (1995) and subsequent literature). Following prior studies of the automotive industry,[48] we assume non-price product characteristics are exogenous. (We allow government subsidies to be endogenous.) We use three cost shifters as instruments for price: the average manufacturing wage in the state of production,[49] an import indicator, and the cost of the lithium ion battery pack (where applicable).

We describe the sources of these variables in Section 5.1.

7.1.3 Demand estimates

Our estimates of demand parameters are broadly consistent with prior work on this industry, and produce reasonable elasticity estimates.

Table 6 shows the estimated linear and nonlinear parameters (except for the magnitudes of fixed effects). We find large and significant unobserved heterogeneity parameters on

[48]This assumption is used in Berry, Levinsohn, and Pakes (1995) and Grieco, Murry, and Yurukoglu (2024), though it has recently been challenged by Petrin, Ponder, and Seo (2022). According to industry experts, the technical characteristics of a vehicle are determined early in the design process, and are largely fixed until the vehicle's next redesign.

[49]This instrument is also used by Wollmann (2018), in a setting with no imports (heavy-duty trucks).

all the dimensions we consider, especially body style indicators (truck, SUV, van). Most relevant to substitution between EVs and gasoline vehicles, we find substantial heterogeneity in preferences for fuel economy (where EVs are most similar to hybrid and efficient gasoline vehicles).

Table 6: Estimates of demand parameters

	Logit		Random coeff.	
	Estimate	SE	Estimate	SE
Linear parameters (β)				
Price−Subsidy	-1.56	0.46	-2.90	2.00
Van	-1.71	0.68	-8.21	2.28
SUV	-0.02	0.31	-1.79	1.56
Truck	-1.90	0.79	-9.83	5.15
Footprint	0.55	0.58	1.19	4.12
Horsepower	1.43	0.50	3.32	1.58
Fuel economy	0.56	0.34	0.11	1.64
EV/PHEV/Hybrid	-1.69	0.68	-3.31	2.02
EV/PHEV	0.67	0.48	-0.46	2.89
EV	-2.83	0.87	-8.33	7.03
Electric range	1.51	0.72	0.07	2.70
Elec. use	-0.49	0.46	0.16	1.29
Weight	2.62	1.71	3.83	5.90
New model	0.05	0.13	-0.38	0.60
log(# trims)	0.84	0.15	1.21	0.58
Unobserved heterogeneity (Σ)				
Van			3.98	0.11
SUV			2.49	0.03
Truck			4.67	0.14
Footprint			2.20	0.15
Horsepower			1.31	0.05
Fuel economy			1.89	0.09
US brand			1.65	0.02

Note: Estimates from random coefficients logit demand system, except for magnitudes of fixed effects (on make, model year, and state), for specifications estimated using fitted transaction prices. The coefficient on characteristic k for consumer i is $\beta_k + \Sigma_k v_i$, where v_i is unobserved heterogeneity. The specification labeled Logit sets Σ to zero. The specification labeled 'Random coeff.' estimates Σ using second choice survey data. Standard errors are clustered at the make-model level.

The estimated own-price elasticities, shown in Table 7, are somewhat less elastic than prior literature for non-electric vehicles, but more elastic than prior work that has focused on

Table 7: Average elasticities implied by demand estimates

Type	Logit	Random coeff.
Electric	-9.05	-15.83
Gas/Hybrid	-4.88	-8.72

Note: Mean own-price elasticities across products, regions, and years, weighted by quantity sold. Columns correspond to demand specifications.

electric vehicles. Estimated own-price elasticities from other studies of the US EV market (surveyed in Cole, Droste, Knittel, Li, and Stock (2023)) range from -1.0 to -3.3, but other estimates from the US auto market are more elastic. For example, Beresteanu and Li (2011) finds an average own-price elasticity of -8.4 in the 1999–2006 period, and Grieco, Murry, and Yurukoglu (2024) finds own-price elasticities between -6.5 and -9.4 (depending on income group) in 2018.

In estimation, we use the covariances between first and second choices (obtained from the MaritzCX survey) as micro-moments. Our estimated model fits these moments well, as shown in Table 8. By comparison, a standard logit model predicts covariances close to zero.

Table 8: Covariances between first and second choice

Characteristic	Data	Model	Logit
Van	0.016	0.017	-0.000
SUV	0.166	0.155	-0.001
Truck	0.103	0.094	-0.001
Footprint	0.175	0.162	-0.001
Horsepower	0.491	0.461	-0.004
Fuel economy	0.574	0.518	0.004
US brand	0.101	0.099	0.004

Note: Data from MaritzCX survey of buyers of new model year 2015 passenger vehicles. Figures are covariances between the characteristic for the buyer's first choice and second choice (in logs, except for indicator variables). The Model column shows the predictions from the random coefficients demand model presented in Table 6. The Logit column shows the predictions from a logit demand model estimated without second choice moments.

If we instead estimate demand using national prices (MSRPs), we find similar coefficients on characteristics but less elastic demand. These results are shown in Appendix D.2.

7.2 Marginal cost estimates

The demand estimates and the first order conditions from the pricing model (Section 4) together give estimates of marginal cost. We adapt existing techniques for estimating marginal costs from Nash-in-prices equilibria (Nevo 2001; Grieco, Murry, and Yurukoglu 2024) to accommodate the use of flexible and national pricing and allow for regional variation in subsidies and taxes.

For flexible firms, we use cross-region price variation and region-level price elasticities to recover region-by-region marginal costs mc_{jmt}. For national firms, we only observe national prices and lack the flexibility to recover region-by-region marginal costs; we therefore add the assumption that marginal costs only differ due to regulatory credits and recover a national marginal cost mc_{jt}.

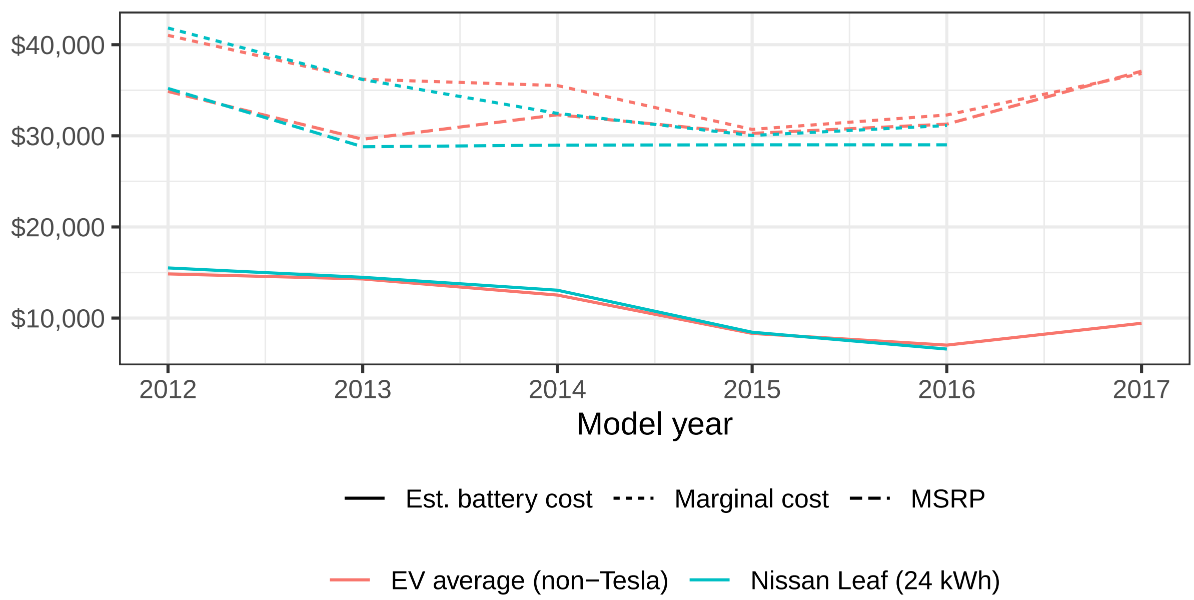

Figure 2: Prices and estimated marginal costs, selected EVs

Note: MSRP is from MSN Autos. Marginal costs are estimated from random coefficients demand system and market-by-market Nash–Bertrand pricing. Battery cost is estimated using MSN Autos data on battery pack size and BloombergNEF data on average battery pack cost per kilowatt-hour. EV average excludes Tesla and is sales-weighted. All figures measured in nominal dollars.

Our estimated marginal costs for selected electric vehicles (aggregated by sales) are shown in Figure 2, which compares them to prices. Marginal costs for the lowest-priced Nissan Leaf trend downward, even as the price remains flat from 2013 onward.

Although these estimates do not directly use data on battery pack costs, they track industry trends well. The trend of declining marginal cost is consistent with the falling battery prices in this period, while the rise after 2015 is consistent with increases in the battery pack size in later-model EVs.

8 Counterfactual simulations

We now use counterfactual simulations of alternative policy designs to answer the central questions of the paper within a rich oligopoly model of the industry. What were the consequences of states' choices to use the supply-side ZEV policy rather than demand-side alternatives? How did the resulting pricing spillovers affect the quantities of EVs induced by the policy and overall welfare?

Our first simulation, like our theoretical model of a monopolist in Section 3, considers the case where the per-vehicle amount of the implicit producer subsidy (or tax) from the ZEV program is held constant, but it is instead shifted completely to a consumer subsidy (or tax).[50] Given our assumption that firms knew ZEV credit prices in each period with certainty, the shadow prices induced by the tradeable credit program were economically equivalent to a subsidy (for EVs) or a tax (for non-EVs). In the "dollar-equivalent" counterfactual, we shift the ZEV program's implicit producer subsidy for EVs to a consumer subsidy, and shift the implicit producer tax on non-electric vehicles to a consumer tax.[51] In the results that follow, we treat both the supply-side and the demand-side policies as *explicit* subsidies and taxes.[52] For further details on the implementation of the counterfactual simulations, see

[50]Similar demand-side 'feebate' policies are used to control greenhouse gas emissions from cars in some jurisdictions (Durrmeyer and Samano 2018). A greenhouse gas-based feebate system was proposed in California in 2008, but not passed.

[51]In all counterfactuals, we hold all other subsidy amounts fixed, including existing state consumer subsidies and the federal income tax credit. We do not model budgetary constraints on existing programs or the quantity-based phase-out schedule of the federal income tax credit. We also assume federal greenhouse gas credit prices remain unchanged, shutting down an alternative channel for spillovers across states (Goulder, Jacobsen, and van Benthem 2012).

[52]Another approach would be re-solving for the equilibrium credit price under alternative policy scenarios.

Appendix E.

Results from the "dollar-equivalent" exercise are presented in Table 9. Consistent with the theoretical model in Section 3, we find that this shift would increase the quantity of EVs sold in the regulated ZEV region by 97,500 during the study period, relative to 229,000 EVs sold with existing policies in place. Conversely, the shift would decrease the quantity of EVs sold in the non-ZEV region by 49,700, relative to 144,300 EVs sold with existing policies. In total, we find a net increase of 47,800 EVs sold across the United States from the demand-side program relative to the existing supply-side program, a 13% increase relative to the existing policy regime. While theoretically ambiguous in our Section 3 model, the impact of increasing the share of consumer subsidy on overall EV quantity is positive and economically meaningful in this setting.

Product-by-product price and quantity effects are shown in Figure 3. All Teslas see price increases in the non-ZEV states and price decreases in California, net of subsidies. Other products see small quantity changes, as consumers substitute to Teslas in California and away from Teslas in the non-ZEV states, and even smaller price changes.

In an alternative counterfactual analysis in which we assume that all automakers – not just Tesla – set prices nationally, we find qualitatively similar results from shifting to demand-side subsidies and taxes. Results are presented in Appendix Table E.12. The quantity of EVs sold in the ZEV region increases by 145,800 under the demand-side policy with fully national pricing, while the quantity of EVs sold in the non-ZEV region decreases by 84,600. Intuitively, under a more constrained pricing regime, introducing effective price discrimination through a demand-side ZEV program has a larger impact on quantity of EVs sold in each region. In total, EV quantity increases by 61,200 nationally, a 16% increase relative to existing policies with fully national pricing.

For a policymaker whose goal is to increase adoption of a nascent product – the stated goal

However, this exercise would require many additional assumptions about firm conduct in the credit market. We are better able to highlight the core economics of this paper by treating both policies as explicit subsidies and taxes.

Table 9: Comparison of ZEV program as dollar-equivalent demand- or supply-side policy

	Demand-Side ZEV Program	Supply-Side ZEV Program	No ZEV Program	Demand- vs. Supply-Side
Quantity of EVs sold				
ZEV Region	326,500	229,000	61,300	97,500
Non-ZEV Region	94,500	144,300	99,200	-49,800
National	421,000	373,200	160,500	47,700
Consumer surplus				
ZEV Region	$156.42b	$155.92b	$155.76b	$504m
Non-ZEV Region	$385.79b	$385.99b	$385.81b	-$199m
National	$542.22b	$541.91b	$541.57b	$305m
Producer surplus from vehicles sold				
ZEV Region	$101.62b	$101.66b	$101.75b	-$32m
Non-ZEV Region	$258.33b	$258.10b	$258.32b	$231m
National	$359.95b	$359.75b	$360.08b	$199m
GHG reduction from new vehicles sold				
ZEV Region	$59.55b	$58.86b	$57.97b	$699m
Non-ZEV Region	$104.50b	$104.73b	$104.52b	-$222m
National	$164.06b	$163.58b	$162.49b	$477m
Net fiscal revenue, ZEV program only				
ZEV Region	-$1.99b	-$1.00b	–	-$988m
Non-ZEV Region	–	–	–	–
National	-$1.99b	-$1.00b	–	-$988m
Net fiscal revenue, all programs				
ZEV Region	-$6.72b	-$4.81b	-$2.26b	-$1,902m
Non-ZEV Region	-$1.82b	-$2.23b	-$1.86b	$406m
National	-$8.54b	-$7.04b	-$4.12b	-$1,497m
Total surplus net of fiscal cost				
ZEV Region	$310.89b	$311.62b	$313.23b	-$731m
Non-ZEV Region	$746.80b	$746.58b	$746.79b	$215m
National	$1,057.69b	$1,058.20b	$1,060.02b	-$515m

Note: This table shows the simulated quantity, welfare, and fiscal effects of implementing the ZEV policy as a demand-side subsidy and tax or as the existing supply-side subsidy and tax policy, holding fixed the dollar amount per vehicle sold. It also shows the simulated scenario with neither policy, for comparison. Throughout, we assume only Tesla uses national pricing, and all other products are priced regionally. All amounts are aggregated across the study period; dollar amounts are in 2017 USD. Welfare amounts are across the entire new vehicle market. Environmental externalities are measured relative to the outside good benchmark (used car). Total surplus includes consumer surplus, environmental externalities, and firm profits earned on new vehicle sales. The fiscal cost of the ZEV program is the value of net credits earned across the study period. The fiscal cost of all policies also includes existing federal and state subsidy policies; it does not include the federal GHG program.

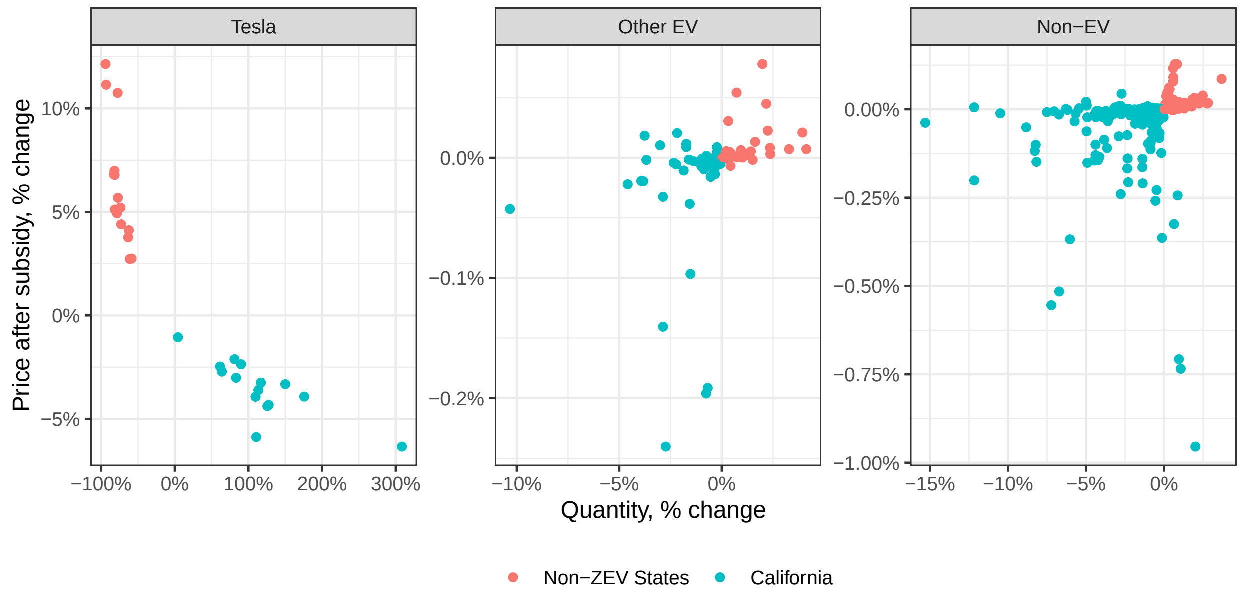

Figure 3: Dollar-equivalent counterfactual: price and quantity effects

Note: This figure shows simulated product-level price and quantity effects of the first counterfactual, which replaces the supply-side ZEV policy with a dollar-equivalent demand-side policy. Prices shown are net of consumer subsidies. Both prices and quantities are in percentage change units.

of California regulators in implementing the ZEV program – the interaction of the regional policy with national pricing creates tradeoffs between quantity sold in own region, spillover quantity in non-regulated regions, and overall quantity in all regions. For the ZEV program, our model predicts that both overall and ZEV region quantity of EVs sold would increase under the demand-side policy, though other empirical settings may present a tradeoff between these outcomes. Additional tradeoffs exist between deployment in the regulator's own region and spillovers in other regions: if the ZEV program were an explicit subsidy, greater adoption of EVs in the ZEV region instead of the non-ZEV region would present fiscal tradeoffs, as the policymaker would only incur subsidy expenditures for products sold in the regulated region. Treating credit prices as an explicit subsidy, we find that the ZEV program would pay \$7,600 per EV sold nationally under the counterfactual demand-side program, in which more EVs are sold in the regulated region, but \$6,300 per EV sold nationally under a supply-side program, which induces more spillover sales.

Welfare outcomes, like quantity outcomes, also differ under the alternative policy and pricing regimes we consider. Under the counterfactual demand-side ZEV program, our baseline model predicts that consumer surplus increases in the ZEV region but decreases in the non-ZEV region; overall national consumer surplus increases by $305 million. Producer surplus from vehicles sold in the ZEV region decreases from shifting to a demand-side ZEV program, while producer surplus from vehicles sold in the non-ZEV region increases. Overall producer surplus increases by $199 million. Lastly, the environmental externality closely tracks the quantity of EVs sold, as the average EV is responsible for fewer GHG emissions than the average substitute good, including the outside good.[53] Shifting to the demand-side ZEV program would reduce the GHG externality by $477 million across the US market, driven by increased national adoption of EVs in this scenario. Results from our alternative counterfactual analysis assuming fully national pricing are again qualitatively similar; these results are reported in Appendix Table E.12.

