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Providing the Spark: Impact of Financial Incentives on Battery Electric Vehicle Adoption[⋆]

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Abstract

To overcome adoption barriers and promote battery electric vehicles (BEVs) as an energy efficient consumer transportation option, a number of states offer subsidies to consumers for BEVs. We use a national data set of vehicle registrations and state-level financial incentives to assess the impact of vehicle purchase subsidies on adoption using both difference-in-differences and synthetic controls methods. We find that incentives offered as direct purchase rebates generate increased levels of new BEV registrations at a rate of approximately 8 percent per thousand dollars of incentive offered. Between 2011 and 2015, vehicle rebate incentives are associated with an increase in overall BEV registrations of approximately 11 percent. Our findings indicate incentives offered as state income tax credits do not have a statistically significant effect on BEV adoptions, though we caution this may be a result of limited temporal variation in BEV incentives across our sample. Responses to rebate incentives do not differ significantly by the make of the vehicle purchased (i.e., Tesla and non-Tesla vehicles). We combine our results with recent assessments of marginal environmental costs of electric vehicle charging and measure net welfare effects of BEV subsidy programs. Our analysis indicates these programs are not welfare-improving if only considering benefits associated with avoided emissions. Additional benefits associated with long-term market growth, production cost savings, network externalities, or accelerated innovation could substantially impact the net welfare outcomes.

Keywords: Electric vehicles, tax incentives, rebates, technology adoption
JEL classification: Q55; L98; O38; H71

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1. Introduction

Battery electric vehicles (BEVs) represent a frontier of commercially-produced vehicle technology and are often promoted as an important component of efforts to reduce transportation-sector reliance on fossil fuels. Despite their advertised benefits, BEVs face barriers to adoption including high upfront costs relative to conventional vehicles and consumer apprehension about reliability, range, and unfamiliar technology (Hidrue et al., 2011; Egbue and Long, 2012). Each of these barriers arises from the fact that BEVs are a significant departure from traditional internal combustion engine technology. To overcome these barriers and promote adoption of alternative fuels vehicles, the Federal government and some entities at the state and local levels in the United States subsidize consumer BEV purchases.

Given the widespread availability of BEV incentive programs, the potentially high cost of offering incentives worth thousands of dollars per vehicle, and the unique attributes of the BEV market, it is important to understand consumer response to these subsidies and to quantify the benefits and costs of their implementation. Assessment of the impact of BEV subsidies is valuable for policymakers considering adoption of new programs or renewal of existing incentive schemes.[1] Additionally, the results of our analysis can inform strategies for incentivizing future transportation technology innovation; the barriers to BEV adoption are similar to those faced by other emerging vehicle technologies (e.g., natural gas and hydrogen fuel cells) and represent more substantial hurdles than those encountered by other recent innovations in consumer automobile technology.[2]

Our analysis uses BEV registration data and information about state BEV subsidies in the United States to quantify the impact of state-level financial incentives on BEV adoptions. We take advantage of heterogeneity in subsidy types and vehicle model offerings in our sample to explore various subsidy responses in the BEV market. Specifically, we examine

[1] At the time of this writing, a number of states are considering the renewal of existing subsidies. Tabuchi, Hiroko. 2017. "Behind the Quiet State-by-State Fight Over Electric Vehicles." *New York Times.* `https://nyti.ms/2mwqlYV`. Accessed March 2017.

[2] BEVs represent a fundamentally distinct vehicle technology from traditional hybrid vehicles (e.g., Toyota Prius) and plug-in hybrids (e.g., Chevrolet Volt). Unlike hybrids that represent an incremental change to conventional vehicles by providing higher mile-per-gallon realizations through supplementary electric power, BEVs are solely powered by electricity. This results in an increased reliance on alternative fueling infrastructure and possible consumer reluctance to adopt BEV technology (Tal et al., 2013; Egbue and Long, 2012).

i) whether consumer response depends on the type of incentive offered and ii) whether there is heterogeneity in response for adopters that purchase Tesla vehicles versus those that purchase other BEV models. Our analysis also provides suggestive evidence of the extent to which charging infrastructure and fuel costs (both gasoline and electricity) are correlated with BEV adoption, though our choice of empirical specification precludes definitive, causal interpretations of these results.

As one of the primary justifications for offering incentives to BEV adopters is a reduction in fossil-fuel emissions, we use our estimates to assess the economic efficiency of state BEV incentive programs.[3] To do so, we combine our estimates of state-level incentive effects with the spatially detailed emissions damage estimates of Holland et al. (2016).

To assess efficacy of state-level BEV subsidies on consumer adoption, we employ a fixed-effects regression model and a national panel data set of vehicle registrations and state-level policies. We augment our primary analysis with an exploration of BEV incentive impacts using a synthetic controls approach. Our results indicate that state-level financial incentives increase BEV adoptions on the margin. Estimates suggest an increase in BEV registrations of 8% per thousand dollars of incentive offered, or, considering the total value of incentives, approximately an 11% increase in total BEV adoptions compared to the counterfactual scenario in the absence of state-level incentives. Assessing impacts by incentive type, we find significant, positive effects of direct purchase rebates. Tax credits are not revealed as strong drivers of new BEV registrations. However, when incentive effects are estimated as a share of total vehicle purchases, the effects of tax credits are positive and marginally significant. We hypothesize that the lack of a significant finding for tax credits may be the result of a limited number of states offering tax credits that vary in value over the study time period. We also estimate a version of the model that allows for differences in incentive effects by model type, focusing specifically on responses for Tesla purchases. Results indicate no difference in adoption responses to incentives between Tesla and non-Tesla buyers.

Total incentive effects are used in conjunction with environmental damage estimates to estimate program costs and net welfare impacts. We find that benefits in the form of avoided

[3]For example, Massachusetts explicitly cites greenhouse gas emissions reductions as a goal of the state's electric vehicle rebate program (MA EEA, 2015).

damages from vehicle emissions are not sufficient to outweigh the program and welfare costs of these policies. A sensitivity analysis of these results indicates that only in a setting with favorable assumptions about vehicle lifetimes and incentive uptake are state-level incentives welfare-improving when benefits are based solely on avoided environmental damage.

To the best of our knowledge, our study is the first to isolate the impacts of state-level incentives on the rate of adoption of BEVs in the United States and to examine these effects by subsidy and model type. We are also the first to apply synthetic controls methods to this problem, mitigating concerns about violations of the parallel trends assumption that must hold for difference-in-difference estimation. Our results provide a detailed examination of state-level financial subsidy impacts that complements the findings of Li et al. (2017) regarding network effects in the electric vehicle market. The application of our findings to a state-level welfare analysis is the first to incorporate the detailed spatial damage estimates of Holland et al. (2016) to estimate net national welfare implications of state-level BEV policies.

Our analysis contributes to the current literature that explores the design and impact of incentives for advanced vehicle technologies. The number of studies that utilize historical data to analyze the BEV market is relatively small, as the market is newer and sales levels are lower than the markets for conventional vehicles and hybrids. DeShazo et al. (2014) conduct a stated-preference study of new car buyers in California and estimate that California's state-level rebate program can be credited with generating approximately 10,000 plug-in vehicles (i.e., BEVs and plug-in hybrids). This is a 7% increase in sales in the combined BEV and plug-in hybrid market, equivalent to a 0.2 percentage point increase in market share. Sierzchula et al. (2014) assemble cross-sectional data on BEV adoptions and relevant market characteristics from 30 countries in 2012 and estimate the impact of BEV incentives globally. The authors find that the presence of incentives and the availability of charging infrastructure have the most significant influence on BEV adoption levels across countries, though the magnitudes of both effects are small. With respect to subsidy impacts, the authors find a $1,000 financial incentive increase corresponds to an EV market share increase of 0.06 percentage points. Point estimates also suggest that one vehicle charging station per 100,000 residents is associated with an EV market share increase of 0.12 percentage points.

The analysis of Li et al. (2017) explores the presence of network effects in the market for electric vehicles. The authors' results suggest that incentive effects are magnified by feedback loops that arise from subsequent expansion of charging infrastructure. Taken together, these studies indicate subsidy policies have been effective in modifying electric vehicle adoption behavior. Our study extends this line of inquiry and examines whether responses differ across subsidy types or across vehicle models.

