Regulatory Mandates and Electric Vehicle Product Variety*

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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-pull tools like consumer incentives? We study an important 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 the interaction between imperfect competition and endogenous product entry. After showing that firms internalized much of the social benefit of entry under the mandate, we evaluate a counterfactual policy that replaces the mandate with a demand-pull subsidy and tax regime. Holding fixed the regulator's stated target, electric vehicle sales in regulated states, the demand-pull 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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1 Introduction

The tools used by policymakers to intervene in product markets include supply-side tools, which use regulations and mandates to alter the incentives to produce goods, and demand-pull tools, which use subsidies and taxes to alter consumer incentives to purchase goods. Environmental policymakers often use these tools to promote socially beneficial products, even though they rarely target the exact market failure motivating the policy, such as pollution externalities or spillovers from research and development. Policymakers seeking to encourage new types of products, particularly alternative fuel vehicles, have adopted both types of policies, sometimes at the same time. When product market competition is national, regional supply-side and demand-pull policies designed toward the same goal may generate different markups over marginal cost and, as a result, 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 the most prominent 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 ask whether the ZEV mandate was structured to induce welfare-improving or welfare-reducing product entry, and investigate the consequences of policymakers' choice to use a mandate rather than rely only on demand-pull policies.

Our empirical study builds on the well-known theoretical result that imperfectly competitive product markets can feature more or fewer products than the social optimum, because each firm does not capture the negative effect its product will have on other firms' profits ("business stealing", following Mankiw and Whinston (1986)) or the positive effect it will have on inframarginal consumer surplus (Spence 1976). Policies that subsidize consumers or producers based on quantity will exacerbate both effects. We quantify the magnitudes of these welfare effects under the supply-side mandate and a counterfactual demand-pull policy and determine the direction of the resulting effect empirically.[1]

We begin by documenting a shared characteristic of electric vehicles that were primarily sold in states with the mandate: that the vehicle was designed on the platform of an existing gas-powered vehicle ("non-native"), instead of being designed from the ground up as an electric vehicle ("native"). Native vehicles were sold in high quantities across the US; non-native vehicles were sold in much lower quantities, and overwhelmingly in states with the mandate.

To analyze social welfare and the incentives facing manufacturers, we estimate a model of consumer demand and producer price-setting in the 2009–17 US passenger vehicle market. 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 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 business stealing externality, consumer benefits from variety, and environmental effects.

[1]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).

We find that the social benefits of product entry for electric vehicles are positive and substantial: inframarginal consumers' tastes for variety exceed the business stealing externality and dwarf the short-run environmental effects. When regulatory credits are highly valued, the mandate can allow firms to capture up to half of these social benefits. To complete the welfare analysis, we use accounting estimates to bound the upfront cost of entry, and use observed entry behavior to estimate the benefits of entry that firms anticipate to capture in the long run, beyond the end of our study period.

We then simulate a counterfactual demand-pull policy that replaces the ZEV mandate with a combination of a consumer subsidy for electric vehicles and consumer tax on non-electric vehicles. We set the level of the subsidy and tax to hold fixed the quantity of electric vehicles sold across the affected states. Across a range of entry scenarios, firms capture less of the social benefits of product entry under the demand-pull policy. We then compare welfare under the counterfactual policy to welfare under the ZEV mandate. Across plausible entry scenarios, consumer surplus is between \$1.3 billion and \$790 million lower under the demand-pull policy. Producer surplus, when accounting for entry costs and long run benefits of entry, is between \$280 million and \$540 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 policymakers seeking to encourage the development and adoption of nascent socially beneficial products should account for product variety when designing policy.

1.1 Literature

Industry observers have claimed that the ZEV mandate was influential in automakers' decisions to introduce electric vehicles,[2] 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). An exception is Holland, Mansur, and Yates (2021), which evaluates a hypothetical cap-and-trade system to limit sales of gasoline vehicles over a long horizon.

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 adds to an extensive literature on the effects of supply-side environmental policies in the automobile industry, which has focused primarily on fuel economy standards like the Corporate Average Fuel Economy (CAFE) and state and federal greenhouse gas standards. 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

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

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 (Bresnahan and Yao 1985; 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 this literature is Durrmeyer and Samano (2018), which contrasts fuel economy standards and purchase subsidies within a structural model of demand and supply.

In studying the effect of regulatory mandates on the variety of products available in the market in equilibrium, we contribute 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 quantify how much of the social surplus created by product entry 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

Most major automakers in the US introduced an electric vehicle (EV) during the first generation of the commercial market in the early 2010s, but electric vehicle models varied widely in engineering characteristics and in sales levels. This generation of models fell mainly into two groups: models that were designed from the ground up to be electric vehicles (called "native" vehicles 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.) Table 1 shows selected data for the electric vehicles available in the US in the period we study.

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.[3] 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.[4] 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 mul-

[3]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).

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

tiple causes, including technological breakthroughs by Tesla engineers,[5] but observers most commonly point to cost declines in lithium ion batteries that were driven by consumer technology applications, such as laptops and phones. Compared to nickel-metal hydride batteries, used by early generations of 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]

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.) We 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,[7] requires the largest automakers to sell a quota of non-fossil-fuel ("zero emission") vehicles, nearly always battery electric vehicles.[8] Each manufacturer's quota is based on its past sales of all vehicles in the regulated states, 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 manu-

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

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

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

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

facturers faced the ZEV quota: Chrysler, Ford, GM, Honda, 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.[9] 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.[10]

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

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

[10]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.[11] 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,[12] 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.

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.[13] This difference changed over time, however, as cost of a battery pack of a fixed size

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

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

[13] See "Making electric vehicles profitable" (Yeon Baik, Russell Hensley, Patrick Hertzke, and Stefan Knupfer, McKinsey, 3/8/19), which breaks down the difference in average cost.

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.[14]

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.[15] 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.[16]

Publicly available engineering estimates also put the upfront cost of a native electric vehicle near \$1 billion.[17] 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.[18] 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 production is likely lower than for a gas-powered vehicle.

According to engineering estimates, the upfront cost of an electric vehicle built on

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

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

[16] 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.

[17] 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.

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

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.[19] 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.[20] 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 initial rate of 50 cars per quarter.[21]

Finally, in 2015, Ford announced it would invest $4.5 billion between 2015 and

[19] Source: 2012 Tesla 10-K.

[20] Source: 2010 Tesla 10-K.

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

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.[22] 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 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

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

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.[23] (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.

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

[23] 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).

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 where necessary. 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.[24] (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 with a gross vehicle weight rating under 8500 pounds, and whose base version has a MSRP under $120,000. We remove products that were only sold to fleet or government buyers. We assume that a product without any sales in a given market and year was not offered in that market.[25] 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.)

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

[25]This contrasts with Li (2019), who uses more granular markets and thus encounters products that were offered but had zero 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 manufacturer rebates derived from Automotive News[26] 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 federal program that overlaps with the vehicle types we use was the tax credit for plug-in 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.

3.2 Demographics

Household demographics are taken from American Community Survey microdata[27] for 2009 to 2017. 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.[28]

[26]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.

[27]Via IPUMS (Ruggles et al. 2019).

[28]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

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).

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.

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.[29] 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

77% of U.S. households in 2009.

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

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.

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 static model of firm product entry decisions with a per-period model of pricing and consumer choice. At the beginning of the study period, 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).[30] 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 option, which captures the choice not to buy a new vehicle.[31]

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.

[30] 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).

[31] This could include driving an existing vehicle for longer, buying a used vehicle, or forgoing car ownership.