Combining these results into an overall welfare assessment presents two complications. First, this counterfactual analysis, by construction, holds fixed the amount of the per-vehicle subsidy or tax while shifting its incidence. Changing the quantity of EVs sold in the regulated region means that the total subsidy outlay changes (and analogously the total tax burden). To account for this change, we assess the overall fiscal burden to the regulator, again treating both the supply-side and demand-side policies as explicit subsidies and taxes. These results are presented in the final three panels of Table 9.[54]

The second complication is that evaluating the welfare impact of regional policies requires assumptions about how consumer surplus, producer surplus, and the externality are weighed

[53] As detailed in Appendix Section D.3, the relative emissions of EVs and their close substitutes depend on the assumption that the outside good has the emissions of a typical used vehicle. In the Appendix Table D.11, we instead assume that the outside good has no emissions.

[54] The sum of tax revenue and subsidy outlay does not equal zero for the existing ZEV program, as would be the case for a single period tradeable credit program in equilibrium. In fact, the large automakers accumulated substantial credit balances during the study period (see Appendix Figure A.2), so the implicit subsidy outlay exceeded the implicit tax burden during this period. If automakers believed that the post-2017 ZEV rules (enacted in 2012) would continue as planned, the banked credits may represent expectations of avoided future compliance costs.

by regulators in different regions. We consider three scenarios, corresponding to three potential sets of welfare weights for the regional regulator: "regional market surplus," consisting of consumer surplus, producer surplus, emissions externality, and fiscal costs (including from non-ZEV programs) from products sold in that region; "national market surplus," consisting of all consumer surplus, producer surplus, emissions externalities, and fiscal costs from products sold nationally; and "regional voter surplus," consisting of regional consumer surplus, regional and state (but not federal) fiscal cost, and nationwide externalities. These three potential aggregations of surplus are presented in Table 10; we do not include the deadweight loss from taxation when incorporating fiscal costs into welfare.

Table 10: Welfare evaluation of dollar-equivalent demand- or supply-side ZEV program

Metric	Demand-Side ZEV Program	Supply-Side ZEV Program	No ZEV Program	Demand- vs. Supply-Side
Regional market surplus	$310.89b	$311.62b	$313.23b	-$731m
National market surplus	$1,057.69b	$1,058.20b	$1,060.02b	-$515m
Regional voter surplus	$317.51b	$317.69b	$317.79b	-$187m

Note: This table shows alternative aggregations of the simulated welfare and fiscal effects of implementing the ZEV policy as a demand-side subsidy and tax or as the existing supply-side subsidy and tax policy, holding fixed the dollar amount per vehicle sold. It also shows the simulated scenario with neither policy, for comparison. Throughout, we assume only Tesla uses national pricing, and all other products are priced regionally. All amounts are aggregated across the study period; dollar amounts are in 2017 USD. Fiscal costs and welfare are combined without considering the deadweight loss from taxation. Regional market surplus encompasses consumer surplus, producer surplus, emissions externalities, and state and federal fiscal costs in the regulated region. National market surplus expands regional market surplus to include the non-regulated region. Regional voter surplus encompasses regional consumer surplus, state fiscal costs, and national emissions externalities.

In all three aggregations of surplus, shifting the supply-side ZEV program to a demand-side subsidy and tax program would increase private surplus and reduce the GHG externality. However, the fiscal burden increases substantially with this shift to a demand-side policy, with an additional $988 million fiscal cost from a demand-side ZEV program and additional fiscal costs from other federal and state programs that subsidized EVs. In the "regional market surplus" scenario, welfare decreases by $731 million under the demand-side policy relative to existing policy, driven by $1.9 billion in additional fiscal costs that dwarf the private surplus and externality reduction benefits. In the “national market surplus” scenario, the partly offsetting outcomes in the ZEV and non-ZEV regions mean that welfare decreases by $515 million under the demand-side policy, again driven by large fiscal costs that outweigh private surplus gains and externality reduction. Finally, in the “regional voter surplus” scenario, welfare similarly decreases by $187 million under the demand-side policy, driven by $1.2 billion in additional state-level fiscal costs.

8.1 Budget-balanced counterfactual policies

An additional counterfactual analysis allows us to reinterpret these increased fiscal costs from the demand-side policy in welfare terms. In this simulation, we require both the supply-side and demand-side policies to balance their budget in each period and to achieve the same quantity of EVs sold in the ZEV region as the existing regulatory target. We solve for the level of producer and consumer EV subsidies and conventional vehicle taxes that achieve these outcomes in equilibrium. The budget-balance requirement substantially raises the implicit tax on a non-electric vehicle sold by a large manufacturer.

Results are presented in Table 12 for our baseline model where only Tesla prices nationally, and in Appendix Table E.13 where we assume national pricing for all automakers. The underlying subsidy and tax amounts are presented in Table 11.

As before, we find that the demand-side policy results in fewer spillover sales of EVs in the non-ZEV region; since we hold constant total sales of EVs in the ZEV region, national sales also decrease under the demand-side policy. We also find that smaller subsidies and taxes are required to achieve the EV target in the ZEV region under the demand-side policy. These lower amounts produce welfare gains using any of the three aggregations described above. In addition to reflecting a policymaker’s possible consideration of budgetary and EV quantity effects, this simulation yields more interpretable welfare estimates. Like Durrmeyer and Samano (2018), we compare surplus under two different policy instruments, holding fixed an outcome targeted by the baseline policy. This approach allows us to abstract away

Table 11: Subsidy and tax amounts in counterfactual simulations

	Subsidy (typical EV)			Tax (non-EV)		
Model year	Observed	Budget-Balanced Supply-Side	Budget-Balanced Demand-Side	Observed	Budget-Balanced Supply-Side	Budget-Balanced Demand-Side
2012	$10,890	$10,882	$9,253	$29	$40	$38
2013	$10,890	$10,834	$8,683	$29	$118	$102
2014	$7,200	$7,155	$5,558	$19	$76	$63
2015	$5,850	$5,830	$4,518	$59	$87	$70
2016	$7,200	$7,154	$5,124	$72	$140	$105
2017	$4,380	$4,342	$3,457	$44	$108	$87

Note: This table shows the subsidies and taxes under the observed policy, a budget-balanced supply-side counterfactual policy, and a budget-balanced demand-side counterfactual policy, where both budget-balanced policies are constrained to attain the same total EV sales in the regulated states. All subsidies are scaled by battery range in the same way, and all taxes apply only to non-electric vehicles by six Large Volume Manufacturers. The left panel shows the amount of the subsidy (or value of credits) for the sale of a Nissan Leaf, which earned three credits per sale. The right panel shows the amount of the tax on the sale of a non-EV by a Large Volume Manufacturer. Amounts are shown in nominal dollars.

from the relative weights that the regulator places on the stated policy goal (namely, EVs sold in the ZEV region) versus total surplus.

In all three aggregations of surplus we consider in Table 13, shifting from a budget-balanced supply-side ZEV program to a budget-balanced demand-side subsidy and tax program would increase private surplus, even accounting for fiscal costs from other federal and state programs that subsidized EVs. In the "regional market surplus" scenario, welfare increases by $392 million under the demand-side policy, driven by $285 billion in additional consumer surplus and $131 billion in externality reduction benefits. In the "national market surplus" scenario, the partly offsetting outcomes in the ZEV and non-ZEV regions mean that welfare increases by $605 million under the demand-side policy, driven by consumer surplus gains in the regulated region, producer surplus gains outside the regulated region, and reduced federal fiscal costs. Finally, in the "regional voter surplus" scenario, welfare increases by $213 million under the demand-side policy, dampened only by additional emissions externalities outside of the regulated region.

Table 12: Comparison of budget-balanced demand- or supply-side policy

	Demand-Side ZEV Program	Supply-Side ZEV Program	No ZEV Program	Demand- vs. Supply-Side
Quantity of EVs sold				
ZEV Region	229,000	229,000	61,300	0
Non-ZEV Region	96,000	144,000	99,200	-48,000
National	325,000	372,900	160,500	-48,000
Consumer surplus				
ZEV Region	\$155.23b	\$154.95b	\$155.76b	\$285m
Non-ZEV Region	\$385.80b	\$385.99b	\$385.81b	-\$192m
National	\$541.03b	\$540.94b	\$541.57b	\$93m
Producer surplus from vehicles sold				
ZEV Region	\$101.03b	\$101.05b	\$101.75b	-\$19m
Non-ZEV Region	\$258.33b	\$258.10b	\$258.32b	\$227m
National	\$359.36b	\$359.15b	\$360.08b	\$208m
GHG reduction from new vehicles sold				
ZEV Region	\$58.75b	\$58.62b	\$57.97b	\$131m
Non-ZEV Region	\$104.51b	\$104.72b	\$104.52b	-\$214m
National	\$163.26b	\$163.34b	\$162.49b	-\$82m
Net fiscal revenue, ZEV program only				
ZEV Region	–	–	–	–
Non-ZEV Region	–	–	–	–
National	–	–	–	–
Net fiscal revenue, all programs				
ZEV Region	-\$3.81b	-\$3.81b	-\$2.26b	-\$5m
Non-ZEV Region	-\$1.84b	-\$2.23b	-\$1.86b	\$391m
National	-\$5.65b	-\$6.03b	-\$4.12b	\$386m
Total surplus net of fiscal cost				
ZEV Region	\$311.20b	\$310.81b	\$313.23b	\$392m
Non-ZEV Region	\$746.80b	\$746.59b	\$746.79b	\$213m
National	\$1,058.00b	\$1,057.40b	\$1,060.02b	\$605m

Note: This table shows the simulated quantity, welfare, and fiscal effects of implementing a budget-balanced ZEV-style policy as a demand-side subsidy and tax or as a supply-side subsidy and tax policy, holding the quantity of EVs sold in the ZEV Region fixed at observed levels. It also shows the simulated scenario with neither policy, for comparison. Throughout, we assume only Tesla uses national pricing, and all other products are priced regionally. All amounts are aggregated across the study period; dollar amounts are in 2017 USD. Welfare amounts are across the entire new vehicle market. Environmental externalities are measured relative to the outside good benchmark (used car). Total surplus includes consumer surplus, environmental externalities, and firm profits earned on new vehicle sales. The fiscal cost of both policies are zero by construction. The fiscal cost of all policies also includes existing federal and state subsidy policies; it does not include the federal GHG program.

Table 13: Welfare evaluation of budget-balanced demand- or supply-side ZEV program

Metric	Demand-Side ZEV Program	Supply-Side ZEV Program	No ZEV Program	Demand- vs. Supply-Side
Regional market surplus	\$311.20b	\$310.81b	\$313.23b	\$392m
National market surplus	\$1,058.00b	\$1,057.40b	\$1,060.02b	\$605m
Regional voter surplus	\$317.69b	\$317.48b	\$317.79b	\$213m

Note: This table shows alternative aggregations of the simulated welfare and fiscal effects of implementing a budget-balanced ZEV policy as a demand-side subsidy and tax or as a supply-side subsidy and tax policy. It also shows the simulated scenario with neither policy, for comparison. Throughout, we assume only Tesla uses national pricing, and all other products are priced regionally. All amounts are aggregated across the study period; dollar amounts are in 2017 USD. Fiscal costs and welfare are combined without considering the deadweight loss from taxation. Regional market surplus encompasses consumer surplus, producer surplus, emissions externalities, and state and federal fiscal costs in the regulated region. National market surplus expands regional market surplus to include the non-regulated region. Regional voter surplus encompasses regional consumer surplus, state fiscal costs, and national emissions externalities.

9 Conclusion

We examine the effects of the ZEV mandate, an influential state-level supply-side environmental policy in early generations of the US electric vehicle market. Because of the interaction between national pricing and regional policy variation, the mandate generated cross-state spillovers that would have differed for a comparable demand-side policy. In this setting, policy design tradeoffs between a demand- and supply-side policy depend on how the regulator values additional deployment relative to the fiscal costs of the policy, and on how the regulator values deployment in its own region relative to spillovers in other regions. While our analysis focuses on automakers' pricing decisions, future research might consider the implications of regional policy incidence for product entry incentives, as the entry of new EV models during this period was arguably another important set of spillovers from the ZEV program.

Although electric vehicle characteristics, costs, and quantities have evolved since the period we study, our findings have implications for the consequences of current and future electric vehicle policy, including ongoing debates about extending the ZEV program framework to heavy-duty trucks. More broadly, given changes in pricing flexibility with the rise of e-commerce, our findings also have consequences for the design of a wide range of regional policies that interact with broader product markets.

References

Abuin, Constanza (2025). *Power Decarbonization in a Global Energy Market: The Climate Effect of U.S. LNG Exports*. URL: https://constanzaabuin.github.io/assets/pdf/Abuin-GlobalPowerDecarbonization.pdf. Pre-published.

Adams, Brian and Kevin R. Williams (2019). "Zone Pricing in Retail Oligopoly". In: *American Economic Journal: Microeconomics* 11.1, pp. 124–156. ISSN: 1945-7669. DOI: 10.1257/mic.20170130.

Aguirre, Iñaki, Simon Cowan, and John Vickers (2010). "Monopoly Price Discrimination and Demand Curvature". In: *The American Economic Review* 100.4, pp. 1601–1615. ISSN: 0002-8282. JSTOR: 27871267.

Aldy, Joseph E. and Sarah Armitage (2022). "The Welfare Implications of Carbon Price Certainty". In: *Journal of the Association of Environmental and Resource Economists* 9.5, pp. 921–946. ISSN: 2333-5955. DOI: 10.1086/720768.

Allcott, Hunt, Reigner Kane, Maximilian S. Maydanchik, Joseph S. Shapiro, and Felix Tintelnot (2024). *The Effects of "Buy American": Electric Vehicles and the Inflation Reduction Act*. DOI: 10.3386/w33032. National Bureau of Economic Research: 33032. Pre-published.

Anderson, Soren T. and James M. Sallee (2011). "Using Loopholes to Reveal the Marginal Cost of Regulation: The Case of Fuel-Economy Standards". In: *American Economic Review* 101.4, pp. 1375–1409. ISSN: 0002-8282. DOI: 10.1257/aer.101.4.1375.

— (2016). "Designing Policies to Make Cars Greener". In: *Annual Review of Resource Economics* 8.1, pp. 157–180. DOI: 10.1146/annurev-resource-100815-095220.

Archsmith, James, Erich Muehlegger, and David S. Rapson (2022). "Future Paths of Electric Vehicle Adoption in the United States: Predictable Determinants, Obstacles, and Opportunities". In: *Environmental and Energy Policy and the Economy* 3, pp. 71–110. ISSN: 2689-7857. DOI: 10.1086/717219.

Bedsworth, Louise Wells and Margaret R. Taylor (2007). "Learning from California's Zero-Emission Vehicle Program". In: *California Economic Policy* 3.4. ISSN: 15538737.

Beresteanu, Arie and Shanjun Li (2011). "Gasoline Prices, Government Support, and the Demand for Hybrid Vehicles in the United States". In: *International Economic Review* 52.1, pp. 161–182. ISSN: 0020-6598. JSTOR: 23016626.

Berry, Steven, James Levinsohn, and Ariel Pakes (1995). "Automobile Prices in Market Equilibrium". In: *Econometrica* 63.4, pp. 841–890. DOI: 10.2307/2171802.

— (2004). "Differentiated Products Demand Systems from a Combination of Micro and Macro Data: The New Car Market". In: *Journal of Political Economy* 112.1, pp. 68–105. DOI: 10.1086/379939.

Burlig, Fiona, James B. Bushnell, David S. Rapson, and Catherine Wolfram (2021). *Low Energy: Estimating Electric Vehicle Electricity Use*. w28451. National Bureau of Economic Research. DOI: 10.3386/w28451.

Busse, Meghan, Jorge Silva-Risso, and Florian Zettelmeyer (2006). "$1,000 Cash Back: The Pass-Through of Auto Manufacturer Promotions". In: *American Economic Review* 96.4, pp. 1253–1270. ISSN: 0002-8282. DOI: 10.1257/aer.96.4.1253.

Cavallo, Alberto (2018). *More Amazon Effects: Online Competition and Pricing Behaviors*. DOI: 10.3386/w25138. National Bureau of Economic Research: 25138. Pre-published.

Chandra, Ambarish, Sumeet Gulati, and James M. Sallee (2017). "Who Loses When Prices Are Negotiated? An Analysis of the New Car Market". In: *The Journal of Industrial Economics* 65.2, pp. 235–274. ISSN: 1467-6451. DOI: 10.1111/joie.12125.

Chetty, Raj, Adam Looney, and Kory Kroft (2009). "Salience and Taxation: Theory and Evidence". In: *The American Economic Review* 99.4, pp. 1145–1177. ISSN: 0002-8282. JSTOR: 25592504.

Cole, Cassandra, Michael Droste, Christopher Knittel, Shanjun Li, and James H. Stock (2023). "Policies for Electrifying the Light-Duty Vehicle Fleet in the United States". In: *AEA Papers and Proceedings* 113, pp. 316–322. ISSN: 2574-0768. DOI: 10.1257/pandp.20231063.

Conlon, Christopher and Jeff Gortmaker (2020). "Best Practices for Differentiated Products Demand Estimation with PyBLP". In: *The RAND Journal of Economics* 51.4, pp. 1108–1161. ISSN: 1756-2171. DOI: 10.1111/1756-2171.12352.

— (2023). *Incorporating Micro Data into Differentiated Products Demand Estimation with PyBLP*. DOI: 10.3386/w31605. National Bureau of Economic Research: 31605. Pre-published.

Conlon, Christopher and Julie Holland Mortimer (2021). "Empirical Properties of Diversion Ratios". In: *The RAND Journal of Economics* 52.4, pp. 693–726. ISSN: 1756-2171. DOI: 10.1111/1756-2171.12388.

Cowan, Simon (2012). "Third-Degree Price Discrimination and Consumer Surplus". In: *The Journal of Industrial Economics* 60.2, pp. 333–345. ISSN: 0022-1821. JSTOR: 23324510.

D'Haultfœuille, Xavier, Isis Durrmeyer, and Philippe Février (2019). "Automobile Prices in Market Equilibrium with Unobserved Price Discrimination". In: *The Review of Economic Studies* 86.5, pp. 1973–1998. ISSN: 0034-6527. DOI: 10.1093/restud/rdy064.

Davis, Lucas W. (2019). "How Much Are Electric Vehicles Driven?" In: *Applied Economics Letters* 26.18, pp. 1497–1502. ISSN: 1350-4851. DOI: 10.1080/13504851.2019.1582847.

Davis, Lucas W. and Christopher R. Knittel (2018). "Are Fuel Economy Standards Regressive?" In: *Journal of the Association of Environmental and Resource Economists* 6.S1, S37–S63. ISSN: 2333-5955. DOI: 10.1086/701187.

DellaVigna, Stefano and Matthew Gentzkow (2019). "Uniform Pricing in U.S. Retail Chains". In: *The Quarterly Journal of Economics* 134.4, pp. 2011–2084. ISSN: 0033-5533. DOI: 10.1093/qje/qjz019.

Dixon, Lloyd, Isaac R. Porche III, and Jonathan Kulick (2002). *Driving Emissions to Zero: Are the Benefits of California's Zero Emission Vehicle Program Worth the Costs?* Santa Monica, CA: RAND Corporation.

Durrmeyer, Isis and Mario Samano (2018). "To Rebate or Not to Rebate: Fuel Economy Standards Versus Feebates". In: *The Economic Journal* 128.616, pp. 3076–3116. ISSN: 0013-0133. DOI: 10.1111/ecoj.12555.

