Regulatory Mandates and Electric Vehicle Product Variety*

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February 23, 2022

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Abstract

When should policies to encourage new types of products use supply-side tools, like regulations and mandates, and when should they use demand-side tools like consumer incentives? When prices are set nationally but policy varies by state, supply-side and demand-side tools are no longer equivalent. We study an important state-level supply-side policy in the early electric vehicle industry: the zero-emission vehicle mandate in California and nine other states. Focusing on the 2009–17 period, we examine two channels for policy effects: imperfect competition and endogenous product entry. Using a structural model of new vehicle pricing, demand, and product entry, we compare the mandate to a counterfactual demand-side policy that instead uses a consumer subsidy and tax. Holding fixed the regulator's stated target, electric vehicle sales in regulated states, the demand-side policy creates a weaker incentive for socially beneficial product entry and generates lower consumer and total surplus. When fewer products are introduced, producers avoid entry costs, but forego long-run benefits of entry.

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*We are grateful to our advisors (Pinter: Ariel Pakes, Robin Lee, and Dennis Yao; Armitage: Joseph Aldy, Edward Glaeser, Robin Lee, and James Stock) for their support and guidance. We also thank Jeff Gortmaker, Myrto Kalouptsidi, Stephanie Kestelman, Jing Li, Erica Moszkowski, Charles Murry, Mathias Reynaert, Gregor Schubert, Elie Tamer, Tom Wollmann, Ron Yang, Anthony Yu, and David Zhang; participants at the Harvard Industrial Organization and Environmental Economics workshops and 2019 Harvard Environmental Economics Program conference; and three industry experts. Armitage gratefully acknowledges financial support from the NBER Pre-Doctoral Fellowship in Energy Economics and the Joseph Crump Fellowship at Harvard University.

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1 Introduction

Policymakers seeking to encourage sales of environmentally friendly products face a choice of which tools to use: supply-side tools, which use regulations and mandates to alter the incentives to produce goods, and demand-side tools, which use subsidies and taxes to alter consumer incentives to purchase goods. Policymakers seeking to encourage new types of products, particularly alternative fuel vehicles, have adopted both types of tools, sometimes at the same time.

Standard theory predicts that supply-side and demand-side tools are typically equivalent if the policy covers the entire market. In the United States, however, environmental policy is increasingly made at the state level, while product markets are nationally integrated.[1] In an industry in which firms set national prices, state-level demand-side tools generate price variation across regions, while state-level supply-side tools do not. As a result, the two tools generate different firm incentives, producing different markups over marginal cost and different incentives for product entry. The effects on consumer, producer, and total welfare will then differ.

We study the electric vehicle industry between 2009 and 2017, and a prominent state-level supply-side policy that shaped it: the zero-emission vehicle (ZEV) mandate adopted by California and nine other states. The mandate required the largest automakers to meet a quota of electric vehicles of 0.4–1.5% of their statewide sales. To obtain credit toward the quota, the automaker could sell electric vehicles in the state or buy credits from other automakers. The goal of the mandate was to induce sales of electric vehicles to reach mass-market quantities, and particularly to encourage the entry of electric vehicles. During this period, 18 electric vehicle models were introduced in the US, and policymakers and some industry observers credited the ZEV mandate for much of this entry. Against this policy background, we investi-

[1] See, e.g., "Can America's Blue States Tackle Climate Change on Their Own?" (Jonathan Eyer and Matthew E. Kahn, Harvard Business Review, 6/6/17).

gate the consequences of policymakers' choice to use a mandate rather than rely on demand-side policies, focusing on pricing in oligopoly and product entry.

Our study of product entry builds on the established theoretical result that imperfectly competitive product markets can feature more or fewer products than the social optimum, because firm gains from product introduction come partly at the expense of other firms (the business stealing effect of Mankiw and Whinston (1986)) and do not include the inframarginal consumer surplus from added product variety (Spence 1976). Policies that subsidize consumers or producers based on quantity will exacerbate both effects. Using a model of consumer demand and firm profits, we quantify the magnitudes of the effects on competitors' profits, on consumers, and on environmental damages under both the existing policy and a counterfactual demand-side policy.[2]

We begin by showing descriptive evidence that the ZEV mandate has induced product entry, by identifying a set of electric vehicle models that are sold primarily in states with the mandate and not in other states. We document that electric vehicle models designed on existing vehicle platforms were sold in low quantities and almost entirely in states with the mandate. By contrast, most models that were designed from the ground up as an electric vehicle sold in larger quantities across the US.

To analyze social welfare and the incentives facing manufacturers, we estimate a model of consumer demand and producer price-setting in the market for new passenger vehicles in the United States from 2009 to 2017. We adopt a Berry, Levinsohn, and Pakes (1995)-style model of discrete choice demand, with differentiated products and heterogeneous consumer tastes, and Bertrand competition with multiproduct firms. We adapt the standard model to account for nationwide pricing and heterogeneity across states in environmental regulation. The estimated model parameters

[2] Even a policy directly targeting the environmental externality, such as a carbon tax, may have ambiguous welfare effects when markets are imperfectly competitive and entry is endogenous (Fowlie, Reguant, and Ryan 2016).

deliver estimates of markups over marginal cost and consumer surplus, and predict how these quantities change if products are not introduced. Combining these components using a static entry model, we compare the private benefits and social welfare effects of product entry, accounting for the effect on competitors, consumer benefits from variety, and environmental effects. We find that the social benefits of product entry for electric vehicles are positive and substantial: the gain from inframarginal consumers' tastes for variety exceeds the negative effect on competitor profits and dwarfs the short-run environmental effects. If firms place a high value on regulatory credits, the mandate can allow firms to capture up to half of these social benefits. To complete the welfare analysis, we use accounting estimates of the upfront cost of entry and observed entry behavior to estimate the benefits of product introduction that firms anticipate to capture in the long run, beyond the end of our study period.

We then simulate a counterfactual demand-side policy that replaces the ZEV mandate with a budget-neutral combination of a consumer subsidy for electric vehicles and consumer tax on non-electric vehicles. Without any change in the product set, the policy results in \$1.4 billion lower consumer surplus and \$570 million higher producer surplus across the nationwide market for new vehicles. We then simulate the effect on product entry, accounting for the possibility of multiple equilibria. Across a range of entry scenarios, firms capture less of the social benefits of product entry under the demand-side policy. Allowing product entry to respond exacerbates the effect on consumer surplus, by reducing product variety: across entry scenarios, consumer surplus is between \$1.8 billion and \$1.4 billion lower under the demand-side policy. The effect on producer surplus is ambiguous, because of avoided upfront cost and foregone long-run benefits: between \$420 million and \$680 million higher. Because of the low sales of electric vehicles in this period, the environmental effects of both policies are small. These results imply that, though a mandate can induce producers to incur greater entry costs, it can also encourage product variety from which consumers benefit. Our results suggest that state-level and national policymakers seeking to encourage the development and adoption of nascent socially beneficial products face different problems, and the choice of policy tool matters for state-level policy in ways that would not matter for national policy.

1.1 Literature

Industry observers have claimed that the ZEV mandate was influential in automakers' decisions to introduce electric vehicles,[3] but the literature on the effects of electric vehicle policy has focused on other policies. This literature (reviewed most recently in Rapson and Muehlegger (2021)) has quantified the effects of purchase subsidies (Tal and Nicholas 2016; Jenn, Springel, and Gopal 2018; Muehlegger and Rapson 2018; Muehlegger and Rapson 2020; Remmy 2020; Xing, Leard, and Li 2021); public and private investment in complementary infrastructure, particularly charging stations (Li 2019); and a combination of both (Li, Tong, Xing, and Zhou 2017; Zhou and Li 2018; Springel forthcoming). Two exceptions are Holland, Mansur, and Yates (2021), which evaluates a hypothetical cap-and-trade system to limit sales of gasoline vehicles over a long horizon, and Cole, Droste, Knittel, Li, and Stock (2021), which evaluates a hypothetical future national ZEV mandate.

To our knowledge, this paper is the first systematic welfare analysis of the ZEV mandate. 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).

Our study of the ZEV mandate broadens an extensive literature on the effects of supply-side environmental policies in the automobile industry, which has focused pri-

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

marily on fuel economy standards like the Corporate Average Fuel Economy (CAFE) and state and federal greenhouse gas standards. Like the ZEV mandate, fuel economy standards simultaneously target pollution externalities (for which they are less efficient than a fuel tax (Sallee 2011b)) and market failures that result in too little innovation in equilibrium (Jaffe, Newell, and Stavins 2005). Unlike policies that target electric vehicles, which operate by supporting entirely new types of products, fuel economy standards operate by altering the mix of existing product types and encouraging improvements to existing technologies. This literature has documented effects of fuel economy 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).

The closest work to ours in the fuel economy standards literature is Durrmeyer and Samano (2018), which contrasts supply-side fuel economy standards and purchase subsidies within a structural model of demand and supply. In their model, a standard that operates firm-by-firm induces a different shadow cost of regulation at each firm, while a purchase subsidy equalizes shadow costs across firms. Standards with credit trading among firms, like CAFE since 2011, are equivalent to purchase subsidies in their setting.

Other work has examined the effects of purchase subsidies, particularly for hybrid vehicles in the early 2000s (Sallee 2011a; Beresteanu and Li 2011) and consumer subsidies and taxes to encourage fuel efficiency (Durrmeyer and Samano 2018; Durrmeyer forthcoming). Sallee (2011a) documents a difference between national demand-side and supply-side subsidies for the second-generation Toyota Prius, and argues for a mechanism based on dynamics in consumer perceptions.

Our study of the interaction between state-level policy and national prices connects to a literature on uniform pricing across markets, which has largely examined retail chains. This literature has shown that uniform 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).

In studying the effect of regulatory mandates on the variety of products available in the market in equilibrium, we relate regulatory policy to a literature on the determinants of equilibrium product variety and welfare effects of changes in product variety, both theoretical (Spence 1976; Mankiw and Whinston 1986) and empirical (Eizenberg 2014; Berry, Eizenberg, and Waldfogel 2016; Wollmann 2018; Fan and Yang 2020; Brand 2020). Like Petrin (2002), we measure how much of the social surplus created by new products is captured by firms.

Our computations of environmental damages build on a literature comparing the emissions of electric vehicles to those of their closest gas-powered substitutes (Holland, Mansur, Muller, and Yates 2016; Holland, Mansur, Muller, and Yates 2020; Muehlegger and Rapson 2020; Xing, Leard, and Li 2021), which has generally found that, during the early 2010s, electric vehicle adoption had a small effect on short-run pollution damages, and in some regions worsened them. Of these, Xing, Leard, and Li (2021) also uses a random coefficients discrete choice model to study the consequences of substitution between electric and non-electric vehicles.

2 Institutional background

We study the period covered by model years 2009 to 2017, which saw the introduction of the first generation of commercially available electric vehicles (EVs) in the US. Most major automakers in the US introduced an electric vehicle during the period, but models varied widely in engineering characteristics and in sales levels. Table 1 shows selected data for the models available in the US in this period, including the timing of product introduction, sales in the study period, manufacturer suggested retail price, and battery range.

The first generation of models fell mainly into two groups: models that were designed from the ground up to be electric vehicles (called "native" within the industry) and models that used existing platforms from gas-powered vehicles ("non-native"). The native vehicles received upgrades during our study period, with longer ranges and increased efficiency, and usually had high sales. The non-native electric vehicles were typically not upgraded, typically had low sales, and dropped out of the market by 2021. (The one exception is the BMW i3, a low-sales model whose platform was designed from the ground up to support electric and plug-in hybrid versions.)

Native electric vehicle platforms offer a superior combination of engineering characteristics, but cost more to develop and require dedicated production lines. In particular, 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 a internal combustion engine.[4] Reasons manufacturers gave for opting for non-native electric vehicles included the lower upfront cost and the flexibility from making gas-powered and electric vehicles on the same production line.[5] Non-native models also adopted the branding and design of the gas-powered vehicles they were based on.

The timing of the first generation of commercially available electric vehicles, most of which entered the US market between 2010 and 2015, has been attributed to rapid cost declines in lithium ion batteries driven by consumer technology applications, such

[4]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).

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

as laptops and phones. Compared to nickel-metal hydride batteries, used in the late 1990s and early 2000s by the Toyota Prius and the short-lived GM EV1, lithium ion batteries offer much more usable charge for the same amount of weight, allowing for a longer electric range, and can charge and discharge more quickly.[6] Tesla engineers have been credited with demonstrating that lithium ion batteries were feasible for electric vehicle applications.[7]

In this paper, we classify the major passenger vehicles available in this period into four technology types: conventional gas-powered vehicles with combustion engines (including flex-fuel ethanol); hybrids, which combine a combustion engine with a battery pack that cannot be charged externally; plug-in hybrids, whose battery packs are larger and can be charged externally; and battery electric vehicles. (Less commonly used technologies for passenger vehicles in this period include diesel, natural gas, and hydrogen.) Industry sources sometimes refer to plug-in hybrids and battery electric vehicles collectively as plug-in vehicles.

2.1 Policy of interest: ZEV mandate

The Zero Emission Vehicle (ZEV) mandate, adopted by California and nine other states,[8] requires the largest automakers to sell a quota of non-fossil-fuel ("zero emission") vehicles, nearly always battery electric vehicles.[9] Each manufacturer's quota is based on a moving average of its past sales of non-electric vehicles in California, and manufacturers can trade credits with each other and bank credits for later use. Industry observers have claimed that some low-sales electric vehicles, dubbed 'compliance cars', entered the market primarily to comply with the ZEV mandate. In our study period, six manufacturers faced the ZEV quota: Chrysler, Ford, GM, Honda,

[6] See "Car Industry: Charging up the Future" (Jeff Tollefson, Nature, 11/26/08).

[7] See "Plugged In" (Tad Friend, The New Yorker, 8/17/09).

[8] New York, Massachusetts, Vermont, Maine, Connecticut, Rhode Island, Oregon, New Jersey, and Maryland (starting 2011).

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

Nissan, and Toyota.

The number of credits earned for a battery electric vehicle is a function of the range the vehicle can travel on a full battery; each manufacturer accumulates credits by selling vehicles, and the manufacturer's credit requirement is a percentage of its statewide sales of non-electric vehicles.[10] For example, in California in model year 2017, Nissan earned three credits for each sale of the Leaf electric vehicle and faced a quota of 3,800 credits (3% of its California sales volume of 127,800), which translated to a quota of 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, it could have drawn on its bank of 50,800 credits or purchased credits from another manufacturer.)

If an automaker missed its quota in any given year, it has two years to make up the deficit. After that point, in order to return to compliance, it is required to pay a penalty of $5,000 per credit and also make up the deficit.[11]

In this period, the requirement did not strictly apply state-by-state, but instead allowed each state's quota to be met with vehicles sold in any of the regulated states. This rule, called the travel provision, allowed automakers to earn credits in all regulated states for a sale in any of them. As a result, automakers could (and often did) meet their requirements only by selling vehicles in California, which had the largest population of the participating states, better charging infrastructure, and generous government subsidies to consumers.

In addition to the mandate on zero emission vehicles, the ZEV program included a mandate on clean gasoline vehicles, hybrids, and plug-in hybrids, collectively dubbed Partial Zero Emission Vehicles (PZEVs). The mandate applied to automakers that

[10] Statewide sales of non-electric vehicles are constructed as a moving average of past years; see Section A.1 for details.

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

faced the ZEV mandate and an additional group of mid-sized automakers.[12] The ZEV and PZEV mandates were not entirely separate, as excess ZEV credits could count toward the PZEV credit requirement. Nonetheless, each manufacturer's sales of hybrids and clean gasoline vehicles each year was well over PZEV requirements, and there was little trading of PZEV credits among manufacturers. As a result, we assume that the Partial Zero Emission Vehicle mandate was not a binding constraint on any automaker.

Amendments to make the program stricter were announced in 2012 and took effect in model year 2018. The most important changes to the ZEV mandate were to reduce the number of credits earned per vehicle, add to the list of manufacturers who faced the ZEV quota,[13] and replace the travel provision with a cross-state transfer mechanism that did not allow double-counting. In addition, the PZEV mandate was restricted to plug-in hybrids only. Manufacturers anticipating stricter post-2018 regulation may have earned surplus credits before 2018 in order to bank them.