The discrete choice model we use also rules out supply constraints in which a product has a fixed production level, which induces unobserved variation across consumers in choice sets. A related issue is that Tesla faced production delays and high demand, and used waitlists rather than prices for rationing (like the second generation Toyota Prius, as documented in Sallee (2011a)).We therefore assume that the relevant choice is the final decision to accept delivery, and the inconvenience of the waitlist process is captured in the unobserved characteristic. (We do not model the dynamic decision to enter the waitlist.)

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.

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 option, $j = 0$, 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 $\beta_i = \beta + \Pi d_i + \Sigma v_i$, where d_i is a vector of observed demographics, $v_i \sim N(0, I)$ is a vector of individual taste differences unobserved by the econometrician (independent across consumers and independent of all observed

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

variables), and Π and Σ are matrices of parameters. (We assume that Σ is a diagonal matrix.)

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 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. 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. 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.

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 $\mathbf{p}_t$ be the vector of prices in year t. The firm's problem is

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

where M_{mt} is the market size in region m in year t. The firm's first order condition 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 $\mathbf{p}_t$ 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 earns 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.

Specifically, we will consider two regulations, greenhouse gas (GHG) and ZEV.[33]

[33] As described in section 3.3, we assume that CAFE standards were not binding in this period

Consider product j in region m and model year t.

Let $c_{jmt,GHG}$ and $c_{jmt,ZEV}$ be the net change in credits from selling one unit of j. To determine $c_{jmt,GHG}$, we take the difference 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, $c_{jmt,ZEV}$ is the number of credits earned (generally a function of electric range); for non-EVs sold by large manufacturers, $c_{jmt,ZEV}$ is the additional number of credits that must be surrendered when a non-EV is sold.[34]

Now let $r_{mt,GHG}$ and $r_{mt,ZEV}$ be the value of each credit on the credit market. (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 the long run benefit of entry. We apply this framework to firm decisions to introduce electric vehicles, holding fixed the entry of non-electric vehicles (by that firm and by other firms). We use the model and the observed pattern of entry to estimate lower bounds on the long run benefits of electric vehicle entry, net of the entry cost. Using accounting data and further assumptions, we separate entry cost from long run benefits. We then predict entry under counterfactual policies and determine the contribution of entry costs and benefits to welfare.

because of federal greenhouse gas regulation.

[34]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 practice, the number is a fixed percentage of a moving average of non-EV sales in prior years (as detailed in Section A.1).

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 and spillovers across projects within a firm. 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.

The product entry decision is made once at the beginning of the study period, and then profits are collected throughout the study period. First, at $t = 0$, each firm simultaneously chooses whether to introduce each electric vehicle, and pays an entry cost for each introduction. Then, in each period $t = 1, \ldots, T$, information is revealed and firms set prices and collect observed variable profits. At the end ($t = T$), each firm collects the long run benefit for products it introduced. (Most firms only have one electric vehicle, or none. When a firm has multiple electric vehicles, we restrict the strategy space to entering all of the electric vehicles seen in our data or withholding one.)

All firms share an information set $\mathcal{I}$ at $t = 0$. (There is no private information.) In our main specification we assume that $\mathcal{I}$ contains marginal costs and demand parameters, but not product quality ξ or credit prices r. (In our alternative specification, firms are only uncertain about credit prices.) Credit prices r are endogenous to ξ because credit supply and demand depends on vehicle sales; we assume firms all have the same belief about r, and vary r across scenarios. We assume that firms have complete information about costs. (According to industry experts and trade press, firms believed in 2009 that battery prices were going to fall, though they may have disagreed on how quickly.)

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 benefits net of entry cost. 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 profit for firm f in period t is

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

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

Assumption 1 *Let $SC_j \geq 0$ be entry cost and $\pi^0_j(\mathcal{J}_{ft}, \mathcal{J}_{-f,t}) \geq 0$ be expected long run benefit. Then the firm's total expected payoff is*

$$\sum_{t=1}^{T} \delta^t E[\pi_{ft}(\mathcal{J}_{ft}, \mathcal{J}_{-f,t}) \mid \mathcal{I}] + \sum_{j \in \mathcal{J}_{ft}} \left(\delta^T \pi^0_j(\mathcal{J}_{ft}, \mathcal{J}_{-f,t}) - SC_j \right).$$

To simplify notation, we write the present discounted value of the incremental profit from introducing product j as $\Delta_j \pi_f$:

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

Putting those together, we can characterize the equilibrium strategy of any firm in the product entry game: introducing j dominates if the sum of incremental profit and long run benefit is larger than the entry cost.

Proposition 1 *It is a (weakly) dominant strategy for firm f to introduce product j if and only if*

$$\Delta_j \pi_f(\mathcal{J}_{ft}, \mathcal{J}_{-f,t}) + \delta^T \pi^0_j(\mathcal{J}_{ft}, \mathcal{J}_{-f,t}) - SC_j \geq 0.$$

We will call $\Delta_j \pi_f(\mathcal{J}_{ft}, \mathcal{J}_{-f,t}) + \delta^T \pi_j^0(\mathcal{J}_{ft}, \mathcal{J}_{-f,t}) - SC_j$ *the private entry incentive.*

In any Nash equilibrium of this game, no firm expects to benefit from introducing or removing a product from the product set. If the observed pattern of product entry is an equilibrium, we can obtain a lower bound on $\delta^T \pi_j^0(\mathcal{J}_{ft}, \mathcal{J}_{-f,t}) - SC_j$ for each product.

In reality, not all products are available in all periods. When taking this model to data, we treat the timing of delay (or early exit) as known from the beginning when the firm makes the entry decision.

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 welfare we exclude profits or losses from 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.

In the exposition that follows, all quantities are present discounted values (including π_j^0), and implicitly condition on the product set. When taking to data, we use $\delta = 1$, and $t = 1, \ldots, T$ corresponding to model years 2009 through 2017.

We define total welfare, denoted W, as

$$W = CS + Env + \sum_f (\pi_f - v_f) + \sum_j (\pi_j^0 - SC_j) \tag{4}$$

where CS is consumer surplus, Env is the negative of environmental damages, π_f is firm f's variable profit, and v_f is firm f's net profit from regulatory credits.[35]

[35] That is, $v_{ft} = \sum_{j \in \mathcal{J}_{ft}} \sum_{m \in \mathcal{M}} v_{jmt} s_{jmt}(\mathbf{p}_t^*) M_{mt}$.

We account for long run benefits to a given firm, but not long run consequences for others (such as information spillovers across firms or future business stealing) or 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.[36] We assume no deterioration in the gasoline or electric efficiency of the vehicle over time. Because we measure environmental damages at the time of purchase, we do not capture the time path of emissions or consumers' ability to respond to market conditions by driving their existing vehicles for longer. In particular, since the emissions from electricity use are changing rapidly over this period (Holland, Mansur, Muller, and Yates 2020) and electric vehicles are driven fewer miles each year (Davis 2019; Burlig, Bushnell, Rapson, and Wolfram 2021), we overestimate the damages of electric vehicles. We are also unable to measure the incremental emissions from a consumer's choice of the outside option; we assume the outside option has zero emissions.

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 closely parallel Mankiw and Whinston (1986); we also include environmental externalities. For a given firm f, rewrite (4) to separate firm

[36]This 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.

f's profit from the other terms:

$$W = \left(\pi_f + \sum_{j \in \mathcal{J}_f} (\pi_j^0 - SC_j)\right) - v_f + (\pi_{-f} - v_{-f}) + CS + Env + \sum_{j \notin \mathcal{J}_f} (\pi_j^0 - SC_j)$$

where $\pi_{-f} = \sum_{g \neq f} \pi_g$ and $v_{-f} = \sum_{g \neq f} v_g$.