Environmental Protection Agency and National Highway Traffic Safety Administration (2010). *Joint Technical Support Document: Rulemaking to Establish Light-Duty Vehicle Greenhouse Gas Emission Standards and Corporate Average Fuel Economy Standards*. EPA-420-R-10-901.

Eyer, Jonathan and Matthew E. Kahn (2017). "Can America's Blue States Tackle Climate Change on Their Own?" In: *Harvard Business Review*. ISSN: 0017-8012.

Fowlie, Meredith, Mar Reguant, and Stephen P. Ryan (2016). "Market-Based Emissions Regulation and Industry Dynamics". In: *Journal of Political Economy* 124.1, pp. 249–302. ISSN: 0022-3808. DOI: 10.1086/684484.

Goldberg, Pinelopi Koujianou (1998). "The Effects of the Corporate Average Fuel Efficiency Standards in the US". In: *The Journal of Industrial Economics* 46.1, pp. 1–33. ISSN: 0022-1821. JSTOR: 117529.

Goulder, Lawrence H., Mark R. Jacobsen, and Arthur A. van Benthem (2012). "Unintended Consequences from Nested State and Federal Regulations: The Case of the Pavley Greenhouse-Gas-per-Mile Limits". In: *Journal of Environmental Economics and Management* 63.2, pp. 187–207. ISSN: 0095-0696. DOI: 10.1016/j.jeem.2011.07.003.

Greene, David L., Sangsoo Park, and Changzheng Liu (2014). "Public Policy and the Transition to Electric Drive Vehicles in the U.S.: The Role of the Zero Emission Vehicles Mandates". In: *Energy Strategy Reviews*. US Energy Independence: Present and Emerging Issues 5, pp. 66–77. ISSN: 2211-467X. DOI: 10.1016/j.esr.2014.10.005.

Grieco, Paul L E, Charles Murry, and Ali Yurukoglu (2024). "The Evolution of Market Power in the U.S. Automobile Industry". In: *The Quarterly Journal of Economics* 139.2, pp. 1201–1253. ISSN: 0033-5533. DOI: 10.1093/qje/qjad047.

Hargaden, Enda Patrick and Barra Roantree (2020). *Does Statutory Incidence Matter? Earnings Responses to Social Security Contributions*. URL: https://www.hargaden.com/enda/StatutoryIncidence_HargadenRoantree_v15.pdf (visited on 07/28/2023). Prepublished.

Holland, Stephen P., Erin T. Mansur, Nicholas Z. Muller, and Andrew J. Yates (2016). "Are There Environmental Benefits from Driving Electric Vehicles? The Importance of Local Factors". In: *The American Economic Review* 106.12, pp. 3700–3729. ISSN: 0002-8282. JSTOR: 24911358.

— (2020). "Decompositions and Policy Consequences of an Extraordinary Decline in Air Pollution from Electricity Generation". In: *American Economic Journal: Economic Policy* 12.4, pp. 244–274. ISSN: 1945-7731. DOI: 10.1257/pol.20190390.

Holland, Stephen P., Erin T. Mansur, and Andrew J. Yates (2021). "The Electric Vehicle Transition and the Economics of Banning Gasoline Vehicles". In: *American Economic Journal: Economic Policy* 13.3, pp. 316–344. ISSN: 1945-7731. DOI: 10.1257/pol.20200120.

Holmes, Thomas J. (1989). "The Effects of Third-Degree Price Discrimination in Oligopoly". In: *The American Economic Review* 79.1, pp. 244–250. ISSN: 0002-8282. JSTOR: 1804785.

Ito, Koichiro and James M. Sallee (2018). "The Economics of Attribute-Based Regulation: Theory and Evidence from Fuel Economy Standards". In: *The Review of Economics and Statistics* 100.2, pp. 319–336. ISSN: 0034-6535. DOI: 10.1162/REST_a_00704.

Jacobsen, Mark R. (2013). "Evaluating US Fuel Economy Standards in a Model with Producer and Household Heterogeneity". In: *American Economic Journal: Economic Policy* 5.2, pp. 148–187. ISSN: 1945-7731. DOI: 10.1257/pol.5.2.148.

Jenn, Alan, Katalin Springel, and Anand R. Gopal (2018). "Effectiveness of Electric Vehicle Incentives in the United States". In: *Energy Policy* 119, pp. 349–356. ISSN: 0301-4215. DOI: 10.1016/j.enpol.2018.04.065.

Klier, Thomas and Joshua Linn (2012). "New-Vehicle Characteristics and the Cost of the Corporate Average Fuel Economy Standard". In: *The RAND Journal of Economics* 43.1, pp. 186–213. ISSN: 1756-2171. DOI: 10.1111/j.1756-2171.2012.00162.x.

Knittel, Christopher R. (2011). "Automobiles on Steroids: Product Attribute Trade-Offs and Technological Progress in the Automobile Sector". In: *American Economic Review* 101.7, pp. 3368–3399. ISSN: 0002-8282. DOI: 10.1257/aer.101.7.3368.

— (2012). "Reducing Petroleum Consumption from Transportation". In: *Journal of Economic Perspectives* 26.1, pp. 93–118. ISSN: 0895-3309. DOI: 10.1257/jep.26.1.93.

Kopczuk, Wojciech, Justin Marion, Erich Muehlegger, and Joel Slemrod (2016). "Does Tax-Collection Invariance Hold? Evasion and the Pass-Through of State Diesel Taxes". In: *American Economic Journal: Economic Policy* 8.2, pp. 251–286. ISSN: 1945-7731. JSTOR: 24739223.

Kotchen, Matthew and Giovanni Maggi (2025). *Carbon Taxes and Green Subsidies in a World Economy*. DOI: 10.3386/w34080. National Bureau of Economic Research: w34080. Pre-published.

Kwon, Hyuk-soo (2023). *Subsidies versus Tradable Credits for Electric Vehicles: The Role of Market Power in the Credit Market*. Pre-published.

Langer, Ashley and Nathan H. Miller (2013). "Automakers' Short-Run Responses to Changing Gasoline Prices". In: *The Review of Economics and Statistics* 95.4, pp. 1198–1211. ISSN: 0034-6535. JSTOR: 43554822.

Leard, Benjamin and Virginia McConnell (2017). "New Markets for Credit Trading Under U.S. Automobile Greenhouse Gas and Fuel Economy Standards". In: *Review of Environmental Economics and Policy* 11.2, pp. 207–226. ISSN: 1750-6816. DOI: 10.1093/reep/rex010.

— (2021). "Interpreting Tradable Credit Prices in Overlapping Vehicle Regulations". In: *Journal of Environmental Economics and Management* 109, p. 102510. ISSN: 0095-0696. DOI: 10.1016/j.jeem.2021.102510.

Leung, Justin H. (2021). "Minimum Wage and Real Wage Inequality: Evidence from Pass-Through to Retail Prices". In: *The Review of Economics and Statistics* 103.4, pp. 754–769. ISSN: 0034-6535. DOI: 10.1162/rest_a_00915.

Li, Jing (2023). *Compatibility and Investment in the U.S. Electric Vehicle Market*. Working paper.

Li, Shanjun, Lang Tong, Jianwei Xing, and Yiyi Zhou (2017). "The Market for Electric Vehicles: Indirect Network Effects and Policy Design". In: *Journal of the Association of Environmental and Resource Economists* 4.1, pp. 89–133. ISSN: 2333-5955. DOI: 10.1086/689702.

Linn, Joshua (2022). *Is There a Trade-Off Between Equity and Effectiveness for Electric Vehicle Subsidies?* URL: https://media.rff.org/documents/WP_22-7_January_2022.pdf. Pre-published.

— (2023). *Emissions Standards and Electric Vehicle Targets for Passenger Vehicles*. URL: https://media.rff.org/documents/WP_23-05.pdf. Pre-published.

Linn, Joshua and Virginia McConnell (2017). *The Role of State Policies under Federal Light-Duty Vehicle Greenhouse Gas Emissions Standards*. Report. Resources for the Future, p. 29.

McConnell, Virginia and Benjamin Leard (2021). “Pushing New Technology into the Market: California’s Zero Emissions Vehicle Mandate”. In: *Review of Environmental Economics and Policy* 15.1, pp. 169–179. ISSN: 1750-6816. DOI: 10.1086/713055.

McConnell, Virginia, Benjamin Leard, and Fred Kardos (2019). *California’s Evolving Zero Emission Vehicle Program: Pulling New Technology into the Market*. Working paper 19–22. Resources for the Future, p. 51.

Miravete, Eugenio (2024). *On Anticompetitive Third-Degree Price Discrimination*. URL: https://eugeniomiravete.com/PDF/Manifold_3DPD.pdf (visited on 05/01/2025). Pre-published.

Morrow, W. Ross and Steven J. Skerlos (2011). “Fixed-Point Approaches to Computing Bertrand-Nash Equilibrium Prices Under Mixed-Logit Demand”. In: *Operations Research* 59.2, pp. 328–345. ISSN: 0030-364X. JSTOR: 23013173.

Muehlegger, Erich and David S. Rapson (2022). “Subsidizing Low- and Middle-Income Adoption of Electric Vehicles: Quasi-experimental Evidence from California”. In: *Journal of Public Economics* 216, p. 104752. ISSN: 0047-2727. DOI: 10.1016/j.jpubeco.2022.104752.

Muehlegger, Erich J. and David S. Rapson (2023). “Correcting Estimates of Electric Vehicle Emissions Abatement: Implications for Climate Policy”. In: *Journal of the Association of Environmental and Resource Economists* 10.1, pp. 263–282. ISSN: 2333-5955. DOI: 10.1086/721374.

Murry, Charles and Henry S. Schneider (2016). “The Economics of Retail Markets for New and Used Cars”. In: *Handbook on the Economics of Retailing and Distribution*. DOI: 10.4337/9781783477388.00025.

Nevo, Aviv (2001). “Measuring Market Power in the Ready-to-Eat Cereal Industry”. In: *Econometrica* 69.2, pp. 307–342. DOI: 10.1111/1468-0262.00194. JSTOR: 2692234.

Petrin, Amil, Mark Ponder, and Boyoung Seo (2022). *Identification and Estimation of Discrete Choice Demand Models When Observed and Unobserved Characteristics Are Correlated*. DOI: 10.3386/w30778. National Bureau of Economic Research: 30778. Pre-published.

Pigou, A.C. (1920). *The Economics of Welfare*. The Economics of Welfare v. 1. Macmillan and Company, Limited.

Rapson, David S. and Erich Muehlegger (2023). “The Economics of Electric Vehicles”. In: *Review of Environmental Economics and Policy* 17.2, pp. 274–294. ISSN: 1750-6816. DOI: 10.1086/725484.

Remmy, Kevin (2025). *Adjustable Product Attributes, Indirect Network Effects, and Subsidy Design: The Case of Electric Vehicles*. URL: https://kevinremmy.com/pdf/evs_final.pdf. Pre-published.

Rennert, Kevin et al. (2022). “Comprehensive Evidence Implies a Higher Social Cost of CO2”. In: *Nature* 610.7933 (7933), pp. 687–692. ISSN: 1476-4687. DOI: 10.1038/s41586-022-05224-9.

Reynaert, Mathias (2021). “Abatement Strategies and the Cost of Environmental Regulation: Emission Standards on the European Car Market”. In: *The Review of Economic Studies* 88.1, pp. 454–488. ISSN: 0034-6527. DOI: 10.1093/restud/rdaa058.

Sagl, Stephan (2024). *Dispersion, Discrimination, and the Price of Your Pickup*. URL: https://ssagl.github.io/papers/jmp_sagl.pdf. Pre-published.

Sallee, James M. (2011). "The Surprising Incidence of Tax Credits for the Toyota Prius". In: *American Economic Journal: Economic Policy* 3.2, pp. 189–219. ISSN: 1945-7731. JSTOR: 41238098.

Schmalensee, Richard (1981). "Output and Welfare Implications of Monopolistic Third-Degree Price Discrimination". In: *The American Economic Review* 71.1, pp. 242–247. ISSN: 0002-8282. JSTOR: 1805058.

Springel, Katalin (2021). "Network Externality and Subsidy Structure in Two-Sided Markets: Evidence from Electric Vehicle Incentives". In: *American Economic Journal: Economic Policy* 13.4, pp. 393–432. ISSN: 1945-7731. DOI: 10.1257/pol.20190131.

Tal, Gil and Michael Nicholas (2016). "Exploring the Impact of the Federal Tax Credit on the Plug-In Vehicle Market". In: *Transportation Research Record* 2572.1, pp. 95–102. ISSN: 0361-1981. DOI: 10.3141/2572-11.

Varian, Hal R. (1985). "Price Discrimination and Social Welfare". In: *The American Economic Review* 75.4, pp. 870–875. ISSN: 0002-8282. JSTOR: 1821366.

— (1989). "Chapter 10 Price Discrimination". In: *Handbook of Industrial Organization*. Vol. 1. Elsevier, pp. 597–654. DOI: 10.1016/S1573-448X(89)01013-7.

Vergis, Sydney and Vishal Mehta (2012). "Technology Innovation and Policy: A Case Study of the California ZEV Mandate". In: *Paving the Road to Sustainable Transport*. Routledge, pp. 157–179. ISBN: 978-0-415-68360-9.

Whitefoot, Kate S., Meredith Fowlie, and Steven J. Skerlos (2017). "Compliance by Design: Influence of Acceleration Trade-offs on CO2 Emissions and Costs of Fuel Economy and Greenhouse Gas Regulations". In: *Environmental Science & Technology* 51.18, pp. 10307–10315. ISSN: 0013-936X. DOI: 10.1021/acs.est.7b03743.

Williams, Roberton C. (2012). "Growing State–Federal Conflicts in Environmental Policy: The Role of Market-Based Regulation". In: *Journal of Public Economics*. Fiscal Federalism 96.11, pp. 1092–1099. ISSN: 0047-2727. DOI: 10.1016/j.jpubeco.2011.08.003.

Wollmann, Thomas G. (2018). "Trucks without Bailouts: Equilibrium Product Characteristics for Commercial Vehicles". In: *American Economic Review* 108.6, pp. 1364–1406. ISSN: 0002-8282. DOI: 10.1257/aer.20160863.

Xing, Jianwei, Benjamin Leard, and Shanjun Li (2021). "What Does an Electric Vehicle Replace?" In: *Journal of Environmental Economics and Management* 107, p. 102432. ISSN: 0095-0696. DOI: 10.1016/j.jeem.2021.102432.

Zettelmeyer, Florian, Fiona Scott Morton, and Jorge Silva-Risso (2006). *Scarcity Rents in Car Retailing: Evidence from Inventory Fluctuations at Dealerships*. DOI: 10.3386/w12177. National Bureau of Economic Research: w12177. Pre-published.

Zhou, Yiyi and Shanjun Li (2018). "Technology Adoption and Critical Mass: The Case of the U.S. Electric Vehicle Market". In: *The Journal of Industrial Economics* 66.2, pp. 423–480. ISSN: 1467-6451. DOI: 10.1111/joie.12176.

Ziegler, Micah S. and Jessika E. Trancik (2021). "Re-Examining Rates of Lithium-Ion Battery Technology Improvement and Cost Decline". In: *Energy & Environmental Science* 14.4, pp. 1635–1651. ISSN: 1754-5706. DOI: 10.1039/D0EE02681F.

A Appendix: Further institutional details

A.1 Electric vehicle market

The major passenger vehicles available in this period fell into one of four technology types:

1. Battery electric vehicles (BEVs), which have no internal combustion engine and rely solely on an electric motor and battery. (In this paper, we use "electric vehicle" and "battery electric vehicle" interchangeably.)

2. Plug-in hybrids (PHEVs), which have an internal combustion engine and a battery that can be charged externally.

3. Hybrids (HEVs), which have an internal combustion engine and a battery that cannot be charged externally.

4. Conventional gasoline-powered vehicles with internal combustion engines (ICEs), including flex-fuel ethanol.

Less commonly used technologies for passenger vehicles in this period include diesel, natural gas, and hydrogen fuel cells. Although hydrogen fuel cell vehicles were treated by the regulation as zero-emission vehicles, with generous credit allowances, few were sold during the study period.

A.1.1 Electric vehicle sales

We chart the growth in EV sales over our study period in Figure A.1. Sales grew at a steady pace between calendar years 2013 and 2017, both in ZEV states and in non-ZEV states. This steady pace contrasts with rapid year-on-year growth from 2012 to 2013 and from 2017 to 2018. In addition, EVs made up a notably higher share of the new vehicle market in California, as opposed to the other states.

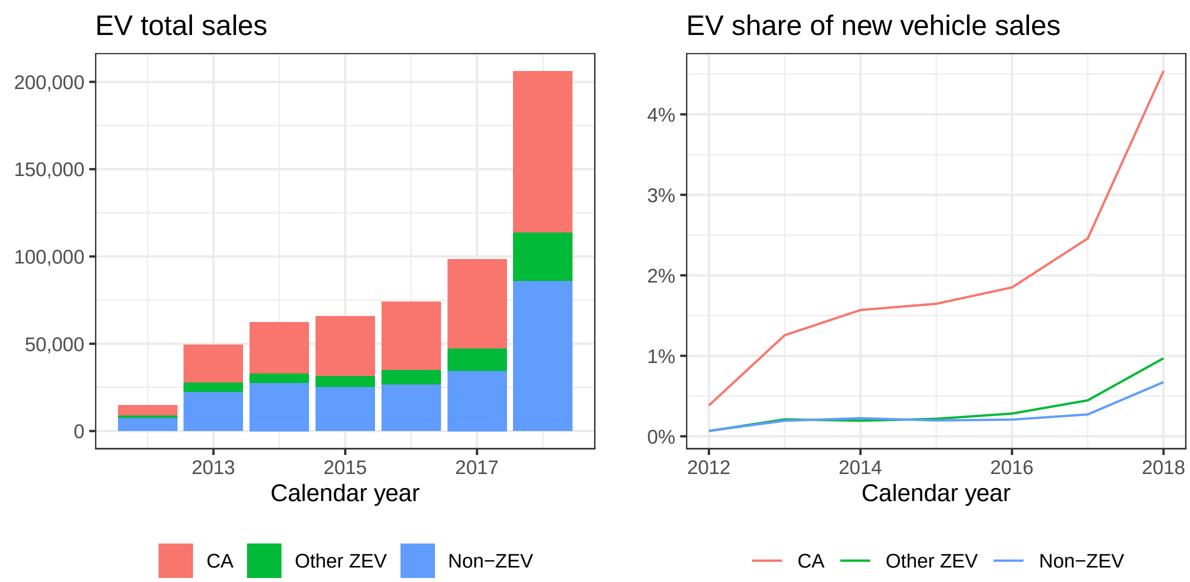

Figure A.1: EV sales by year and region

Note: This figure shows sales and leases of EVs in levels (left) and as a share of overall new passenger vehicle sales and leases (right). Data are shown separately for California, the other ZEV states, and non-ZEV states. Generated using S&P Global data on new vehicle registrations.

A.1.2 Electric vehicle characteristics

Table A.1 extends Table 1 with additional characteristics of the electric vehicles sold in this period.

Industry observers classified early electric vehicle models into two groups: models that were designed from the ground up to be electric vehicles ("native") and models that used existing platforms from gas-powered vehicles ("non-native").

A native electric vehicle has dedicated space for the battery pack, allowing for greater battery capacity and a more spacious interior than a vehicle that must fit a battery pack in a space designed for an internal combustion engine. [55]

Non-native electric vehicles had a lower upfront cost to manufacture and offered the flexibility of making gas-powered and electric vehicles on the same production line.[56] Non-

[55] See "What a teardown of the latest electric vehicles reveals about the future of mass-market EVs" (Antoine Chatelain, Mauro Erriquez, Pierre-Yves Moulière, and Philip Schäfer, McKinsey, 3/21/18).