Section A.1 describes the rules of the ZEV mandate in greater detail.

2.2 Cost structure of electric vehicles

Electric vehicles have higher marginal costs than gas-powered vehicles, but the difference is falling throughout the period. Upfront costs of new native models are comparable to those of new gas-powered models, while upfront costs of non-native models are relatively low.

The marginal cost of a vehicle consists primarily of the labor and parts involved in assembly. Although electric vehicles have simpler powertrains than gas-powered vehicles, the resulting savings are dwarfed by the per-vehicle cost of the battery pack.[14]

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[12] 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).

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

[14] See "Making electric vehicles profitable" (Yeon Baik, Russell Hensley, Patrick Hertzke, and

This difference changed over time, however, as cost of a battery pack of a fixed size fell rapidly through this period. Figure 4 shows estimates of industry averages from BloombergNEF, which show a decline of 80% (in real terms) from 2011 to 2018.[15]

The upfront costs of introducing a new vehicle include the design of the vehicle platform, body, and powertrain; the engineering work required to pass safety tests and improve driver comfort; research and development; and the costs of retooling production lines. Industry estimates of the magnitude of these costs are around $1 billion for native electric vehicles, and $100–$400 million for non-native electric vehicles.

The upfront cost of a new gas-powered model and platform is at least $1 billion, and as high as $6 billion if the engine and transmission are also new.[16] Examining only redesigns of existing vehicle models, Blonigen, Knittel, and Soderbery (2017) estimate redesign costs ranging from $850 million to $3 billion, depending on vehicle class.[17]

Publicly available engineering estimates also put the upfront cost of a native electric vehicle near $1 billion.[18] In addition to final assembly, most electric vehicle makers, native and non-native, make the battery pack and motor in-house. Manufacturers vary in their choices to make or buy the other components.[19] Because electric vehicles are mechanically simpler than internal combustion engines, requiring fewer parts and fewer assembly steps, the cost of developing a powertrain and setting up

Stefan Knupfer, McKinsey, 3/8/19), which breaks down the difference in average cost.

[15]Estimates from other sources are roughly similar; see Nykvist and Nilsson (2015) and Ziegler and Trancik (2021) for comparisons.

[16]See "Why Does It Cost So Much For Automakers To Develop New Models?" (Terry Shea, Translogic, 6/27/10).

[17]Wollmann (2018) estimates sunk costs for commercial trucks using entry and exit behavior and finds much smaller amounts ($5 to $25 million). New truck models are usually adaptations of existing models and require less design work than new car models.

[18]See, for example, "Making electric vehicles profitable" (Yeon Baik, Russell Hensley, Patrick Hertzke, and Stefan Knupfer, McKinsey, 3/8/19), which compares the fixed costs of native and non-native electric vehicles.

[19]See "Trends in electric-vehicle design" (Mauro Erriquez, Thomas Morel, Pierre-Yves Moulière, and Philip Schäfer, McKinsey, 10/25/17).

production may be lower compared to a gas-powered vehicle.

According to engineering estimates, the upfront cost of an electric vehicle built on an existing platform is much lower. We have three accounting estimates: first, the cost of the powertrain for the Toyota RAV4 EV; second, the research and development (R&D) costs and capital investment for the Tesla Roadster (a non-native model which used the Lotus Elise chassis); and third, projections from Ford in 2015 of its future investments in its EV program. These estimates provide only rough guidance — in particular, they are from different times and represent different quantities — but together form an approximate range of reasonable figures, all of them much lower than the $1 billion benchmark for a new gas-powered model. (These figures exclude earlier investments in the vehicle platform when it was only used for gas-powered cars.)

The cost of the powertrain for the Toyota RAV4 EV comes from a contract between Toyota and Tesla from 2010–12, in which Toyota agreed to pay Tesla $60 million to develop the RAV4 EV powertrain.[20] Tesla would then manufacture the powertrain components in its own facilities and ship them to Toyota for final assembly. This suggests that it would have cost Toyota more than $60 million to produce the RAV4 EV powertrain in-house, and provides a lower bound on the total cost to a major automaker of developing a non-native electric vehicle.

The R&D costs and capital investment for the Tesla Roadster prior to its introduction in 2010, as measured by accounting standards, totaled $125 million.[21] Tesla was one of a group of early electric vehicle startups developing non-native vehicles, and the first to sell a highway-capable vehicle to consumers. This estimate of upfront costs includes R&D costs that were likely unnecessary once electric vehicle design was more established, but also excludes the cost of setting up manufacturing beyond the

[20]Source: 2012 Tesla 10-K.

[21]Source: 2010 Tesla 10-K.

initial rate of 50 cars per quarter.[22]

Finally, in 2015, Ford announced it would invest \$4.5 billion between 2015 and 2020 to develop 13 EVs, of which some or all would use existing platforms, in addition to the EV and hybrid program it already had.[23] This translates to an average upfront investment of \$350 million per model.

We argue that it is reasonable to extrapolate these estimates to other non-native electric vehicles in this generation for two reasons. First, general technological improvement over time was mainly in batteries, and so mainly affected marginal cost, not upfront cost. Second, these vehicles all had production volumes below mass-market levels, so manufacturers would have made similar choices for production scale. (Facing a product with a much higher volume, a manufacturer may choose to pay more upfront for optimizations that reduce marginal cost.)

2.3 Descriptive evidence

What is the relationship between the ZEV mandate and product entry? The main distinction that arises from the sales data is between native and non-native electric vehicles, as shown in Figure 1. Between their introduction and model year 2017, non-native EVs had 91% of their sales in states with the mandate; the figure for native EVs was 54%. In addition, except for the BMW i3, native EVs had much higher sales — 15,000 per year or more — while non-native EVs sell between 500 and 5,000 vehicles per year during the study period.

Though the decision to sell a vehicle primarily in states with the mandate suggests that the vehicle was likely not profitable without the mandate, the mandate was not the only difference between these groups of states. States with the mandate had denser charging stations and, often, more generous consumer incentives for EVs. We

[22]See "Tesla Motors Announces 2008 Roadster Production Schedule and Achievement of Critical Milestones on Crash Tests and Range Testing" (press release, 4/20/10).

[23]Source: "Ford Investing \$4.5 Billion in Electrified Vehicle Solutions, Reimagining How to Create Future Vehicle User Experiences" (press release, 12/10/15).

will use the demand model to disentangle the mandate from these factors.

In states with the mandate, did the buyers of native and non-native EVs differ along demographic characteristics? Figure 2 shows data from California buyers of electric vehicles who claimed rebates from the California Vehicle Rebate Program between 2010 and March 2016, grouped into equal-sized bins by census tract median income.[24] (More recent data are difficult to interpret because the program instituted an income requirement in March 2016.) We divide vehicles into non-native, native non-Tesla (predominantly the Nissan Leaf), and Tesla. Though the share of EVs that are non-Tesla and native is roughly the same in higher- and lower-income areas, 47% of the EVs purchased by residents of areas in the lowest-income group (with a median income below $56,000 per year) are non-native. This percentage falls to 20% in the highest-income group, with the difference made up by Tesla vehicles. The difference in Tesla adoption is not surprising — in this period, Tesla prices were $60,000 or more — but the Nissan Leaf and most non-native vehicles were priced similarly in the low $30,000 range. These results suggest that, if the ZEV mandate increased the entry of non-native electric vehicles, the benefits accrued mostly to consumers in lower- and middle-income areas.

3 Data

To study demand, we combine US new vehicle registrations by model and fuel type, product characteristics collected from various sources, and statistics from consumer surveys.

[24]Census tract median income from 2011–15 is drawn from the American Community Survey via the National Historical Geographic Information System (Manson, Schroeder, Van Riper, Kugler, and Ruggles 2020).

3.1 Product characteristics and sales

For sales, we use the universe of US new vehicle registrations in calendar years 2009 through 2017, obtained from IHS Markit (formerly R.L. Polk). This dataset contains the count of registrations for each model year, make, model, fuel type, and state. (In some cases, the dataset is further broken down by trim.) Our data contain both sales and leases; we treat both as sales. We use state-level data for the ten ZEV states, and aggregate the rest of the US into one region for our analysis.

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 manufacturer suggested retail price (MSRP) and technical specifications, including size, horsepower, weight, and battery capacity. 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. In addition, when battery capacity is not provided, we back it out from the federal IRC 30D subsidy amount (if possible) or obtain it from news sources. Like Reynaert (2021), we summarize fuel economy using the dollar cost (at time of purchase) of driving one mile, constructed by combining fuel economy data with average fuel prices by state and year from the US Energy Information Administration.[25] (Except for fuel costs and subsidies, product characteristics are the same across states.)

Our main dataset is restricted to 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

[25]For plug-in hybrids, we weight electric and gas modes using the EPA utility factor.

given market and year was not offered in that market.[26] We restrict to model years 2009 through 2017. (Because we lack sales data before January 2009, we assume that the sales of model year 2009 vehicles in calendar year 2009 are a representative sample of all model year 2009 sales.)

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 lowest-priced trim that accounted for at least 1% of the group's national sales total.

For each vehicle's price to consumers, we use MSRP minus a measure of average manufacturer rebates derived from Automotive News[27] and federal and state government incentives. In the period we study, state government incentives generally went only to electric vehicles, plug-in hybrids, and hybrids; the only relevant federal program was the tax credit for plug-in hybrids and electric vehicles (IRC 30D). The IRS provides the federal tax credit amount for each vehicle model, and we collect state incentive amounts from government websites and the Alternative Fuels Data Center. We use nominal dollars throughout (including for household income, described below).

Table 2 shows summary statistics of our product characteristics data.

[26]This contrasts with Li (2019), who uses more granular markets and thus encounters products that were offered but had zero sales.

[27]We take the maximum consumer rebate observed in each quarter and average across quarters, and ignore manufacturer rebates to dealers. This roughly approximates the findings by Busse, Silva-Risso, and Zettelmeyer (2006) of high pass through for customer rebates and low pass through for dealer rebates. The Automotive News data do not distinguish between national and regional rebates.

3.2 Demographics

Household demographics are taken from American Community Survey microdata for 2009 to 2017.[28] Demographics from a given calendar year t are matched to our market for model year t. The variables we use include income (in nominal dollars), location (Public Use Microdata Area), and college education. We exclude households with income below $10,000. The market size we use is the number of households in each state and year, from American Community Survey 1-year estimates.[29]

The county-level temperature factor demographic, which proxies for consumers' perceptions of the effects of extreme weather on battery performance, uses the formula from Holland, Mansur, Muller, and Yates (2016) and historical temperature data from the North American Land Data Assimilation System (via Holland, Mansur, Muller, and Yates (2016)'s replication files). The temperature factor ranges from 0 to 1; a constant temperature of 68° F yields 1, while a constant temperature of 19.4° F or 116.6° F yields 0.67. Among US counties, the temperature factor ranges from 0.825 (Cavalier County, North Dakota) to 0.993 (Orange County, California).

Micro-moments, which match consumers' observable demographics to their vehicle choices, are drawn from surveys of vehicle purchasers. Data related to consumer location (for California buyers only) are drawn from the California Vehicle Rebate Program's survey of rebate recipients, which matches the make and fuel type of a plug-in hybrid or electric vehicle to the census tract of the buyer. (We only use data before the program introduced an income requirement in March 2016.) Data on the education of electric vehicle buyers is drawn from summary tables in Xing, Leard, and Li (2021), which use the MaritzCX survey of new vehicle buyers.

[28]Data obtained via IPUMS (Ruggles et al. 2019).

[29]Because, on average, 77% of sales in model year t are made in calendar year t, we take the market size for model year 2009 (for which we are missing data from calendar year 2008) to be only 77% of U.S. households in 2009.

3.3 Regulation

We estimate average ZEV credit prices by dividing the quantity of credits sold by Tesla, obtained from state regulators, by the revenue Tesla earned from those sales, as reported in quarterly filings and shareholder letters.[30] This accounts 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 are unable to observe if the price paid per credit varies across buyers. We weight credits from different states equally because they were interchangeable under the travel provision. Table 3 shows our estimates of the prices of ZEV credits, along with Tesla's share of total credit sales in the corresponding period.

The number of ZEV credits earned by each vehicle comes from public data from the California Air Resources Board and New Jersey Department of Environmental Protection.

We estimate the number of greenhouse gas regulation (GHG) credits earned by each vehicle using formulas from the regulation, fuel consumption from FuelEconomy.gov, and vehicle size data from MSN Autos. We assume a constant credit price of $40 per megagram of CO_2, based on estimates summarized in Leard and McConnell (2017). In order to approximate the findings of Leard and McConnell (2017) that Corporate Average Fuel Economy (CAFE) standards were not binding on automakers while the GHG regulation was in effect, we set the CAFE credit price to zero during our study period. Prior to 2012, the GHG regulation applied differently in twelve states (the ZEV states plus Pennsylvania and Washington) than in the rest of the country; given our data limits, we approximate this by modeling GHG as applying only in the ZEV states.

[30]This method has also been used by bloggers and (independently) by McConnell, Leard, and Kardos (2019).

3.4 Environmental damages

We use estimates from prior literature to determine CO_2 emissions per mile for different types of vehicles, and apply a social cost of carbon of $41 per megagram. 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. (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.) We then convert to vehicle emissions using vehicle-specific electricity consumption per mile (in FuelEconomy.gov data). We determine CO_2 emissions per mile from gas vehicles by multiplying gasoline consumption per mile (in FuelEconomy.gov data) by 8887 grams of CO_2 per gallon (from EPA).

Section 4.3 describes how these emissions enter our welfare calculations.

4 Model

We combine a model of pricing and consumer choice each period with a static model of firm product entry decisions. At the beginning of the study period, prior to the entry of electric vehicles in the data, firms simultaneously choose which electric vehicles to enter. Then, in each model year, firms set prices and consumers choose which products to purchase.

To study consumer surplus and substitution among alternatives, we use a random coefficients logit model of consumer demand for automobiles. To estimate marginal costs, we use a Nash–Bertrand pricing model (featuring state-level markets and national pricing), with regulatory credits explicitly included in the profit function.

We also adopt a simple static model of product entry as a framework for measuring private entry incentives and comparing them to social welfare. We later use this model to predict entry under counterfactual policies.

4.1 Demand and pricing

Our analysis is built on a discrete choice model of demand for new vehicles in the vein of Berry, Levinsohn, and Pakes (1995) and Berry, Levinsohn, and Pakes (1999).[31] 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. (The outside good could include driving an existing vehicle for longer, buying a used vehicle, or forgoing car ownership.)

We assume that consumers do not respond to beliefs about future product availability or future changes to product characteristics or prices. We also do not model state dependence: 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 or products with fixed production levels, which would induce unobserved variation in consumer choice sets as products become unavailable to late-arriving consumers. Our method is thus imperfect for Tesla, which used waitlists to manage the combination of high demand and production delays (like the second generation Toyota Prius, as documented in Sallee (2011a)). We do not observe waitlist entries, so our estimates subsume this process in the unobserved characteristic.

Let the set of geographical regions (states) 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. As described in 3.1, products are defined by make, model, technology type, and (within electric vehicles) battery

[31] Papers with similar approaches to estimating automobile demand include Petrin (2002), Remmy (2020), Reynaert (2021), and Grieco, Murry, and Yurukoglu (2021), as well as Li (2019) (who only models the plug-in vehicle market).

size.

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

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

where p_{jt} is the price of product j (set nationally), subsidy_{jmt} is the government subsidy for j in m, x_{jmt} is a vector of observed characteristics, 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 markets. Indirect utility from purchasing the outside good, $j = 0$, is $u_{i0mt} = \varepsilon_{i0mt}$.

We parameterize taste heterogeneity as follows: $\alpha_i = \alpha/y_i$, where α is a parameter and y_i is consumer income;[32] and $\beta_i = \beta + \Pi d_i + \Sigma\nu_i$, where d_i is a vector of observed demographics, $\nu_i \sim N(0, I)$ is a vector of individual taste differences unobserved by the econometrician (independent across consumers and independent of all observed variables), and Π and Σ are matrices of parameters. (We assume that Σ is a diagonal matrix. We also estimate a constrained specification where Σ is set to zero.)