To examine incremental changes in welfare components, we next define notation. Recall that $\Delta_j \pi_f$ is the difference in firm f's profits with and without the introduction of product j. Analogously, let $\Delta_j(\cdot)$ be the difference in the value of a welfare component with and without the introduction of product j. If firm f chooses to introduce product j, the change in total welfare (given the rest of the product set) is given by

$$\Delta_j W = \underbrace{(\Delta_j \pi_f + \pi_j^0 - SC_j)}_{\text{private entry incentive}} - \Delta_j v_f + \underbrace{(\Delta_j \pi_{-f} - \Delta_j v_{-f} + \Delta_j CS + \Delta_j Env)}_{\text{sum of externalities}}.$$

The $\pi_j^0 - SC_j$ terms for all other products drop out.

This expression demonstrates that product introduction has externalities, whose total may be positive, negative, or zero. The $\Delta_j \pi_{-f}$ term is the negative effect of entry on other firms' profits, commonly called the business stealing externality (Mankiw and Whinston 1986); the $\Delta_j CS$ term is the consumer benefit from variety (Spence 1976); and the $\Delta_j Env$ term is 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 using the following criterion: whether the credit value (v) terms align private incentives with social welfare. If $\Delta_j v_f$ is equal to the sum of the externalities, then $\Delta_j W$ is equal to the private entry incentive and the firm fully internalizes the social welfare effects of product introduction. If $\Delta_j v_f$ is larger than the sum of the externalities, there may exist an incentive for inefficient entry; if $\Delta_j v_f$ is smaller than the sum of the externalities, incentives for entry may be insufficient.

This criterion can be computed without estimates of entry costs and long run benefits, because these terms are included in the private entry incentive. Without estimates of those terms, however, we cannot test whether the pattern of product entry is efficient.

5 Estimating the demand model

Identification of our demand model relies primarily on the assumption that the observed product characteristics are exogenous to unobserved quality ξ, which we implement using the differentiation instruments of Gandhi and Houde (2019). To estimate the coefficient on endogenous price, we also use government subsidies, cost shifters based on production locations, and (for electric vehicles and plug-in hybrids) a proxy for lithium ion battery costs. To recover heterogeneity in consumer tastes based on observed demographics, we add micro-moments from survey data as in Petrin (2002).

5.1 Instrumental variables

We assume that characteristics of all products are mean-independent of all products' quality shocks ξ.[37] We thus take each product's own characteristics as exogenous, and add the local differentiation instruments of Gandhi and Houde (2019). Specifically, for each product j and a subset of characteristics k,[38] we construct three instruments using PyBLP (Conlon and Gortmaker 2020): the characteristic value x_{jk}, the number of products j' by the same firm for which $x_{j'k}$ is within one standard deviation of x_{jk}, and the number of products j' by other firms for which $x_{j'k}$ is within one standard deviation of x_{jk}. As described by Gandhi and Houde (2019), the primary role of the

[37] 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).

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

differentiation instruments is to estimate random coefficient parameters.

We assume that government subsidies are exogenous.[39] 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.)

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),[40] 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).

5.2 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.

[39]This instrument is also used by Li (2019).
[40]This instrument is also used by Wollmann (2018).

5.3 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.[41] 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 5.2 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, v_i) using Monte Carlo integration with 200 draws per market. The weight matrix is determined by two-step GMM, clustering observations 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

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

make-model level to allow for within-model correlation in unobserved quality across regions, across time, and across fuel type and battery size variants.

5.4 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.

6 Estimating the pricing model

We estimate marginal costs by solving the Nash–Bertrand first order conditions (3). This method is an adaptation of the method in Berry, Levinsohn, and Pakes (1995) 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

Interpreting our estimates of welfare using the static product entry framework described in Section 4.2, 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. Comparing accounting estimates of entry costs with observed variable profit, we estimate long run benefits 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 — business stealing, 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 hold prices fixed for simplicity.) Business stealing then comes from other firms' profits, computed using marginal cost estimates and the predicted shares. Environmental effects come from predicted changes in shares (as described in Section 4.3).

In our baseline specification, we assess the incentives under full information about ξ, using each product's estimated ξ from the demand model. In our alternative specification, firms choose entry without knowing product quality in advance; they instead take an average over the distribution of ξ, which we approximate using a normal distribution. In both specifications, we try three paths for r: no ZEV mandate

($r_{mt,ZEV} = \$0$), the observed realization of $r_{mt,ZEV}$, and a scarce-credit scenario ($r_{mt,ZEV} = \$5000$). We assume the credit price for GHG remains fixed.

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, business stealing 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 estimates that the closest substitutes for electric vehicles are other electric or clean vehicles.

The percentage of the externality captured by credit values is given in Figure 5 for each product. 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.

When the welfare calculations are averaged over 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 the difference between entry cost and long run benefits.[42] To separate these terms, we use the accounting estimates from

[42] Our approach is an application of the framework in Pakes, Porter, Ho, and Ishii (2015).

Section 2.2 to bound entry costs.

For any product j, let $f(j)$ be the firm that produces product j. Proposition 1 gives an equilibrium strategy that depends on unobserved variables and variables that can be estimated from the demand model:

$$\text{enter if } SC_j - \pi_j^0 \leq \Delta_j \pi_{f(j)}.$$

For electric vehicles that entered, we can therefore obtain an upper bound on $SC_j - \pi_j^0$ for each j. To estimate $\Delta_j \pi_{f(j)}$, 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. (We hold prices fixed for simplicity.) We try three paths for r, as described in Section 7.1.

Because we do not have data on products that were not introduced, we are unable to use entry behavior to estimate upper bounds on π_j^0. Nonetheless, industry sources suggest that it is unlikely to be very large for non-native vehicles. Later generations of electric vehicles were built on dedicated platforms, so the designs of non-native models did not carry over. In addition, the non-native vehicles in our data were typically designed for the US market, had low or no sales outside the US,[43] and exited before 2021. For the non-native models introduced early in our study period, then, it is unlikely that π_j^0 is greater than the entry cost. (A large value of π_j^0 would also imply that the firm would benefit from introducing j without selling a single unit.)

Simplified model. For counterfactuals, we simplify the model by assuming that the long run benefit is proportional to entry cost. Though highly stylized, this captures that higher upfront investment in the period we study may translate to larger cost savings in future generations of electric models.[44]

[43] The main exception is the Volkswagen e-Golf, which sold well in Norway.

[44] Alternatively, we could interpret the long run benefit as a discounted scrap value of exit; in a different setting, Wollmann (2018) assumes that the scrap value of product exit is proportional to

For j in the set of non-native electric vehicle models that enter prior to 2017, denoted $\mathcal{J}_{NN}$, assume that $\pi_j^0 = \kappa \cdot SC_j$ and $\kappa \in [0, 1)$. Let $[\underline{SC}, \overline{SC}]$ be the range of accounting estimates. Then, for each $j \in \mathcal{J}_{NN}$,

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

giving a lower bound on the proportionality factor κ using entry patterns:

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

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. We also obtain an upper bound on SC_j for each j, given a value of κ: $SC_j \leq (1-\kappa)^{-1}\Delta_j \pi_{f(j)}$.