[56] See "The Battery-Driven Car Just Got a Lot More Normal" (Bradley Berman, The New York Times, 5/4/12).

Table A.1: Battery electric vehicles: additional characteristics

Model	Native?	Non-ZEV State %	Battery	Elec. use	Fed. Subsidy
Tesla Model S	Yes	44%	40–100	0.32–0.38	$7,500
Nissan LEAF	Yes	57%	24–30	0.29–0.34	$7,500
Tesla Model X	Yes	44%	60–100	0.36–0.39	$7,500
Chevrolet Bolt EV	Yes	27%	60	0.28	$7,500
Fiat 500e		0%	24	0.29–0.30	$7,500
Volkswagen e-Golf		2%	24.2–35.8	0.28–0.29	$7,500
Ford Focus		30%	23	0.31–0.32	$7,500
BMW i3	Yes*	36%	21.6–33.2	0.27–0.29	$7,500
Chevrolet Spark		1%	19–21	0.28	$7,500
smart fortwo		15%	17.6	0.31–0.33	$7,500
Kia Soul		26%	27	0.32	$7,500
Mercedes-Benz B-Class		6%	28	0.40	$7,500
Tesla Model 3	Yes	8%	75	0.27	$7,500
Toyota RAV4		3%	24	0.44	$7,500
Mitsubishi i-MiEV		69%	16	0.30	$7,500
Honda Clarity	Yes*	0%	25.5	0.30	$0
Honda Fit		1%	20	0.29	$0
Hyundai Ioniq	Yes*	2%	28	0.25	$7,500

Note: Includes battery electric vehicles sold in the US in model years 2012–17. Compiled from data from MSN Autos, FuelEconomy.gov, online sources, and IHS. Columns are: model name; whether the model is a native EV according to press reports (Yes* indicates platform shared with a hybrid/plug-in hybrid); share of sales outside ZEV states (2012–17); battery capacity (in kilowatt-hours); EPA electricity consumption (in kilowatt-hours per mile); and federal subsidy amount (nominal dollars). The federal subsidy applied to sales, not leases; the Honda Fit EV and Honda Clarity EV were only available for lease.

native models also adopted the branding and design of the gas-powered vehicles on which they were based.

As shown in the table, non-native EVs generally had smaller batteries than native EVs. In addition, non-native EVs were mostly sold in states with the ZEV mandate. Industry observers, suspecting that these models were only manufactured to meet the mandate, dubbed them compliance cars.

A.2 Details of the ZEV mandate

The California Air Resources Board (CARB) first introduced a ZEV mandate in 1990, but it mainly applied to demonstration projects and commercial fleets until zero-emission vehicles became available to consumers around 2010.[57] We focus on the phase of the regulation that existed from model year 2009 to 2017, which featured stable rules and a quota that increased predictably from year to year.[58]

Manufacturers earned ZEV credits for sales of zero-emission vehicles, and large manufacturers used credits to meet a yearly quota.[59] Each large manufacturer's quota was based on its sales of non-electric vehicles, so that larger manufacturers of non-electric vehicles faced a larger requirement (Figure A.4). The number of credits earned for selling a battery electric vehicle depended on the vehicle's range on a full battery charge. Manufacturers could trade credits with each other and bank credits for later use.

If an automaker missed its quota in any given year, it had two years to make up the deficit. After that point, in order to return to compliance, it was required to pay a penalty of $5,000 per credit and also make up the deficit.[60] Figure A.2 shows total credit balances by year.

[57] The exception was the short-lived GM EV1, produced in the late 1990s.

[58] The ZEV mandate is codified in Title 13 of the California Code of Regulations: the pre-2009 phase in §1962, the 2009–17 phase in §1962.1, and the 2018–25 phase in §1962.2.

[59] "Large" was defined using a moving average of vehicle sales in California. During this period, the large manufacturers were Chrysler, Ford, GM, Honda, Nissan, and Toyota.

[60] Between 2009 and 2017, no manufacturer was noncompliant. One manufacturer had a deficit that it made up the following year.

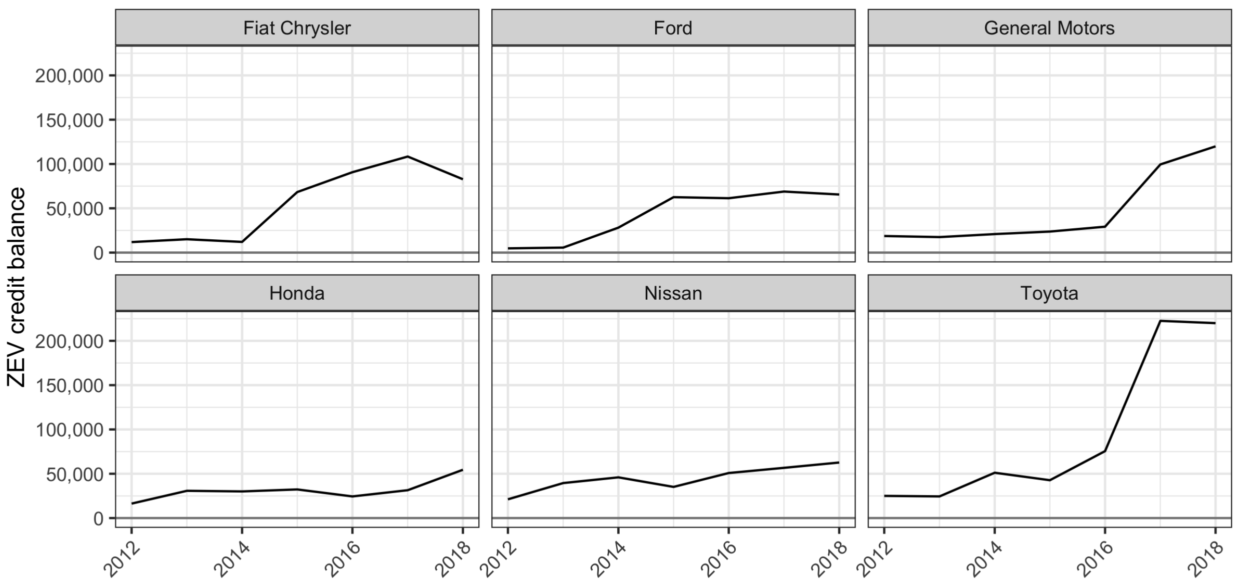

Figure A.2: ZEV credit balances for large manufacturers over time

Note: The figure illustrates ZEV credit balances at the end of each model year, 2012—2018, for the six large-volume manufacturers (California credits only). Trades in other states, which can affect California balances through the travel provision, are ignored. A typical electric vehicle earned two credits while a long-range electric vehicle (such as a Tesla) earned four. Data come from California Air Resources Board disclosures.

Amendments to make the program stricter were announced in 2012 and took effect in model year 2018 as part of California's Advanced Clean Cars package. The most important changes were to reduce the number of credits earned per vehicle, to add to the list of manufacturers who faced the ZEV quota,[61] and to replace the travel provision with a cross-state transfer mechanism that did not allow double-counting. In addition, the PZEV mandate was tightened to include only plug-in hybrids. Manufacturers anticipating stricter post-2018 regulation may have earned surplus credits before 2018 in order to bank them.

A.2.1 Credit earning

The number of credits earned per vehicle was a function of its range. (The regulation used the Urban Dynamometer Driving Schedule range, which is about 40% higher than the EPA range.) As shown in Table A.2, most electric vehicles earned between two and four credits and did not qualify for fast refueling (outside of a brief period in which Tesla vehicles qualified).[62]

Table A.2: ZEV credits, model years 2009–2017

	Criteria			
Tier	UDDS Range (mi)	Fast Refueling	Credits	Sample Model
Type I	$[50, 75)$	–	2	–
Type I.5	$[75, 100)$	–	2.5	Mitsubishi i-MiEV
Type II	≥ 100	–	3	Nissan Leaf
Type III	≥ 200	–	4	Chevrolet Bolt
Type III	≥ 100	Yes	4	Tesla Model S (40 kWh)*
Type IV	> 200	Yes	5	Tesla Model S (60 kWh)*
Type V	≥ 300	Yes	7 or 9	Tesla Model S (85 kWh)*

Note: Source: 13 CCR §1962.1(d)(5)(A). Type V vehicles earned 7 credits until July 2015, and 9 credits afterward. *The Tesla Model S only qualified for fast refueling credits in model years 2012 and 2013 on the basis of an experimental battery swap program. After rule changes in 2013, only hydrogen fuel cell cars qualified for fast refueling.

Credits could also be earned without selling zero-emission vehicles to consumers: for

[61] This change added BMW, Daimler, Hyundai, Kia, and Volkswagen, by reducing the sales threshold at which the quota would apply.

[62] See "Tesla profits could be challenged by Calif. credit-rule change" (Mark Rechtin, Automotive News, 8/5/13).

example, by placing zero-emission vehicles in commercial fleets or demonstration projects.

Figure A.3 shows the total number of ZEV credits earned annually by manufacturer.

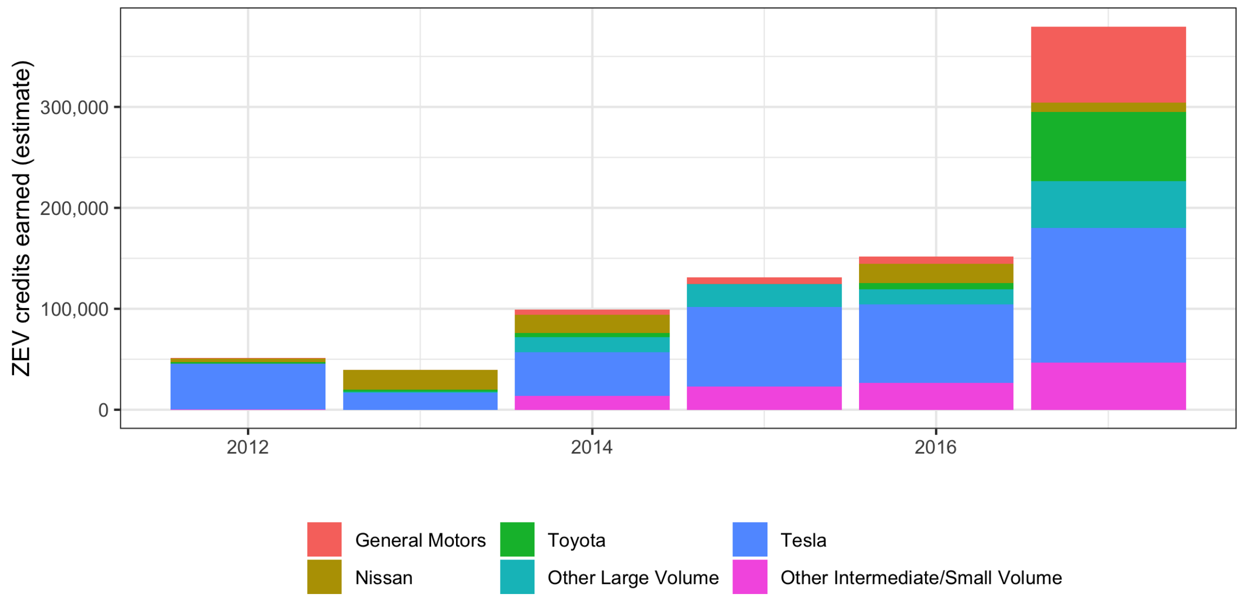

Figure A.3: ZEV credit earning by manufacturer (2012–2017)

Note: This figure shows an estimate of to ZEV credits earned through the sale of ZEV vehicles by manufacturer and model year (California credits only). Note that Tesla, Subaru, Kia, Hyundai, and some other manufacturers earned ZEV credits even though they were not subject to the mandate during this period. A typical electric vehicle earned two credits while a long-range electric vehicle (such as a Tesla) earned four. To calculate credit earning, we start with the year-to-year balance change (from yearly California Air Resources Board disclosures), remove credit trades, and remove our estimate of the minimum ZEV requirement. We may not capture ZEV credits used to meet PZEV requirements in the same year they were earned.

A.2.2 Credit requirement

The credit requirement in each year was formulated as a fixed percentage of the manufacturer's statewide production volume of non-zero-emission passenger cars and light-duty trucks.[63] The manufacturer chose in each year whether its production volume was its same-year sales or a function of past sales. In model years 2009 through 2011, the past-sales function was the average of sales in model years 2003–2005; in model years 2012 through

[63]Before 2009 only light-duty trucks under 3750 pounds loaded weight were counted; between model years 2009 and 2012 this cutoff was gradually raised to 8500 pounds.

2017, the past-sales function in year t was the average of sales in model years $t-6$ through $t-4$ (13 CCR §1962.1(b)(1)(B)).

The credit requirement percentage for applicable manufacturers is shown in Table A.3. The translation of the percentage into credit units is shown in Figure A.4

Table A.3: Large Volume Manufacturer requirements by model year, 2009–2017

Model Years	Minimum ZEV
2009–2011	2.475%
2012–2014	0.790%
2015–2017	3.000%

Note: Source: 13 CCR §1962.1(b)(2). In model years 2009–2011, large manufacturers could opt for a lower ZEV requirement of 0.205% if they did not use traded credits to meet it. Although the credit requirement is written as a percentage, it is the number of ZEV credits that must be surrendered each model year for each unit of production volume.

A.2.3 Credit trading

Most large manufacturers actively purchased ZEV credits during the study period, except Nissan. The ZEV credit trading market had one large seller in this period (Tesla, with 83% of sales) and a handful of buyers, including Toyota (37%), Ford (20%) and Fiat Chrysler (14%). However, Tesla was far from the only supplier: Nissan also sold credits, and Fiat Chrysler sold credits in some years and purchased them in others.

Figures A.5 and A.6 show the number of credits purchased and sold each year.

A.2.4 Cross-state interaction: travel provision

The travel provision allowed manufacturers to count credits from certain vehicles sold in one ZEV state toward requirements in all ZEV states. This option did not have to be exercised in the same model year the car was delivered; a credit could be banked or traded and then traveled later.

In model years 2010–2017, credits for ZEVs traveled proportionally. Suppose an eligible vehicle by manufacturer m, which earned x credits, was placed into service in a ZEV state

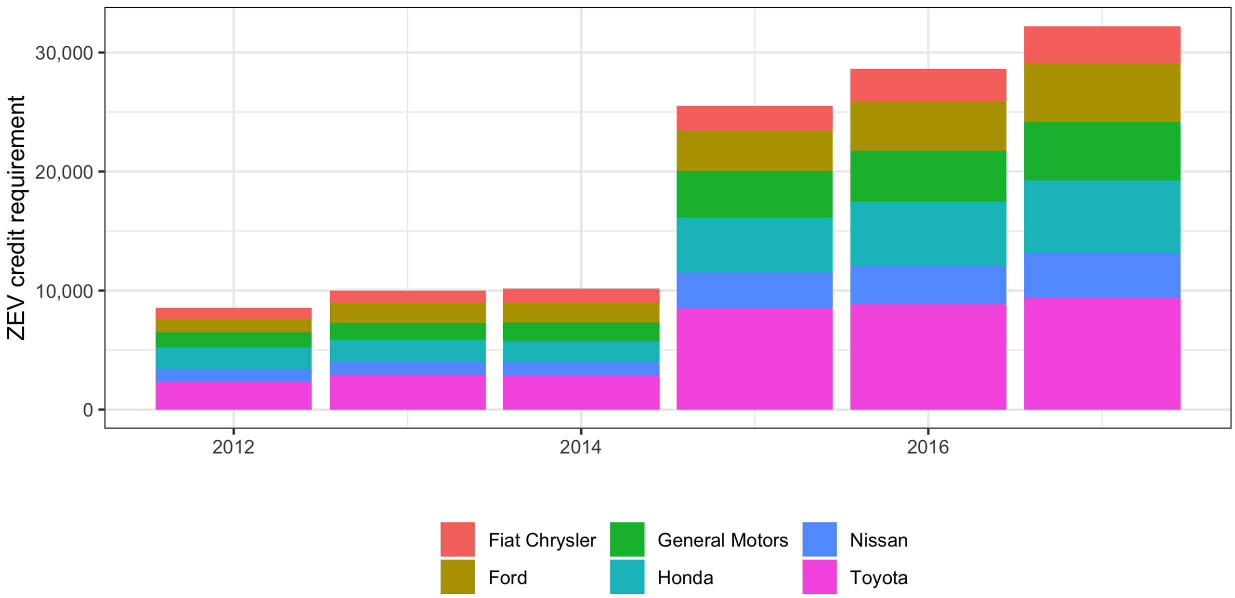

Figure A.4: ZEV credit requirements by manufacturer (2012–2017)

Note: This figure shows California ZEV credit requirements for each of the large manufacturers by model year, 2012–2017. Only ZEV requirements are included, not PZEV requirements that could be met using ZEV credits. The "large manufacturers" group consists of the six manufacturers that were subject to the ZEV mandate for the entire period (Chrysler/Fiat Chrysler, Ford, GM, Honda, Nissan, and Toyota). A typical electric vehicle earned two credits while a long-range electric vehicle (such as a Tesla) earned four. We estimate requirements by applying the credit requirements in Table A.3 to the California production volumes provided in 2009–2017 California Air Resources Board disclosures. Due to data availability, we use the same-year method to calculate 2012–14 production volumes and the past-sales method to calculate 2015–17 production volumes.

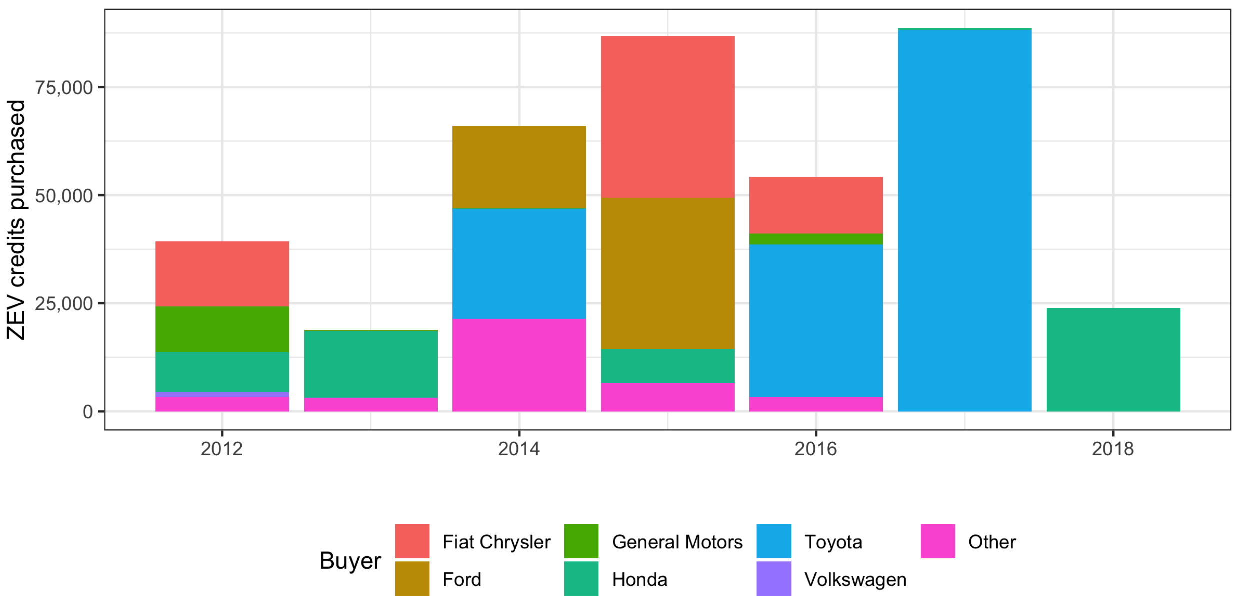

Figure A.5: ZEV credit purchases over time

Note: This figure shows ZEV credit purchases by manufacturer and model year from 2012–2018 (California credits only). The group labeled "Other" combines the three manufacturers that were classified as intermediate-volume throughout the period (and thus not subject to the ZEV mandate): Subaru, Jaguar Land Rover, and Mazda. A typical electric vehicle earned two credits while a long-range electric vehicle (such as a Tesla) earned four. Data come from California Air Resources Board disclosures.