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

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

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

This specification assumes that consumers value a \$1 government subsidy and a \$1 reduction in price equally. This requires that consumers both know about subsidies (subsidies on electric vehicles are typically included in the price dealers advertise) and

[32]This approximation to a Cobb–Douglas-style indirect utility function is taken from Berry, Levinsohn, and Pakes (1999).

believe at the time of purchase that they will be able to take advantage of them.

The product characteristics that enter x_{jmt} are technical characteristics (horsepower-weight ratio, drivetrain), proxies for size (weight, number of doors, wheelbase, footprint), electric range and battery size for electric and plug-in hybrid vehicles, fuel costs per mile, an indicator for the first year a model is available, and fixed effects for fuel type, body style (sedan, SUV, truck, etc.), make, model year, and state.[33] The demographics that enter d_i are a temperature factor capturing the frequency of extreme temperatures and an indicator for college education.

Pricing. We assume prices form a Nash equilibrium of a Bertrand game among multiproduct firms, who set national prices to maximize model-year profits.[34] We build on earlier models of the US auto industry by using market shares for separate geographic regions within the US, and explicitly modeling the effect of state and national regulations on the pricing decision. Our method assumes that marginal costs are the same across regions, so that the profit from a selling a vehicle only varies geographically due to differences in regulation. We assume that marginal costs do not depend on quantity, which rules out capacity constraints.

Consider a firm f with product set $\mathcal{J}_{ft}$. For each product $j \in \mathcal{J}$, 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_t be the vector of prices in year t. The firm's problem is

$$\max_{\{p_{jt}\}_{j\in\mathcal{F}}} \sum_{j\in\mathcal{J}_{ft}} \sum_{m\in\mathcal{M}} (p_{jt} + v_{jmt} - mc_{jt}) s_{jmt}(p_t) M_{mt}, \tag{2}$$

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

[33] Fixed effects for model year and state capture differences in consumer preferences for a new car over time (for example, due to macroeconomic shocks) and across states.

[34] See Appendix A.2 for evidence that national pricing is an appropriate model of the industry.

with respect to p_{jt} is

$$0 = \sum_{m \in \mathcal{M}} \left(s_{jmt} + \sum_{k \in \mathcal{J}_{ft}} (p_{kt} + v_{kmt} - mc_{kt}) \frac{\partial s_{kmt}}{\partial p_{jt}} \right) M_{mt}. \tag{3}$$

Under these assumptions, the equilibrium price vector p_t is the joint solution to all firms' first order conditions.

Regulation. Selling an additional vehicle changes the firm's credit holdings under various national and state regulations, which we model using the v_{jmt} term in the profit function. Specifically, selling an alternative fuel vehicle may earn credits under the greenhouse gas (GHG) and ZEV regulations, while selling a gas vehicle may increase the firm's total regulatory requirement. When the regulations are binding upon firms (that is, when credits have non-zero value) 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 3.3. 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.[35] If firms are certain about future credit prices, the mandate will operate as a producer subsidy and tax; with uncertainty, the results will generally differ (as in Weitzman (1974)). We only consider scenarios in which firms are certain about credit prices.

Specifically, we consider two regulations, greenhouse gas (GHG) and ZEV.[36] Consider product j in region m and model year t.

From the details of the regulation we obtain $c_{jmt,GHG}$ and $c_{jmt,ZEV}$, the net change in credits from selling one unit of j. To determine $c_{jmt,GHG}$, we take the difference

[35] In reality, the credit trading market is characterized by one large seller (Tesla, with 83% of sales) and a handful of buyers, including Toyota (37%), Ford (20%) and Fiat Chrysler (14%). We abstract away from the modeling issues that market power may present.

[36] As described in section 3.3, we assume that CAFE standards were not binding in this period because of federal greenhouse gas regulation.

between the vehicle's statutory emissions and its 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. For electric vehicles in ZEV states, $c_{jmt,ZEV}$ is the number of credits earned (generally a function of electric range). For non-EVs sold by large manufacturers in ZEV states, $c_{jmt,ZEV}$ is the additional number of credits that must be surrendered when a non-EV is sold.[37]

Now let $r = (r_{mt,GHG}, r_{mt,ZEV})$ be the vector of credit values on the two credit markets. (When a regulation does not apply, such as ZEV outside of states with the mandate, we set this to zero.) Then the net value of regulatory credits earned from selling an additional unit of j in region m and model year t is

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

4.2 Static product entry model

We examine entry incentives using a static model in which a firm compares an upfront entry cost to two types of benefits: variable profit until some fixed date and a term capturing the the long-run benefit of entry. We apply this framework to firm decisions to introduce electric vehicles, with non-electric vehicle offerings by that firm and by other firms held fixed. We later use the conditions for equilibrium in the model and the observed pattern of entry, together with accounting data on entry cost, to estimate lower bounds on the long-run benefit of electric vehicle entry. We then use this model to predict electric vehicle entry under counterfactual policies and determine the contribution of entry costs and benefits to welfare.

We use a static model of simultaneous product introduction decisions to capture the generational nature of electric vehicle development. Most electric vehicles in-

[37]In our model, the number of credits a regulator requires the manufacturer to surrender is a fixed percentage of its non-EV sales that year in ZEV states. In practice, the number is a fixed percentage of a moving average of California non-EV sales in prior years, as detailed in Section A.1.

troduced during our study period were the outcome of development programs that started in the early 2000s. According to industry experts, early engineering decisions constrained the characteristics of these vehicles. Few automakers devoted resources to producing more than one EV at a time, and second-generation EVs only entered the market starting in 2017. Therefore, we consider it unlikely that firms chose the timing of product introduction or adjusted their decisions significantly after observing other firms' decisions.[38]

The entry cost captures the upfront investments that must be made when developing a new model, as described in Section 2.2. These include research and development, design, production line setup, and compliance with government safety standards.

The long-run benefit of entry captures variable profit after the end of our study period, spillovers across projects within a firm, and the scrap value when the product exits. In rapidly developing technologies like electric vehicles, investments in early projects may lower the entry costs of later products. In addition, introducing a product in the US may lower that product's entry costs in non-US markets.

Both the long-run benefit and the entry cost are allowed to vary across products, but do not depend on quantity or on the product set in the study period. As a result, the expected long-run benefit does not capture quantity-based outcomes, like learning by doing, or the effect of entry decisions on competition in later periods.[39]

By assuming observed entry decisions form a pure strategy Nash equilibrium of the product entry game, we obtain an upper bound on each product's entry cost net of long-run benefit. This bound is not sharp: we only consider the condition that no firm can profitably deviate by removing an electric vehicle from its product set, ignoring deviations that remove multiple EVs by the same firm (for the few firms

[38]Our setting contrasts with the modular truck manufacturing studied by Wollmann (2018), in which new product introduction only requires relatively minor, well-defined changes to existing products, and thus can be done quickly.

[39]For example, our model does not capture mechanisms by which first-generation product introduction, by lowering future costs, can induce greater concentration in later generations (Dasgupta and Stiglitz 1988).

with more than one electric vehicle) or alter offerings of non-electric vehicles.

In order to combine these bounds with accounting data on entry cost, we assume that all non-native EVs have the same ratio of long-run benefit to entry cost. This assumption captures that higher upfront investment in first-generation EVs may translate to larger cost savings in future generations of electric models.[40]

The timing of the model is as follows. Firms simultaneously decide at the beginning of the study period which electric vehicles to introduce, products enter and exit on known and fixed timelines, and profits are collected from entry until exit or the end of the study period. Specifically, each firm begins the study period with a (possibly empty) set of potential electric vehicle products. At $t = 0$, each firm chooses which electric vehicles to introduce, and pays an entry cost for each introduction. Then, in each period $t = 1, \ldots, T$, products enter and exit according to their fixed timelines, firms set prices conditional on the product set, and firms collect variable profits. At the end ($t = T$), each firm collects the long-run benefit for each electric vehicle it introduced.

All firms share an information set $\mathcal{I}_0$ at $t = 0$. There is no private information, and all unknown variables are revealed to firms at the beginning of $t = 1$. Across all specifications, $\mathcal{I}_0$ includes the observable characteristics, marginal costs, and entry and exit timeline of all potential products, all of which are exogenously determined.[41] By treating each product's entry and exit timeline as fixed and known to the firm when it makes the entry decision, we rule out a product exiting during the study period in response to an unexpected shock. For products that were not sold in every state, we also treat the state-level pattern of entry as fixed.

In our main specification, $\mathcal{I}_0$ does not contain product quality ξ. Firms instead

[40] In a different setting, Wollmann (2018) models the scrap value of product exit as proportional to the sunk cost of entry.

[41] The assumption that firms are fully informed about marginal costs is a departure from prior literature (e.g., Wollmann (2018)). According to industry experts, firms believed in 2009 that battery prices were going to fall, though they may have disagreed on how quickly.

form expectations of profits using the unconditional distribution of ξ across products. (In our alternative specification, $\mathcal{I}_0$ contains product quality.)

In our model, firms have the same belief about the time path of credit prices r, and we examine three scenarios for beliefs. In all scenarios, firms are fully certain about credit prices (even if incorrect ex post). This is a simplification, because credit prices clear a market whose supply and demand sides both depend on vehicle sales, and thus depend on the realization of ξ. We adopt this approach because firm valuations of credits depend on beliefs about the long-run trajectory of sales and future ZEV policy, which we do not observe. (Unfortunately, this also means we cannot model the effect of product entry decisions on credit prices. Instead, we assume that removing one product from the product set does not change credit prices.) We look at three scenarios for the ZEV component of r: no ZEV mandate ($r_{mt,ZEV} = \$0$), the observed realization of $r_{mt,ZEV}$, and a scarce-credit scenario ($r_{mt,ZEV} = \$5000$). In all scenarios, we assume the credit price for GHG remains fixed at \$40 per megagram of CO_2.

Variable profits. Variable profits are obtained from the per-period profit function (2), which explicitly accounts for the effects of product entry on other products by the same firm. Let $\mathcal{J}_{ft}$ be the set of products by firm f in period t and let $\mathcal{J}_{-f,t}$ be the set of products by other firms. Then variable profit for firm f in period t is

$$\pi_{ft}(\mathcal{J}_{ft}, \mathcal{J}_{-f,t}) = \sum_{j \in \mathcal{J}_{ft}} \sum_{m \in \mathcal{M}} (p^*_{jt}(\mathcal{J}_{ft} \cup \mathcal{J}_{-f,t}) + v_{jmt} - mc_{jt}) s_{jmt}(p^*_t(\mathcal{J}_{ft} \cup \mathcal{J}_{-f,t})) M_{mt},$$

where $p^*_t(\mathcal{J}_{ft} \cup \mathcal{J}_{-f,t})$ is the Nash equilibrium of the pricing game given the product set.

We will adopt the following notation to make exposition of the product entry model simpler. Write firm f's product set across all periods as $\mathcal{J}_f = \bigcup_{t=1,\ldots,T} \mathcal{J}_{ft}$ and the set of other firms' products across all periods as $\mathcal{J}_{-f} = \bigcup_{t=1,\ldots,T} \mathcal{J}_{-f,t}$. Then write the present discounted value of variable profit as

$$\pi_f(\mathcal{J}_f, \mathcal{J}_{-f}) = \sum_{t=1}^{T} \delta^t \pi_{ft}(\mathcal{J}_{ft}, \mathcal{J}_{-f,t})$$

and its expectation as $\overline{\pi}_f(\mathcal{J}_f, \mathcal{J}_{-f}) = E[\pi_f(\mathcal{J}_f, \mathcal{J}_{-f}) \mid \mathcal{I}_0]$. Now, write the present discounted value of the incremental variable profit from introducing product j as $\Delta_j \pi_f(\mathcal{J}_f, \mathcal{J}_{-f})$:

$$\begin{aligned}
\Delta_j \pi_f(\mathcal{J}_f, \mathcal{J}_{-f}) &= \begin{cases} \pi_f(\mathcal{J}_f, \mathcal{J}_{-f}) - \pi_f(\mathcal{J}_f \setminus \{j\}, \mathcal{J}_{-f}), & j \in \mathcal{J}_f \\ \pi_f(\mathcal{J}_{ft} \cup \{j\}, \mathcal{J}_{-f,t}) - \pi_f(\mathcal{J}_f, \mathcal{J}_{-f}), & j \notin \mathcal{J}_f \end{cases} \\
&= \begin{cases} \sum_{t=1}^{T} \delta^t \left(E[\pi_{ft}(\mathcal{J}_{ft}, \mathcal{J}_{-f,t}) - \pi_{ft}(\mathcal{J}_{ft} \setminus \{j\}, \mathcal{J}_{-f,t}) \mid \mathcal{I}_0] \right), & j \in \mathcal{J}_f \\ \sum_{t=1}^{T} \delta^t \left(E[\pi_{ft}(\mathcal{J}_{ft} \cup \{j\}, \mathcal{J}_{-f,t}) - \pi_{ft}(\mathcal{J}_{ft}, \mathcal{J}_{-f,t}) \mid \mathcal{I}_0] \right), & j \notin \mathcal{J}_f \end{cases},
\end{aligned}$$

and its expectation as $\Delta_j \overline{\pi}_f(\mathcal{J}_f, \mathcal{J}_{-f}) = E[\Delta_j \pi_f(\mathcal{J}_f, \mathcal{J}_{-f}) \mid \mathcal{I}_0]$.

Payoff from entry. The payoff to firm f is the sum of variable profits until T and, for each product the firm introduces, the product's long-run benefit net of entry cost. For each product j, let $SC_j \geq 0$ be entry cost and $\delta^{-T} \pi_j^0 \geq 0$ be the expected long-run benefit collected at T. (The value of this benefit at $t = 0$ is therefore π_j^0.) Both terms are fixed and do not depend on firm actions or the actions of other firms. Summing these components, we arrive at the total payoff.

Assumption 1 *Firm f's total expected payoff, given $\mathcal{J}_f$ and $\mathcal{J}_{-f}$, is*

$$\overline{\pi}_f(\mathcal{J}_f, \mathcal{J}_{-f}) + \sum_{j \in \mathcal{J}_f} \left(\pi_j^0 - SC_j \right).$$

Now we examine $\mathcal{J}_f$ as (pure strategy) Nash equilibrium play in the simultaneous-move product entry game. In equilibrium, no firm expects removing any one EV from its product set to be a profitable deviation. Therefore, if the firm's product set includes product j in equilibrium, the sum of its incremental variable profit and long-run benefit must be larger than its entry cost.

Proposition 1 *Suppose a pure strategy Nash equilibrium of the product entry game exists. Let firm f's product set in this equilibrium be $\mathcal{J}_f$. Then for each $j \in \mathcal{J}_f$,*

$$\Delta_j \overline{\pi}_f(\mathcal{J}_f, \mathcal{J}_{-f}) + \pi_j^0 - SC_j \geq 0.$$

We will call $\Delta_j \overline{\pi}_f(\mathcal{J}_f, \mathcal{J}_{-f}) + \pi_j^0 - SC_j$ the private entry incentive.

As described in Section 7.2, we use this condition to obtain an upper bound on the net entry cost, $SC_j - \pi_j^0$, for each non-native EV that entered. We use a proportionality assumption in order to interpret the net entry cost using industry estimates of SC_j.

Assumption 2 *There exists κ such that for all non-native EVs j, $\pi_j^0 / SC_j = \kappa$.*

We therefore write the net entry cost as $(1 - \kappa)SC_j$, and the private entry incentive as $\Delta_j \overline{\pi}_f(\mathcal{J}_f, \mathcal{J}_{-f}) - (1 - \kappa)SC_j$.

4.3 Social welfare

We use a social welfare function to evaluate the effects of policy changes and to compare the equilibrium of the product entry game to the socially efficient pattern of entry. Total welfare combines consumer surplus, environmental effects, and producer surplus (which itself combines variable profit, long-run benefit, and entry cost).