Our analysis also augments existing research on vehicle incentives based on the market for traditional hybrid vehicles. Incentive offerings in the hybrid market received substantial focus in the mid and late 2000s. Diamond (2009) finds that the increase in market share of hybrids in the United States between 2001 and 2009 was likely influenced by gasoline price increases during this period rather than by vehicle incentives.[4] In contrast, analysis by Gallagher and Muehlegger (2011) yields significant, positive estimates of incentive effects. Gallagher and Muehlegger's results also suggest the magnitude of incentive impact varies based on the incentive's form; sales tax waivers are found to have a significant positive relationship with hybrid vehicle sales, while income tax credits are not. The authors hypothesize that their result is due to consumer discounting and the lag in receipt of income tax credit value. This finding is one impetus for our study and a similar finding in the BEV market could have implications for the design of programs, incentives, or other policies to support BEV adoption. Outside of the United States, Chandra et al. (2010) find support at the province level that tax rebate incentives influenced hybrid vehicle adoptions in Canada. The authors utilize within-province, temporal variation in tax rebates and hybrid sales across a broad time period (1989-2006) to identify hybrid vehicle market share increases on the order of 31-38 percent per 1,000 Canadian dollars (34-42% per $1,000 USD) of incentive.

Beresteanu and Li (2011) implement the methods of Berry et al. (1995) to assess hybrid vehicle demand based on the market share of hybrids in 22 metropolitan statistical areas nationally. Allowing for heterogeneous consumer preferences, the authors conclude that consumers prefer more fuel efficient vehicles and that the value of "local support" (i.e., HOV

[4]Diamond's results also suggest an inverse relationship between hybrid vehicle incentives and adoptions during this period, though this relationship was attributed to spurious correlation, assumed to be a result of coinciding incentive phase-outs and hybrids gaining market traction.

lane access and parking privileges) is not a significant driver of adoption.

We use the findings of these studies of the market for hybrids as a benchmark to inform our model. We modify our approach to account for differences in BEV and hybrid markets with respect to consumer perception, vehicle technology, infrastructure requirements, incentive offerings, and macroeconomic climate during initial commercialization. Our findings provide new evidence, in a unique and valuable market context, that state-level vehicle incentives can influence adoption of emerging vehicle technologies. Our results indicate that the incentive format may be an important factor in determining consumer response to BEV purchase subsidies, in line with the results of Gallagher and Muehlegger (2011). Our estimates of the implied costs of emissions reductions resulting from the subsidies corroborates prior findings that suggest that financial incentives for energy-efficient product adoption is a relatively expensive approach to reducing emissions when compared to alternative policies (Chandra et al., 2010; Beresteanu and Li, 2011; Knittel, 2009; Davis et al., 2014).

2. Background

States have long offered financial incentives to consumers for vehicles powered by electricity, but BEV models have only recently been added to mainstream automobile manufacturers' model lineups. After a few sporadic attempts at reemergence in the 20th century, the current era of the BEV began with the introduction of Tesla's Roadster in 2008. A high performance, electric sports car, the Roadster was produced in limited numbers and was listed at a base price in excess of $100,000. The first of the current electric vehicles priced for the majority of the consumer segment was Nissan's LEAF. During our period of study, the LEAF is the best-selling BEV model in the United States, with Tesla's Model S ranking second. Together, the LEAF and Model S represent approximately 75% of BEV registrations through 2015. Figure 1 displays quarterly totals of new BEVs registered nationally. Due to the Roadster's production constraints and market segment target, our analysis begins shortly after the release of the LEAF (Q1 2011) and extends through the end of 2014.[5]

[5]Nissan's LEAF was first available in the United States in December 2010. Fewer than one-half of one percent of the BEVs in our sample were registered prior to 2011. We therefore begin our analysis in Q1 2011.

Federal and state incentives for advanced vehicle technologies are offered in a variety of forms. The Energy Improvement and Extension Act of 2008 initiated the national Plug-In Electric Drive Vehicle Credit for vehicles purchased after December 31, 2009. For qualifying vehicles, this incentive is a \$2,500 base income tax credit that increases in value based on a vehicle's battery capacity. The maximum credit amount is \$7,500 (for which the LEAF and Model S are both eligible). In addition to the federal incentive for BEVs, individual states enacted advanced-vehicle incentives during this period that varied in incentive duration, value, and type. Detailed accounting of these incentives by state is reported in Table 2. Between 2010 and 2014, 15 states provided financial incentives for consumer adoption of BEVs. Of these, eight states varied the maximum subsidy value.[6] The most generous state-level incentives offered during this period came in the form of direct vehicle rebates, state income tax credits, and state sales and use tax exemptions. Direct vehicle rebates and state sales and use tax exemptions are available to consumers at the time of vehicle purchase. State income tax exemptions are granted based on the consumer's income tax liability and are only redeemable at the end of the tax year. Over our study period, state incentive type offerings are mutually exclusive. That is, no state offered a vehicle purchase rebate and an income tax credit.

BEV registrations by incentive availability are presented in Figure 2. States with incentives in place at any point during the study period display higher levels of BEV registrations as a share of total new vehicle registrations than states that did not offer incentives. The pattern present in this figure is suggestive of differences in consumer adoption behavior across states with and without BEV incentives. To ascribe a causal relationship to this pattern, we must control for underlying differences in the populations. The empirical method outlined below controls for confounding factors across populations and uses variation in incentive response across states to measure incentive effects.[7]

[6] States with new or varying policies: MA, MD, PA, TN, TX, WV; States with incentives that expired during the study period and were not renewed: HI, OR, TN, WV.

[7] The group of states with varying incentive levels in our study (i.e., the "treatment" group) are geographically, politically, and demographically diverse. We confirm that there is no policy selection through the use of a probit model of a policy indicator on state attributes. The model has low predictive power and none of the model's explanatory variables are statistically significant. Results of this analysis are available on request. Our model estimates are therefore not likely to be biased due to endogenous policy implementation.

3. Data

Our data are an unbalanced state-model panel. Summary statistics for all variables are included in Table 1. Vehicle models represent combined make and model designations (e.g., Nissan LEAF, Tesla Model S). Vehicle registration data are from R. L. Polk & Co. and are reported quarterly. In this context, vehicle registration counts are preferable to vehicle sales data as eligibility for incentive policies is based on the location of vehicle registration, rather than the location of the vehicle sale.[8]

The registration data set is comprised of multiple, annual snapshots of total vehicle registrations in the United States. Registration data includes personal vehicles only (i.e., registrations attributed to fleet, government, dealerships, and rental entities are excluded). We use these vehicle registration counts and the vehicles' original registration dates to compute the number of new vehicle registrations of each model, in each quarter, in each state. The method by which we assembled this "flow" measure of BEVs from initial registration dates implicitly assumes that i) the number of BEVs removed from service during our study period is either small or does not vary systematically across states, and ii) that movement of BEVs across state lines after their initial registration is minimal.

The first assumption is necessary because we do not observe vehicles that were registered and subsequently removed from service prior to the beginning of 2014. As our analysis covers four years of data and few BEVs were registered prior to the start of our dataset, we anticipate that this is not a significant concern.[9] In the event that scrappage did occur, we assume that it did not systematically differ across states and is therefore captured by the inclusion of time-model fixed effects.

The second assumption is required because we observe the registration location of the vehicle at the beginning of each data snapshot and do not observe any prior changes in location (i.e., we cannot trace individual vehicles spatially). We assume that the number of

In the presence of such a selection problem, our estimates of policy effect should be interpreted as upper bounds.

[8]This is especially relevant in the case of Tesla models where vehicles are potentially purchased out of state and transported to the final registration location.

[9]Oak Ridge National Laboratory's Transportation Energy Data Book cites a survival rate between 94.1% and 100% for vehicles under six years of age (Davis, Diegel, and Boundy, 2014).

vehicle transfers out of incentive states is likely to be small as a number of states require three to five years of vehicle registration within the state after the incentive is granted. We assume that consumers adhere to these requirements.[10]

Our analysis relies on a time series of incentive levels for each state over the study time period compiled from the Department of Energy's Alternative Fuels Data Center (AFDC) supplemented with information gathered from individual states' statutes and legislative proceedings. One other incentive frequently studied in the literature is the availability of single-occupant HOV lane access. Only one state altered its HOV lane access incentive during our study period.[11] Due to this lack of temporal variation, we omit HOV access from our consideration of incentive impacts. Other studies, however, find that HOV access is an important factor in BEV adoption.[12]

West Virgina offered one of the largest incentives for BEVs between 2011 and 2013, but had one of the lowest levels of BEV adoption over the same period. To avoid spurious results based on large percentage changes (but small absolute changes) in BEV adoptions in West Virginia, we omit the state from our national analysis.