7.3 Product entry parameter estimates

Combining the upper bounds on $SC_j - \pi_j^0$ with accounting estimates for SC_j, we obtain lower bounds on π_j^0. Figure 6 compares incremental variable profit $\Delta_j \pi_{f(j)}$ (our estimated upper bounds on $SC_j - \pi_j^0$) with accounting estimates of SC_j. When incremental variable profit falls short of entry cost, the long run benefit required to justify entry is larger; when incremental variable profit is higher than entry cost, no long run benefit is required to justify entry.

While all native models except the BMW i3 recover their entry cost without long run benefits, about 40% of non-native models do not, with required long run benefits of up to $50 million per product when entry costs are low. If firms can see product quality ξ at the time of entry, it is still the case that about 40% of non-native electric vehicles require positive long run benefits, but the identity of the 40% changes, and required long run benefits range up to $78 million per product. Some

the sunk cost of entry.

models that deliver high expected variable profits before conditioning on ξ, such as the Mercedes and Ford models, deliver much lower variable profits when ξ is conditioned on. Likewise, some models deliver low expected variable profits before conditioning on ξ and higher variable profits when ξ is conditioned on.

Simplified model. From accounting estimates, we use $\underline{SC}$ =$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-pull policy

What are the welfare effects of achieving the same quantity target by a demand-pull policy? We simulate potential equilibria of the product entry and pricing models under a counterfactual policy that only uses consumer incentives.[45] In particular, we set the ZEV credit price to zero and instead 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.

We set the specific level of the rebate and tax using two constraints. 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 rebate must equal total collection through the tax, across all of the regulated states. This computation requires the rebate and tax to be set simultaneously with prices, and the regulator to have the same amount of information as the firms. We adopt total electric vehicle sales as the target because it is easily

[45] This type of policy is commonly known as a 'feebate', and is used in France to control greenhouse gas emissions from cars (Durrmeyer and Samano 2018).

measured and explicitly mentioned as a goal in regulator reports.

We compute these rebate and tax levels under a variety of entry scenarios. For each, we then test whether the scenario is an equilibrium in the product entry game under different values of product entry parameters, by checking if any firm can profitably deviate in its EV entry decision. Next, we compute consumer and producer surplus under this counterfactual, and compare to observed welfare with the ZEV mandate. In computing producer surplus, we report a range of estimates given the bounds on entry cost and long run benefit from Section 7.3.

To account for the effect of the rebate and tax on consumer prices, we adopt the approximation to the Nash–Bertrand equilibrium that Knittel and Metaxoglou (2014) use for merger simulation: first, the observed prices are used to calculate shares and share derivatives, and then equations (3) are solved for prices.[46]

Formally, the setup is as follows. The policymaker controls the rebate 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, 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 $z_m(\tau_t^0 e_j - \tau_t^1(1 - e_j))$. Let $q_{jmt}(\tau_t^0, \tau_t^1)$ be the quantity sold under the demand-pull policy, which depends implicitly on price adjustment. 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

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

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

[46] Computing the exact Nash–Bertrand price equilibrium is in progress.

8.1 Results

Rebate and tax amounts. Table 5 shows the magnitude of the rebate and tax that implement this policy, under the scenario in which entry is unaffected and the scenario in which four (of eleven) non-native electric vehicles stay out of the market. The rebate amounts are substantial: around \$9,000 in 2012, 2013, and 2015, exceeding \$13,000 in 2014 and 2016. (Because of the small market share of electric vehicles, the tax on non-EVs is usually under \$100 per vehicle.) This additional rebate is on top of the \$7,500 federal tax credit and existing state rebates (\$2,500 in California).

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 rebate, 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 stay out of the market. Figure 7 shows the uncaptured social benefit, measured as the sum of the externalities of product entry minus the incremental profit from GHG credits. Across all the entry scenarios we consider, the uncaptured benefit is larger under the demand-pull policy than under the mandate.

Counterfactual entry scenarios. If the demand-pull policy induces firms to capture less of the social benefits of product entry, we may expect fewer products to enter. Given a value of entry cost and long run benefit, we can test a product entry scenario by computing whether any firm has an incentive to deviate: either it has 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 profit of the product, which we write $\Delta_j \pi_{f(j)}^{cf}$, against the entry cost net of long run benefits, $SC_j(1-\kappa)$. 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:

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

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 8 shows the results. Across the entry scenarios in which the n lowest-selling non-native electric vehicles stay out, the scenarios with $n = 8, 9, 10, 11$ are rejected for all $\kappa \in [\underline{\kappa}, 1)$. The remaining scenarios are rejected for some values of κ.

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 rebate and tax on welfare are theoretically ambiguous.

We quantify welfare effects using the simplified model of product entry and total welfare from (4), 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 9. 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 \$1.3 billion and \$790 million lower and producer surplus is between \$280 million and \$540 million higher, for a total loss of between \$960 million and \$360 million from switching to the demand-pull policy. Even without the loss of product variety (as when κ is close to one) consumers are still worse off under the demand-pull policy.

9 Conclusion

We examine the effects of the ZEV mandate, an influential supply-side environmental policy in early generations of the US electric vehicle market. As intended, the mandate induced manufacturers to introduce electric vehicles, which were largely based on existing vehicle platforms and not sold in the rest of the US. Rather than inducing socially excessive entry, the mandate allowed entrant firms to capture more of the social surplus generated by their products. The mandate induced more entry than a comparable demand-pull policy would have, with consequences for the distribution of welfare between consumer and producer surplus. These findings have consequences for future policies to encourage new, socially beneficial types of consumer products. 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
Hyundai Ioniq	*	2017	$<$1,000	$29,500	124
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

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.

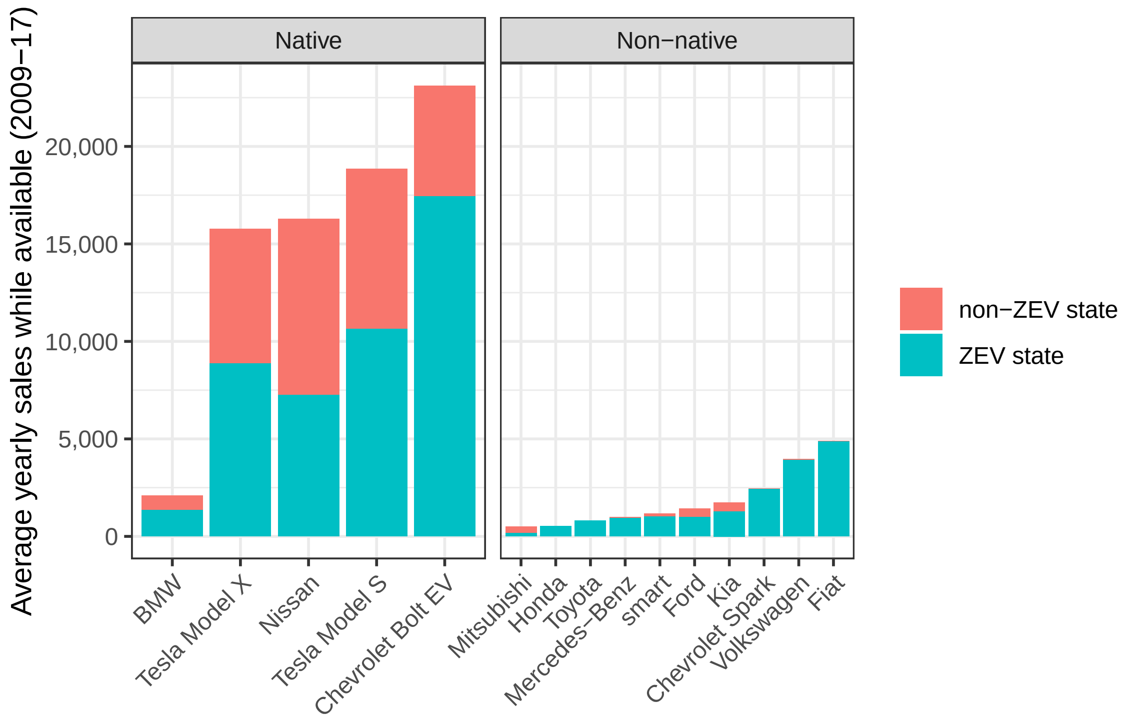

Figure 1: Average yearly sales by model, selected EVs, by ZEV states and non-ZEV states

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.