When calculating producer surplus, we depart from the variable profit defined in Section 4.1 by excluding the value of regulatory credits. A credit is not a socially useful asset, only a mechanism for firms to internalize environmental externalities that we have already accounted for.

For the exposition that follows, we define present discounted values based on a discount factor δ and a time period $t = 1, \ldots, T$, and condition on the full product set $\mathcal{J} = \{\mathcal{J}_f\}_f$. When taking to data, we use $\delta = 1$ and time periods corresponding to model years 2009 through 2017.

Welfare is broken into consumer surplus, producer surplus, and environmental damages. Let $CS(\mathcal{J})$ be the present discounted value of consumer surplus and let $Env(\mathcal{J})$ be the present discounted value of negative environmental damages. The present discounted value of producer surplus, denoted $PS(\mathcal{J})$, is defined as follows. As in Section 4.2, let $\pi_f(\mathcal{J}_f, \mathcal{J}_{-f})$ be the present discounted value of firm f's profits, including regulatory credits. Let $v_f(\mathcal{J}_f, \mathcal{J}_{-f})$ be the present discounted value of profits or losses from regulatory credits, similarly defined:

$$v_f(\mathcal{J}_f, \mathcal{J}_{-f}) = \sum_{t=1}^{T} \delta^t \sum_{j \in \mathcal{J}_{ft}} \sum_{m \in \mathcal{M}} v_{jmt} s_{jmt}(p_t^*(\mathcal{J}_{ft} \cup \mathcal{J}_{-f,t})) M_{mt}.$$

Then producer surplus is

$$PS(\mathcal{J}) = \sum_f \left(\pi_f(\mathcal{J}_f, \mathcal{J}_{-f}) - v_f(\mathcal{J}_f, \mathcal{J}_{-f}) + \sum_{j \in \mathcal{J}_f} (\pi_j^0 - SC_j) \right), \tag{4}$$

and total welfare, denoted $W(\mathcal{J})$, is

$$W(\mathcal{J}) = CS(\mathcal{J}) + Env(\mathcal{J}) + PS(\mathcal{J}). \tag{5}$$

Total welfare includes π_j^0, long-run benefits of a product to the firm that introduced it, but excludes benefits or costs for other firms outside product-market competition (such as through information spillovers), effects on consumer surplus or environmental externalities in future technological generations, and complementarities in entry costs across products.

Environmental damages capture the CO_2 emissions from vehicles, and are calculated by assuming that every vehicle purchased is driven 150,000 miles over its lifetime, as in the calculations of Holland, Mansur, Muller, and Yates (2016).[42] We assume no deterioration in the efficiency of the vehicle over time. Since the emissions from electricity use are lower over most of the period than the estimates we use (Holland, Mansur, Muller, and Yates 2020), and electric vehicles are driven fewer miles per year than gas vehicles (Davis 2019; Burlig, Bushnell, Rapson, and Wolfram 2021), we overestimate the damages of electric vehicles.

We also ignore consumers' ability to respond to market conditions by driving existing vehicles for longer by assuming that the outside good (not purchasing a new vehicle) has zero emissions. This assumption is only accurate if consumers who choose the outside good do not drive or already own a vehicle that has not reached 150,000 miles. This approach rules out, for example, a consumer responding to price increases by choosing to drive an existing car past the 150,000 mile mark.[43]

4.3.1 Product entry and welfare

Using the product entry model, we ask whether the private incentives to introduce a product are aligned with the effect of product entry on social welfare. Each firm's product entry decision affects consumers, other firms, and the environment, and the total of these externalities can be positive or negative in equilibrium. By comparing these externalities and the incentives created by the mandate, we can determine how well the policy is aligning private incentives with social welfare.

The consumer and producer externalities that arise from our product entry model and social welfare function parallel Mankiw and Whinston (1986); we also include environmental externalities. For a given firm f, rewrite (4) to separate firm f's profit

[42]This number is lower than the statutory lifetime miles traveled in the GHG regulation, which is 195,264 miles for cars and 225,865 miles for light trucks.

[43]An alternative approach that captures the intensity margin is the discrete-continuous model of Goldberg (1998).

from other firms:

$$PS(\mathcal{J}) = \pi_f(\mathcal{J}_f, \mathcal{J}_{-f}) - v_f(\mathcal{J}_f, \mathcal{J}_{-f}) + \sum_{j\in\mathcal{J}_f}(\pi_j^0 - SC_j)$$
$$+ \sum_{g\neq f}\left(\pi_g(\mathcal{J}_g, \mathcal{J}_{-g}) - v_g(\mathcal{J}_g, \mathcal{J}_{-g}) + \sum_{j\in\mathcal{J}_g}(\pi_j^0 - SC_j)\right).$$

We can therefore compare the private entry incentive for a particular product j with the effect of j's entry on total welfare. Consider a product j to be produced by firm f and two product sets, $\mathcal{J}^0$ and $\mathcal{J}^1$, that only differ by the inclusion of j (that is, $j \notin \mathcal{J}_f^0$, $\mathcal{J}_f^1 = \mathcal{J}_f^0 \cup \{j\}$, and $\mathcal{J}_g^1 = \mathcal{J}_g^0$ for $g \neq f$). Then

$$PS(\mathcal{J}^1) - PS(\mathcal{J}^0) = \Delta_j\pi_f(\mathcal{J}_f^1, \mathcal{J}_{-f}^1) - (v_f(\mathcal{J}_f^1, \mathcal{J}_{-f}^1) - v_f(\mathcal{J}_f^0, \mathcal{J}_{-f}^1)) + (\pi_j^0 - SC_j)$$
$$+ \sum_{g\neq f}\left(\pi_g(\mathcal{J}_g^1, \mathcal{J}_{-g}^1) - \pi_g(\mathcal{J}_g^1, \mathcal{J}_{-g}^0) - (v_g(\mathcal{J}_g^1, \mathcal{J}_{-g}^1) - v_g(\mathcal{J}_g^1, \mathcal{J}_{-g}^0))\right).$$

Since we assumed they do not depend on the product set, the $\pi^0 - SC$ terms for all other products drop out.

The effect on welfare thus combines the ex-post analog of firm f's private entry incentive, the effect on firm f's regulatory credits, and the uncaptured externalities for other firms, consumers, and the environment:

$$W(\mathcal{J}^1) - W(\mathcal{J}^0) = \underbrace{\Delta_j\pi_f(\mathcal{J}_f^1, \mathcal{J}_{-f}^1) + (\pi_j^0 - SC_j)}_{\text{private entry incentive (ex post)}}$$
$$- \underbrace{v_f(\mathcal{J}_f^1, \mathcal{J}_{-f}^1) - v_f(\mathcal{J}_f^0, \mathcal{J}_{-f}^1)}_{\text{regulatory credits}}$$
$$+ \sum_{g\neq f}\left(\pi_g(\mathcal{J}_g^1, \mathcal{J}_{-g}^1) - \pi_g(\mathcal{J}_g^1, \mathcal{J}_{-g}^0) - (v_g(\mathcal{J}_g^1, \mathcal{J}_{-g}^1) - v_g(\mathcal{J}_g^1, \mathcal{J}_{-g}^0))\right)$$
$$+ CS(\mathcal{J}^1) - CS(\mathcal{J}^0) + Env(\mathcal{J}^1) - Env(\mathcal{J}^0).$$

This expression demonstrates that product introduction has externalities, whose total may be positive, negative, or zero. These include the negative effect of entry on other firms' profits, which is related to the business stealing effect (Mankiw and Whinston 1986); the consumer benefit from variety (Spence 1976); and the net environmental effect of consumer substitution from cleaner and dirtier alternatives.

Therefore, we assess the effects of a supply-side policy on entry incentives by testing whether the value of regulatory credits aligns private incentives with social welfare. This test does not require any estimates of the magnitudes of entry costs and long-run benefits, but it is only a test of incentives, not whether there is over- or under-entry in equilibrium. If the value of regulatory credits is less the sum of the externalities, for example, the firm does not fully internalize the benefits to others of product introduction, but when accounting for entry cost, entry on the whole may be welfare-enhancing or welfare-reducing.

5 Estimating the demand model

We estimate demand parameters using a generalized method of moments estimator following Berry, Levinsohn, and Pakes (1995), Petrin (2002), and Conlon and Gortmaker (2020). It only uses the model of demand, not pricing, and works by simultaneously matching model-predicted to observed market shares, matching model-predicted micro-moments to observed survey data, and fitting unobserved quality ξ to be uncorrelated with instrumental variables.

The micro-moments, as in Petrin (2002), recover heterogeneity in consumer tastes based on observed demographics, Π. Instrumental variables based on cost and price shifters (government subsidies, cost shifters based on production locations, and a proxy for lithium ion battery costs) identify consumer preference for price, α, in a way that accounts for the dependence of price and unobserved quality ξ. As described in Gandhi and Houde (2019), instrumental variables based on characteristics of competing products help to estimate consumer preference heterogeneity, Σ.

5.1 Demand estimation method

We estimate demand parameters using a demand side-only version of the generalized method of moments estimator from Petrin (2002), implemented using PyBLP (Conlon and Gortmaker 2020). 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. Notation is as follows. For product j in state m and model year t, let z_{jmt} be a vector of instruments; stack the row vectors z'_{jmt} to form a matrix Z. Let $\xi(\theta)$ be the vector ξ which solves the system of market share equations (1) given parameters θ.[44] Defining $\mathbf{G}_1(\theta) = Z'\xi(\theta)$, the key assumption is that $E[\mathbf{G}_1(\theta)] = 0$. The micro-moments simply match the model's predictions of the moments from Section 5.3 to the values from data; defining $\mathbf{G}_2(\theta)$ to be the difference between model-implied moments and moments from data, the key assumption is that $E[\mathbf{G}_2(\theta)] = 0$.

Define $\mathbf{G}(\theta) = (\mathbf{G}_1(\theta), \mathbf{G}_2(\theta))$, and denote the sample analog of $\mathbf{G}$ by $\hat{\mathbf{G}}$. The estimates are then computed by solving

$$\min_{\theta} \hat{\mathbf{G}}(\theta)' W \hat{\mathbf{G}}(\theta),$$

where W is a positive definite weight matrix.

We adopt many of the best practices in PyBLP recommended in Conlon and Gortmaker (2020). We solve the system of equations (1) using SQUAREM with the Berry, Levinsohn, and Pakes (1995) contraction map and tolerance 10^{-14}. We compute the integral over (d_i, ν_i) using Monte Carlo integration with 200 draws per market. The weight matrix is determined by two-step GMM, clustering observations

[44] We assume that markets are large enough that observed market shares equal choice probabilities.

at the make-model level, and the minimization problem is solved using L-BFGS-B.

Standard errors are computed by the GMM formula, clustering observations at the make-model level to allow for within-model correlation in unobserved quality across regions, across time, and across fuel type and battery size variants.

5.2 Instrumental variables

We assume that characteristics of all products are mean-independent of all products' quality shocks ξ.[45] We implement this assumption as follows: for each product j, region m, and model year t, the product's quality ξ_{jmt} is restricted to be mean-independent of both the product's own characteristics x_{jmt} and the local differentiation instruments of Gandhi and Houde (2019),[46] which measure the availability of close substitutes along observable dimensions. Specifically, for each product j and a subset of characteristics k,[47] the local differentiation instruments are the count of products j' for which $x_{j'k}$ is within one standard deviation of x_{jk}, separated into products by the same firm as j and products by other firms. As described by Gandhi and Houde (2019), the primary role of the differentiation instruments is to estimate random coefficient parameters.

We assume that government subsidies are exogenous.[48] Subsidy levels are deterministic functions of vehicle characteristics, typically range or battery capacity; though the exact function varies over time, this is a response to changes in funding and not a response to the unobserved quality of particular vehicles. Subsidies do not depend on vehicle price, except some programs that exclude vehicles whose MSRP is above a cutoff level. (In practice, products are rarely priced close to the cutoff.)

[45]According to industry experts, the technical characteristics of a vehicle are determined early in the design process. The electric range of non-native first-generation electric vehicles, for example, was typically determined by space constraints and the energy density of the battery chemistry used. 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).

[46]We use PyBLP (Conlon and Gortmaker 2020) to construct the local differentiation instruments.

[47]We use all characteristics except make, model year, and state fixed effects.

[48]This instrument is also used by Li (2019).

For additional cost shifter instruments, we use the average manufacturing wage in the area of production (the 2009–17 average from the Quarterly Census of Employment and Wages),[49] and (for vehicles with a lithium ion battery) a proxy for the cost of the battery obtained by multiplying the battery size (in kilowatt-hours) and BloombergNEF's measure of the industry-wide average battery pack price (in dollars per kilowatt-hour).

5.3 Micro-moments

We use two sets of micro-moments that help to identify demographic parameters in Π. The first matches electric vehicle purchases to county-level climate, using data from the California rebate program prior to 2016. We calculate a temperature factor, which proxies for consumers' perceptions of the effects of extreme weather on battery performance, for each county. Then, for each model year (inferred based on purchase date) we calculate the mean temperature factor among buyers of electric vehicles. The second micro-moment, taken from Xing, Leard, and Li (2021), is the statistic that across model years 2010 through 2014, 81% of electric vehicle purchasers nationally had a college degree.

5.4 Demand estimates

Table 4 shows the estimated linear (β) and nonlinear (Π, Σ) parameters (except for the magnitudes of fixed effects). All else equal, consumers prefer vehicles that are gas-efficient, but are relatively insensitive to electric efficiency. Consumers on average dislike hybrids and electric vehicles, but have heterogeneous preferences.

Because we obtain estimates of Σ that are close to zero, we also estimate a constrained model that sets $\Sigma = 0$, so that all heterogeneity across consumers comes from observed demographics. We use the constrained model for the estimates and

[49]This instrument is also used by Wollmann (2018).

counterfactuals that follow.

The estimates imply own-price elasticities in line with prior literature for electric vehicles, but not non-electric vehicles. In the constrained model, the estimated sales-weighted average own-price elasticity of demand for electric vehicles is -2.22; estimates from other studies using US data (surveyed in Cole, Droste, Knittel, Li, and Stock (2021)) range from -1.0 to -2.7. The estimated average own-price elasticity for non-electric vehicles is -1.69, much more inelastic than other estimates from the US market. 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 (2021) finds own-price elasticities between -6.5 and -9.4 (depending on income group) in 2018.

6 Estimating the pricing model

We estimate marginal costs by solving the Nash–Bertrand first order conditions (3) given demand parameters. This method adapts existing techniques for sequential demand and supply estimation (e.g., Nevo (2001)) to accommodate national pricing and state variation in regulation, and relies only on prices, quantities, and demand elasticities.

6.1 Marginal cost estimates

The demand estimates and the additional assumption of the pricing model together give estimates of marginal cost. Figure 3 shows trends in sales-weighted average prices and estimated marginal costs for non-Tesla electric vehicles. Marginal costs fall until 2015, and then rise; the rise is mainly attributable to increases in the battery pack size in later-model EVs. The trend of declining marginal cost is consistent with the falling battery prices in this period described in Section 2.2 and shown in Figure 4.

7 Estimating product entry incentives

Using the framework for product entry incentives and welfare in Section 4.3.1, we compare our estimates of credit value to the effects of product entry on the profits of other firms, consumers, and the environment. We find that the mandate allowed firms to capture 25–50% of the externalities of entry, as opposed to less than 10% under the greenhouse gas program alone.

Using the static product entry framework described in Section 4.2, we compare accounting estimates of entry costs with observed variable profit in order to estimate a lower bound on long-run benefit. We estimate a long-run benefit for non-native electric vehicles of at least 78% of entry cost.

7.1 Social welfare and entry incentives

As discussed in Section 4.3.1, we can use the demand and pricing model to test whether the credit value is properly aligning private entry incentives with the social welfare effects of entry. If the incremental value of credits is close to the sum of the product entry externalities, then the firm is internalizing those externalities when choosing product entry.

We quantify the three externalities — the effect on other firms, consumer surplus, and environmental effects — and compare them to incremental credit value $\Delta_j v_f$ under various assumptions about credit prices. To do so, for each electric vehicle j, we predict changes in consumer surplus and market shares if j is dropped. We then compute other firms' profits, using marginal cost estimates and the predicted shares, and environmental effects from predicted changes in shares (as described in Section 4.3).