To control for the effect that recent expansion of electric vehicle charging infrastructure may have on BEV adoptions, we construct a measure of aggregate charging charging station counts from the National Renewable Energy Laboratory of the United States Department of Energy. We include both public and private charging station locations. Public locations include free and paid stations in publicly accessible parking garages and lots (e.g., municipal garages, retail store parking lots, and Tesla's network of charging stations), while private charging locations require proprietary access (e.g., stations in private residential or business parking facilities accessible only by authorized residents, employees, or patrons).

Gasoline prices used in our analysis are a state-wide average of prices reported by the

[10]These assumptions are made for simplicity, but are not necessary for the validity of the findings presented below. If vehicle registration states have changed in our sample over time (i.e., if our assumption is violated), our dependent variable is measured with less precision. In this case, the reported standard errors are larger than if this measurement error were not present, and any current findings of statistical significance would remain.

[11]North Carolina made HOV lane travel legal for single-occupant BEVs in May of 2011.

[12]For example, Tal and Nicholas (2014) find that 38% of LEAF drivers in California reference the HOV sticker as a primary motivator for purchasing their BEVs.

Council for Community and Economic Research's Cost of Living Index. Residential electricity prices for each state were obtained from the EIA. Both retail gasoline and residential electricity prices are converted to December 2014 real prices. Fuel price effects are included in our model on a dollars-per-mile basis. We assume fuel prices follow a random walk as in Klier and Linn (2010) and therefore use contemporaneous fuel prices in our calculations of total vehicle fuel cost. Energy demand for BEVs and for competitive, conventional vehicles are obtained from the Environmental Protection Agency's fueleconomy.gov.

To control for potential time-variant, state-level attributes, we incorporate a number of demographic statistics reported annually including age, sex, and educational attainment from the U.S. Census. We include quarterly reports of median household income by state from the Bureau of Economic Analysis.

As noted in Kahn (2007), the level of environmentalism of particular states may drive adoptions of alternative fueled vehicles. To control for the impact of any possible within-state, temporal variation in environmental attitudes, we construct an index of state-level environmentalism based on voting records of each state's members of Congress from the League of Conservation Voters.

4. Empirical strategy

Our empirical approach builds on that of Gallagher and Muehlegger (2011) with modifications that address differences in potential determinants of adoption for hybrids and BEVs. We employ a fixed-effects specification, denoted in equation (1), to examine the relationship between state-level incentives and vehicle adoptions while controlling for BEV infrastructure effects, fuel costs, and demographic attributes.

$$
\begin{aligned}
\ln\left(\text{BEVperCap}_{smt}\right) = {} & \beta \text{Incentive}_{smt} + \lambda \text{Charging}_{s,t-1} + \\
& \gamma_1 \text{DPM}_{gas,smt} + \gamma_2 \text{DPM}_{elec,smt} + \delta \mathbf{X}_{st} + \alpha_{sm} + \theta_{mt} + \epsilon_{smt} \qquad (1)
\end{aligned}
$$

The dependent variable, $\ln\left(\text{BEVperCap}_{smt}\right)$, is the log of model m battery electric vehicle registrations per million residents in state s in quarter t. We record the incentive variable (Incentive_{smt}) at the maximum incentive value in thousands of dollars based on a vehicle model's eligibility in each state. Equation (1) is first estimated without distinguishing between incentive types before breaking out distinct incentive categories (e.g., direct vehicle rebates and state income tax credits). Because the incentive variable is coded as the maximum incentive value, coefficient estimates should be interpreted as an intent-to-treat estimator. We address the implications of this in the context of our welfare analysis included in Section 6. In some cases, incentives are offered for both BEVs and other alternative fueled vehicles. The policy effects estimated by our model are therefore likely lower bounds for the effectiveness of BEV incentives,

Our analysis also accounts for infrastructure availability, a concern not present in the market for traditional hybrids but potentially important for BEVs and other emerging technologies. Charging station data ($\text{Charging}_{s,t-1}$) are coded as total charging stations within a state by quarter. Charging station availability is included as a stock measure in an effort to account for levels of charging accessibility. The number of available charging stations is lagged one quarter to avoid concerns about endogeneity of charging station stock and BEV adoptions.[13]

Estimates of fuel costs are included in vehicle dollars-per-mile terms. We compute electricity cost ($\text{DPM}_{elec,smt}$) and gasoline cost($\text{DPM}_{gas,smt}$) for each vehicle model in our sample. Fuel prices used for this calculation vary quarterly by state. Dollar-per-mile values for electric vehicles are based on the kWh/mile ratings included in Table A1. Dollar-per-mile costs for similar gasoline models are based on the average fuel economy in each BEV model's vehicle class. Our specification assumes that both gasoline and electricity fuel prices are exogenous to the level of BEV adoption; BEVs represent a small share of vehicle and electricity demand during our study period and are therefore unlikely to influence fuel prices.

Our model incorporates fixed effects at two levels. We control for unobserved, time-invariant, state-level characteristics through the use of state-model fixed effects (α_{sm}). To

[13]We contend that charging station stock is plausibly exogenous as many public charging stations during this period were installed in an effort for businesses to appear "green" and were not primarily a revenue-generator (CSE, 2013; CSE and CARB, 2012). In the event that our exogeneity assumption is violated, estimates of incentive effects are biased downward and are therefore conservative. The causal effect of charging infrastructure expansion on electric vehicle adoptions is best addressed in a framework that accounts for network externalities such as the model of Li et al. (2017).

control for national trends that vary over time (e.g., macroeconomic factors and national vehicle availability and policies), we include year-quarter-model fixed effects (θ_{mt}). We also account for any potentially time-varying, state-level attributes with a set of demographic controls ($\mathbf{X}_{st}$), including average age, log of per capita income, education attainment rates, and environmentalism index scores.

The error term (ϵ_{smt}) is assumed to be uncorrelated with all independent variables included in the regression. Standard errors are clustered at the state level to address the possibility of within-group correlation in regressors and error terms.

The model proposed here estimates the effect of state-level subsides on state-level BEV registrations in reduced form. These estimated effects therefore include both demand- and supply-side responses. While assumptions about these responses will not significantly influence interpretation of the reduced form estimates, they will have implications for the subsidies' financial incidence and welfare effects calculated in Section 6. Relevant considerations include state-level and national elasticities of vehicle supply, consumers' perceived values of subsidies (especially relevant for tax credits), and the elasticity of substitution among vehicle models.

5. Results

5.1. Primary results

Table 3 presents estimation results for regressions of incentive level on various sets of explanatory variables. The dependent variable for all regressions in Table 3 is not differentiated by incentive type. Results in all columns include fuel price and demographic controls as well as the full set of fixed effects. Column (1) reports the regression of log BEV registrations per capita on the incentive value in thousands of dollars. Columns (2) through (4) incorporate charging infrastructure, fuel prices, and demographic controls, respectively. A joint hypothesis for the fuel price variables alone is not statistically significant. As theory indicates fuel cost may play a role in vehicle purchase behavior, we include it in our preferred specification. An F-test that tests the relevance of the full set of controls in our preferred specification (Table 3, Column 4) is significant.

In all cases, the estimate for the incentive variable is interpreted as the change in BEV registrations per capita per $1,000 change in subsidy value, holding all other factors constant. Specifically, our point estimates in Table 3 suggest an increase in per capita BEV registrations of approximately 7% per thousand dollars of incentive. Across specifications, this subsidy estimate is stable, positive, and statistically significant. Our estimate of 7% is slightly larger than Gallagher and Muehlegger's (2011) value of approximately 6% for HEVs in the United States.[14] Our estimate is smaller than the Sierzchula et al. (2014) estimate, which is equivalent to a 15% change in per capita BEV registrations per thousand dollars of incentive.

The regression results of Table 3 also indicate a statistically significant, positive relationship between charging infrastructure and BEV adoption for private stations only, a result that may indicate consumers factor charging at workplaces or other, gated access sites into their purchasing decisions. A positive correlation between charging infrastructure and BEV adoptions is in line with existing work on the topic (Li et al., 2017; Wood et al., 2015; Sierzchula et al., 2014), however infrastructure serves here as an important control to alleviate omitted variable bias in estimating our coefficient of interest and does not explicitly model the simultaneous determination of infrastructure expansion.