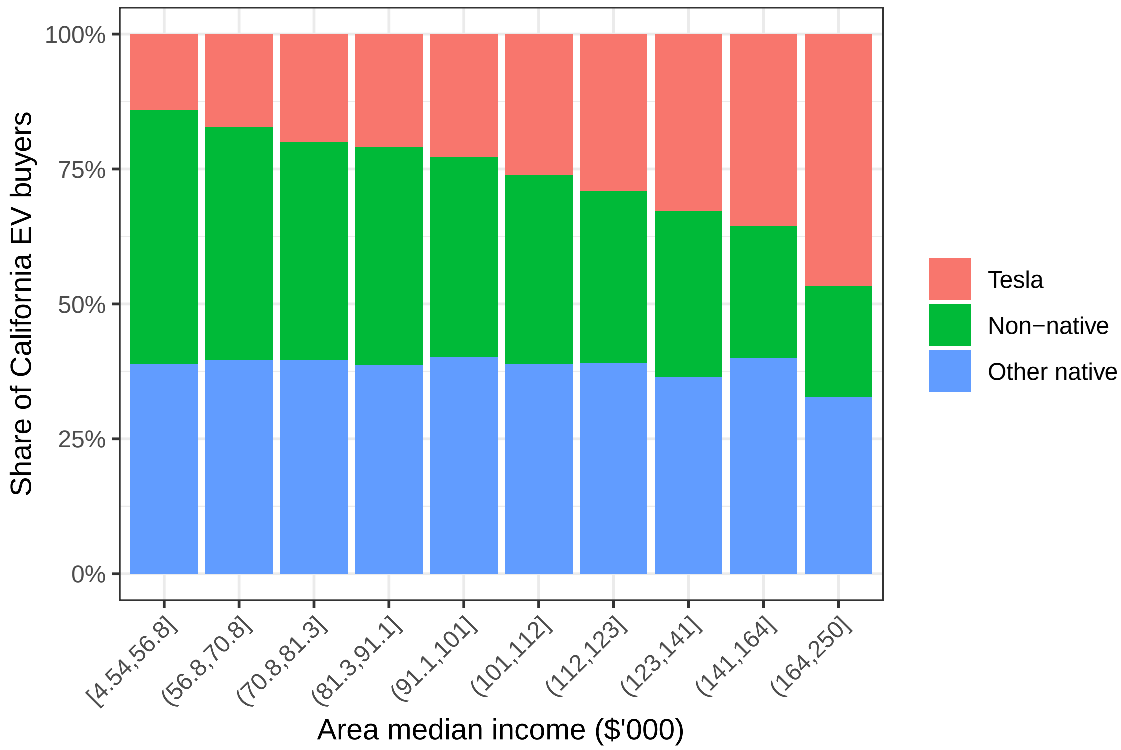

Figure 2: Breakdown of EV sales by non-native, Tesla, and other native, by census tract median income (California, 2010–16)

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	0.00	315.00	3.17	0.54	21.43
Gas cost/mi	0.00	0.33	0.13	0.12	0.05
Electric cost/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. 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: Revenue from Tesla quarterly reports and shareholder letters. The number of credits sold by each manufacturer in each year was provided by state regulatory agencies in the ten ZEV states.

	estimate	se
Linear parameters (β)		
Displacement (L)	0.23	0.07
Doors	-0.20	0.09
wheelbase	-0.03	0.02
HP/Weight	-4.29	5.23
Weight (tons)	-0.65	0.41
Gas cost/mi	-14.46	2.16
Electric cost/mi	-0.41	2.40
PHEV Range	0.01	0.02
EV Range	-0.01	0.02
Battery (kWh)	0.02	0.06
Footprint	0.12	0.04
New model	-0.01	0.07
Hybrid	-2.33	0.18
PHEV	-2.55	0.41
EV	-10.62	10.02
Coupe	0.66	0.25
Hatchback	0.57	0.33
SUV	1.87	0.32
Sedan	1.37	0.31
Truck	0.99	0.40
Van	1.06	0.44
Wagon	0.93	0.39
FWD	0.47	0.17
RWD	0.09	0.15
Demographics (Π)		
(price-subsidy)/income	-8.09	3.36
EV*College	1.08	0.47
EV*Temp. Factor	7.18	10.61
Unobserved heterogeneity (Σ)		
(constant)	0.00	2.92
EV	0.00	4.62

Table 4: Estimates of demand parameters

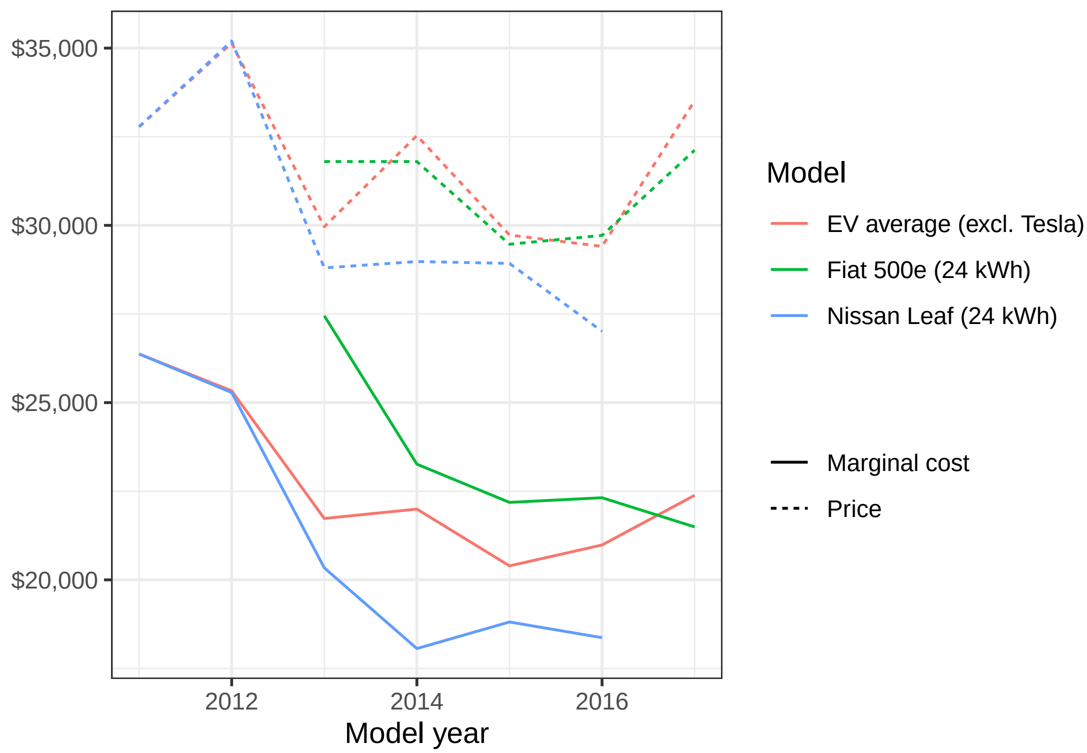

Figure 3: Prices and estimated marginal costs, selected EVs

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.