We hold product prices fixed to simplify calculations. (Improvements to instead recompute the Nash–Bertrand price equilibrium are in progress.) Other firms will optimally respond to a product removal by raising or lowering their prices, depending on substitution patterns, which will also affect quantities for the firm's other products. Therefore, accounting properly for price changes could increase or decrease the sum of the externalities and incremental credit value.

We compute welfare with and without information about the realization of ξ. In our ex post specification, we assess the incentives and externalities under full information about ξ, using each product's estimated ξ from the demand model. In our ex ante specification, which more closely aligns with our model of firm information, we compute incentives and externalities as an expectation over ξ, which we approximate using a normal distribution calibrated to the distribution of estimated ξs. We use three scenarios for credit prices, ignoring uncertainty, as described in Section 4.2.

We estimate that the sum of the externalities is positive for all products. That is, there are social benefits from product entry that are not internalized by private firms in the absence of regulatory credits. In all cases, consumer surplus is the positive externality, the effect on other firms' profits is negative but smaller, and the environmental benefit is small in absolute value and sometimes negative. The small environmental benefit reflects both the low sales of electric vehicles and the implication of our demand specification that the closest substitutes for electric vehicles are other electric or clean vehicles.

As noted in Fan and Yang (2020), the positive effect on consumer surplus may be partially driven by an unwanted feature of logit demand systems: high draws of the independent Type 1 Extreme Value shocks for some consumers for the products being considered. (Work to calculate consumer surplus with this effect removed, following the method of Fan and Yang (2020), is ongoing.)

The percentage of the externality captured by credit values is given in Figure 5 for each product. In the ex post specification, using estimated values of ξ, GHG credits alone make up about 10% of the entry externalities; under realized ZEV prices, 25–

50% of the externality is captured by credit values. Even in the $5000 ZEV credit scenario, most firms do not internalize the full benefits of product entry.

In the ex ante specification, which averages over the distribution of ξ, the gap between credit values and the sum of externalities is wider. GHG credits alone make up 9–17% of entry externalities, while in the $5000 ZEV credit scenario, credit value is still only 25–45% of the sum of entry externalities.

7.2 Estimation of product entry parameters

We estimate bounds on product entry parameters in order to predict product introduction under counterfactual policies and measure total welfare. By assuming the entry pattern observed in the data is a Nash equilibrium of the product entry game described in Section 4.2, we can estimate an upper bound on the entry cost net of long-run benefit.[50] To separate these terms, we use the accounting estimates from Section 2.2 to bound entry costs.

For any non-native electric vehicle model j, let $f(j)$ be the firm that produces product j. Proposition 1 gives a necessary condition for equilibrium play that depends on unobserved variables and variables that can be estimated from the demand model:

$$\text{introduce if } (1-\kappa)SC_j \leq \Delta_j \pi_{f(j)}.$$

To estimate expected incremental variable profit $\Delta_j \pi_{f(j)}$, we compare firm profits in the observed equilibrium (obtained from the demand model) with profits in the scenario in which j is dropped and market shares adjust. To reduce the computational burden, we hold product prices fixed.[51] We try three paths for r, as described in Section 4.2, and ignore the potential effect of product introduction on credit prices.

[50] Our approach is an application of the framework in Pakes, Porter, Ho, and Ishii (2015), and has elements in common with Wollmann (2018).

[51] Incorporating equilibrium price changes is in progress.

In our main specification, the shared firm information set $\mathcal{I}_0$ does not contain product quality ξ. Firms instead form expectations of profits using the distribution of ξ across products. We approximate this expectation by calculating average profits over 50 draws of the ξ vector. Specifically, for each j, we draw ξ_j i.i.d. from a normal distribution with mean and variance calibrated to the distribution of estimated ξs across products. In our alternative specification, $\mathcal{I}_0$ contains product quality.

Using these estimates for all non-native EVs, we can obtain a lower bound on κ, the ratio of expected long-run benefit to entry cost. This estimate uses only the incremental variable profit of the least profitable product and the lower bound on entry cost. When incremental variable profit falls short of entry cost, the long-run benefit required to justify entry is larger, giving a higher implied lower bound on κ. By contrast, if incremental variable profit is higher than entry cost, entry can be rationalized by any value of $\kappa \geq 0$.

Consider $j \in \mathcal{J}_{NN}$, the set of non-native ("NN") electric vehicle models that enter before 2017. Let $[\underline{SC}_{NN}, \overline{SC}_{NN}]$ be the range of accounting estimates. Then, for each $j \in \mathcal{J}_{NN}$,

$$(1-\kappa)\underline{SC}_{NN} \leq (1-\kappa)SC_j \leq \Delta_j \pi_{f(j)},$$

giving a lower bound on κ, which we denote $\underline{\kappa}$:

$$\kappa \geq \underline{\kappa} \equiv 1 - (\underline{SC}_{NN})^{-1} \min_{j \in \mathcal{J}_{NN}} \Delta_j \pi_{f(j)}.$$

That is, the long-run benefit for the least profitable product observed in the data must be large enough to recover the lowest possible entry cost.

Because we do not have data on products that were not introduced, we are unable to use entry behavior to estimate an upper bound on κ. For the non-native models introduced early in our study period, we assume that $\kappa \leq 1$. For products with positive $\Delta_j \pi_{f(j)}$, this assumption does not restrict entry in equilibrium: the model generates the same prediction for any $\kappa \geq 1$. (The exact value of κ matters for welfare calculations.)

Given a particular value of κ, the entry rule also implies an upper bound on SC_j for each product j that entered: $SC_j \leq (1-\kappa)^{-1}\Delta_j \pi_{f(j)}$.

7.3 Product entry parameter estimates

We begin by estimating incremental variable profit for each electric vehicle j using the demand and supply model. These estimates are shown in Figure 6, where they are compared to accounting estimates of entry cost. While all native models except the BMW i3 recover their entry cost without long-run benefits, about half of non-native models do not, with expected incremental variable profits as low as \$50 million (as compared to entry costs that start at \$100 million). We estimate a long-run benefit for non-native electric vehicles of at least 78% of entry cost.

These figures are generally robust to the inclusion of unobserved product quality ξ in firm information sets, but the identities of the lowest-profit products depends on which information set is assumed. For example, the Mercedes and Ford models have high expected incremental variable profits based on observable characteristics and costs, but low realized values of ξ that cause the realized incremental variable profits to be much lower.

We next estimate a lower bound on κ for non-native EVs. From accounting estimates, we use $\underline{SC}_{NN}$ =\$100 million. Under the realized credit price path, the lowest expected incremental variable profit is \$47 million when ξ is not conditioned on, and \$22 million when ξ is conditioned on. (We exclude products that entered during model year 2017.) Therefore, we obtain $\underline{\kappa} = 0.53$ when ξ is not conditioned on, and 0.78 when ξ is conditioned on.

8 Counterfactual demand-side policy

What are the welfare effects of achieving the same quantity target by a demand-side policy? We simulate the effects of replacing the ZEV mandate with a counterfactual policy that only uses consumer incentives.[52] In particular, we eliminate ZEV credits 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. By simulating the new equilibria of pricing and product entry, we measure the welfare effects of changing to the counterfactual policy.

Under national pricing, a subsidy for consumers in one region will introduce a difference between the consumer price in that region and the consumer price elsewhere, while a subsidy for producers in a region will not. A firm's incentive to adjust prices in response to the regional subsidy is dampened by the demand response among consumers in other regions. This effect, in turn, creates different markups and incentives for product introduction.

We set the specific level of the subsidy and tax by targeting two outcomes: electric vehicle quantity and budget balance. First, the policy must achieve the same total electric vehicle sales each year across the ten regulated states as observed data. Second, the policy must be budget-balanced: total expenditure on the subsidy must equal total collection through the tax, across all of the regulated states. We adopt total electric vehicle sales as the target because it is easily measured and explicitly mentioned as a goal in regulator reports.

To account for the effect of the subsidy and tax on consumer prices, we recompute the Nash–Bertrand price equilibrium by solving equations (3).[53] This computation

[52] This type of policy is known as a 'feebate', and is commonly used to control greenhouse gas emissions from cars. A greenhouse gas-based feebate system was proposed in California in 2008, but not passed (Durrmeyer and Samano 2018).

[53] We use SciPy's implementation of Steffensen's Method with Aitken's Δ^2 convergence acceleration, applied to the sequence generated by iterating the pricing equations. Conlon and Gortmaker (2020) document that this sequence does not always converge; in our case, it does.

requires the subsidy and tax to be set simultaneously with prices, and the regulator to have the same amount of information as the firms.

The structure of the counterfactual policy mimics that of the ZEV mandate, but minor differences remain. The subsidy amount follows the ZEV formula for credits per vehicle, generating a larger subsidy for vehicles with a longer battery range. Unlike the ZEV mandate's quota, which only applies to large automakers, the consumer tax applies to all non-EVs sold in the ten regulated states. In addition, while the ZEV mandate allows firms to smooth out the policy over multiple years using credit banking, there is no similar mechanism to smooth out the consumer subsidy.

To assess the effect of product introduction, we compute these subsidy and tax levels under a variety of plausible entry scenarios. We then restrict attention to scenarios that could be equilibria in the product entry game, by checking if any firm can profitably deviate in its EV entry decision. In computing producer surplus, we report a range of estimates given the bounds on entry cost and long-run benefit from Section 7.3.

Formally, the setup is as follows. The policymaker controls the subsidy τ_t^0 and tax τ_t^1 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 $z_m(\tau_t^0 c_j e_j - \tau_t^1(1-e_j))$. Let $q_{jmt}(\tau_t^0, \tau_t^1)$ be the quantity sold under the demand-side policy, which depends implicitly on price adjustment and requires full knowledge of the demand model. The sales constraint is therefore

$$\sum_m z_m \sum_j e_j(q_{jmt}(\tau_t^0, \tau_t^1) - q_{jmt}^0) = 0,$$

the budget balance constraint is

$$\sum_m z_m \sum_j (\tau_t^0 c_j e_j - \tau_t^1 (1 - e_j)) q_{jmt}(\tau_t^0, \tau_t^1) = 0,$$

and the policymaker chooses (τ_t^0, τ_t^1) to solve this system of equations.

8.1 Results

We begin by measuring the effects of the demand-side policy if the product set is held fixed. The required consumer subsidy is larger than the value of a corresponding ZEV credit, and relative prices adjust in a way that lowers consumer surplus and raises total variable profit. We then turn to the effects of the demand-side policy on entry incentives. We measure the additional consumer surplus loss from the reduced product variety. Across the equilibria that are supported by our estimates of product entry parameters, the effect of endogenous entry on producer surplus ranges from a small negative effect to a small positive effect. In some equilibria, foregone long-run benefits exceed avoided entry costs, but in others they do not.

8.1.1 Without entry margin

The left panel of Table 5 shows the magnitude of the consumer subsidy and tax that implement this policy. The subsidy amount varies from \$2,300–\$3,600 before range multipliers, which is substantial and larger than the ZEV credit prices in Table 3. This amount translates to \$7,000–\$10,700 per vehicle for a Nissan Leaf. (Because of the small market share of electric vehicles, the tax on non-EVs is under \$150 per vehicle.) This additional subsidy is on top of the \$7,500 federal tax credit and existing state rebates (\$2,500 in California).

The main effect of the policy is to raise EV prices outside the regulated states, as the ZEV mandate no longer holds down national prices. In the ZEV states, net consumer prices after subsidies are higher for the products that are only sold in ZEV states, and lower for the products that are sold nationally. Price comparisons for EVs, in California and the non-ZEV states, are shown in Figure 7.

Without any change in the product set, the price changes resulting from the switch to a demand-side policy result in $1.4 billion lower consumer surplus and $570 million higher producer surplus.

8.1.2 Social welfare and entry incentives

We next measure how much the firm captures of the externalities of product entry (consumer surplus, avoided environmental externalities, and changes in other firms' surplus, as described in Section 7.1). For each product j, we drop the product from the choice set, let market shares adjust (holding fixed GHG credit prices, the subsidy, and prices), and compute the difference in consumer surplus and profits. The sum of entry externalities stays constant or rises slightly; because the credit term no longer includes ZEV credits, a smaller portion of the externalities is being captured.

We repeat this calculation across scenarios in which the n lowest-selling non-native electric vehicles avoid entering the market. Figure 8 shows the uncaptured social benefit, measured as the sum of the externalities of product entry minus the private gain from GHG credits. Across all the entry scenarios we consider, the uncaptured benefit is larger under the demand-side policy than under the mandate.

8.1.3 With entry margin

If the demand-side policy alters the variable profits earned from electric vehicle sales, it is possible that fewer products will enter. We can test a variety of product entry scenarios by computing variable profits and assessing whether any firm has an incentive to deviate: a product which is out but faces a positive entry incentive, or a product which is in and faces a negative entry incentive. We use the simplified model in Section 7.3, and adopt the specification in which product quality ξ is in all firms' information sets.

Over a range of values of $\kappa \in [\underline{\kappa}, 1)$, we test whether a given scenario is a potential equilibrium by examining whether any firm has an incentive to deviate by entering or removing a single product. (We do not consider the hypothetical entry of products that were not observed in the data.) We do so by comparing the counterfactual incremental variable profit of the product, which we write $\Delta_j \pi^{cf}_{f(j)}$, against the entry cost net of long-run benefit, $SC_j(1-\kappa)$. Because we do not observe SC_j, we use the bounds derived in Section 7.3, and use the data to assign $d_j(\kappa) \in \{\text{in, out, unknown}\}$ as follows:

$$\begin{cases} \text{out}, & \Delta_j \pi^{cf}_{f(j)} < \underline{SC}(1-\kappa), \\ \text{in}, & \Delta_j \pi^{cf}_{f(j)} > \min\{\overline{SC}(1-\kappa), \Delta_j \pi_{f(j)}\}, \\ \text{unknown}, & \text{otherwise} \end{cases} .$$

For each κ, we then say that the scenario is rejected if any product is out and has $d_j(\kappa) = \text{in}$, or the product is in and has $d_j(\kappa) = \text{out}$. (In this computation, we ignore incentives to deviate by products that were only introduced in 2017.)

Figure 9 shows the results. Entry scenarios in which the n lowest-selling non-native electric vehicles avoid entering, the scenarios with $n = 7, 8, 9, 10$ (of ten) are rejected for all $\kappa \in [\underline{\kappa}, 1)$. The remaining scenarios are rejected for some values of κ.

Subsidy and tax amounts. In order to replace the lost sales from the models that stay out, the incentive for EVs needs to be increased. The right panel of Table 5 shows the subsidy and tax in the scenario in which four (of ten) non-native electric vehicles stay out of the market. The subsidy is up to 27% higher than in the scenario in which the product set is unchanged.

Effects on welfare. Reduced product variety decreases consumer surplus, variable profit for producing firms, and total entry costs, but increases variable profit for non-producing firms. The environmental effects of reduced variety depend on whether consumers who would have purchased the electric vehicles that did not enter instead purchase more- or less-polluting alternatives. The effects of the subsidy and tax on welfare are theoretically ambiguous.

We quantify welfare effects using the simplified model of product entry and total welfare from (5), and the ratio of long-run benefit to entry cost ranging from $\underline{\kappa} = 0.78$ to 1. We assume that entry costs and long-run benefits do not change, for simplicity.

Let π_f^{cf} be firm f's counterfactual variable profit, and let $\mathcal{J}_f^{cf}$ be firm f's counterfactual product set. The difference in producer surplus combines the difference in variable profit, avoided entry costs, and foregone long-run benefits:

$$\sum_f \left(\pi_f^{cf} - \pi_f + \sum_{j \in \mathcal{J}_f \setminus \mathcal{J}_f^{cf}} SC_j (1 - \kappa) \right).$$

Because we do not have point estimates of SC_j or κ, we hold κ fixed and compute bounds on the difference in consumer surplus. For each $\kappa \in [\underline{\kappa}, 1]$, we use $SC_j \in [\underline{SC}, \min\{\overline{SC}, (1-\kappa)^{-1} \Delta_j \pi_{f(j)}\}]$.