Table 4 includes results of incentive effects by incentive type. Point estimates across specifications are stable and significant for direct vehicle rebates. Incentive effects for tax credits are not statistically distinguishable from zero.[15] This result is in line with the finding of Gallagher and Muehlegger (2011) that incentives realized at the time of purchase have a larger effect than those available with a time delay. While the state-level incentive types studied in the hybrid vehicle market (e.g., state income tax credits and sales tax waivers) are different than those in the BEV market (e.g., state income tax credits and vehicle purchase rebates), our results indicate similar degrees of consumer responsiveness to incentives across

[14]Unlike Gallagher and Muehlegger's result, the coefficients on our parameters of interest remain statistically significant across model specifications. The change in significance in Gallagher and Muehlegger's models is likely driven in part by the inclusion of different measures of gasoline price impacts. Our model results are robust to alternative fuel price specifications, including measures of fuel price levels and dollars-per-mile in levels and logs.

[15]The direction and magnitude of these point estimates hold when dividing the analysis by incentive policy action (i.e., separating policies that begin during the sample period and those that end), as displayed in Table 5.

markets.

In addition to heterogeneous responses by type of incentive, we hypothesize incentive response may also differ by consumer type. While we do not possess consumer-level purchase data and demographics, the types of BEV models offered during our period of study may reveal differences in consumer responses based on the type of BEV consumers ultimately purchased. Tesla's BEVs are significantly different from the other BEVs included in our study with respect to vehicle segment, price, and driving range. We posit that consumers who purchase a Tesla model are potentially different from those that purchase other BEV models in our data and their response to incentives may differ as well. Table 6 reports coefficient estimates for incentive, charging infrastructure, and fuel cost measures that are allowed to vary by model type. Columns (1) and (4) repeat results from column (4) of Table 3 and Table 4, respectively. Columns (2) and (5) allow separate impacts of incentive levels for Tesla and non-Tesla models, while columns (3) and (6) include a fully interacted model in which incentives and all controls are interacted with a Tesla indicator. The results of the fully interacted models indicate no statistically significant difference in response to incentive type by incentive model. While there may be a difference in response between Tesla and non-Tesla buyers, it is likely not one we can reveal with the aggregated nature of our data and the observed level of variation in incentives offered as tax credits between 2011 and 2015.

5.2. Parallel trends

Our analysis of state-level incentives assumes that BEV adoption trends in the absence of BEV policy in treated states would not differ from observed trends in non-treated states. Violation of this parallel trends assumption introduces bias in difference-in-difference estimates of the treatment effect. While we can not observe BEV adoption rates in the absence of purchase incentives for treatment states, we can compare adoption patterns in the periods prior to policy implementation. We implement two approaches to explore the presence and effect of pretrends in the data.[16]

[16] As pointed out by a referee, the consistency of estimates in the regressions of Table 5 provides additional, suggestive evidence that the parallel trends assumption holds; each regression specification implicitly allows for different time trends through the inclusion of temporal fixed effects.

Testing for pretrends. We test for the presence of pre-trends by conducting a difference-in-difference style regression that allows for flexibility in pre- and post-treatment period effects. Treated states are classified into two groups: those with incentives active during the full study period (i.e., full treatment) and those with incentive levels that change during our observation window (i.e., varying treatment). The varying treatment group is further divided into states within which incentives expire and states with newly-implemented incentives. To examine the effects before and after treatment change, we regress BEV adoptions per capita on indicator variables for time relative to treatment variation and state treatment status, as described in Equation 2.

$$\ln\left(\text{BEVperCap}_{smt}\right) = \sum_{c=-6}^{c=6} \beta_t \mathbb{1}_{st}(t - T_s = c)\mathbb{1}_s(Treat) + \lambda \text{Charging}_{s,t-1} + \gamma_1 \text{DPM}_{gas,smt} + \gamma_2 \text{DPM}_{elec,smt} + \delta \mathbf{X}_{st} + \alpha_{sm} + \theta_{mt} + \epsilon_{smt} \quad (2)$$

In this specification, $\mathbb{1}_s(Treat)$ indicates whether a state's treatment status changes at any point over the study period, taking the value of one for each state s with varying treatment and zero otherwise. We explicitly measure the presence of lead and lag effects by interacting the treatment indicator with a dummy variable that denotes the number of quarters (c) relative to the treatment time (T_s). For states with incentives that are enacted, we use states with no incentive over the full period as controls. States with full treatment are used as controls for states where incentives expire.

Results of this estimation are included in Figure 3. States with incentives that come online show a slight positive trend prior to policy implementation, but none of the point estimates are statistically distinguishable from zero. After policies are enacted, policy effects are positive and sustained throughout our assessment window. States with incentives that are discontinued display a positive jump two quarters prior to incentive expiration and return to zero afterward. This is consistent with the hypothesis that consumers anticipate program expiration and modify their purchases accordingly.

The results of these tests for pretrends are informative and generally support the supposition that adoption trends are parallel between treated and control groups. The wide confidence intervals on the estimates for enacted policies (Figure 3a) and the upward trend in point estimates in quarters prior to policies taking effect prevents us from treating this test as definitive evidence that the parallel trends assumption holds. To further explore the general conclusion of the above difference-in-differences estimation, we augment our study by measuring treatment effects using synthetic control methods.

Estimated effects with synthetic controls. Matching methods, such as propensity score matching or synthetic controls estimation are alternatives to estimating treatment effects. Neither of these methods require the parallel trends assumption, as they rely on selecting control groups based on observable covariates and outcomes. Synthetic controls are preferable to alternative matching methods when single, untreated units are not good matches to treated units in the sample (Abadie et al., 2015). This is the case in our data where state-level BEV adoption behavior is heterogeneous across states. We construct synthetic versions of treated states based on outcome values in the pre-treatment period. Our estimation strategy follows that of Abadie et al. (2010). This method allows us to negate any observed pre-trend present in treated states. The candidate control states are chosen from the set of states that did not have a BEV incentive policy at any time between 2011 and 2015.

One of the limitations of this method is the necessity for sufficient observations prior to the intervention; a lack of pre-intervention periods results in poor matching. For this reason, we focus our analysis on two states in our sample that enacted incentives in Q2 2014: Massachusetts and Texas. Results of the synthetic control analysis are presented in Figure 4. Outcome levels between the treated and synthetic states are closely matched prior to incentives taking effect, but deviate sharply after. Results indicate an increase in BEV share of total registrations of 39 percent for incentive policy in Massachusetts and 34 percent in Texas. This initial effect is sustained in Massachusetts over subsequent policy periods. The effect is constant in Texas as well, though diminishes in the final observation period.

Though the pre-treatment outcomes reported in Figure 4 track closely together, it is possible that post-treatment outcome differences are a result of chance, rather than a product of BEV policies. While synthetic control methods do not allow for direct computation of confidence intervals, causal inference can be aided by conducting placebo tests. We conduct "in-space placebos" by assigning treatment to other non-treated states in our sample and comparing estimated outcomes to treated-state outcomes (Abadie et al., 2015).

Specifically, we assign incentives identical to those implemented in Massachusetts and Texas to states that did not enact incentives during our study period. The bold lines in Figure 5 report the difference between the treated and synthetic outcomes for Massachusetts (panel (a)) and Texas (panel (b)). Each of the light lines in the figure represent this difference for placebo (untreated) states when assigned treatment in Q2 2014.[17] In both cases, the observed treatment effect in the period of policy implementation is at the upper bound of the observed placebo estimates.

While the timing of incentive availability and the relative youth of the BEV market makes a synthetic controls analysis of all incentive states difficult, results obtained from a study of these two states provide further evidence that of the efficacy of BEV incentive policies.

5.3. Robustness

Our models presented in Table 3 and Table 4 assume responses are linear in the level of the vehicle incentive offered. We also estimate a version of our model with our variable of interest in log form. These results are reported in columns (1) and (2) of Table 7. Results are similar across specifications and indicate a 10 percent increase in incentive level produces a 0.31 percent increase in per capita BEV adoptions. At the mean incentive level of approximately $3,000, a $1,000 increase in incentives leads to a one percent increase in BEV adoptions.