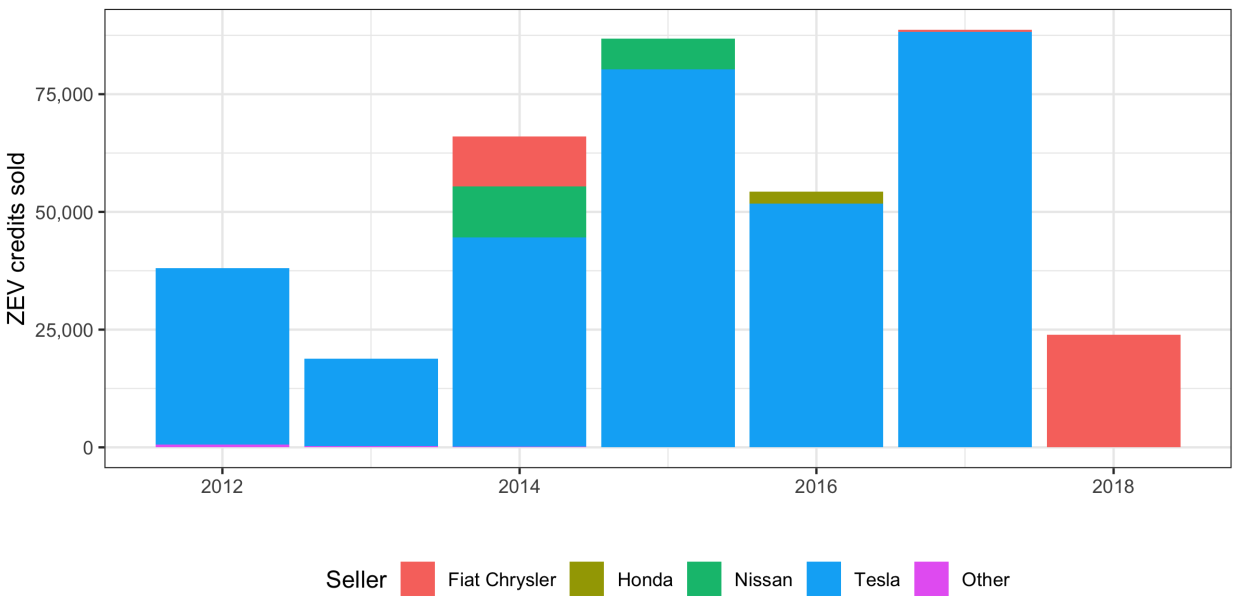

Figure A.6: ZEV credit sales over time

Note: This figure shows ZEV credit sales by manufacturer and model year from 2012–2018 (California credits only). The group labeled "Other" combines five manufacturers not subject to the mandate: four small EV-only manufacturers and Mitsubishi. A typical electric vehicle earned two credits while a long-range electric vehicle (such as a Tesla) earned four. Data come from California Air Resources Board disclosures.

in model year t. Then, if the manufacturer chose to travel the credit, it translated into the following in each state s (including the state where it was originally placed into service):

$$x \cdot \frac{\text{Sales Volume}_{m,t,s}}{\text{Sales Volume}_{m,t,\text{CA}}},$$

where Sales Volume is the same-year sales of non-zero-emission cars and light-duty trucks in the state.

A.2.5 Regulation goals

Throughout the 2000s and 2010s, CARB described its goal as commercial-scale volumes of zero-emissions vehicles, rather than a specific emissions target. In 2003, CARB stated:[64]

> The specified volumes are based on the principle that early production for new types of vehicles proceeds in stages in which volumes typically grow from tens to hundreds and then to thousands. This growth pattern has been affirmed in staff discussions with automobile and fuel cell manufacturers. The numbers are also generally consistent with the U.S. Department of Energy targets when those targets are scaled to California rather than national coverage. In its discussion of possible approaches, the Board noted that these target volumes present a realistic goal. The resulting production totals will require manufacturers to mount a substantial research and development program, which is the key factor needed for successful commercialization.

By 2009, automakers had developed hybrid ("AT PZEV") and low-emissions ("PZEV") vehicles but battery electric vehicles remained in the demonstration stage. CARB wrote in 2009 that its goal was the commercialization of a wide array of new technologies:[65]

[64]CARB, January 2004. "Final Statement of Reasons for Rulemaking, Including Summary of Comments and Agency Responses." `https://ww3.arb.ca.gov/regact/zev2003/fsor.pdf`, p. 20.

[65]CARB, November 2009. "White Paper: Summary of Staff's Preliminary Assessment of the Need for Revisions to the Zero Emission Vehicle Regulation." `https://web.archive.org/web/20190605062308/https://www.arb.ca.gov/msprog/zevprog/2009zevreview/zevwhitepaper.pdf`, p. 6.

> What remains in the ZEV regulation are pre-commercial technologies, many of which have the potential to achieve very low GHG emissions, and thus contribute to meeting the Governor's 2050 GHG reduction target. The goal of the revised ZEV program should be to help move these demonstration, low GHG emitting technologies to commercialization, include FCVs, BEVs, and Enhanced AT PZEVs, which currently include plug-in HEVs (PHEV) and hydrogen internal combustion engine (HICE) vehicles. Following the successful mechanisms used to facilitate commercialization of PZEVs and AT PZEVs, the regulation would move ZEVs and Enhanced AT PZEVs from demonstration volumes, meaning hundreds (100s) and thousands (1,000s) per year, through pre-commercial volumes, meaning tens of thousands (10,000s) per year, to commercialization, meaning hundreds of thousands (100,000s) per year. Once this is achieved, the ZEV regulation would no longer be needed, and like the PZEV and AT PZEV technologies, they could be considered in setting future LEV performance-based emission standards.

By 2017, after battery electric vehicle sales had grown substantially, CARB viewed the policy as necessary to ensure the continued steady growth of electric vehicle volumes. In 2017, CARB wrote:[66]

> The current market has benefited from multiple purchase incentives that have substantially discounted ZEVs and PHEVs such that their prices are more aligned with those of conventional vehicles. But, between 2018 and 2025, these and other incentives are expected to phase out. While decreased reliance on incentives is essential for building a self-sustaining market, it is unclear what consumer response will be without purchase and other incentives (like high occupancy vehicle (HOV) lane access). Consumer awareness of ZEVs is still low and top motivations like saving money on fuel are less influential as gasoline prices remain low. Given the

[66] CARB, 2017. "Summary Report for the Technical Analysis of the Light Duty Vehicles Standards." `https://ww2.arb.ca.gov/sites/default/files/2020-01/ACCMTRSummary_Ac.pdf`, p. ES-7.

market uncertainties that still exist in these early years, regulatory stability of the 2018 through 2025 model year standards can help ensure a continued path of increasing, but achievable, ZEV volumes.

A.3 Federal greenhouse gas regulation

The EPA GHG regulation was deployed starting in model year 2012, with an optional phase-in period from 2009–2011, and was developed in coordination with an overhaul to federal CAFE standards to allow credit trading among firms.[67] A manufacturer earned or lost credits for each vehicle sold according to the difference between the vehicle's greenhouse gas emissions and a target based on the vehicle's footprint.[68] A manufacturer aggregated these credit gains and losses, denominated in units of megagrams of CO_2, across its entire fleet. Credit balances could temporarily run negative (that is, firms could borrow from the future). Firms could buy and sell credits freely in bilateral transactions, but a firm could not sell more credits than it had available in its balance.

Specifically, a product j in model year t had an associated target target_{jt}, calculated as a function of vehicle footprint, and an emissions rating emissions_{jt}, calculated as a function of fuel economy. (Electric vehicles were assigned emissions of zero.) Denoting its sales as sales_{jt}, the manufacturer's credit earning or loss in year t was therefore

$$\sum_j (\text{emissions}_{jt} - \text{target}_{jt}) \cdot \text{sales}_{jt}.$$

The allowance for larger footprints makes the GHG regulation an example of attribute-based regulation, as discussed in Anderson and Sallee (2016). A supplementary process allowed manufacturers to earn credits for other reductions in greenhouse gas emissions not reflected in fuel economy, particularly improvements to air conditioning.

[67] The EPA GHG and post-2012 CAFE regulations are described in detail in Leard and McConnell (2017). The two policies are tightly linked because tailpipe greenhouse gas emissions are proportional to gasoline consumption.

[68] Footprint, defined as wheelbase times track width, is a measure of vehicle size.

Compared to the ZEV mandate, the GHG regulation applied to a larger set of manufacturers, targeted a metric that was closer to the CAFE standards that had existed for decades, and featured more limits on credit banking. All manufacturers with over 5000 vehicles sold in the US faced the regulation, though some manufacturers that sold up to 400,000 vehicles received additional allowances. Credits generally expired five years after being earned, although a one-time exception allowed credits earned in 2010–2015 to be valid until 2021.

Tesla was a major seller of GHG credits, but not as dominant as it was in the ZEV credit market. According to Tesla financial statements, it sold GHG credits on long-term contracts, rather than in ad-hoc transactions. In most years, all its sales were to one automaker, Fiat Chrysler; in 2019, it also sold credits to GM.

A.4 State subsidies to consumers

Figure A.7 summarizes the number of state-level subsidy programs associated with each model year for BEVs and PHEVs, respectively.

Figure A.8 presents the median and inter-quartile range of subsidies available for three different 2017 models to illustrate both inter- and intra-model heterogeneity in subsidy amounts.

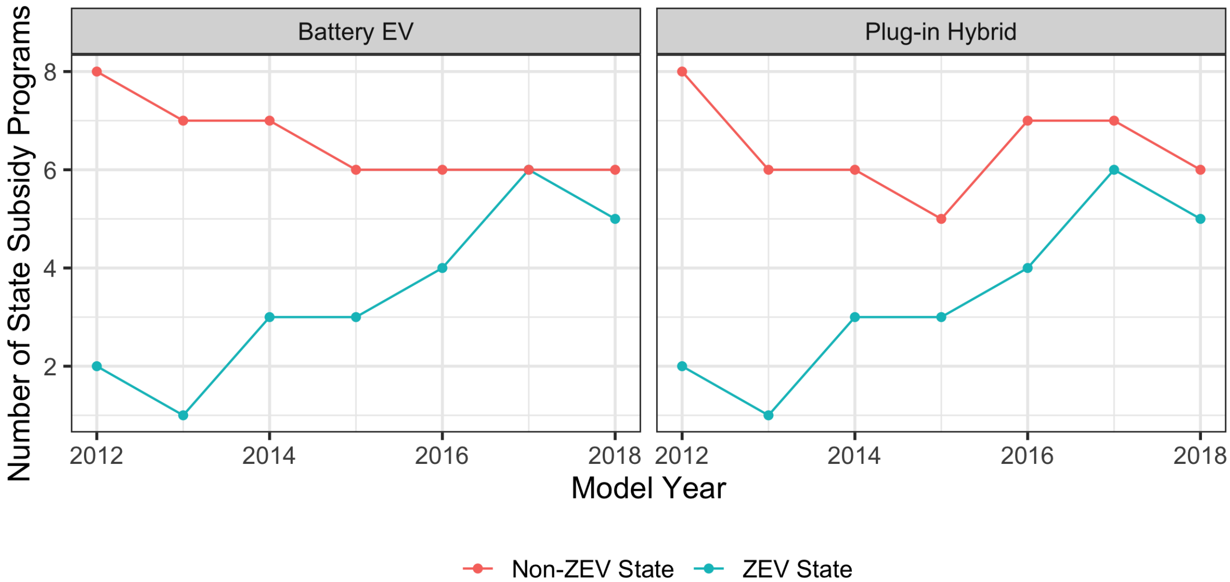

Figure A.7: Number of Active Subsidy Programs by Vehicle Type and State ZEV Status

Note: During the study period, there were nine ZEV states and 41 non-ZEV states, so a much higher proportion of ZEV states had active subsidy programs. Subsidy programs are associated with vehicle model years following the procedure described in the text. We include point-of-sale rebates and income tax credits but not sales or excise tax credits.

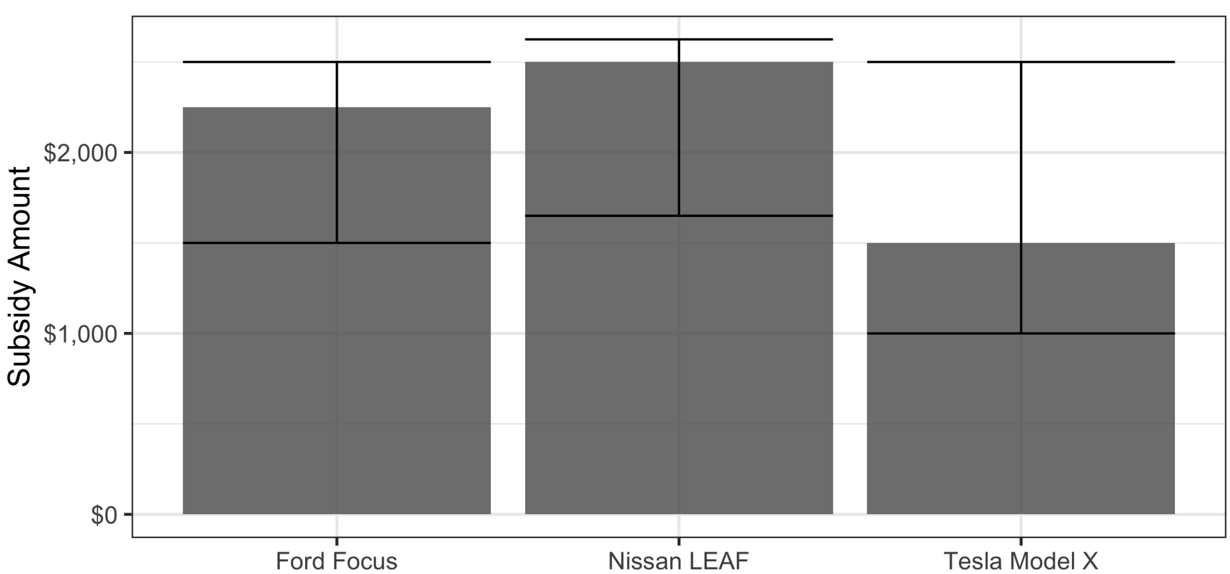

Figure A.8: Median and Inter-Quartile Range of State Subsidy Amounts Available by Model (2017 Model Year)

Note: When subsidy amounts depended on the specific trim, we considered subsidies available for the base trim. Subsidy amounts reflect those available to middle-income households, as defined by state rules.

B Appendix: Theory

B.1 Concavity of profit function

In our theoretical analysis, we rely on an assumption of strict concavity of each regional profit function, following Schmalensee (1981) and Aguirre, Cowan, and Vickers (2010). Note that it is sufficient to assume that the profit function without policy is concave: adding sub in the ZEV market shifts constant marginal costs, and replacing p with $p - t$ acts as a horizontal shift of the profit function, so concavity is maintained with our policy set-up.

As noted in the main text, concavity of the demand function is sufficient to guarantee concavity of the profit function, but if demand is convex, we require that it is not too convex. In particular, we require $q''_N(p) < \frac{-2q'_N(p)}{p-mc}$ in region N and $q''_Z(p-t) < \frac{-2q'_Z(p-t)}{p+sub-t-mc}$ in region Z. Aguirre, Cowan, and Vickers (2010) describes conditions under which the concavity assumption would hold for constant-elasticity, exponential, and other demand functions with constant positive curvature.

Finally, note that concavity of the profit function guarantees that there is an unique solution to the firm's optimization problem in the main text, given by the solution to the first-order condition, both with and without policy.

B.2 Impact of consumer subsidy on total quantity

We adapt the derivation in Schmalensee (1981) and Aguirre, Cowan, and Vickers (2010) for the impact of monopolist price discrimination on total output to our setting of regional subsidy variation. A monopolist's total profits, across regulated market Z and non-regulated market N:

$$\pi = \pi_Z + \pi_N = (p + sub - t - mc) \cdot q_Z(p - t) + (p - mc) \cdot q_N(p) \tag{15}$$

The firm's first-order-condition (FOC) gives:

$$\begin{aligned}\frac{\partial\pi}{\partial p} &= \frac{\partial\pi_Z}{\partial p} + \frac{\partial\pi_N}{\partial p} = 0 \\ &= q_Z(p-t) + (p+sub-t-mc)\cdot q_Z'(p-t) + q_N(p) + (p-mc)\cdot q_N'(p) = 0\end{aligned} \tag{16}$$

Applying the implicit function theorem, totally differentiate the FOC with respect to t to solve for the comparative static $\frac{dp}{dt}$:

$$\begin{aligned}2q_Z'(p(t)-t)\cdot(p'(t)-1) + (p(t)+sub-t-mc)\cdot q_Z''(p(t)-t)\cdot(p'(t)-1) \\ + 2q_N'(p(t))\cdot p'(t) + (p(t)-mc)\cdot q_N''(p(t))p'(t) = 0\end{aligned} \tag{17}$$

Substituting $\pi_Z'' = 2q_Z'(p-t)+(p+sub-t-mc)\cdot q_Z''(p-t)$ and $\pi_N'' = 2q_N(p)+(p-mc)\cdot(q_N''(p))$ into equation 17, we have:

$$\begin{aligned}&\pi_Z''\cdot(p'(t)-1) + \pi_N''\cdot p'(t) = 0 \\ &\Rightarrow p'(t) = \frac{\pi_Z''}{\pi_Z''+\pi_N''}\end{aligned} \tag{18}$$

Given our assumption that $\pi_Z'' < 0$ and $\pi_N'' < 0$, we have $\frac{dp}{dt} \in (0,1)$.

Next, total quantity is given by:

$$Q = q_Z + q_N, \text{ or } Q(t) = q_Z(p-t) + q_N(p) \tag{19}$$

Totally differentiate Q with respect to t:

$$\frac{dQ}{dt} = q_Z'(p-t)(\frac{dp}{dt}-1) + q_N'(p)\frac{dp}{dt} \tag{20}$$

From substituting equation 18 into equation 20, then substituting for π_Z'' and π_N'' and simplifying, we have:

$$
\begin{aligned}
\frac{dQ}{dt} &= q_Z'(p-t)\Big(\frac{-\pi_N''}{\pi_N''+\pi_Z''}\Big) + q_N'(p)\Big(\frac{\pi_Z''}{\pi_N''+\pi_Z''}\Big) \\
&= \Big(\frac{1}{\pi_Z''+\pi_N''}\Big)\Big(q_N(p)'\Big[2q_Z'(p-t) + (p+sub-t-mc)q_Z''(p-t)\Big] \\
&- q_Z'(p-t)\Big[2q_N'(p) + (p-mc)q_N''(p)\Big]\Big) \\
&= \Big(\frac{-q_N'(p)q_Z'(p-t)}{\pi_Z''+\pi_N''}\Big)\Big(\frac{(p-mc)q_N''(p)}{q_N'(p)} - \frac{(p+sub-t-mc)q_Z''(p-t)}{q_Z'(p-t)}\Big)
\end{aligned}
\tag{21}
$$

This expression matches equation 3 in the main text. Given concavity of the profit function and downward sloping demand, the first term in parentheses is positive. Therefore, the sign of $\frac{dQ}{dt}$ depends on the sign of the second term in parentheses, as discussed in the main text.