The results across the range of entry scenarios we consider are shown in Figure 10. For each κ, we calculate the maximum upper bound and minimum lower bound on producer surplus across the scenarios that are not rejected, and the maximum and minimum of non-producer welfare (consumer surplus and environmental damages) across the same scenarios.

When long-run benefits are very low, producers gain by avoiding entry costs, while consumers lose from reduced variety. When long-run benefits are at the level implied by observed entry, $\kappa \geq \underline{\kappa}$, consumer surplus is between \$1.8 billion and \$1.4 billion lower and producer surplus is between \$420 million and \$680 million higher, for a total loss of between \$1.3 billion and \$750 million from switching to the demand-side policy. When long-run benefits are high, there is no response on the entry margin.

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. The mandate allowed entrant firms to capture more of the social surplus generated by their products. Because of the interaction between national pricing and regional policy variation, the mandate generated higher consumer surplus and lower producer surplus than a comparable demand-side policy would have, and may have induced more entry and greater product variety. These findings have consequences for future state policies to encourage new, socially beneficial types of consumer products within national markets. Though electric vehicle product variety, costs, and quantities have evolved significantly since the period we study, our findings may also have implications for the welfare consequences of current and future electric vehicle policy.

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10 Tables and figures

Model	Native?	Introduced	Sales (to 2017)	Price	Range (mi)
Ford Focus		2012	9,000	\$26,437–\$38,138	76–115
Mitsubishi i-MiEV		2012	2,000	\$22,995–\$29,125	59–62
Toyota RAV4		2012	2,000	\$48,967–\$49,717	103
Fiat 500e		2013	24,000	\$29,467–\$32,120	84–87
Honda Fit		2013	1,000	\$36,625	82
smart fortwo		2013	6,000	\$23,488–\$25,000	58–68
Chevrolet Spark		2014	7,000	\$22,870–\$26,685	82
Mercedes-Benz B-Class		2014	4,000	\$39,900–\$41,450	87
Kia Soul		2015	5,000	\$30,450–\$33,700	93
Volkswagen e-Golf		2015	12,000	\$28,538–\$33,450	83–125
Nissan LEAF	X	2011	114,000	\$27,010–\$35,200	73–107
Tesla Model S	X	2012	113,000	\$57,400–\$135,000	139–315
Tesla Model X	X	2016	32,000	\$74,000–\$145,000	200–289
Chevrolet Bolt EV	X	2017	23,000	\$36,453	238
Tesla Model 3	X	2017	1,000	\$35,000	310
BMW i3	X*	2014	8,000	\$40,692–\$42,400	81
Honda Clarity	X*	2017	1,000	\$36,620	89
Hyundai Ioniq	X*	2017	<1,000	\$29,500	124

Table 1: Summary of electric vehicles in the US in 2009–17

Note: Compiled from MSN Autos and IHS data. Prices are MSRP after average manufacturer rebates. All years are model years. Native designation assigned by authors based on press reports. *EV and hybrid/plug-in hybrid versions developed jointly on the same platform.

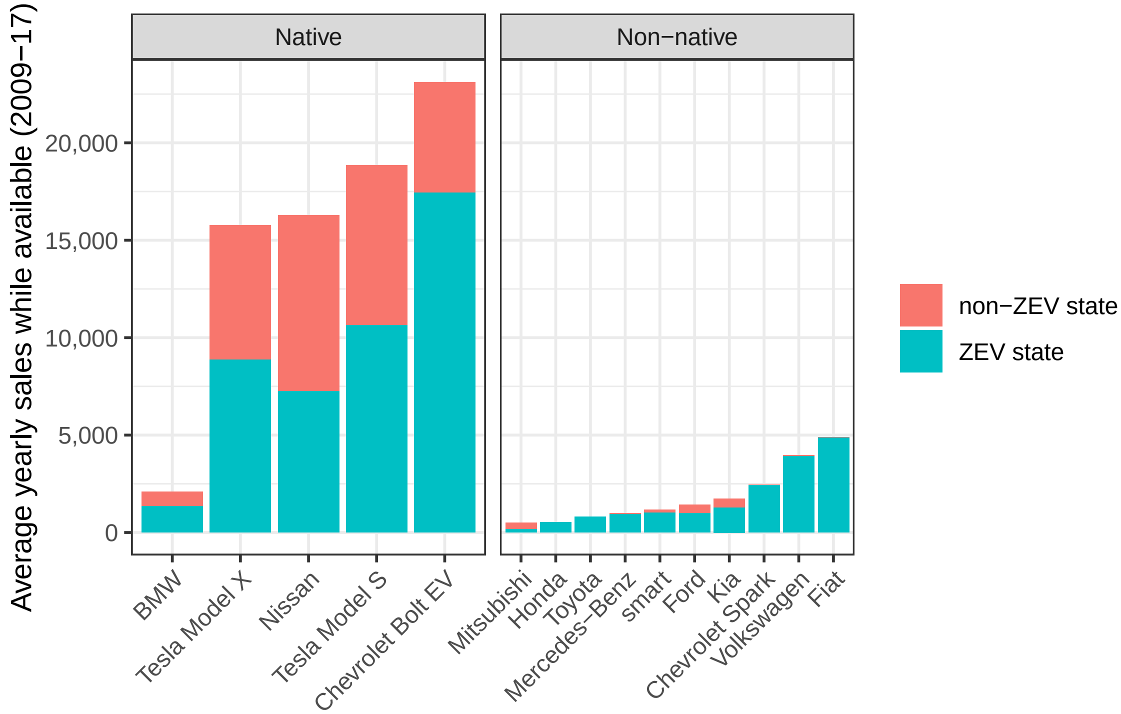

Figure 1: Average yearly sales by model, selected EVs, by ZEV states and non-ZEV states

Note: Derived from IHS data. Average is only taken over the years the model was available. Native vs. non-native classification assigned by authors from news reports.

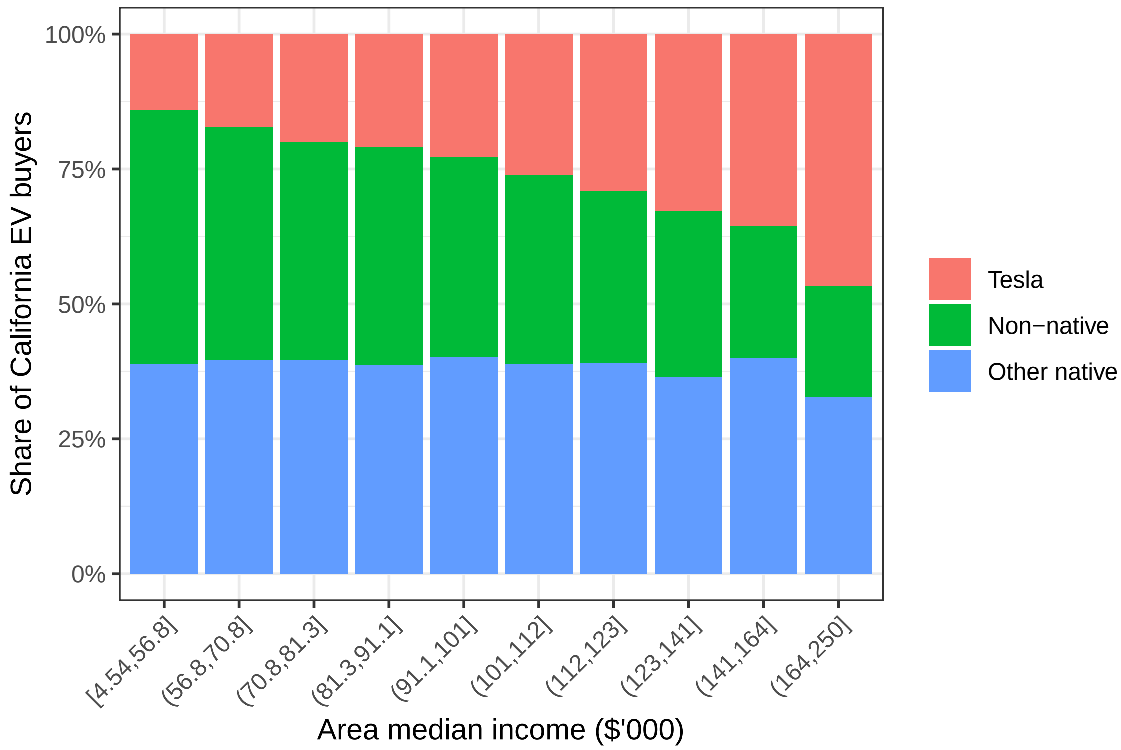

Figure 2: Breakdown of EV sales by non-native, Tesla, and other native, by census tract median income (California, 2010–16)

Note: Derived from California Vehicle Rebate Program survey data from inception to March 2016. Buyers are divided into ten equally sized groups by census tract median income.

	Min	Max	Mean	Sales-weighted mean	SD
Model year	2009.00	2017.00	2013.14	2013.52	2.61
Products per market	240.00	332.00	286.42	296.81	20.94
Inside good share	0.05	0.18	0.12	0.12	0.03
Price	7969.17	145000.00	36687.69	24948.22	21394.87
Govt subsidy	0.00	12500.00	305.02	47.33	1442.06
Doors	2.00	5.00	3.72	3.71	0.81
Weight (lbs)	1808.00	6000.00	3827.84	3649.65	821.03
Footprint (sq ft)	25.78	68.70	48.04	48.37	5.60
Wheelbase (in)	73.50	145.70	110.16	110.47	8.73
New model	0.00	1.00	0.09	0.05	0.28
HP/Weight	0.03	0.19	0.06	0.06	0.02
Displacement (cc)	0.00	8390.00	2957.67	2769.29	1242.60
Hybrid	0.00	1.00	0.09	0.03	0.28
PHEV	0.00	1.00	0.02	0.00	0.14
EV	0.00	1.00	0.02	0.00	0.14
Battery (kWh)	0.00	100.00	1.00	0.17	6.49
Electric range (mi)	0.00	315.00	3.17	0.54	21.43
Gas cost (dollars/mi)	0.00	0.33	0.13	0.12	0.05
Electric cost (dollars/mi)	0.00	0.09	0.00	0.00	0.01

Table 2: Summary statistics, vehicle characteristics and sales data

Note: Compiled from data from MSN Autos, FuelEconomy.gov, Ward's Automotive Yearbook, and IHS. Columns are the minimum, maximum, unweighted mean, sales-weighted mean, and unweighted standard deviation across products. Prices are MSRP after average manufacturer rebates. All years are model years.

Window	Revenue (m)	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%

Table 3: Estimated credit prices

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.

	Demographics		Full	
	Estimate	SE	Estimate	SE
Linear parameters (β)				
Displacement (L)	0.24	0.07	0.23	0.07
Doors	-0.21	0.09	-0.20	0.09
Wheelbase	-0.03	0.02	-0.03	0.02
HP/Weight	-4.17	5.17	-4.29	5.23
Weight (tons)	-0.60	0.40	-0.65	0.41
Gas cost (dollars/mi)	-14.82	2.13	-14.46	2.16
Electric cost (dollars/mi)	-41.04	1.88	-0.41	2.40
PHEV Range	0.01	0.02	0.01	0.02
EV Range	-0.02	0.02	-0.01	0.02
Battery (kWh)	0.06	0.05	0.02	0.06
Footprint	0.12	0.04	0.12	0.04
New model	-0.01	0.07	-0.01	0.07
Hybrid	-2.33	0.18	-2.33	0.18
PHEV	-1.73	0.40	-2.55	0.41
EV	-6.42	8.91	-10.62	10.02
Coupe	0.67	0.24	0.66	0.25
Hatchback	0.56	0.33	0.57	0.33
SUV	1.88	0.31	1.87	0.32
Sedan	1.38	0.30	1.37	0.31
Truck	1.00	0.39	0.99	0.40
Van	1.12	0.42	1.06	0.44
Wagon	0.94	0.39	0.93	0.39
FWD	0.46	0.17	0.47	0.17
RWD	0.06	0.14	0.09	0.15
Demographics (Π)				
(price-subsidy)/income	-8.27	3.29	-8.09	3.36
EV*College	1.08	0.22	1.08	0.47
EV*Temp. Factor	4.75	9.52	7.18	10.61
Unobserved heterogeneity (Σ)				
(constant)			0.00	2.92
EV			0.00	4.62

Table 4: Estimates of demand parameters

Note: Estimates from random coefficients logit demand system, except for magnitudes of fixed effects (on make, model year, and state). The coefficient on characteristic k for consumer i is $\beta_k + \Pi_k d_i + \Sigma_k v_i$, where d_i is a vector of demographics and v_i is unobserved heterogeneity. The specification labeled Demographics sets $\Sigma = 0$ so that heterogeneity only comes from demographic variation. The specification labeled Full allows Σ to be nonzero. Standard errors are clustered at the make-model level.

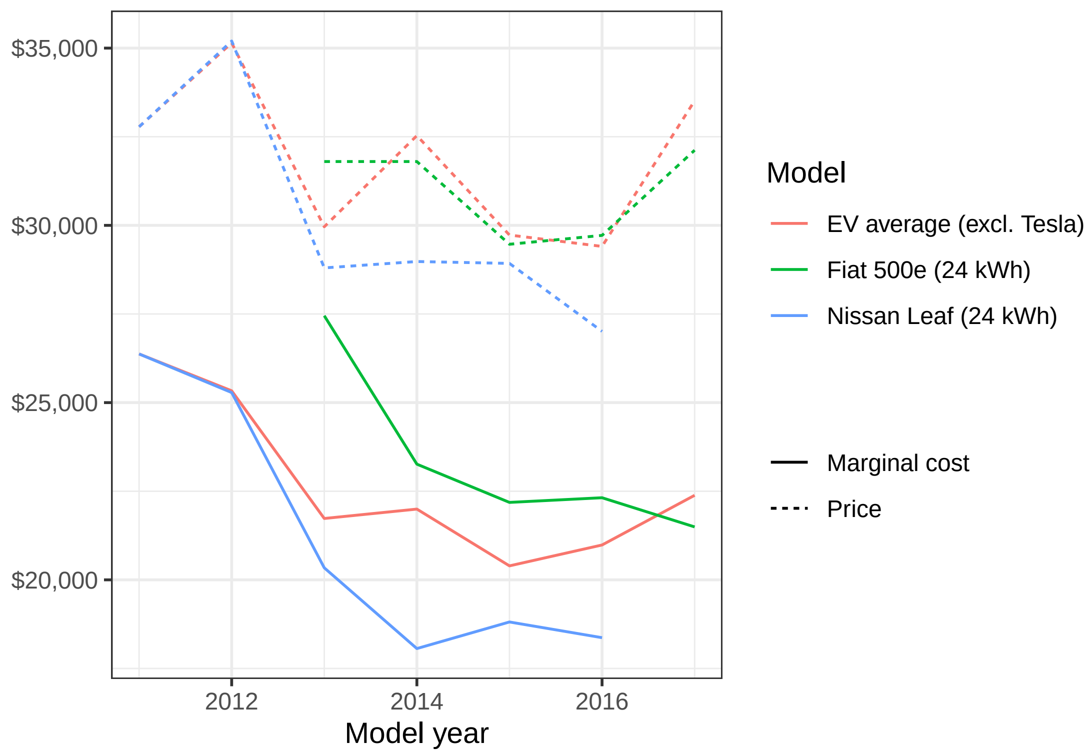

Figure 3: Prices and estimated marginal costs, selected EVs

Note: Prices are MSRP after average manufacturer rebate (from MSN Autos and Automotive News). Marginal costs are estimated from our demand system and national Nash–Bertrand pricing. EV average is sales-weighted.