Our current dependent variable, registrations per capita, captures changes in the BEV market due to overall vehicle market changes and due to changes in BEV adoption relative to other vehicles. To solely address changes in BEV adoption relative to other vehicles, we estimate a version of our model in which the dependent variable is BEVs as a share of new registrations (i.e., market share). Results of these specifications are reported in columns (3) through (6) of Table 7 and indicate results of similar magnitude to those of our primary specifications. In level form, tax credits are a significant, positive driver of registrations while rebates are not. Isolating the change in BEV adoptions as a portion of overall vehicle sales indicates that some consumers may be substituting BEVs for other vehicles in the presence

[17]Three untreated states in our sample produce a root mean square prediction error in the pre-treatment period of more than 1.5 times the error observed in our treated states. We exclude these from the figure.

of tax credits. This substitution pattern is not present in markets with incentives in the form of rebates.

6. Estimated impacts of state-level BEV policies

6.1. Theoretical framework for welfare estimation

The results of the preceding section indicate BEV subsidy programs are effective in generating new BEV registrations, particularly incentives offered as direct purchase rebates. In the context of subsidy program assessment, this analysis addresses only one measure of the program's impact: induced, marginal changes in BEV adoptions. While our analysis is not well suited to draw conclusions about other measures of consumer response to these policies (e.g., the level of intertemporal substitution or cross-sectional substitution between vehicle types), we are uniquely positioned to generate estimates of the marginal social benefits of these programs. In this section we combine our estimates of BEV policy effects with existing literature on the environmental impacts of electric vehicles to assess net program and welfare costs associated with state BEV subsidy programs.

To illustrate our welfare estimation, we assume locally linear supply and demand curves in the market for BEVs as shown in Figure 6. Panel (a) of Figure 6 depicts a state in which social benefits of BEVs exceed private benefits. Panel (b) represents a state in which social benefits of BEVs are smaller than private benefits. We assume the difference in marginal private benefits and marginal social benefits is driven by externalities from vehicle operation. In the analysis that follows, we focus on foregone emissions that would be produced from gasoline-powered vehicles net of emissions attributed to marginal electricity generation for BEV battery charging. Benefits along this dimension are estimated on a geographically resolved basis by Holland et al. (2016). It is important to note that externalities associated with BEV adoption need not be limited to emissions impacts. We discuss the implications of externalities beyond emissions impacts at the conclusion of this section.

Our assessment of BEV incentive benefits focuses on marginal changes in equilibrium quantities of BEVs induced by a BEV subsidy; our reduced form empirical strategy does not address impacts for inframarginal buyers. Marginal BEV registrations are represented in the figure by ΔQ. Direct program costs–including both marginal BEV adoptions induced by the subsidy and infra-marginal adoptions–for marginal BEV adoptions induced by the subsidy are represented in both panels of Figure 6 by area $ABCDE$. In the stylized model presented here we assume all marginal BEV buyers receive the full value of the incentive, but relax this assumption in sensitivity analyses below. Marginal welfare benefits of vehicle subsidies, in the form of producer and consumer surplus gains are represented by area AB and DE, respectively. The total value of externalities that result from marginal BEV adoptions is area XBC in panel (a) (welfare gains) and by DY in panel (b) (welfare loses).

Net program benefits are therefore equal to total environmental benefits plus consumer and producer surplus gains net of total program costs. Based on the illustration in Figure 6, this translates to

$$\begin{aligned}
\Delta W_a &= XBC + AB + DE - (1+\lambda)ABCDE && \text{(3a)}\\
&= XBC - (C + \lambda \cdot ABCDE) &&\\
\Delta W_b &= -DY + AB + DE - (1+\lambda)ABCDE && \text{(3b)}\\
&= -DY - (C + \lambda \cdot ABCDE) &&
\end{aligned}$$

In both scenarios, C is the private deadweight loss from the subsidy (i.e., direct program costs minus the gain in producer and consumer surplus), while λ represents the marginal cost of funds to finance the state-level subsidy.[18]

To compute estimates of net program and welfare costs, we use total per-mile marginal emissions benefits (damages) at the state-model level estimated by Holland et al. (2016). These estimates measure the difference in marginal emissions between electric vehicles and similar gasoline-powered vehicles. The externality costs of Holland et al. (2016) vary spatially, by model, and incorporate damages from six pollutants generated by vehicle use and electricity-generation: NO_x, VOCs, $PM_{2.5}$, SO_2, and CO_2. To estimate total externalities that result from marginal vehicle substitution, we multiply these costs by estimates of life-

[18]The marginal cost of funds is a measure of the additional costs associated with revenue generation required to provide the subsidy. It is the additional cost incurred when raising public monies and represents a deadweight loss (Browning, 1993). We assume a marginal excess burden of 0.4 in accordance with Browning (1987). For similar analysis with an application to welfare effects of vehicle HOV lane access, see Bento et al. (2014).

time vehicle miles traveled. To measure total emissions benefits (costs) from new BEVs, we multiply per-vehicle damages by ΔQ. From these values we subtract deadweight loss and total marginal excess burden to derive net welfare impacts. Following from our assumption of locally linear demand curves, deadweight loss is assumed to equal $0.5 \cdot \Delta Q \cdot Subsidy$.

As noted in Section 4, our impact estimates are the result of a reduced-form empirical strategy that is agnostic to structural assumptions about demand and supply behavior in the market for electric vehicles. In contrast, our welfare analysis requires a number of assumptions about the market for BEVs. We make our assumptions in an effort to estimate an upper bound of the benefit of the incentive policies.

With respect to demand in the market for BEVs, we assume that induced changes in marginal BEV registrations 1) displace similar, gasoline-powered vehicles and 2) do not represent intertemporal substitution of vehicle purchases. The level to which the demand for BEVs follows these assumptions in practice is subject to debate, but both assumptions maximize program benefits. The first assumption suggests that demand for new vehicles is relatively elastic as consumers are willing to substitute to other vehicle types for new vehicle purchases. The assumption that consumers choose between BEV and gasoline-powered vehicles maximizes the benefits associated with foregone emissions when BEVs result in fewer emissions than gasoline-powered vehicles and minimizes the costs when emissions from BEVs are higher than gasoline-powered vehicles.[19] A lack of intertemporal substitution of vehicle purchases means that any benefits to BEV ownership for induced BEV purchases are attributed to the incentive programs for the lifetime of the vehicle. While this assumption likely overstates average consumer substitution patterns, it maximizes accrued benefits for vehicles attributed to the program.[20]

On the supply side, we assume a perfectly elastic national supply curve such that induced

[19] With the exception of the Nissan LEAF, whose counterfactual vehicle is the hybrid Toyota Prius, the comparison vehicles in the Holland et al. (2016) analysis are conventional, gasoline-powered vehicles. Our choice of assumed comparable vehicles is also necessitated by the fact that reestimation of marginal damages for other vehicle types is beyond the scope of this paper.

[20] Li et al. (2013) study consumer response to the Consumer Assistance to Recycle and Save (CARS) Act, or the Cash-for-Clunkers program, and find the program produces short-term intertemporal substitution in which consumers respond to incentive availability by accelerating the trade-in of eligible vehicles. This type of product substitution would substantially decrease the benefits estimated by our model as demonstrated in our sensitivity tests.

demand (and hence any associated positive benefit) is a result of new production. In the case of inelastic supply, a change in marginal BEV sales would represent a reallocation of vehicles across state lines. We account for this scenario in our sensitivity analyses and find that, with the exception of extreme scenarios, net welfare impacts are qualitatively similar to our baseline results.

6.2. Results

We estimate the quantity of marginal BEV registrations in each state that result from state-level BEV rebates using the parameters of our empirical model reported in the column (4) of Table 4. National totals of new BEV registrations per quarter are graphed in Figure 7. We plot quarterly values for observed, new BEV registrations along with predicted registrations in the presence and absence of state-level BEV incentives. Results indicate that approximately 11 percent of BEV registrations are attributed to state incentives.

Results of our welfare analysis displayed in Table 8 indicate that the environmental impacts of the programs are negative in most states. This result is not surprising, as many of the states that offer incentives are in areas where emission impacts from BEVs are greater than those from gasoline vehicles. In fact, application of the results of Holland et al. (2016) to our estimates indicate BEV subsidies have positive emissions benefits in only two of the states that offer rebates: California and Texas. At a national level, total environmental benefits are positive, but are driven in large part by the high level of adoptions and associated benefits attributed to BEVs in California. Overall, welfare impacts are negative. Our results therefore indicate that state-level BEV policies are not welfare improving based solely on the value of foregone emissions. However, the declining emissions intensity of generation in the U.S. could decrease the upstream emissions associated with BEVs and substantially increase the environmental benefits associated with BEV adoption.