B.3 Impact of consumer subsidy on share purchased in regulated region

The region Z share is given by:

$$
s_Z = \frac{q_Z(p-t)}{q_Z(p-t)+q_N(p)}
$$

Totally differentiate with respect to t:

$$
\begin{aligned}
\frac{ds_Z}{dt} &= \frac{q_Z'(p-t)(p'(t)-1)[q_Z(p-t)+q_N(p)] - [q_Z'(p-t)(p'(t)-1) + q_N'(p)p'(t)]q_Z(p-t)}{(q_Z(p-t)+q_N(p))^2} \\
&= \frac{q_Z'(p-t)(p'(t)-1)q_N(p) - q_N'(p)p'(t)q_Z(p-t)}{(q_Z(p-t)+q_N(p))^2}
\end{aligned}
$$

The numerator determines the sign of this expression. Given concavity of the profit function, we have $\frac{dp}{dt} \in (0,1)$ (see previous section). Therefore, the first part of the numerator is positive and the second part of the numerator (which is subtracted from the first) is negative; the overall expression is positive.

B.4 Impact of consumer subsidy on total welfare

We adapt the derivation in Schmalensee (1981) for the impact of monopolist price discrimination on total welfare to our setting of regional subsidy variation. Total welfare is given by:

$$W = \int_{p-t}^{\infty} q_Z(x)dx + (p + sub - t - mc + e)q_Z(p-t) + \int_{p}^{\infty} q_N(x)dx + (p - mc + e)q_N(p) - sub \cdot q_Z(p-t) \tag{22}$$

Differentiate with respect to t:

$$\frac{dW}{dt} = (p - t - mc + e)q_Z(p-t)q'_Z(p-t)(p'(t) - 1) + (p - mc + e)q'_N(p)p'(t) \tag{23}$$

Next, add and subtract $p_{t=0} \cdot [q'_Z(p-t)(p'(t) - 1) + q'_N(p)p'(t)]$, where $p_{t=0}$ represents the price set by the manufacturer when the entire subsidy sub is provided as a producer subsidy (i.e., $t = 0$).

$$\begin{aligned}\frac{dW}{dt} &= (p_{t=0} - mc + e)q'_Z(p-t)(p'(t) - 1) + (p_{t=0} - mc + e)q'_N(p)p'(t) \\ &+ (p - t - p_{t=0})q'_Z(p-t)(p'(t) - 1) + (p - p_{t=0})q'_N(p)p'(t) \\ &= \underbrace{(p_{t=0} - mc + e)\frac{dQ}{dt}}_{\text{Output effect, incl. externality}} + \underbrace{(p - t - p_{t=0})q'_Z(p-t)(p'(t) - 1) + (p - p_{t=0})q'_N(p)p'(t)}_{\text{Misallocation effect}}\end{aligned} \tag{24}$$

As described in the main text, the output effect has an ambiguous sign, depending on the sign of $\frac{dQ}{dt}$.

The misallocation effect is negative, as follows. Recall from above that $p'(t) \in (0, 1)$, so the sign of the first term of the misallocation effect matches the sign of $(p - t - p_{t=0})$, while the sign of the second term is opposite that of $(p - p_{t=0})$. Because we have $p'(t) \in (0, 1)$ across the relevant range of t, we know that $p_{t=0} < p(t)$ for $t > 0$, and $p(t) - t < p_{t=0}$. Therefore, $(p - t - p_{t=0}) < 0$, so the first term is negative, while $(p - p_{t=0}) > 0$, so the second term is also negative. Thus the overall misallocation effect is negative.

B.5 Impact of consumer subsidy on regional welfare

In this section, we assume that regional welfare depends on consumer surplus, producer surplus, and the externality from products sold in that region. Therefore, welfare in the two regions is given by:

$$W_Z = \int_{p-t}^{\infty} q_Z(x)dx + (p + sub - t - mc + e) \cdot q_Z(p-t) - sub \cdot q_Z(p-t) \tag{25}$$

$$W_N = \int_{p}^{\infty} q_N(x)dx + (p - mc + e) \cdot q_N(p) \tag{26}$$

Totally differentiating W_Z with respect to t yields:

$$\begin{aligned} \frac{dW_Z}{dt} &= -q_Z(\frac{dp}{dt} - 1) + (p + sub - t - mc + e)q'_Z(p-t)(\frac{dp}{dt} - 1) + (\frac{dp}{dt} - 1)q_Z \\ &\quad - sub \cdot q'_Z(p-t)(\frac{dp}{dt} - 1) \\ &= (p - t - mc + e)q'_Z(p-t)(\frac{dp}{dt} - 1) \end{aligned} \tag{27}$$

From above, we have $\frac{dp}{dt} = \frac{\pi''_Z}{\pi''_Z + \pi''_N}$. For $\pi''_Z < 0$ and $\pi''_N < 0$, we have $\frac{dp}{dt} \in (0,1)$. $q'_Z(p-t) < 0$ by our assumption of downward sloping demand. Therefore, as long as the consumer subsidy is not too large (for example, assuming $t \leq e$), then this expression is positive.

Likewise, totally differentiating W_N with respect to t yields:

$$\begin{aligned} \frac{dW_N}{dt} &= -q_N(\frac{dp}{dt}) + (p - mc + e)q'_N(p)\frac{dp}{dt} + (\frac{dp}{dt})q_N \\ &= (p - mc + e)q'_N(p)\frac{dp}{dt} \end{aligned} \tag{28}$$

This expression is negative given downward sloping demand and $\frac{dp}{dt} \in (0,1)$.

C Appendix: Data

C.1 Aggregating products

Like prior literature on the automotive industry, we must choose the granularity of our product definition. New passenger vehicles vary on many dimensions, not all of which are easily captured in the datasets we use. Each manufacturer has one or more **makes** (brands), each of which is associated with a number of **models**. Each model is associated with a number of **trims**, each of which has a MSRP and standardized product characteristics. The trims within a model are typically similar on most dimensions but vertically differentiated: higher MSRPs are associated with generally popular characteristics like size and acceleration. Within a trim, individual vehicles vary based on options, add-ons, and color.

To construct our dataset of product characteristics, we merge multiple datasets:

- R.L. Polk data on new vehicle registrations
- MSN Autos data on MSRPs and characteristics (our main data source)
- FuelEconomy.gov data on fuel economy and related characteristics
- Ward's Automotive Yearbook data on characteristics and production locations
- New Jersey Department of Environmental Protection data on for ZEV categorizations

These datasets do not uniformly agree on definitions of a model (and do not always agree with the MaritzCX survey's definitions). We attempt to follow the MSN Autos data when possible, within the constraints imposed by the granularity of the R.L. Polk data.

We then aggregate the dataset up to our preferred product level: model year, make, model, fuel type (gas/hybrid/plug-in hybrid/electric), and battery size. We assign each product the characteristics of its "base trim" (the trim with the highest national sales in the Polk data) and sum up the quantities sold.

C.2 Extrapolation for calendar year 2012

The registration data we obtain from S&P Global only contains registrations from January 2012 onward.[69] In order to incorporate model year 2012 vehicles into our demand and cost estimates, we make an estimate of the model year 2012 sales that occurred in calendar year 2011 using within-make cross-year consistency in release schedules. For each vehicle make, and across calendar years 2012–2018, we compute the share of sales for which the calendar year is earlier than the model year (model year 2013 vehicles sold in 2012, model year 2014 vehicles sold in 2013, and so on). We then assume that, for each product, the share of model year 2012 vehicles sold in calendar year 2011 is equal to its make's average.

Table C.4 shows the extrapolation factors for a selected group of vehicle makes. The factors vary across traditional automakers (and even across Honda and Acura, which are manufactured by the same firm) and Tesla is an outlier.

C.3 Federal and state incentives

We manually collected detailed information on state consumer incentive programs using the US Department of Energy's Alternative Fuels Data Center (AFDC) and historical state websites using the Internet Archive's Wayback Machine. Data gathered included subsidy amounts; eligibility criteria including customer and vehicle characteristics; whether the incentives could be collected at point of sale or was claimed through tax credits; and program start and end dates.

To collect the federal IRC 30D subsidy for battery electric and plug-in hybrid vehicles, we obtained the federal tax credit amount for each vehicle model from the EPA's FuelEconomy.gov website.

We then made several assumptions to map these incentive programs to our demand

[69] An earlier version of this paper used the S&P Global dataset (then sold by IHS Markit) from January 2009 onward, but the terms of the earlier data contract required us to delete that data in 2022. When we negotiated the re-purchase of the data from S&P Global in 2023, we were informed by S&P Global staff that all data from before 2012 had been deleted.

Table C.4: Extrapolation factors for missing sales, by make

Make	% of Sales
Tesla	0.04%
Nissan	12.29%
Honda	13.88%
Buick	15.24%
Dodge	16.22%
Toyota	16.24%
Ford	19.06%
GMC	20.80%
Chevrolet	22.01%
Jeep	22.37%
Volkswagen	22.55%
Lexus	22.87%
Chrysler	23.25%
Mazda	25.44%
BMW	27.17%
Hyundai	29.23%
Mercedes-Benz	29.88%
Kia	31.45%
Subaru	36.16%
Acura	37.67%

Note: This table shows our make-level calculation, using S&P Global data on new vehicle registrations in model years 2012–18, of the share of sales that occur in the calendar year prior to the model year. We then use these factors to infer sales in model year 2012 and calendar year 2011.

model. To associate incentive programs with varied start and end dates to particular vehicle model years, we defined a model year as September 1 of the previous calendar year through August 31 of the calendar year matching the model year. If multiple incentives were in place during a model year, we applied the incentive that was available for longer; if an incentive changed exactly halfway through the model year (i.e., on March 1), then we applied the incentive that was active during the second half of the year. If there was only one incentive available during the model year, then we applied that incentive provided that it was in place for at least three months of the model year.

We apply incentive amounts available to "middle income" consumers; California, Oregon, and Pennsylvania provided additional subsidies for low-income households, and California imposed an income cutoff for eligibility starting in 2016.

In the demand specification, we assume that consumers value point-of-sale incentives and tax credits equally. (We distinguish between these two types of incentives in our analysis of pricing heterogeneity described in Section 6.) We also account for avoided sales taxes for alternative fuel vehicles in New Jersey and Washington.

Lastly, we treat the collective non-ZEV states as a single market. Therefore, we aggregate subsidies in non-ZEV states by averaging across individual state programs. We weight each state by the number of households from the American Community Survey 1-year estimates, which is also our measure of market size.

C.4 Transaction prices

We use transaction price data from MaritzCX, a survey of households that recently registered a new vehicle. We consider all observations where vehicle purchase price was reported, excluding only outlier observations with a reported purchase price less than $10,000 or greater than $200,000.

The survey instrument asked consumers to report "purchase price (<u>including</u> tax, before trade-in)." In our baseline specification, we deduct state sales taxes to recover the price charged by the dealer, using annual sales tax rates from the Tax Foundation. We also test robustness to removing average state-level local sales taxes and/or documentation fees. In our baseline specification, we also add point-of-sale incentives to the reported purchase price. We apply point-of-sale incentives to both pre- and post-sales tax prices, depending on whether rebates were taxed in the state. We also test robustness to adding post-sale incentives (often income tax credits).

In the MaritzCX data, some makes are not surveyed in all states. Therefore, in our analysis of transaction prices differences across ZEV and non-ZEV states, we test robustness to dropping makes with incomplete coverage: Tesla, Land Rover, Mini, Porsche, Jaguar, BMW, Mercedes-Benz, and smart.

C.4.1 Aggregating prices for the demand model

In this section, we give the details of the method outlined in Section 5.2.1 for aggregating survey responses up to product-region prices when the sample size is small of zero.

Specifically, we run a predictive regression of mean transaction price on product-level characteristics and a regional dummy. To do so, we construct a dataset of mean transaction prices (reported purchase price, subtracting state sales tax and point-of-sale state incentives) by make, model, year, and fuel type (j), model year t, and region m (ZEV/non-ZEV), along with the number of survey responses used to generate that mean. We then run a weighted least squares regression of the average price on vehicle characteristics, with the number of survey responses as the weight on each observation. The specification we use is:

$$\text{mean price}_{jmt} = \beta_1 \min \text{MSRP}_{jt} + \beta_2 \max \text{MSRP}_{jt} + \beta_3 \, \text{ZEV}_m \text{EV}_j + \beta_4 \, \text{ZEV}_m \text{adv}_j + \gamma_{\text{make}(j),t} + \varepsilon_{jmt},$$

where min MSRP and max MSRP are minimum and maximum MSRPs among trims within that make, model, year, and fuel type (from MSN Autos); ZEV_m is an indicator for a ZEV state; EV_j is an indicator for an electric vehicle and adv_j is an indicator for a hybrid or electric vehicle; the $\gamma_{\text{make}(j),t}$ terms are fixed effects; and ε_{jmt} is the error term. The regression coefficients, which should not be interpreted as causal, are shown in Table C.5.

Table C.5: Selected coefficients from transaction price regression

Variable	Coefficient
min MSRP ($)	0.78
max MSRP ($)	0.19
ZEV state	-84.13
EV	-2926.83
Advanced	-1975.11
ZEV state * EV	-633.58
ZEV state * Advanced	-661.78
(Observations)	3486.00
(R-squared)	0.97

Note: Coefficients from a predictive regression of mean transaction price on product-level characteristics (including make fixed effects, not shown) and a regional dummy. Transaction prices are drawn from the MaritzCX survey of new vehicle buyers, model years 2012–17, restricted to responses where the purchase price is between $10,000 and $200,000. MSRP, EV, and hybrid variables are from MSN Autos (merged to survey responses). The outcome variable is the mean reported transaction price by product, and region (ZEV vs. non-ZEV), removing state sales tax (from Tax Foundation data, using reported state of residence) and applicable point-of-sale government incentives. Regression is weighted by the number of survey responses used to construct the average.

C.5 State and local sales taxes

Data on state and average local sales taxes are collected from the Tax Foundation's annual reports. While not many states changed their sales tax rates during the study period, we verified the timing of all reported changes with additional sources such as archived state websites.

We also collected additional information on fees from Edmunds, which reported state-level information on documentation fees, DMV fees, and whether rebates were taxed on their webpage "What New Car Fees Should You Pay?" Using the Internet Archive, we collected contemporaneous information once annually over our study period.

C.6 Calculation of emissions externalities

Our computations of emissions externalities build both on our estimated demand system and on a literature quantifying the emissions of electric vehicles. Unlike gasoline-powered vehicles, whose emissions are closely related to fuel consumption, electric vehicles mainly cause emissions upstream in the electricity generation process, and the emissions vary by geography and other factors (Holland, Mansur, Muller, and Yates 2016; Holland, Mansur, Muller, and Yates 2020).

Within our demand system, our empirical analysis of the environmental impact of electric vehicle adoption depends on substitution with other vehicles and the outside good. Existing literature does not provide clear guidance on modeling the average emissions of the outside good.[70] We therefore report welfare results using two different approaches.

In our main results, we calibrate the emissions of the outside good to a baseline used gasoline vehicle (similar to an assumption by Allcott, Kane, Maydanchik, Shapiro, and Tintelnot (2024)) at 425.2 grams of CO_2 per mile. The baseline corresponds to a gasoline vehicle with a fuel economy of 20.9 miles per gallon, which is the fleet average among model year 2007–2011 non-electric vehicles in the 2017 National Household Travel Survey. This approach likely overestimates the greenhouse gas savings from electric vehicle adoption, as the remaining lifetime of the used vehicle, whether recently purchased or already owned by the household, is likely to be shorter than that of a new electric vehicle.

As an alternative approach, we assume that the outside good is not to drive, which generates zero greenhouse gas emissions. This approach underestimates the greenhouse gas savings from electric vehicle adoption. Therefore, our two estimates should be understood as approximate bounds on the greenhouse gas impacts of electric vehicle adoption during this period.

Our estimates of environmental impacts also do not include other externalities associated

[70] In analyzing substitution patterns between electric vehicles and other new vehicles, Xing, Leard, and Li (2021) do not model an outside good.

with new vehicle purchases, such as accident fatalities or local air pollutants.

Specifically, our method for calculating the lifetime emissions externality of an additional new vehicle sale is the product of three terms. For a product j sold in region m, the externality is

$$\text{SCC} \times (\text{gas emissions per mile}_j + \text{electric emissions per mile}_{jm} - \text{baseline}) \times \text{miles}_j.$$

Social cost of carbon (SCC). We apply a social cost of carbon of $175 per megagram (metric ton) of CO_2 in 2017 dollars, which is the inflation-adjusted equivalent (using the Consumer Price Index) of the 2020 estimate from Rennert et al. (2022).

Emissions per mile. We use estimates from prior literature to determine CO_2 emissions per mile for different types of vehicles. We assume no deterioration in the efficiency of the vehicle over time.

For electric vehicles, we use estimates by Holland, Mansur, Muller, and Yates (2016) of marginal emissions from electricity use by North American Electric Reliability Corporation (NERC) region, in megagrams of CO_2 per kilowatt-hour, which they estimate from 2010–2012 data.[71] We then convert to vehicle emissions using vehicle-specific electricity consumption per mile (in FuelEconomy.gov data). Since electricity became much less emissions-intensive during our study period (Holland, Mansur, Muller, and Yates 2020), we overestimate the emissions of electric vehicles later in our study period.

For gasoline vehicles, we multiply gasoline consumption per mile (in FuelEconomy.gov data) by a factor of 8887 grams of CO_2 per gallon (from EPA). For plug-in hybrids, we compute emissions for both electric and gas modes and take a weighted average using the EPA utility factor.

[71] Following their approach, we separate California from the rest of the Western Electricity Coordinating Council. In other cases, when NERC regions do not line up with our geographical regions, we take an average, weighting each NERC region using average vehicle miles traveled from EPA MOVES.

Miles driven per vehicle. We assume a new car is driven 195,264 miles over its lifetime and a new light truck is driven 225,865 miles over its lifetime, following the computations used for the GHG and CAFE regulations in effect in this period (Environmental Protection Agency and National Highway Traffic Safety Administration 2010). Since electric vehicles are driven fewer miles per year than gasoline vehicles (Davis 2019; Burlig, Bushnell, Rapson, and Wolfram 2021), we may overestimate the emissions from electric vehicles.

D Appendix: Additional results

D.1 Transaction price heterogeneity

In Figure D.9, we document that reported transaction prices varied within a given model (Nissan Leaf). In Table D.6, we document that the price difference for EVs between ZEV states and non-ZEV states was larger in later years of the period, and smaller in earlier years. In Table D.7, we adopt different assumptions about the prices reported in the survey, and show that while the price difference varies in magnitude, it retains the same sign and is usually significant. In Table D.8, we adopt alternative functional forms and clustering assumptions for the regression, and show that the price difference retains the same sign and is usually significant.