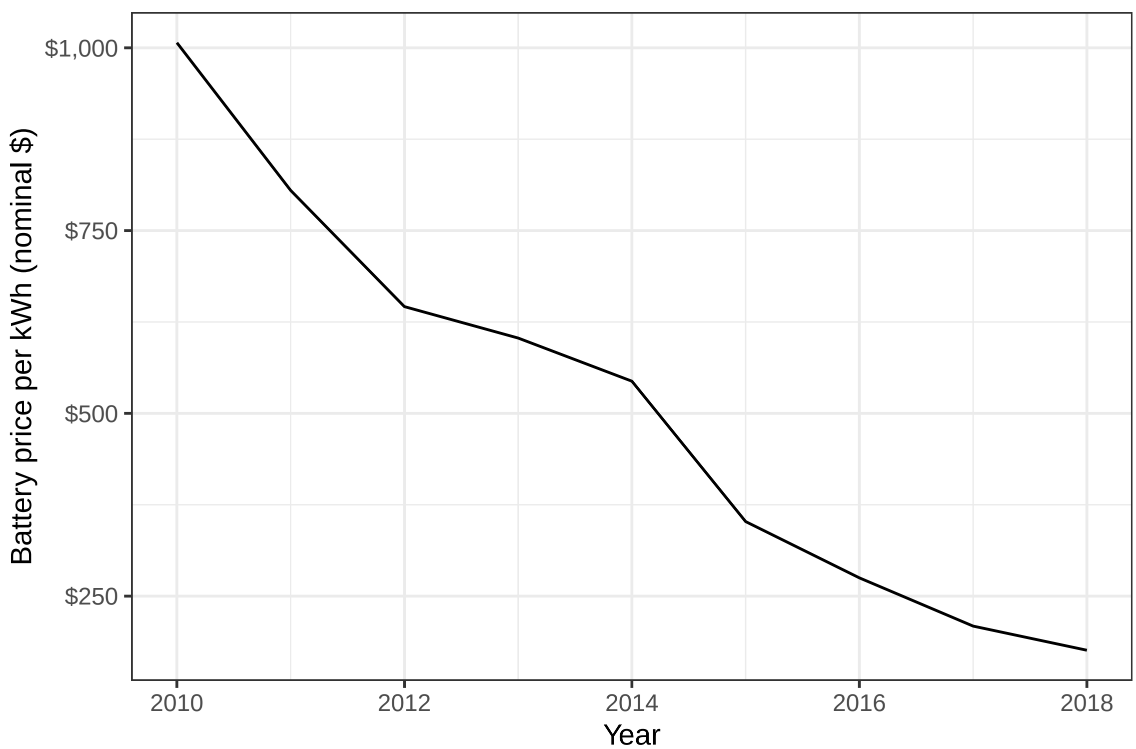

Figure 4: Lithium-ion battery pack prices, 2010–18, from BloombergNEF surveys of the EV industry

Note: Volume-weighted averages from "A Behind the Scenes Take on Lithium-ion Battery Prices" (Logan Goldie-Scot, BloombergNEF, 3/5/19), converted back from 2018 dollars to nominal dollars.

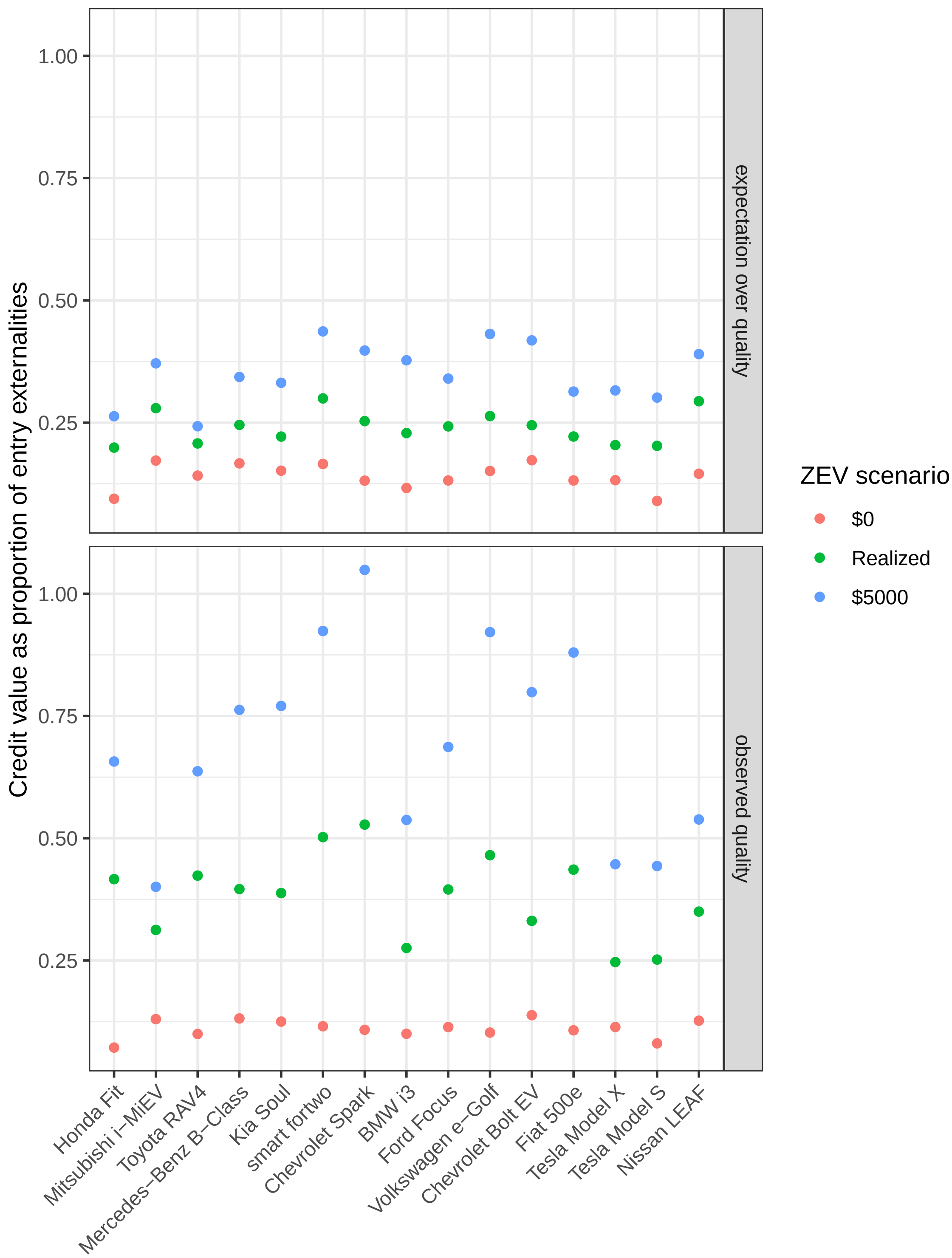

Figure 5: Ratio of credit value to sum of entry externalities, selected EVs

Note: Credit value includes GHG and ZEV credits. Entry externalities are the change in consumer surplus, negative environmental damages, and other-firm profit resulting from entry. Top panel shows averages over draws of product quality; bottom panel shows calculations when product quality is known.

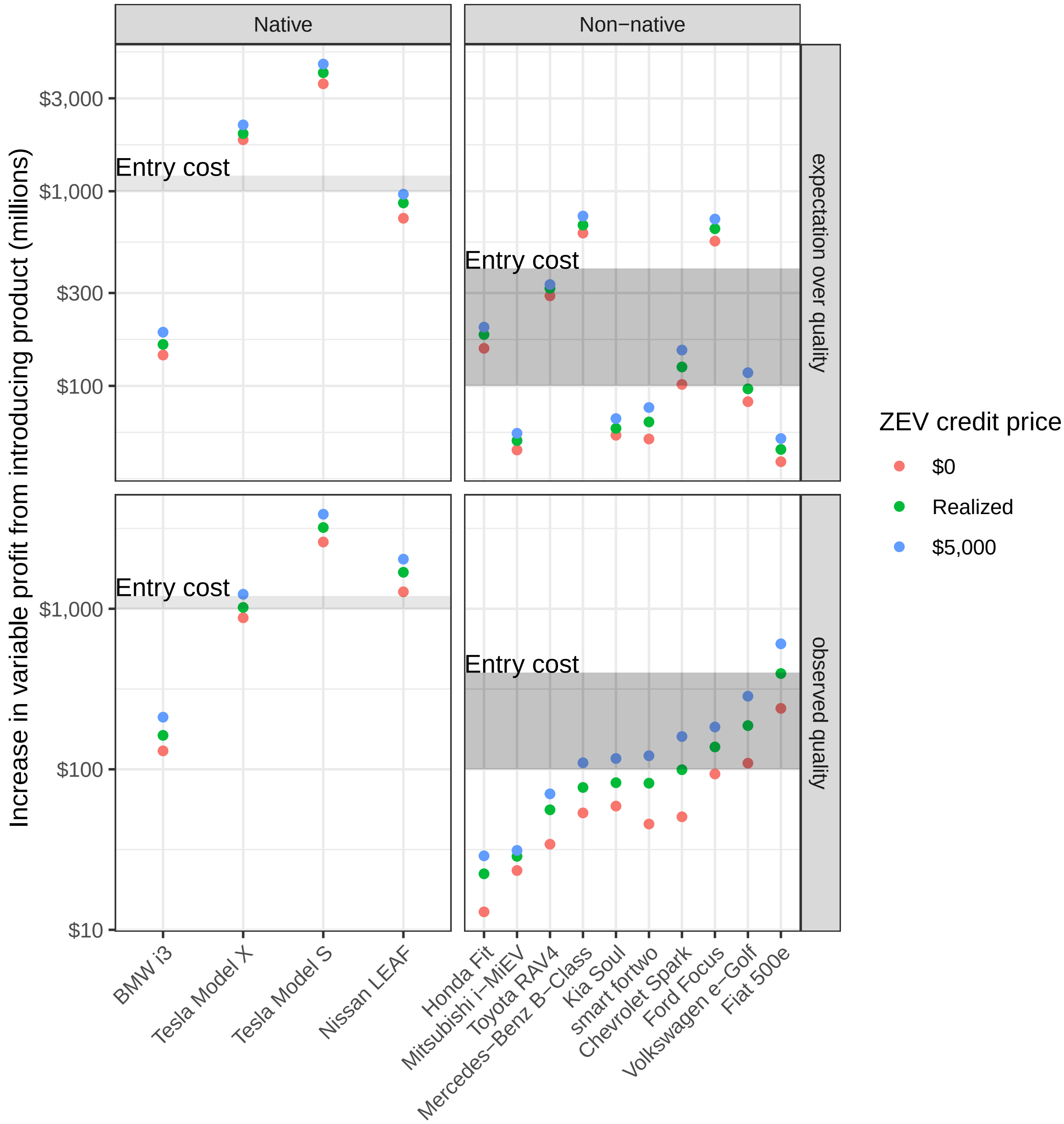

Figure 6: Comparison of incremental firm variable profit with accounting estimates of entry cost

Note: Incremental firm variable profit is the difference between variable profit when the product is in and when it is out, including regulatory credits. It gives an upper bound on entry cost net of unobserved benefit. Entry cost is based on industry accounting estimates. Top panel shows average profits over draws of product quality ξ; bottom panel shows profits using estimated product quality ξ. All profits are shown under three scenarios for the ZEV credit price: \$0, \$5,000, and the path of realized prices.

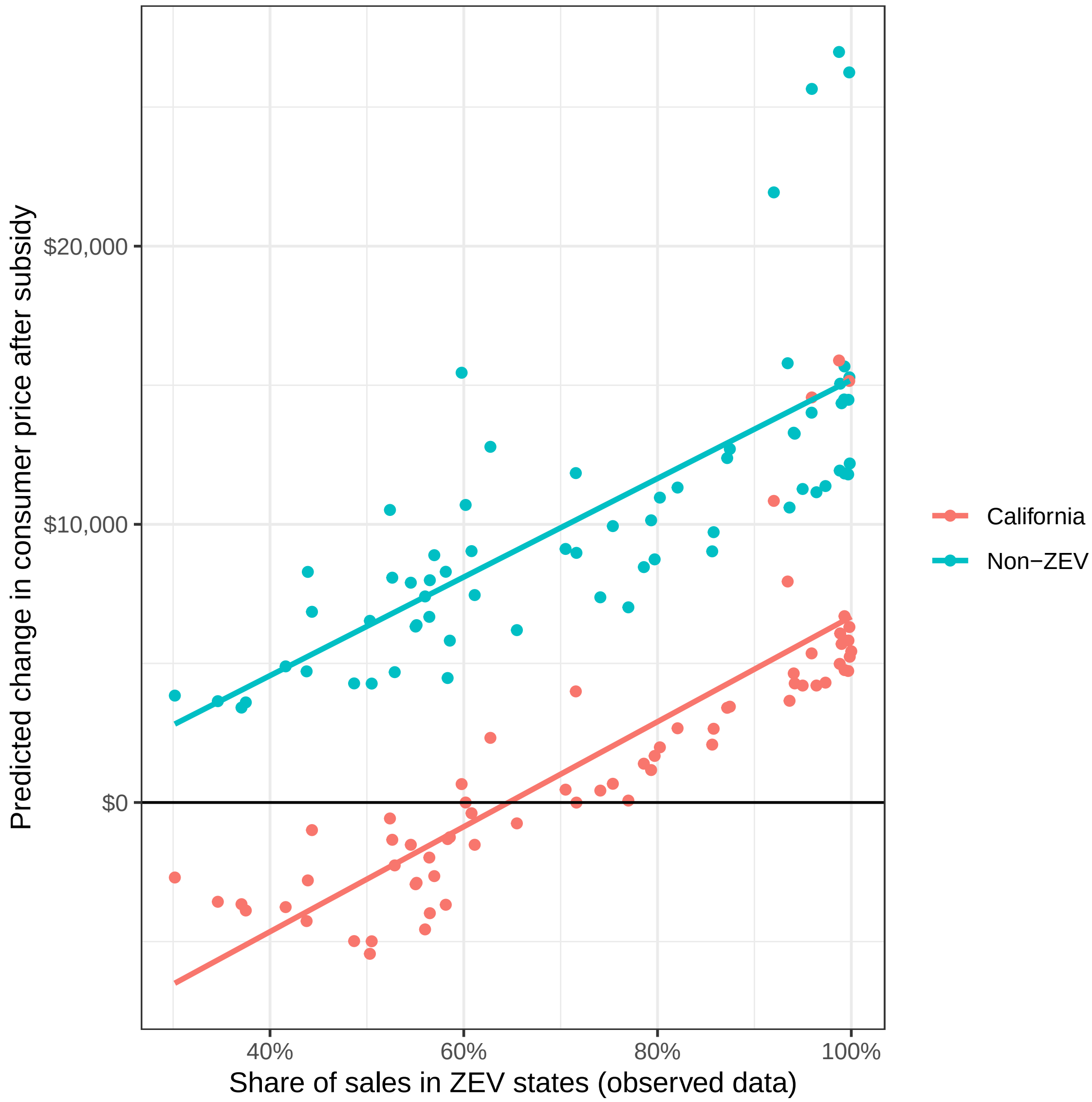

Figure 7: Predicted change in consumer price (including subsidies) for EVs, California and outside regulated states.

Note: For all electric vehicles, this plot shows the predicted change in consumer price (national price minus subsidies) from switching from the ZEV mandate to the counterfactual demand-pull policy, for California and the rest-of-country region only. Products are arranged by the share of their sales that are in the ten regulated states in observed data (under the ZEV mandate). Consumer prices rise for all EVs outside the ten regulated states; consumer prices in California rise for products that are predominantly sold in regulated states, but fall for products that are sold nationally.