Prior assessments of similar programs compute the cost of avoided CO_2. To provide an additional data point in the literature, we also use our results to compute a dollars-per-ton measure of avoided CO_2. The results of Holland et al. (2016) do not allow us to extract the quantity of CO_2 emissions that result from the programs, but we use the model's assumed level of CO_2 per gallon of gasoline along with the marginal emissions rates of Graff Zivin et al. (2014) to determine net CO_2 emissions from the quantity of induced BEV adoptions that result from state policies during this time period.[21] Based on off-peak (1am to 4am) and minimum-marginal-emissions charging scenarios, program costs per metric ton of CO_2 range from \$73 to \$78. This result assumes incentivized emissions and associated program costs are those from marginal adopters only. Calculating a cost of avoided CO_2 that treats all inframarginal and marginal adoptions as the basis for total program costs and incorporating the marginal cost of public funds, avoided costs per ton are approximately \$447 to \$479.

These results are sensitive to assumptions about the level of intertemporal substitution. A choice of a 10-year lifetime is generous to the subsidy programs. These estimates increase to \$145 to \$156 for a five-year lifetime (ΔQ only) or \$894 to \$958 (marginal and inframarginal program costs with excess burden). Due to the range of existing estimates, both of our computed cost of carbon values match values found in the literature. Chandra et al. (2010) estimate a cost of \$195 per ton of CO_2 for HEV tax credits in Canada. Beresteanu and Li (2011) conclude that HEV adoption incentives in the United States abate a ton of CO_2 at the cost of \$177. Investigations of other vehicle programs include Li et al. (2013) and Knittel (2009), who evaluate impacts for the Cash for Clunkers program in the United States. Li et al. (2013) estimate a cost ranging from \$91 to \$301 per ton of CO_2 abatement, while Knittel's analysis produces a value between \$239 and \$466 per ton. Bento et al. (2014) examine HOV policy for HEVs in California and find an abatement cost equivalent of \$124 per ton of CO_2. Davis et al. (2014) estimate impacts for energy efficiency improvements from refrigerator and air conditioning rebate programs in Mexico and reveal costs ranging from \$457 to \$547. While these values are informative for comparing state-level BEV subsidies in the United States to other policies, program costs and CO_2 benefits do not fully capture the net welfare effects of state-level BEV subsidy programs. Indeed, the purpose of BEV incentives is not only to achieve near- or mid-term emissions reductions, but also to stimulate a relatively nascent market.

Sensitivity tests for results of our welfare analysis are reported in Table 9. We report

[21] For this calculation, we use our MPG values for equivalent gasoline vehicles, kWh measures from Table A1, assume 11,000 vehicle miles traveled per year, and use the ΔQ values from the welfare analysis to compute the total CO_2 savings attributed to marginal BEVs over their substitute gasoline counterparts.

results for an estimated vehicle lifetime of one and 10 years in the column groupings. Our primary welfare analysis relies on average environmental benefits values estimated by Holland et al. The most generous evaluation of environmental benefits would assume the maximum level of estimated environmental benefits for BEVs. Environmental and welfare benefit calculations using this maximum benefit measure are included in columns (3) and (5) of Table 9. We additionally test the sensitivity of the results to differing levels of incentive redemption (r). This redemption parameter impacts our estimation of overall program cost. For example, a redemption level below 100% could represent the percentage of consumers that act as incentive-takers, or could account for consumers in tax credit states with state income tax liabilities that are low enough that they only redeem a portion of the total tax credit value on average. Our primary results assume incentive redemption levels of 100%. Results in Table 9 indicate that only in cases assuming long vehicle lifetimes and incomplete incentive redemption do environmental benefits of state-level BEV incentive exceed program costs and associated welfare effects.

The welfare analysis conducted here provides evidence that state-level financial incentives for BEV adoption are unlikely to be welfare-improving on the basis of foregone transportation sector emissions alone. It should be noted, however, that this analysis does not account for positive benefits attributed to network externalities, increased production efficiencies due to the realization of economies of scale, or benefits of accelerated innovation in the BEV supply chain or vehicle manufacturing. We leave an accounting of these benefits to future work.

7. Conclusions

The effectiveness of subsidies that target new vehicle technologies is critical to the design of cost-effective strategies to reduce transportation-sector emissions. We study the ability of state-level financial incentives to stimulate marginal BEV purchases and find robust evidence that these subsidies have their intended effect. Similar to prior work studying the market for hybrids, financial incentives available at the time of purchase are found to be effective at stimulating product demand. Our results also demonstrate that Tesla buyers do not respond differently to incentives, but we caution that this conclusion should be verified by analysis using transaction-level data before being broadly interpreted.

With regard to relative program costs and benefits, our focused assessment of CO_2 impacts and overall program costs reinforces the findings of the existing literature that implementation and welfare costs for direct financial incentive programs exceed the benefits of avoided near-term emissions. These emissions effects are an important dimension of accounting for the benefits that accrue as a result of advanced vehicle incentive policies and are essential to informing discussions of policy cost-effectiveness. However, further study of non-emissions impacts (e.g., long-term market growth, production cost savings) is necessary to draw conclusions on the overall cost-effectiveness of these policies.

References

Abadie, Alberto, Alexis Diamond, and Jens Hainmueller. 2010. "Synthetic control methods for comparative case studies: Estimating the effect of California's tobacco control program" *Journal of the American Statistical Association* 105 (490):493–505.

Abadie, Alberto, Alexis Diamond, and Jens Hainmueller. 2015. "Comparative politics and the synthetic control method" *American Journal of Political Science* 59 (2):495–510.

Bento, Antonio, Daniel Kaffine, Kevin Roth, and Matthew Zaragoza-Watkins. 2014. "The effects of regulation in the presence of multiple unpriced externalities: Evidence from the transportation sector." *American Economic Journal: Economic Policy* 6 (3):1–29.

Beresteanu, Arie and Shanjun Li. 2011. "Gasoline prices, government support, and the demand for hybrid vehicles in the United States." *International Economic Review* 52 (1):161–182.

Berry, Steven, James Levinsohn, and Ariel Pakes. 1995. "Automobile prices in market equilibrium." *Econometrica: Journal of the Econometric Society*:841–890.

Browning, Edgar K. 1987. "On the marginal welfare cost of taxation." *American Economic Review*:11–23.

Browning, Edgar K. 1993. "Subsidies financed with distorting taxes." *National Tax Journal*:121–134.

Chandra, Ambarish, Sumeet Gulati, and Milind Kandlikar. 2010. "Green drivers or free riders? An analysis of tax rebates for hybrid vehicles." *Journal of Environmental Economics and Management* 60 (2):78–93.

CSE. 2013. "San Diego Regional Plug-in Electric Vehicle (PEV) Readiness Plan." California Center for Sustainable Energy. https://energycenter.org/sites/default/files/docs/nav/programs/pev-planning/san-diego/San_Diego_PEV_Readiness_Planning_Guide-2013_low-resolution.pdf. Accessed November 2015.

CSE and CARB. 2012. “California Plug-in Electric Vehicle Owner Survey.” California Center for Sustainable Energy and California Air Resources Board. https://energycenter.org/sites/default/files/docs/nav/policy/research-and-reports/California%20Plug-in%20Electric%20Vehicle%20Owner%20Survey%20Report-July%202012.pdf. Accessed November 2015.

Davis, Lucas W, Alan Fuchs, and Paul Gertler. 2014. “Cash for coolers: evaluating a large-scale appliance replacement program in Mexico.” *American Economic Journal: Economic Policy* 6 (4):207–238.

Davis, Stacy, Susan Diegel, and Robert Boundy. 2014. “Transportation Energy Data Book.” Oak Ridge National Laboratory. http://cta.ornl.gov/data/tedb33/Edition33_Full_Doc.pdf. Accessed November 2015.

DeShazo, JR, Tamara L Sheldon, and Richard T Carson. 2014. “Designing Policy Incentives for Cleaner Technologies: Lessons from California’s Plug-in Electric Vehicle Rebate Program.” *Working paper*.