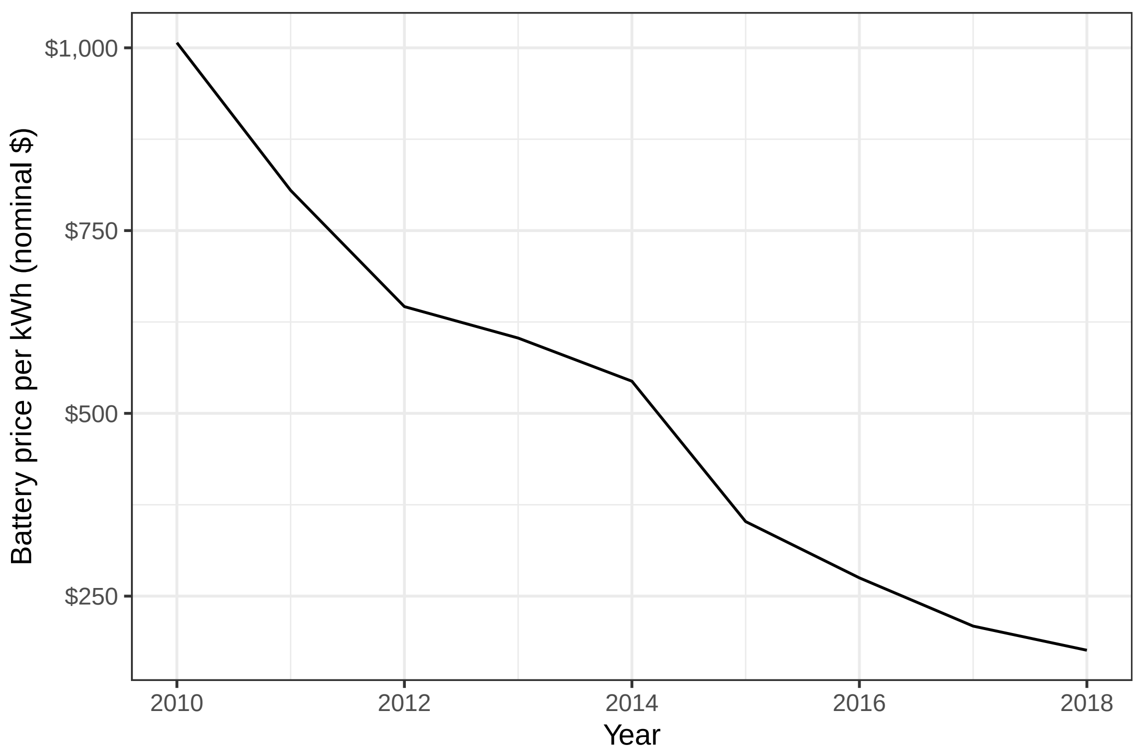

Figure 4: Lithium-ion battery pack prices, 2010–18, from BloombergNEF surveys of the EV industry

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.

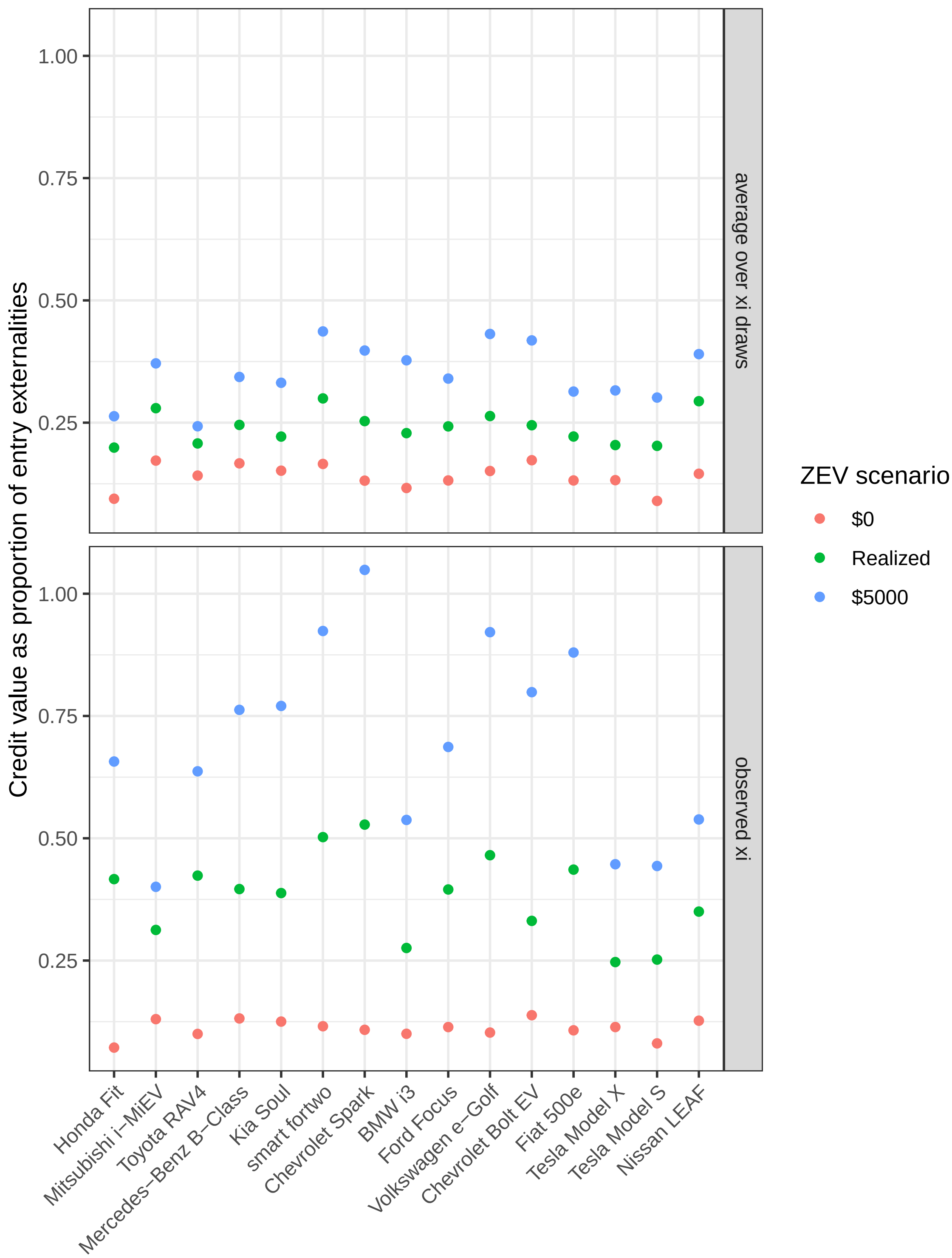

Figure 5: Ratio of credit value to sum of entry externalities, selected EVs

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.