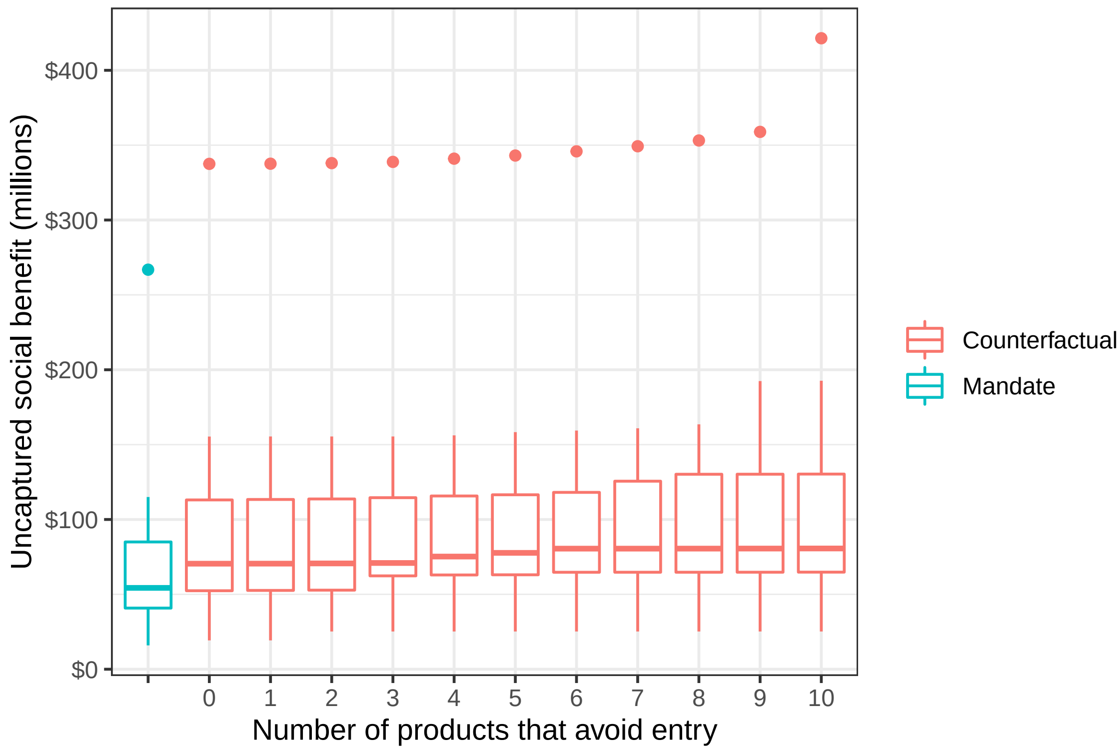

Figure 8: Sum of entry externalities minus credit value, selected EVs, under counterfactual demand-side policy

Note: Credit value consists of GHG credits. Entry externalities are the change in consumer surplus, negative environmental damages, and other-firm profit resulting from entry. All calculations use estimated values of product quality ξ.

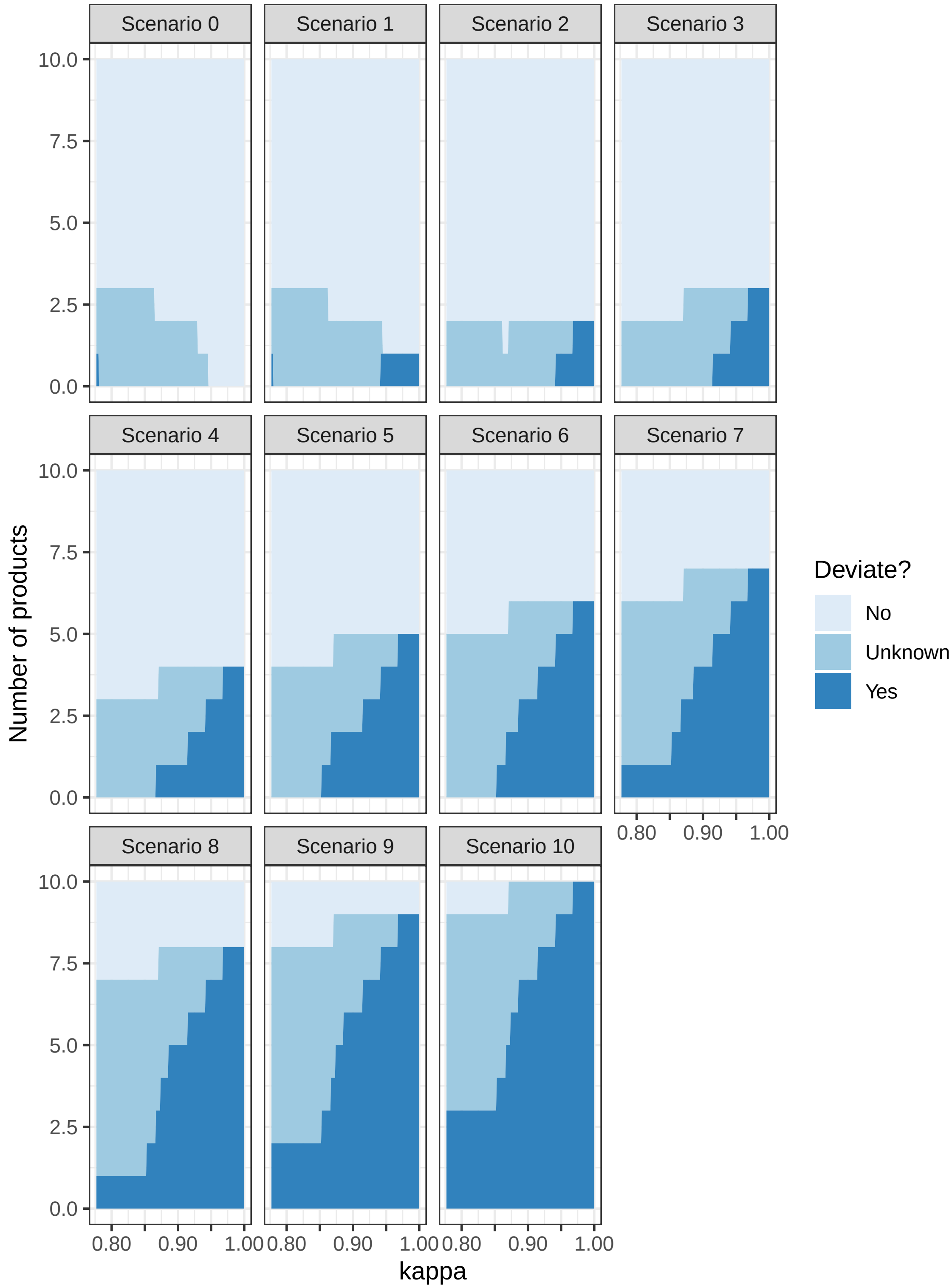

Figure 9: Number of firms with incentives to deviate in each entry scenario, given product entry parameters

Note: Given a value of the ratio of long run benefit to entry cost κ, compute the profit each firm obtains by introducing or removing each non-native electric vehicle, and report whether it is positive. If the sign is ambiguous because of unknown entry cost, report unknown. Scenarios are labeled by the number of models that do not enter.

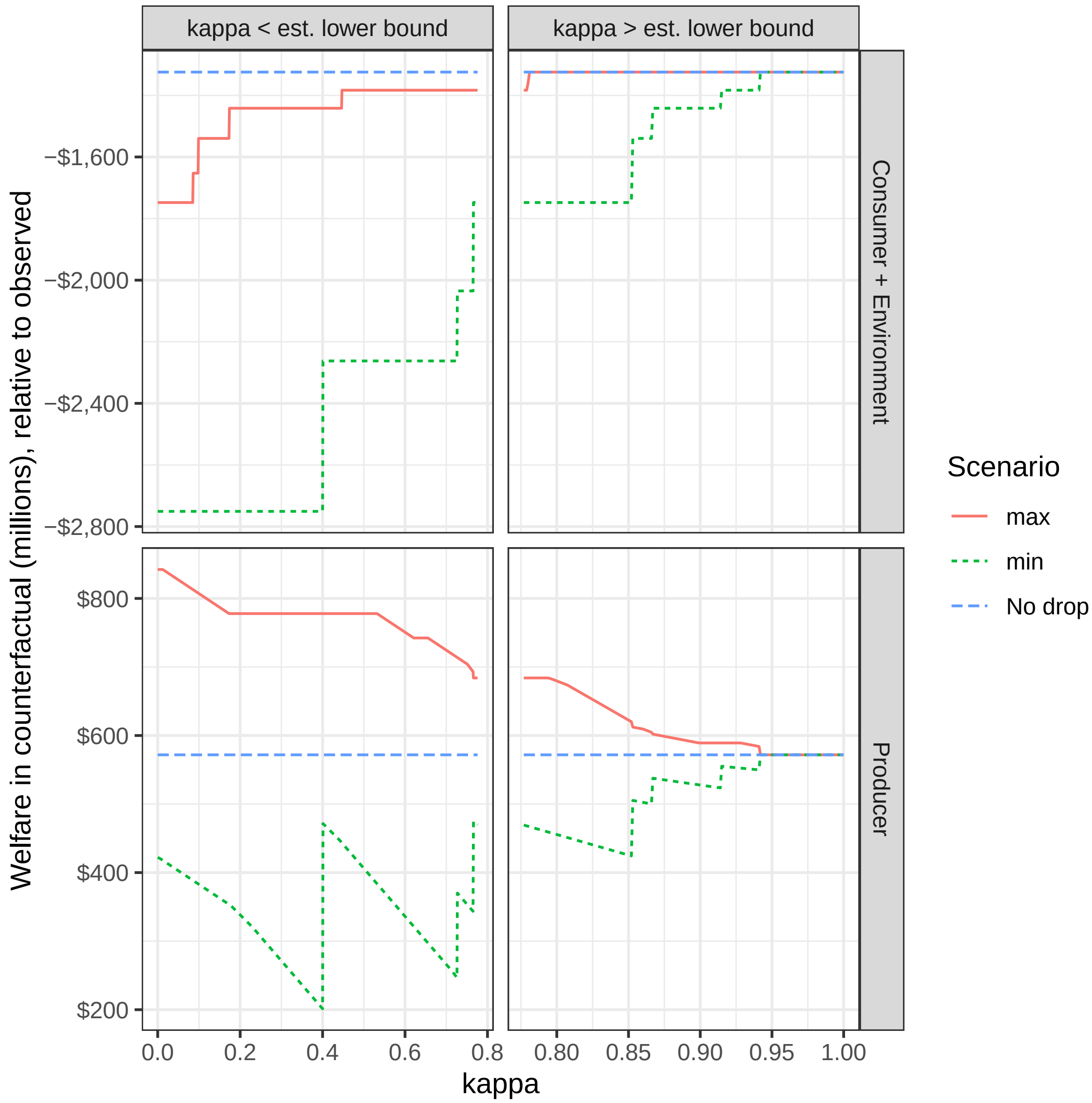

Figure 10: Welfare effect of replacing ZEV mandate with demand-side policy, across entry scenarios

Note: Given a value of the ratio of long run benefit to entry cost κ, compute welfare across scenarios where the n lowest-selling non-native models don't enter. Across the entry scenarios where no firm has an incentive to deviate (or the sign of the incentive to deviate is unknown), take the maximum of the upper bound on welfare and the minimum of the lower bound. Report welfare as a difference from welfare in the observed equilibrium. The scenario where all products stay in is also shown. Results are divided into values of κ rejected by observed entry and values of κ compatible with observed entry.

	Product set unchanged		Product set reduced	
Model year	Subsidy	Tax	Subsidy	Tax
2009	$0	$0	$0	$0
2010	$0	$0	$0	$0
2011	$3,566	$17	$3,566	$17
2012	$2,616	$19	$3,323	$25
2013	$3,697	$83	$3,850	$87
2014	$2,884	$68	$3,593	$86
2015	$2,356	$76	$2,479	$80
2016	$2,993	$126	$3,059	$129
2017	$2,316	$110	$2,402	$114

Table 5: Counterfactual consumer subsidy and tax amounts

Note: This table shows the magnitude of consumer subsidy and tax, within the ten regulated states only, that achieves the same EV sales within the regulated states each year when the ZEV mandate is removed. (Greenhouse gas credits remain with prices unchanged.) The consumer subsidy shown is the amount before range multipliers, and is comparable to the ZEV credit price in Table 3. The tax per non-EV is set by constraining the subsidy outflows and tax inflows to balance. Firms respond by resetting prices in Nash–Bertrand equilibrium. Run under both the scenario where the product set is unchanged and the scenario where the 4 lowest-selling non-native models drop out.

A Appendix

A.1 Details of the ZEV mandate

As shown in Table 6 (source: 13 CCR §1962.1(d)(5)(A)), the number of credits earned per vehicle was a function of its range. (The regulation used the UDDS urban driving range, which is about 40% higher than the EPA range.) In almost all cases, electric vehicles earned between two and four credits and did not qualify for fast refueling. (An exception is the longer-range versions of the Tesla Model S, which qualified in 2012 and 2013 on the basis of an experimental battery swap program.[54])

Table 6: ZEV credits, model years 2009–2017

Tier	Criteria: UDDS Range (mi)	Criteria: Fast Refueling	Credits
Type I	$[50, 75)$	–	2
Type I.5	$[75, 100)$	–	2.5
Type II	≥ 100	–	3
Type III	≥ 200	–	4
Type III	≥ 100	Yes	4
Type IV	> 200	Yes	5
Type V	≥ 300	Yes	7 (9 after 7/2015)

The credit requirement in each year is formulated as fixed percentage of the manufacturer's "production volume" of non-zero-emission passenger cars and light-duty trucks. (Before 2009 only light-duty trucks under 3750 pounds loaded weight were counted; between model years 2009 and 2012 this cutoff was raised to 8500 pounds.) 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 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)).

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

The credit requirement percentage for applicable manufacturers is shown in Table 7 (source: 13 CCR §1962.1(b)(2)).

Table 7: 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%

In model years 2009–2011, large manufacturers could opt for a lower requirement of 0.205% if they did not use traded credits to meet it (13 CCR §1962.1(b)(2)(B)).

A.1.1 Travel provision

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

In model year 2009, credits for ZEVs travel one-for-one between California and the other ZEV states (13 CCR §1962.1(d)(5)(E)). Because model year 2009 ZEVs were not sold commercially, we ignore them.

In model years 2010–2017, credits for ZEVs travel proportionally. Suppose an eligible vehicle by manufacturer m, which earns x credits, is placed into service in a ZEV state in model year t. Then, if the manufacturer chooses to travel the credit, it translates 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 National pricing

The key driver of the differences between the ZEV mandate and our counterfactual policy is the institutional feature of national pricing. Though our setup uses a national posted price that the consumer pays directly to the manufacturer, only Tesla sells vehicles this way. Other manufacturers sell new vehicles through dealerships, which negotiate separately with each consumer. (The structure of the new vehicle market is described in Murry and Schneider (2016).) If price variation is only due to factors unrelated to state-level policy, such as vehicle options and consumer information, then the basic implications of national pricing for policy still hold. The main question, then, is whether the transaction price absorbs cross-state differences in subsidies and mandates.

If manufacturers were to adjust prices across states to reflect policy differences, the most likely mechanism would be through manufacturer incentives to dealers or consumers (the rebates studied by Busse, Silva-Risso, and Zettelmeyer (2006)). We have not found evidence of this for EVs. A 2017 California Air Resources Board (CARB) report (California Air Resources Board 2017) found that manufacturer incentives for EVs in February–August 2016 (as reported by AutoNews) were comparable in Seattle, in a non-ZEV state, to a selection of cities in ZEV states. (Manufacturer incentives for hybrids were somewhat lower in Seattle than in the other cities.)

Turning directly to transaction prices, a 2017 analysis of Kelley Blue Book data by the Energy Information Administration (Bratvold and Cleaver 2017) found that average vehicle sales prices for the 2016 Nissan Leaf SV varied little across metropolitan areas, including between metropolitan areas in ZEV and non-ZEV states.

Though California Air Resources Board (2017) found differences across states in median model sales prices, it did not account for trims. The median price paid for a 2015 Nissan Leaf, across all trims, was $28,900 in California (DMV data) and $25,123 in a group of ten non-ZEV states.[55] The 2015 Nissan Leaf had three trim levels with MSRPs of $29,010, $32,100, and $35,120, respectively (as reported by MSN Autos), so it is possible that California buyers paid more because they opted for higher trim levels. (For this model, median transaction prices were clearly well below MSRP.)

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Busse, Meghan, Jorge Silva-Risso, and Florian Zettelmeyer (Sept. 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`.

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Murry, Charles and Henry S. Schneider (Jan. 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`.

[55]CARB obtained this number from Experian Automotive data from Colorado, Kentucky, North Carolina, North Dakota, New Mexico, Ohio, Oklahoma, Texas, Virginia, and West Virginia.