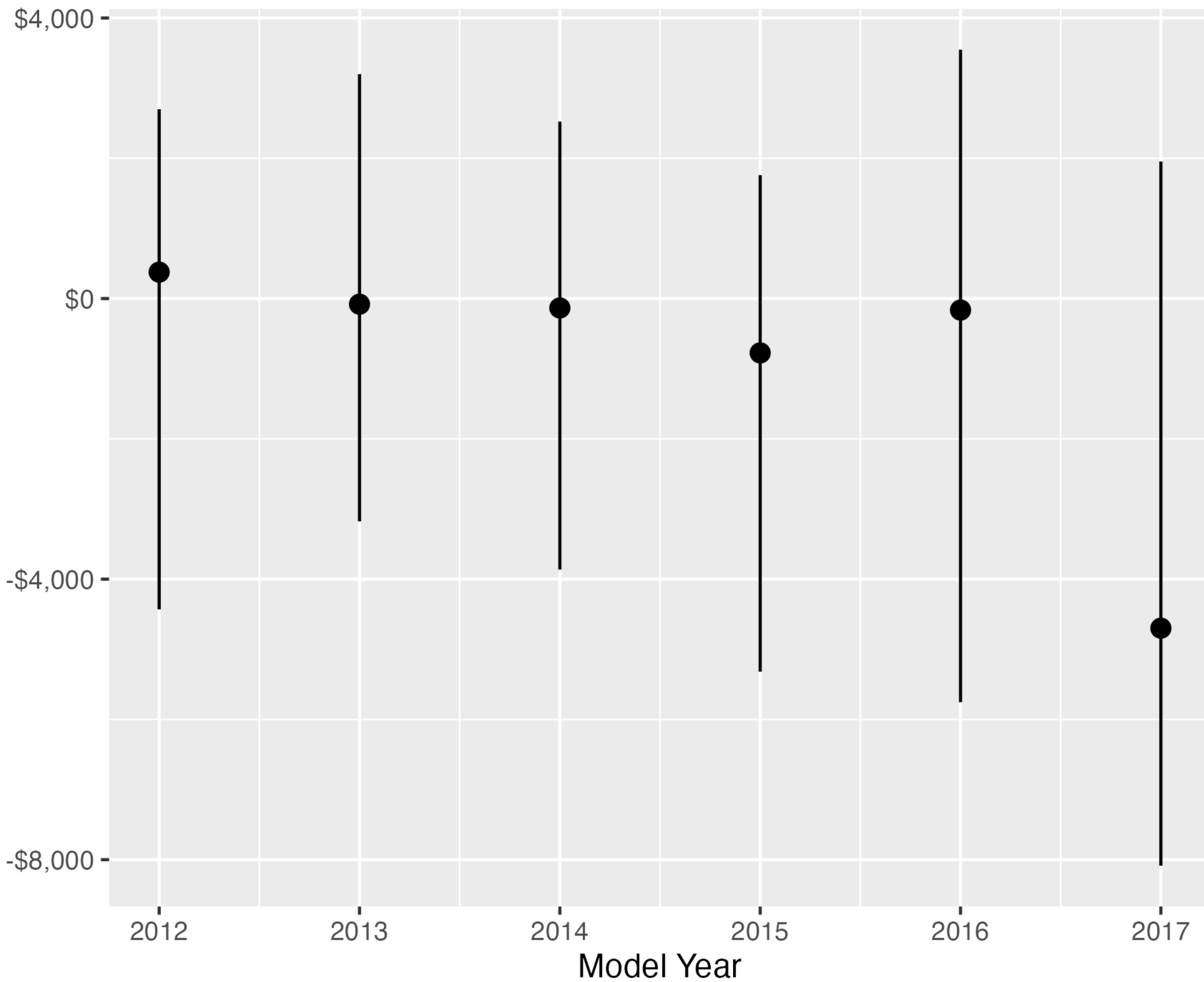

Figure D.9: Difference Between Transaction Prices and MSRP: Nissan LEAF

Note: This figure shows the median and interquartile range of the difference between reported transaction price and MSRP for the Nissan Leaf, by model year. Reported transaction prices are taken from MaritzCX survey data. The Maritz survey instrument instructed respondents to include taxes but exclude trade-in value; we therefore adjust reported transaction prices by the state sales tax in each year. We do not adjust for any point-of-sale or post-sale rebates.

Table D.6: Transaction prices in ZEV and non-ZEV states: by year

	Reported Price	Reported Price Less Sales Tax	Reported Price Less Sales Tax & POS Rebates
ZEV state	83.714	-41.759	-41.711
	(80.317)	(62.988)	(63.004)
ZEV state × 2012	0.000	0.000	0.000
	(.)	(.)	(.)
ZEV state × 2013	-26.257	-55.127	-55.125
	(104.954)	(86.858)	(86.865)
ZEV state × 2014	-58.171	-107.964	-107.958
	(108.583)	(89.107)	(89.112)
ZEV state × 2015	-59.259	-103.120	-103.104
	(108.663)	(87.271)	(87.287)
ZEV state × 2016	-9.503	-68.830	-68.820
	(123.486)	(96.339)	(96.401)
ZEV state × 2017	34.384	28.592	28.612
	(126.798)	(104.887)	(104.900)
ZEV state × EV	-576.864	-670.110	-670.178
	(501.073)	(524.916)	(525.176)
ZEV state × EV × 2012	0.000	0.000	0.000
	(.)	(.)	(.)
ZEV state × EV × 2013	2.632	-290.338	-290.087
	(1145.524)	(1074.329)	(1074.286)
ZEV state × EV × 2014	-279.761	-559.668	-556.681
	(793.473)	(794.784)	(793.761)
ZEV state × EV × 2015	-922.496	-1064.354	-960.669
	(700.447)	(699.366)	(704.629)
ZEV state × EV × 2016	-1294.876*	-1523.089*	-1446.343*
	(773.584)	(844.820)	(844.036)
ZEV state × EV × 2017	-1768.810**	-2092.525**	-1884.310**
	(838.285)	(829.625)	(837.515)
Model+ Fixed Effects	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes
Observations	443,671	443,671	443,671
R^2	0.89	0.89	0.89

Note: Vehicle fixed effects control for model, model year, trim, drive type, body style, and fuel type. We include additional controls for buyer reported demographics: income, age, metro/suburban/small town/farming area residence, retirement status, marital status, household size, and college attainment. Standard errors are two-way clustered by model-model year and state-make-year. We exclude Tesla vehicles since they were not sold at dealerships and were priced nationally.

Table D.7: Transaction prices in ZEV and non-ZEV states: alternative price adjustments

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
ZEV state	65.626*	-92.893***	39.101	-15.799	116.195***	-92.830***	39.164	-15.736	116.258***	-94.349***	37.645	-17.213	114.781***
	(35.284)	(29.304)	(31.288)	(29.556)	(30.899)	(29.308)	(31.293)	(29.559)	(30.903)	(29.302)	(31.282)	(29.542)	(30.881)
ZEV state × PHEV	-326.239	-534.663	-493.147	-458.507	-416.991	-491.356	-449.840	-415.206	-373.690	243.162	284.678	320.641	362.157
	(447.788)	(436.835)	(438.395)	(427.402)	(428.904)	(421.769)	(423.206)	(412.586)	(413.960)	(409.613)	(411.229)	(399.500)	(401.054)
ZEV state × EV	-1223.444***	-1547.133***	-1476.188***	-1299.888***	-1228.942***	-1474.873***	-1403.927***	-1227.635***	-1156.689***	-908.624***	-837.678***	-640.537**	-569.591**
	(437.194)	(448.091)	(455.895)	(440.652)	(448.785)	(425.170)	(432.916)	(418.376)	(426.455)	(282.924)	(286.115)	(271.677)	(275.586)
State Sales Tax Removed	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Avg. Local Sales Tax Removed	No	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
Avg. Documentation Fee Removed	No	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
POS Rebates Removed	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Post-Sale Rebates Removed	No	No	No	No	No	No	No	No	No	Yes	Yes	Yes	Yes
Model+ Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	443,671	443,671	443,671	443,671	443,671	443,671	443,671	443,671	443,671	443,671	443,671	443,671	443,671
R^2	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88

Note: Columns differ in how reported survey price is adjusted. Columns 1, 2, and 6 correspond to specifications in the main text. Vehicle fixed effects control for model, model year, trim, drive type, body style, and fuel type. We include additional controls for buyer reported demographics: income, age, metro/suburban/small town/farming area residence, retirement status, marital status, household size, and college attainment. Standard errors are two-way clustered by model-model year and state-make-year. We exclude Tesla vehicles since they were not sold at dealerships and were priced nationally.

Table D.8: Transaction prices in ZEV and non-ZEV states: alternative specifications

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ZEV state	-92.830***	-93.416***	-53.389*	-93.520***	-0.004***	-84.411**	-92.830***	-92.830***	-92.830***
	(29.308)	(29.315)	(29.353)	(29.296)	(0.001)	(34.529)	(16.560)	(20.372)	(28.410)
ZEV state × PHEV	-491.356	-491.346	-531.540	-490.336	-0.018	-571.491	-491.356***	-491.356	-491.356**
	(421.769)	(421.719)	(423.215)	(421.587)	(0.014)	(417.444)	(123.652)	(419.782)	(248.107)
ZEV state × EV	-1474.873***	-944.224**	-1618.104***	-1472.981***	-0.054***	-1575.368***	-1474.873***	-1474.873***	-1474.873***
	(425.170)	(466.969)	(452.978)	(424.946)	(0.015)	(475.413)	(189.225)	(433.190)	(311.427)
Tesla excluded	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other makes excluded	No	No	Yes	No	No	No	No	No	No
Binned income	No	No	No	Yes	No	No	No	No	No
Price in logs	No	No	No	No	Yes	No	No	No	No
Clustering	SMY, MMY	SMY, MMY	SMY, MMY	SMY, MMY	SMY, MMY	SMY, MMY	None	MMY	SMY
MMY-Trim Fixed Effects	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes
MMY Fixed Effects	No	No	No	No	No	Yes	No	No	No
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	443,671	444,421	417,791	443,671	443,671	443,991	443,671	443,671	443,671
R^2	0.88	0.89	0.87	0.88	0.86	0.84	0.88	0.88	0.88

Note: Outcome variable is reported price, less state sales tax and point-of-sale rebates, in levels (columns 1-4, 6-9) or logs (column 5). Vehicle fixed effects control for model, model year, trim, drive type, body style, and fuel type (columns 1-5, 7-9) or model, model year (column 6). We include additional controls for buyer reported demographics: income (either continuous or binned), age, metro/suburban/small town/farming area residence, retirement status, marital status, household size, and college attainment. Standard errors are either two-way clustered by state-make-year (SMY) and model-model year (MMY) (columns 1-6), one-way clustered by model-model year (column 8) or state-make-year (column 9), or not clustered (column 7), depending on the specification.

D.2 Demand estimation using MSRPs

In this section, we re-estimate demand assuming that consumers face the national price, rather than the estimated price derived from survey data. We use these demand estimates in the counterfactual simulations in which all products are priced nationally, and as a robustness check against any systematic data errors in the reported transaction prices in MaritzCX.

We set each vehicle's national price at MSRP (from MSN Autos) minus average manufacturer rebates to consumers obtained from Automotive News.[72] We ignore manufacturer rebates to dealers, to approximate the findings by Busse, Silva-Risso, and Zettelmeyer (2006) of high pass through for customer rebates and low pass through for dealer rebates.

We obtain similar parameter estimates, shown in Table D.9, and elasticities, shown in Table D.10.

Using these demand estimates, we then estimate marginal costs at the national level using the national pricing first order conditions (equation (12)).

[72]Each week, Automotive News publishes a table of rebate amounts by make and model, without distinguishing between national and regional rebates. First, for each make-model-model year and quarter, we take the maximum consumer rebate observed in that quarter. Then, we take the average across the first five quarters in which that make-model-model year was sold. Data are missing for the second quarter of 2014.

Table D.9: Estimates of demand parameters, using national prices

	Logit		Random coeff.	
	Estimate	SE	Estimate	SE
Linear parameters (β)				
Price−Subsidy	-1.49	0.44	-2.19	1.88
Van	-1.29	0.62	-7.02	1.85
SUV	0.03	0.31	-1.19	1.33
Truck	-1.59	0.72	-7.80	4.74
Footprint	0.06	0.61	2.15	3.51
Horsepower	1.48	0.51	2.97	1.78
Fuel economy	0.55	0.34	0.68	1.44
EV/PHEV/Hybrid	-1.54	0.68	-3.69	2.14
EV/PHEV	1.26	0.53	1.41	2.00
EV	-2.87	0.88	-11.05	5.81
Electric range	1.59	0.81	1.21	1.69
Elec. use	-0.26	0.44	0.24	1.07
Weight	2.93	1.74	2.17	4.76
New model	0.01	0.13	-0.22	0.54
log(# trims)	0.66	0.13	1.12	0.68
Unobserved heterogeneity (Σ)				
Van			3.98	0.11
SUV			2.49	0.03
Truck			4.67	0.14
Footprint			2.20	0.15
Horsepower			1.31	0.05
Fuel economy			1.89	0.09
US brand			1.65	0.02

Note: Estimates from random coefficients logit demand system, except for magnitudes of fixed effects (on make, model year, and state), for specifications estimated using national prices (MSRP after manufacturer rebates to consumers). The coefficient on characteristic k for consumer i is $\beta_k + \Sigma_k v_i$, where v_i is unobserved heterogeneity. The specification labeled Logit sets Σ to zero. The specification labeled 'Random coeff.' estimates Σ using second choice survey data. Standard errors are clustered at the make-model level.

Table D.10: Average elasticities implied by demand estimates, national prices

Type	Logit	Random coeff.
Electric	-7.43	-10.23
Gas/Hybrid	-4.06	-5.71

Note: Mean own-price elasticities across products, regions, and years, weighted by quantity sold. Columns correspond to demand specifications. Demand estimated using national prices (MSRP after manufacturer rebates to consumers).

D.3 Emissions effects of substitution

Our emissions externality calculations relate closely to a literature on the emissions effects of electric vehicle adoption (Holland, Mansur, Muller, and Yates 2016; Holland, Mansur, Muller, and Yates 2020; Muehlegger and Rapson 2023; Xing, Leard, and Li 2021). This literature has generally found that, during the 2010s, electric vehicle adoption had a small effect on short-run emissions (and in some regions worsened them). A principal reason for this finding is that the closest substitutes for electric vehicles were efficient gasoline vehicles, with average fuel economy of 29 MPG (from Xing, Leard, and Li (2021), using a similar structural approach) to 35 MPG (from Muehlegger and Rapson (2023), using a quasi-experimental approach).

We recover similar substitution estimates on a product-by-product level when looking at the effects of small price changes, as detailed in Figure D.10. Our estimates depend crucially on the assumed emissions of the outside good, explained in further detail in Section C.6. In the figure, we ask: if a customer leaves a given product because its price increased a small amount, what are the expected emissions of the product to which the consumer will switch? That is, for each product j, we compute the weighted average of the emissions of other products $k \neq j$, where the weights are given by the diversion ratios from j to k. (Xing, Leard, and Li (2021) call this the emissions of the "composite substitute.")

We find that the results for EVs vary both by region and by the outside good assumption used. (Throughout, we adopt estimates from Holland, Mansur, Muller, and Yates (2016) of electricity grid emissions using 2010–2012 data.) In California, which has a low-emissions electricity grid, EVs (purple) have low emissions per mile. EVs are, on average, lower-emissions than their close substitutes, regardless of the assumption on the outside good. In New Jersey, which has a higher-emissions electricity grid,[73] EVs have similar emissions per mile to hybrids and efficient gasoline vehicles. Substitution away from EVs leads to higher

[73]The ReliabilityFirst region, which contains New Jersey and Maryland, has the highest emissions per unit of electricity among ZEV states (Holland, Mansur, Muller, and Yates 2016).

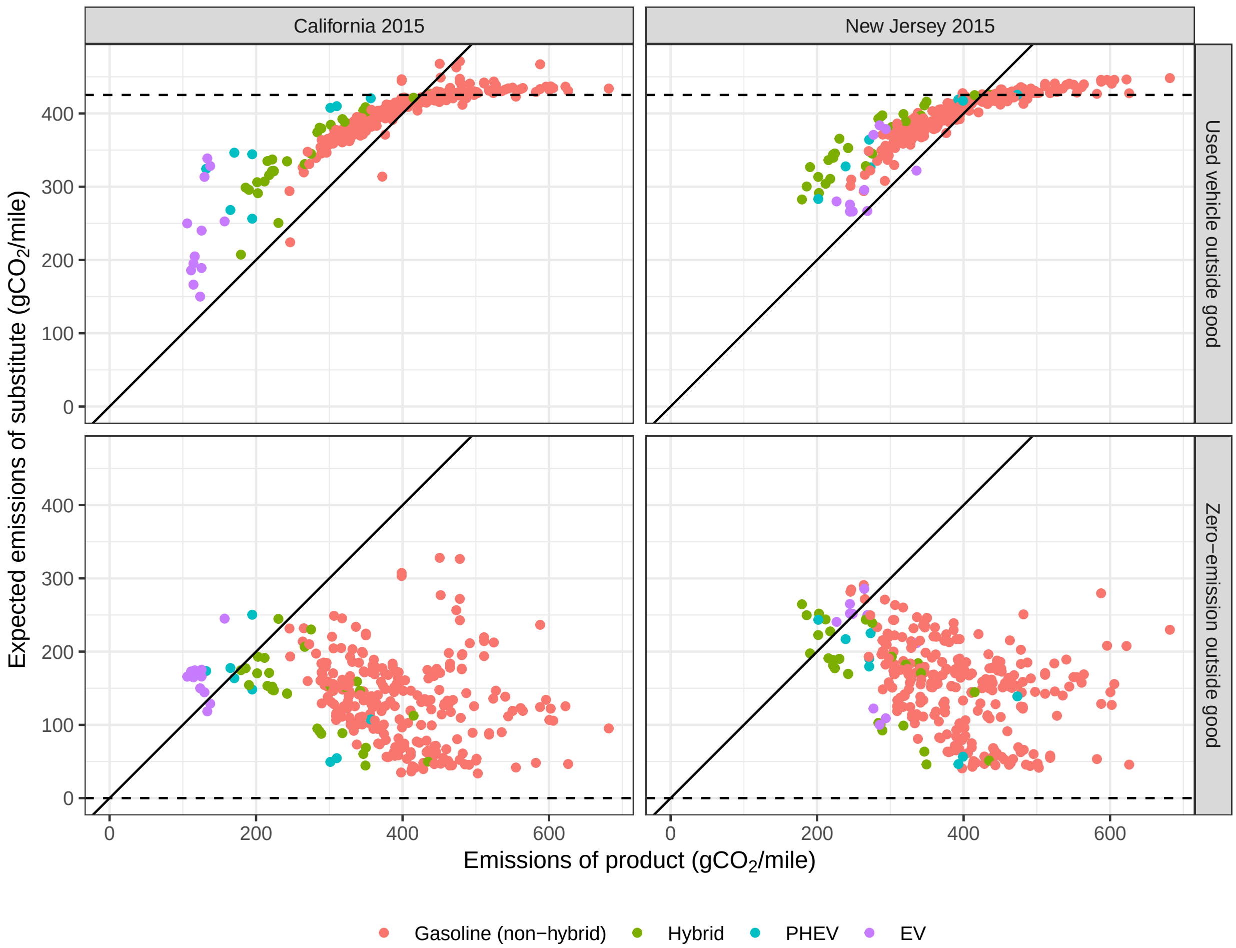

Figure D.10: Expected emissions effects of consumer substitution

Note: This plot shows the expected emissions effects of consumer substitution for each product, under alternative assumptions about the outside good, for model year 2015 vehicles sold in California and New Jersey. We plot each product's emissions per mile against the expected emissions per mile of the alternative product to which a customer would switch if presented with a small price increase. For points above the 45-degree line, a price increase leads on average to the purchase of higher-emissions products; for points below the 45-degree line, a price increase leads on average to the purchase of lower-emissions products. The emissions of the outside good are indicated with a dashed horizontal line: in the top panels, we assume the outside good has the emissions of a typical used vehicle (20.9 MPG), and in the bottom panels, we assume the outside good has no emissions.

emissions on average if the outside good is a used gasoline vehicle, and lower emissions on average if the outside good is zero-emissions.