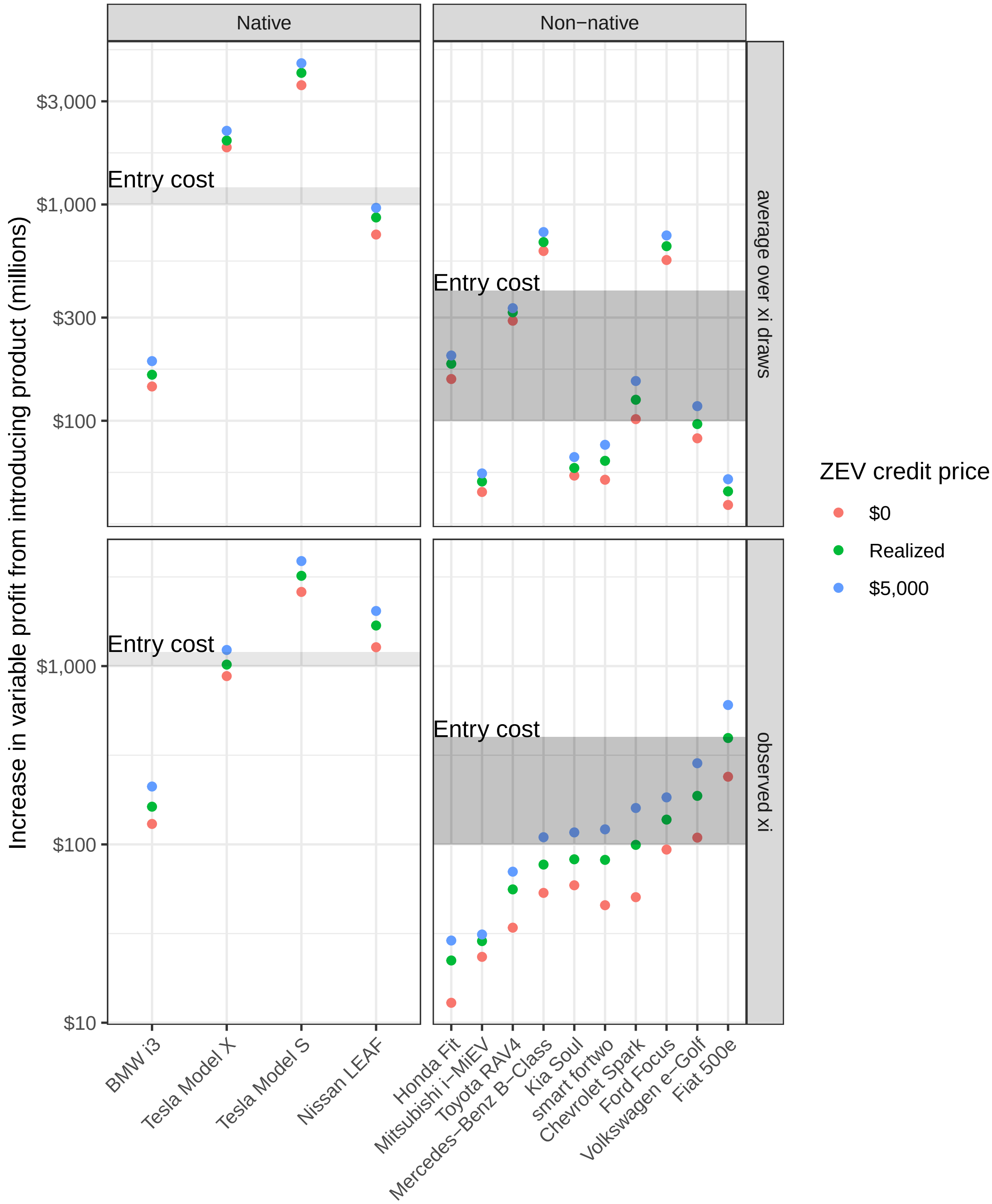

Figure 6: Comparison of incremental firm variable profit with accounting estimates of entry cost

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 averages over draws of product quality ξ; bottom panel shows calculations when product quality ξ is known.

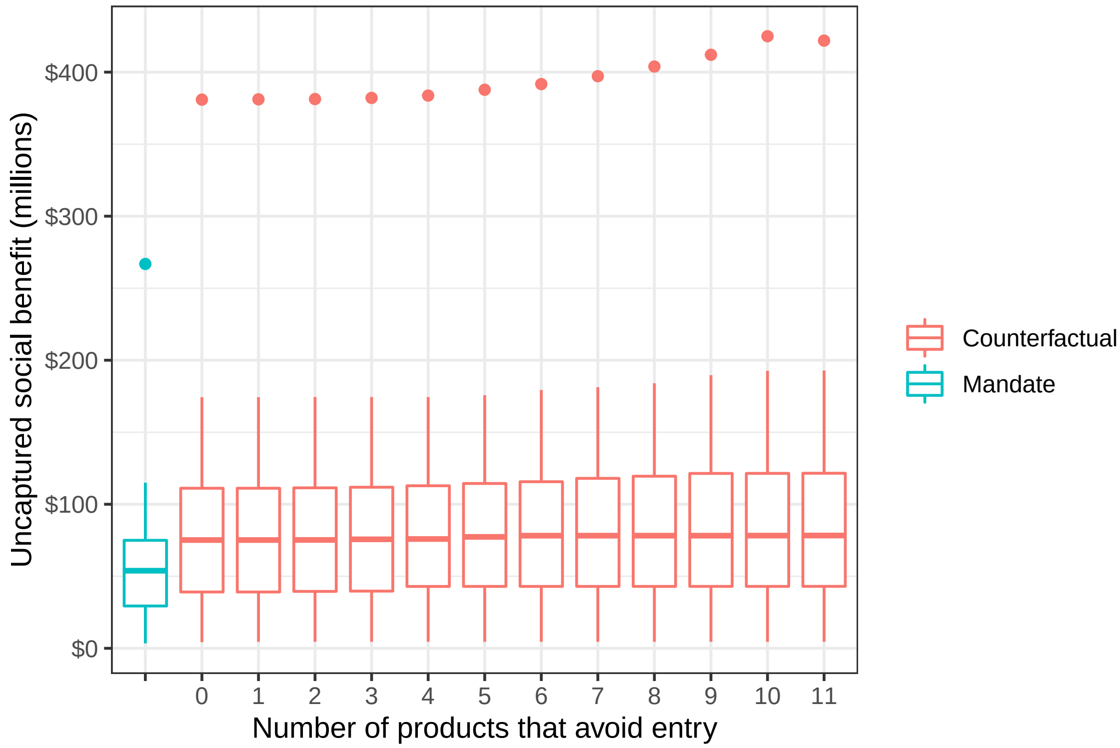

Figure 7: Sum of entry externalities minus credit value, selected EVs, under counterfactual demand-side policy

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.