Diamond, David. 2009. “The impact of government incentives for hybrid-electric vehicles: Evidence from U.S. states.” *Energy Policy* 37 (3):972–983.

Egbue, Ona and Suzanna Long. 2012. “Barriers to widespread adoption of electric vehicles: An analysis of consumer attitudes and perceptions.” *Energy Policy* 48:717–729.

Gallagher, Kelly Sims and Erich Muehlegger. 2011. “Giving green to get green? Incentives and consumer adoption of hybrid vehicle technology.” *Journal of Environmental Economics and Management* 61 (1):1–15.

Graff Zivin, Joshua S., Matthew J. Kotchen, and Erin T. Mansur. 2014. “Spatial and temporal heterogeneity of marginal emissions: Implications for electric cars and other electricity-shifting policies.” *Journal of Economic Behavior & Organization* 107 (2014):248–268.

Hidrue, Michael K, George R Parsons, Willett Kempton, and Meryl P Gardner. 2011. “Willingness to pay for electric vehicles and their attributes.” *Resource and Energy Economics* 33 (3):686–705.

Holland, Stephen P., Erin T. Mansur, Nicholas Z. Muller, and Andrew J. Yates. 2016. "Are there environmental benefits from driving electric vehicles? The importance of local factors." *American Economic Review* 106 (12):3700–3729.

Kahn, Matthew E. 2007. "Do greens drive Hummers or hybrids? Environmental ideology as a determinant of consumer choice." *Journal of Environmental Economics and Management* 54 (2):129–145.

Klier, Thomas and Joshua Linn. 2010. "The price of gasoline and new vehicle fuel economy: evidence from monthly sales data." *American Economic Journal: Economic Policy* 2 (3):134–153.

Knittel, Christopher R. 2009. "The implied cost of carbon dioxide under the cash for clunkers program." *Available at SSRN 1630647.*

Li, Shanjun, Lang Tong, Jianwei Xing, and Yiyi Zhou. 2017. "The Market for Electric Vehicles: Indirect Network Effects and Policy Design" *Journal of the Association of Environmental and Resource Economists* 4 (1):89–133.

Li, Shanjun, Joshua Linn, and Elisheba Spiller. 2013. "Evaluating "Cash-for-Clunkers": Program effects on auto sales and the environment." *Journal of Environmental Economics and Management* 65 (2):175–193.

MA EEA. 2015. "Baker Administration Announces Additional Funding for Electric Vehicle Rebate Program." Massachusetts Executive Office of Energy and Environmental Affairs. https://www.mass.gov/news/baker-administration-announces-additional-funding-for-electric-vehicle-rebate-program. Accessed December 2016.

Sierzchula, William, Sjoerd Bakker, Kees Maat, and Bert van Wee. 2014. "The influence of financial incentives and other socio-economic factors on electric vehicle adoption." *Energy Policy* 68:183–194.

Tal, Gil, M Nicholas, Justin Woodjack, and Daniel Scrivano. 2013. "Who Is Buying Electric

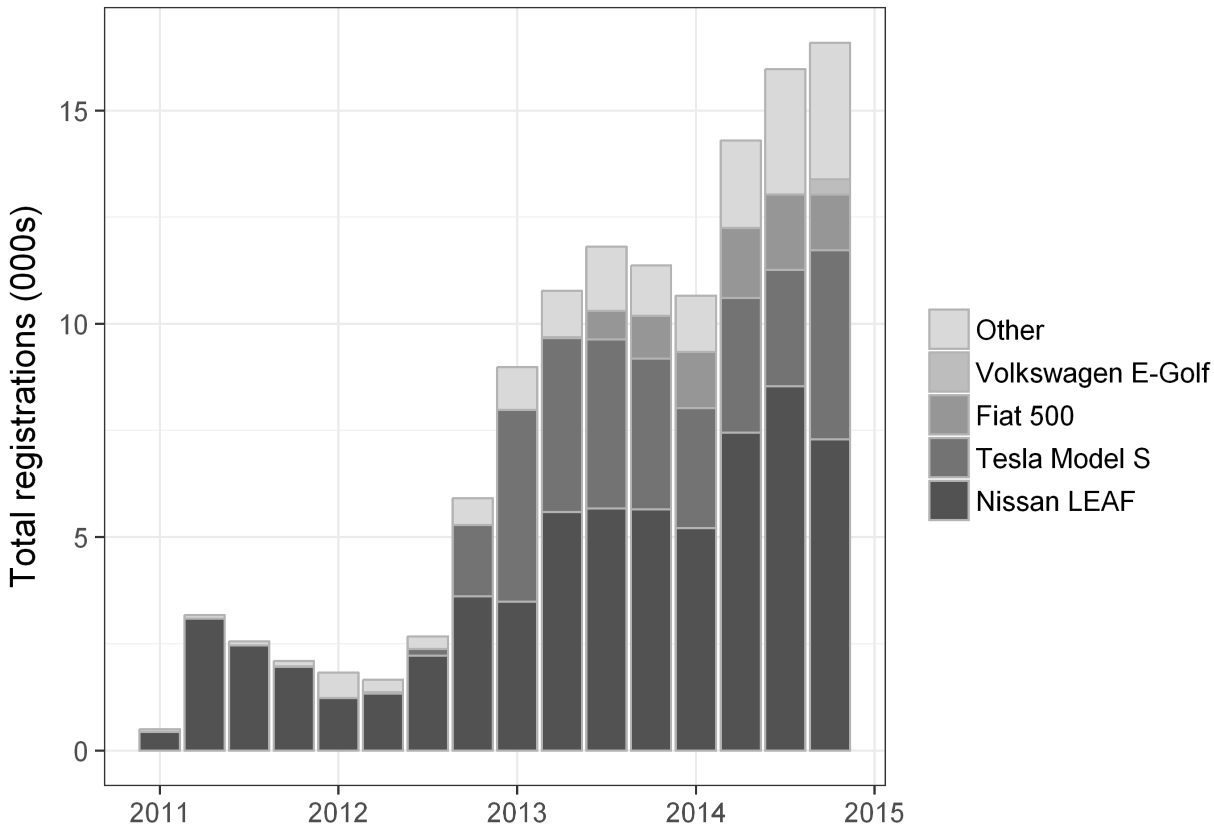
Cars in California? Exploring Household and Vehicle Fleet Characteristics of New Plug-In Vehicle Owners." Tech. rep., Research Report–UCD-ITS-RR-13.

Tal, Gil and Michael A Nicholas. 2014. "Exploring the Impact of High Occupancy Vehicle (HOV) Lane Access on Plug-in Vehicle Sales and Usage in California." Tech. rep., Research Report–UCD-ITS-RR-14-16.

Wood, Eric, Jeremy S Neubauer, and Evan Burton. 2015. "Measuring the Benefits of Public Chargers and Improving Infrastructure Deployments Using Advanced Simulation Tools." Tech. rep., SAE Technical Paper.