For non-EVs, outside good substitution is so substantial that the assumed emissions of the outside good are the main driver of the estimated effects. (Because proportionally little substitution goes to EVs, the emissions of non-EV substitutes does not vary much by region.)

We caution that the diversion ratios used in Figure D.10 are only valid for a small price change. For a large price change, or a change in the product set, substitution patterns may differ (Conlon and Mortimer 2021).

D.3.1 Counterfactual emissions externalities

In this section, we show that counterfactual emissions externalities are sensitive to the assumed emissions of the outside good. These results are largely driven by the substitution patterns described above: if the outside good has no emissions, the marginal vehicle typically (though not always) increases emissions relative to its average substitute, so counterfactuals that result in more new vehicle sales increase aggregate emissions.

In Table D.11, we show how the emissions externality effects shown in Table 9 vary if the outside good is assumed to have no emissions. The aggregate effect of new vehicle sales in each scenario is an increase, rather than decrease, in emissions. Furthermore, the demand-side ZEV program results in fewer (not more) emissions in the ZEV region and more (not fewer) emissions in the non-ZEV region, though the net effect remains a national decrease.

Table D.11: Comparison of estimates of the GHG reduction from new vehicles

	Demand-Side ZEV Program	Supply-Side ZEV Program	No ZEV Program	Demand- vs. Supply-Side
Outside good: Used car				
ZEV Region	\$59.55b	\$58.86b	\$57.97b	\$699m
Non-ZEV Region	\$104.50b	\$104.73b	\$104.52b	-\$222m
National	\$164.06b	\$163.58b	\$162.49b	\$477m
Outside good: No emissions				
ZEV Region	-\$341.02b	-\$340.89b	-\$342.67b	-\$129m
Non-ZEV Region	-\$911.85b	-\$912.07b	-\$911.87b	\$221m
National	-\$1,252.87b	-\$1,252.96b	-\$1,254.54b	\$92m

Note: This table shows the simulated emissions externality reductions associated with new vehicle sales under each of the counterfactual scenarios in Table 9. In our baseline setup, we assume the outside good has the emissions of a typical used car (a 20.9 MPG gasoline car). In the alternative scenario, we assume the outside good has no emissions. Externality reductions are positive numbers, and externality increases are negative numbers. Figures are are shown in 2017 USD (assuming a social cost of carbon of \$175) and are aggregated across all new vehicles sold nationwide in the study period.

E Appendix: Further detail on counterfactual simulations

In Section 8, we describe simulations that replace the ZEV mandate with a counterfactual policy that only uses demand-side subsidies and taxes. Specifically, we eliminate ZEV credits on the producer side and add (1) a consumer subsidy for electric vehicles in the ten regulated states, plus (2) a consumer tax on non-electric vehicles in the ten regulated states. In this section, we give further detail on how the simulations were implemented.

E.1 First counterfactual

In the first counterfactual, we translate the existing supply-side ZEV policy into a demand-side policy, dollar for dollar, abstracting away from budgetary feasibility. This exercise quantifies how national pricing strategies lead to the non-equivalence of supply-side and demand-side policy.

Formally, within the notation of Section 5.4, we remove ZEV from supply-side regulatory credits, so that the value of regulatory credits to the firm is limited to the impact of the GHG program. At the same time, we increase the consumer subsidy by the same amount:

$$\tilde{v}_{jmt} = v_{jmt} - c_{jmt,ZEV}\, r_{mt,ZEV},$$

$$\widetilde{\text{subsidy}}_{jmt} = \text{subsidy}_{jmt} + c_{jmt,ZEV}\, r_{mt,ZEV}.$$

To account for the effect of the subsidy and tax on consumer prices, we recompute the Nash-in-prices equilibrium as the joint solution to the first order conditions (12) and (14). Our solution method is a straightforward adaptation of the contraction mapping of Morrow and Skerlos (2011) to allow for national pricing. To speed up computation, we use SciPy's implementation of Steffensen's Method with Aitken's Δ^2 convergence acceleration.

E.2 Second counterfactual

In the second counterfactual, we we explore a version of the demand-side policy that balances its budget each year (removing implicit inter-temporal financing) and achieves the same quantity of electric vehicles in the regulated states, a stated goal of state regulators. Specifically, we solve for the level of the consumer subsidy and tax each year that attains these two outcomes in equilibrium. To compute counterfactual prices, we assume that the subsidy and tax are set simultaneously with prices, and that the regulator has the same information as the firms.

The subsidy formula follows the ZEV formula for credits per vehicle, generating a larger subsidy for vehicles with a longer battery range. The consumer tax follows the ZEV mandate's quota, applying to non-EVs sold by six large automakers.

Budget balance. Total expenditure on the subsidy must equal total collection through the tax each year, across all of the regulated states. There is no equivalent to credit banking.

Firms in the ZEV program took advantage of credit banking, taking credits out of circulation for later use. Any demand-side equivalent with credit banking would require state governments to provide inter-temporal financing. Since existing consumer subsidy programs already drew on public budgets, it is unclear whether state governments would be willing to provide such funding.

Electric vehicle quantity in ZEV states. The policy must achieve the same electric vehicle sales each year across the ten regulated states as observed data. We use regional electric vehicle sales as the target because it is easily measured and explicitly mentioned as a goal in regulator reports (see Appendix A.2.5).

Formally, the setup is as follows. The policymaker controls the EV subsidy τ_t^{EV} and the non-EV tax $\tau_t^{\text{non-EV}}$ for each model year t. For product j in region m and model year t, let q_{jmt}^0 be the quantity sold in the data. Let $e_j = 1$ if product j is an electric vehicle and 0 otherwise, let c_j be a subsidy multiplier (equal to the number of credits j earns under the ZEV mandate), and let $z_m = 1$ if region m has the regulation and 0 otherwise.

The net consumer subsidy for purchasing j in m and t (in addition to existing subsidy programs) is $z_m(\tau_t^{\text{EV}} c_j e_j - \tau_t^{\text{non-EV}}(1 - e_j))$.

Let $q_{jmt}(\tau_t^{\text{EV}}, \tau_t^{\text{non-EV}})$ be the equilibrium quantity sold under the demand-side policy. The policymaker's problem is then to choose $(\tau_t^{\text{EV}}, \tau_t^{\text{non-EV}})$ to solve the system of equations

$$0 = \sum_{m \in \mathcal{M}} z_m \sum_{j \in \mathcal{C}_{mt}} (\tau_t^{\text{EV}} c_j e_j - \tau_t^{\text{non-EV}}(1 - e_j)) q_{jmt}(\tau_t^{\text{EV}}, \tau_t^{\text{non-EV}}) \qquad \text{(budget balance)}$$

$$0 = \sum_{m \in \mathcal{M}} z_m \sum_{j \in \mathcal{C}_{mt}} e_j (q_{jmt}(\tau_t^{\text{EV}}, \tau_t^{\text{non-EV}}) - q_{jmt}^0). \qquad \text{(EV sales)}$$

To disentangle the effects of budget balance from the effects of supply- versus demand-side policy, we also conduct a comparable exercise to compute a counterfactual budget-balanced supply-side policy. The system of equations appears the same, but quantity only depends on policy through the pricing responses of firms (that is, $q_{jmt}(\cdot)$ function differs).

E.3 Results using national pricing

Table E.12 and Table E.13 replicate the main outcomes assuming that all products are priced nationally. Table E.14 shows the budget-balanced counterfactual subsidy and tax amounts that attain the quantity target, assuming all products are priced nationally.

Table E.12: Comparison of dollar-equivalent demand- or supply-side policy, national pricing

	Demand-Side ZEV Program	Supply-Side ZEV Program	No ZEV Program	Demand- vs. Supply-Side
Quantity of EVs sold				
ZEV Region	374,800	229,000	101,900	145,800
Non-ZEV Region	59,600	144,300	67,000	-84,700
National	434,400	373,200	168,900	61,200
Consumer surplus				
ZEV Region	\$206.95b	\$206.59b	\$206.00b	\$356m
Non-ZEV Region	\$511.66b	\$511.44b	\$511.47b	\$219m
National	\$718.61b	\$718.03b	\$717.47b	\$575m
Producer surplus from vehicles sold				
ZEV Region	\$133.80b	\$133.86b	\$133.79b	-\$65m
Non-ZEV Region	\$342.46b	\$342.26b	\$342.55b	\$201m
National	\$476.26b	\$476.13b	\$476.35b	\$136m
GHG reduction from new vehicles sold				
ZEV Region	\$59.66b	\$58.86b	\$58.15b	\$809m
Non-ZEV Region	\$104.58b	\$104.73b	\$104.45b	-\$140m
National	\$164.25b	\$163.58b	\$162.60b	\$668m
Net fiscal revenue, ZEV program only				
ZEV Region	-\$2.40b	-\$1.00b	–	-\$1,401m
Non-ZEV Region	–	–	–	–
National	-\$2.40b	-\$1.00b	–	-\$1,401m
Net fiscal revenue, all programs				
ZEV Region	-\$7.60b	-\$4.81b	-\$2.63b	-\$2,792m
Non-ZEV Region	-\$1.53b	-\$2.23b	-\$1.59b	\$696m
National	-\$9.14b	-\$7.04b	-\$4.23b	-\$2,096m
Total surplus net of fiscal cost				
ZEV Region	\$392.81b	\$394.50b	\$395.31b	-\$1,692m
Non-ZEV Region	\$957.17b	\$956.20b	\$956.88b	\$975m
National	\$1,349.98b	\$1,350.70b	\$1,352.19b	-\$716m

Note: This table shows the simulated quantity, welfare, and fiscal effects of implementing the ZEV policy as a demand-side subsidy and tax or as the existing supply-side subsidy and tax policy, holding fixed the dollar amount per vehicle sold. It also shows the simulated scenario with neither policy, for comparison. Throughout, we assume **all products** are priced nationally. All amounts are aggregated across the study period; dollar amounts are in 2017 USD. Welfare amounts are across the entire new vehicle market. Environmental externalities are measured relative to the outside good benchmark (used car). Total surplus includes consumer surplus, environmental externalities, and firm profits earned on new vehicle sales. The fiscal cost of the ZEV program is the value of net credits earned across the study period. The fiscal cost of all policies also includes existing federal and state subsidy policies; it does not include the federal GHG program.

Table E.13: Comparison of budget-balanced demand- or supply-side policy, national pricing

	Demand-Side ZEV Program	Supply-Side ZEV Program	No ZEV Program	Demand- vs. Supply-Side
Quantity of EVs sold				
ZEV Region	229,000	229,000	101,900	0
Non-ZEV Region	63,300	144,200	67,000	-80,900
National	292,300	373,200	168,900	-80,900
Consumer surplus				
ZEV Region	$205.69b	$206.31b	$206.00b	-$620m
Non-ZEV Region	$511.58b	$510.75b	$511.47b	$824m
National	$717.27b	$717.06b	$717.47b	$204m
Producer surplus from vehicles sold				
ZEV Region	$133.31b	$132.99b	$133.79b	$321m
Non-ZEV Region	$342.50b	$342.54b	$342.55b	-$42m
National	$475.81b	$475.53b	$476.35b	$279m
GHG reduction from new vehicles sold				
ZEV Region	$58.72b	$58.79b	$58.15b	-$70m
Non-ZEV Region	$104.52b	$104.60b	$104.45b	-$76m
National	$163.24b	$163.38b	$162.60b	-$146m
Net fiscal revenue, ZEV program only				
ZEV Region	–	–	–	–
Non-ZEV Region	–	–	–	–
National	–	–	–	–
Net fiscal revenue, all programs				
ZEV Region	-$3.82b	-$3.81b	-$2.63b	-$13m
Non-ZEV Region	-$1.56b	-$2.23b	-$1.59b	$663m
National	-$5.38b	-$6.03b	-$4.23b	$650m
Total surplus net of fiscal cost				
ZEV Region	$393.89b	$394.27b	$395.31b	-$382m
Non-ZEV Region	$957.04b	$955.67b	$956.88b	$1,369m
National	$1,350.93b	$1,349.94b	$1,352.19b	$987m

Note: This table shows the simulated quantity, welfare, and fiscal effects of implementing a budget-balanced ZEV-style policy as a demand-side subsidy and tax or as a supply-side subsidy and tax policy, holding the quantity of EVs sold in the ZEV Region fixed at observed levels. It also shows the simulated scenario with neither policy, for comparison. Throughout, we assume **all products** are priced nationally. All amounts are aggregated across the study period; dollar amounts are in 2017 USD. Welfare amounts are across the entire new vehicle market. Environmental externalities are measured relative to the outside good benchmark (used car). Total surplus includes consumer surplus, environmental externalities, and firm profits earned on new vehicle sales. The fiscal costs of budget-balanced policies are zero by construction. The fiscal cost of all policies also includes existing federal and state subsidy policies; it does not include the federal GHG program.

Table E.14: Subsidy and tax amounts in counterfactual simulations, with national pricing

	Subsidy (typical EV)			Tax		
Model year	Observed	Budget-Balanced Supply-Side	Budget-Balanced Demand-Side	Observed	Budget-Balanced Supply-Side	Budget-Balanced Demand-Side
2012	$10,890	$10,884	$5,532	$29	$40	$20
2013	$10,890	$10,864	$5,843	$29	$117	$63
2014	$7,200	$7,177	$4,573	$19	$76	$49
2015	$5,850	$5,839	$3,423	$59	$86	$51
2016	$7,200	$7,181	$4,651	$72	$139	$93
2017	$4,380	$4,359	$2,903	$44	$107	$72

Note: This table shows the subsidies and taxes under the observed policy, a budget-balanced supply-side counterfactual policy, and a budget-balanced demand-side counterfactual policy, where both budget-balanced policies are constrained to attain the same total EV sales in the regulated states. All subsidies are scaled by battery range in the same way, and all taxes apply only to non-electric vehicles by six Large Volume Manufacturers. The left panel shows the amount of the subsidy (or value of credits) for the sale of a Nissan Leaf, which earned three credits per sale. The right panel shows the amount of the tax on the sale of a non-EV by a Large Volume Manufacturer. Amounts are shown in nominal dollars. All firms are assumed to set nationally standardized prices.

E.4 Additional results

The price and quantity results in the first counterfactual simulation, for the case where only Tesla employs national pricing, are presented in Table E.15.

Table E.15: Dollar-equivalent counterfactual: price and quantity effects

Vehicle	Region	Change in quantity (%)	Change in quantity	Change in price (%)
Tesla	ZEV	113.1%	99,600	-3.7%
Tesla	Non-ZEV	-76.3%	-50,700	6.1%
Other EV	ZEV	-1.5%	-2,100	0.0%
Other EV	Non-ZEV	1.2%	900	0.0%
Non-EV	ZEV	-0.2%	-42,400	0.0%
Non-EV	Non-ZEV	0.0%	20,800	0.0%

Note: This table shows the simulated price and quantity effects of the first counterfactual, which replaces the ZEV supply-side policy with a demand-side policy of the same dollar magnitude in the same states. Quantity effects are expressed as percentage changes, aggregated across all model years in the data. Price effects are weighted by observed quantity in the data (akin to a Laspeyres index) and measured in nominal dollars.

For the case where all automakers employ national pricing, price and quantity results are presented in Table E.16.

Table E.16: Dollar-equivalent counterfactual: price and quantity effects, national pricing

Vehicle	Region	Change in quantity (%)	Change in quantity	Change in price (%)
Tesla	ZEV	78.2%	68,800	-5.1%
Tesla	Non-ZEV	-66.2%	-44,000	8.1%
Other EV	ZEV	54.6%	77,000	-9.4%
Other EV	Non-ZEV	-52.3%	-40,700	16.0%
Non-EV	ZEV	-0.6%	-151,900	0.1%
Non-EV	Non-ZEV	0.2%	118,900	0.0%

Note: This table shows the simulated price and quantity effects, under a national-pricing supply side, of the first counterfactual, which replaces the ZEV supply-side policy with a demand-side policy of the same dollar magnitude in the same states. Quantity effects are expressed as percentage changes, aggregated across all model years in the data. Price effects are weighted by observed quantity in the data (akin to a Laspeyres index) and measured in nominal dollars.

Table E.17 shows the price and quantity effects of the budget-balanced counterfactual policies.

Table E.17: Budget-balanced counterfactual: price and quantity effects

		Relative to observed		Relative to budget-balanced ZEV	
Vehicle	Region	%Δ Quantity	%Δ Price	%Δ Quantity	%Δ Price
Tesla	ZEV	46.9%	-1.8%	46.7%	-1.8%
Tesla	Non-ZEV	-74.0%	5.6%	-73.8%	5.6%
Other EV	ZEV	-29.3%	7.1%	-29.2%	6.9%
Other EV	Non-ZEV	1.2%	0.0%	1.1%	0.0%
Non-EV	ZEV	-0.3%	0.1%	0.2%	0.0%
Non-EV	Non-ZEV	0.0%	0.0%	0.0%	0.0%

Note: This table shows the simulated price and quantity effects under the second counterfactual, which replaces the ZEV (supply-side) policy with a consumer subsidy and tax in the same states, constrained to attain the same total EV sales in the regulated states and to achieve budget balance. Quantity effects expressed as percentage changes, aggregated across all model years in the data, relative to (1) a counterfactual budget-balanced supply-side (ZEV) policy, and (2) observed data. Price effects use the same comparisons, are weighted by observed quantity in the data (akin to a Laspeyres index), and are measured in nominal dollars.

For the case where all automakers employ national pricing, the effects of the budget-balanced counterfactual policies are presented in Table E.18.

Table E.18: Budget-balanced counterfactual: price and quantity effects, national pricing

		Relative to observed		Relative to budget-balanced ZEV	
Vehicle	Region	%Δ Quantity	%Δ Price	%Δ Quantity	%Δ Price
Tesla	ZEV	9.6%	-0.7%	9.7%	-0.7%
Tesla	Non-ZEV	-62.6%	7.2%	-62.6%	7.2%
Other EV	ZEV	-6.0%	1.8%	-6.1%	1.8%
Other EV	Non-ZEV	-50.6%	15.3%	-50.6%	15.3%
Non-EV	ZEV	-0.4%	0.1%	-0.2%	0.1%
Non-EV	Non-ZEV	0.2%	0.0%	0.3%	-0.1%

Note: This table shows the simulated price and quantity effects under the second counterfactual, which replaces the ZEV (supply-side) policy with a consumer subsidy and tax in the same states, constrained to attain the same total EV sales in the regulated states and to achieve budget balance. All firms are assumed to set nationally standardized prices. Quantity effects expressed as percentage changes, aggregated across all model years in the data, relative to (1) a counterfactual budget-balanced supply-side (ZEV) policy, and (2) observed data. Price effects use the same comparisons, are weighted by observed quantity in the data (akin to a Laspeyres index), and are measured in nominal dollars.