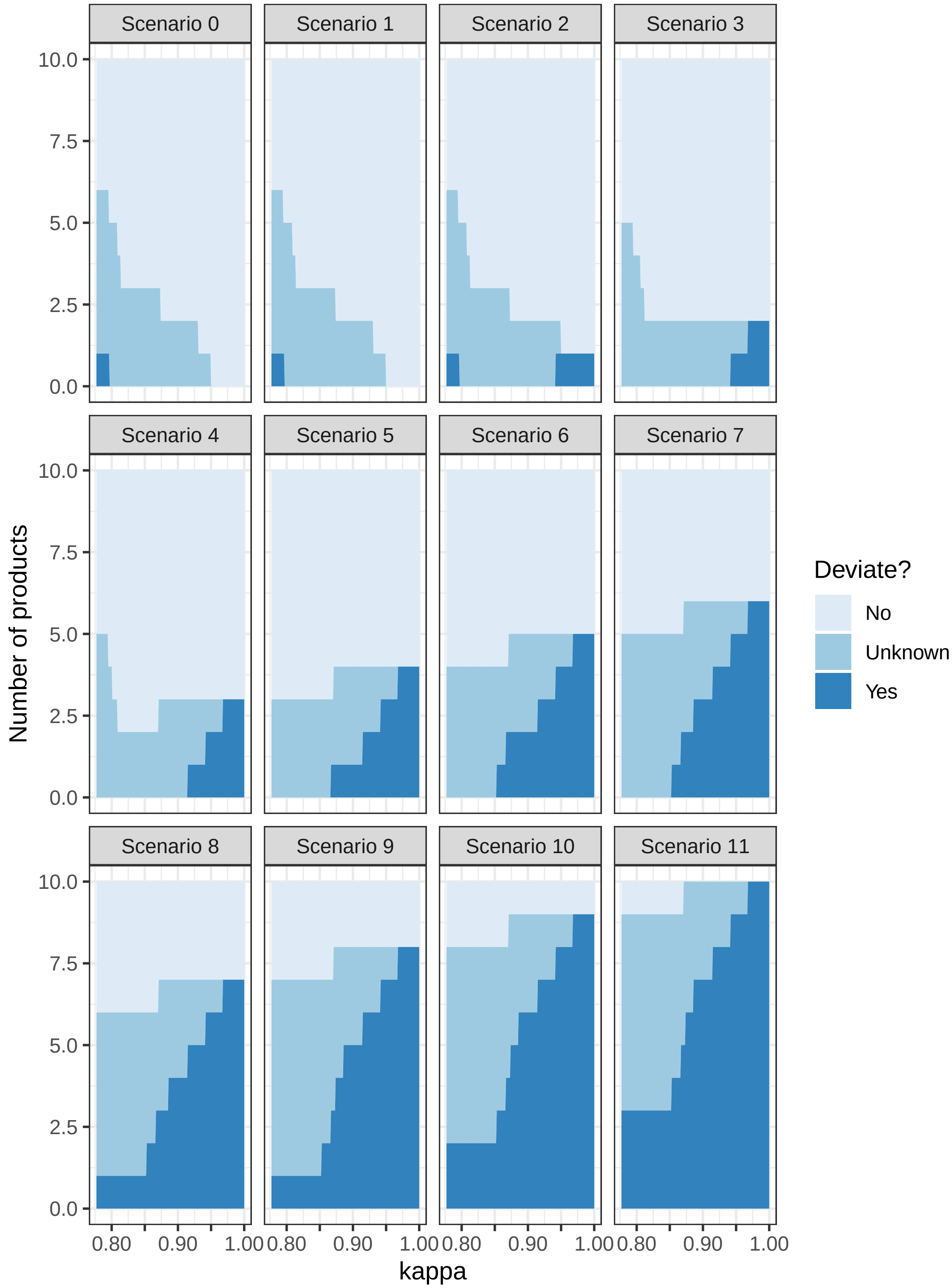

Figure 8: Number of firms with incentives to deviate in each entry scenario, given product entry parameters

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.

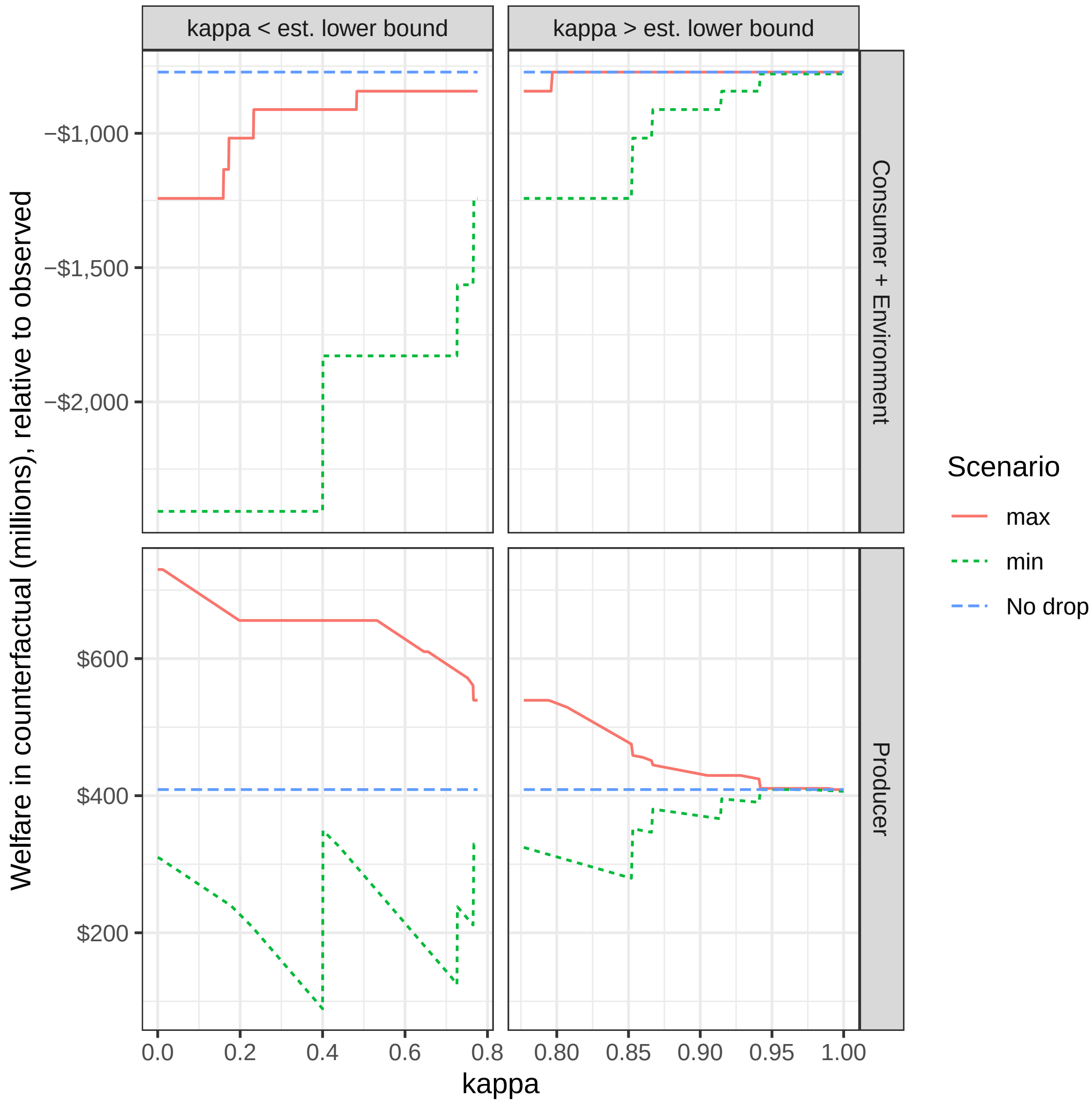

Figure 9: Welfare effect of replacing ZEV mandate with demand-side policy, across entry scenarios

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	Rebate	Tax	Rebate	Tax
2009	$0	$0	$0	$0
2010	$0	$0	$0	$0
2011	$7,219	$12	$7,219	$12
2012	$5,857	$14	$8,220	$19
2013	$7,328	$49	$8,015	$53
2014	$6,255	$43	$7,689	$53
2015	$4,814	$47	$4,814	$47
2016	$6,801	$80	$6,832	$81
2017	$4,584	$59	$4,694	$60

Table 5: Counterfactual consumer rebate and tax amounts

Note: Run under both the scenario where the product set is the same as with the mandate and the scenario where the 4 lowest-selling non-native models drop out. ZEV credits are removed from the profit function and GHG credits remain (with prices unchanged). Calculated by setting total yearly EV sales across regulated states to observed levels and constraining rebate outflows and tax inflows to balance. Firms respond by (approximately) resetting prices.

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.[47])

Table 6: ZEV credits, model years 2009–2017

	Criteria		
Tier	UDDS Range (mi)	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)).

[47]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%