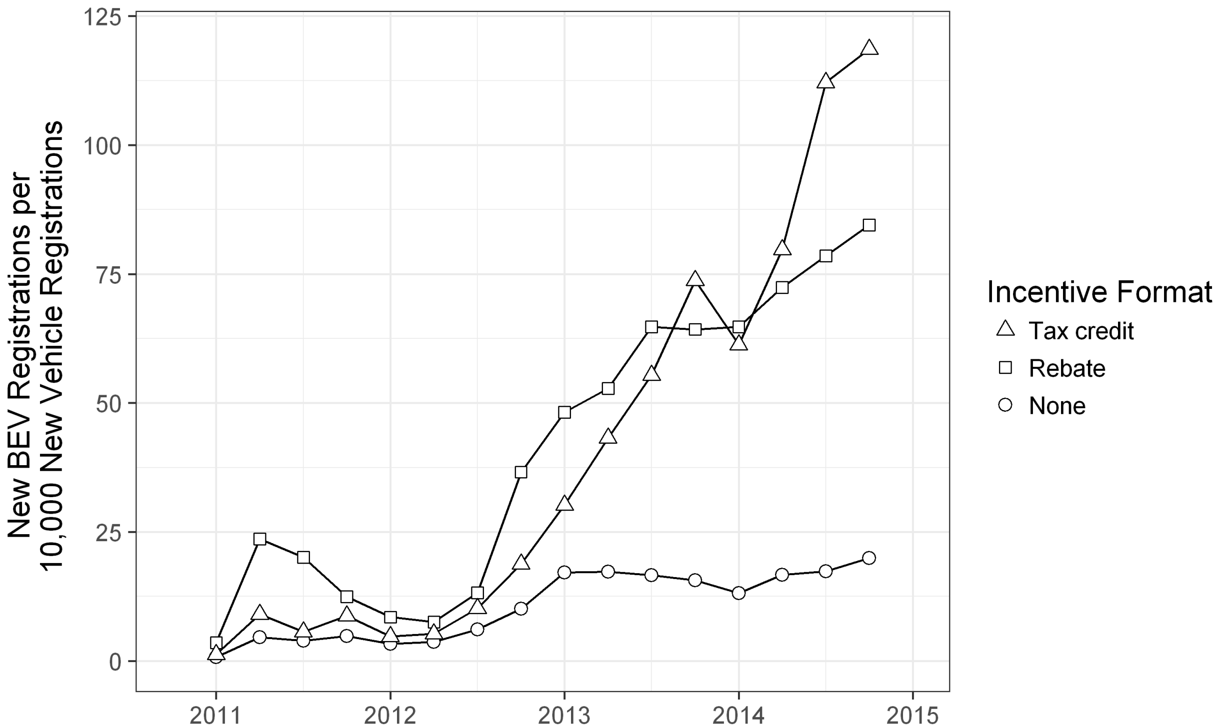
Figures

Figure 1: New BEV Registrations by Model and Quarter



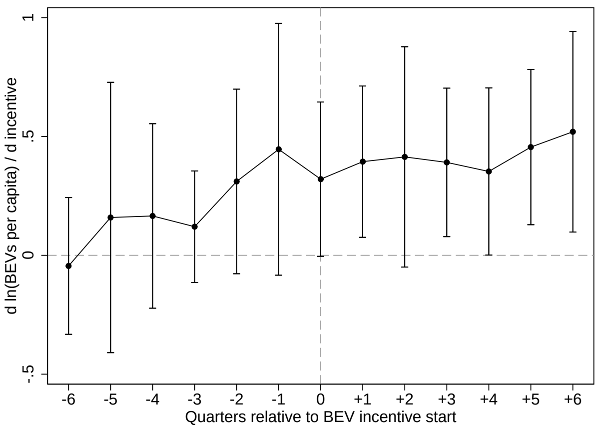
Notes: Vehicle registration data from R.L. Polk & Co. Top five vehicle models by total registrations shown. New registrations denote flows (i.e., an individual BEV is counted only once in this figure).

Figure 2: BEV Share of New Registrations by Incentive Type

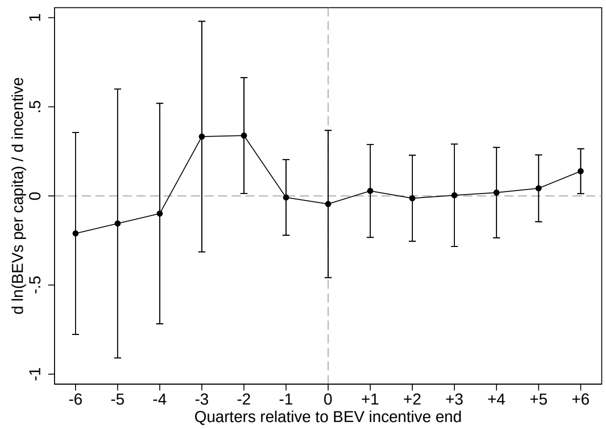


Notes: Vehicle registration data from R.L. Polk & Co. Points represent total new BEV registrations per 10,000 total new vehicle registrations. Observations grouped based on the type of BEV incentive offered during the study time period.

Figure 3: Tests for Lead and Lag of Policy Effects

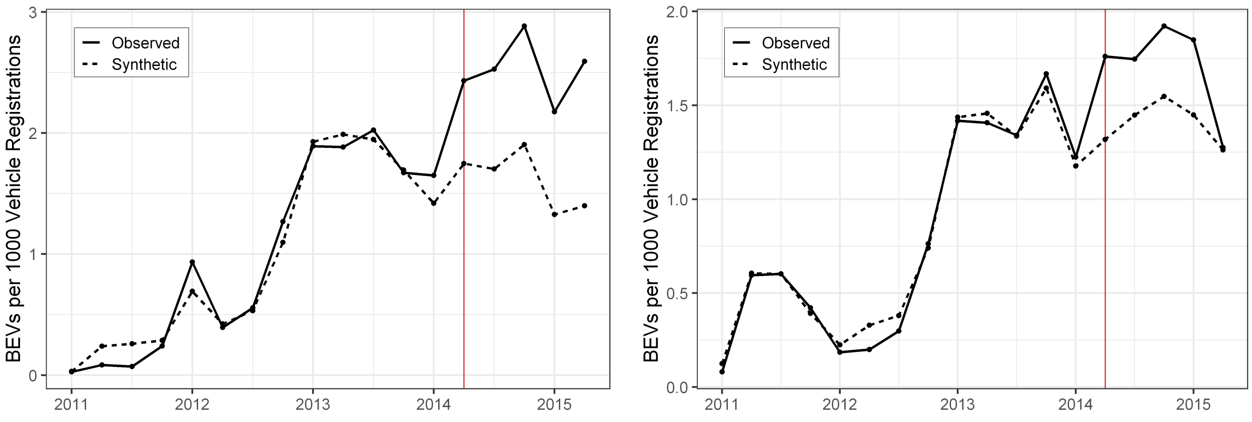


(a) Policies enacted (2011-2014)



(b) Policies expiring (2011-2014)

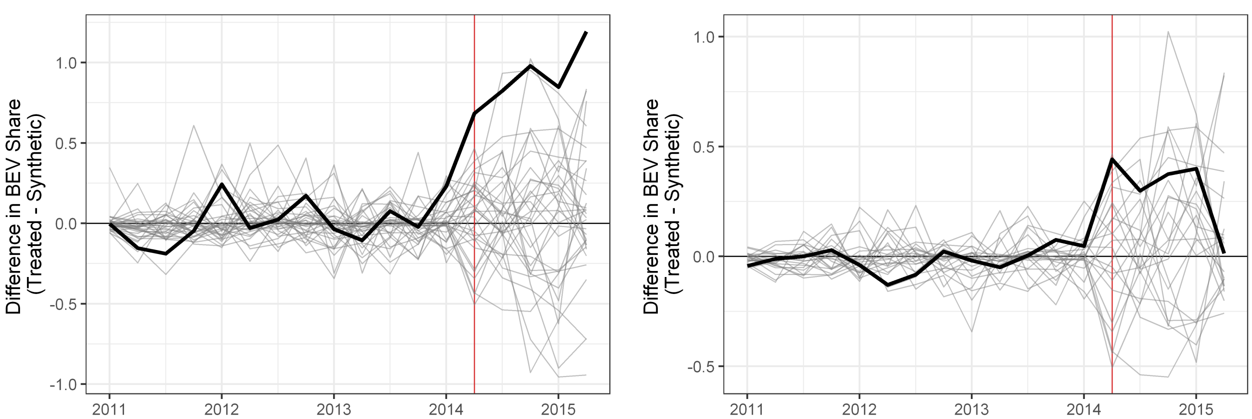
Figure 4: Synthetic Control Estimation



(a) Massachusetts

(b) Texas

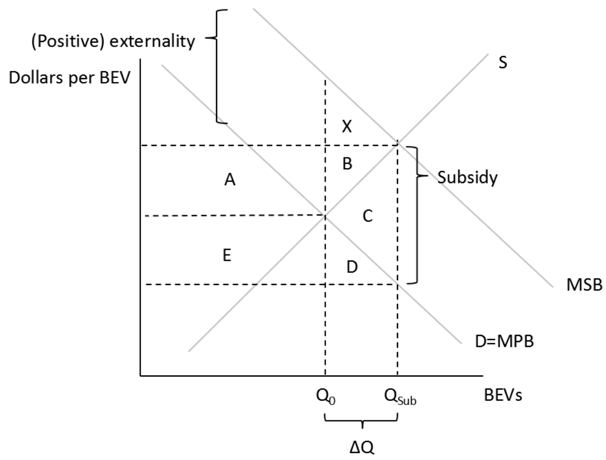
Figure 5: Synthetic Controls Placebo Tests



(a) Massachusetts

(b) Texas

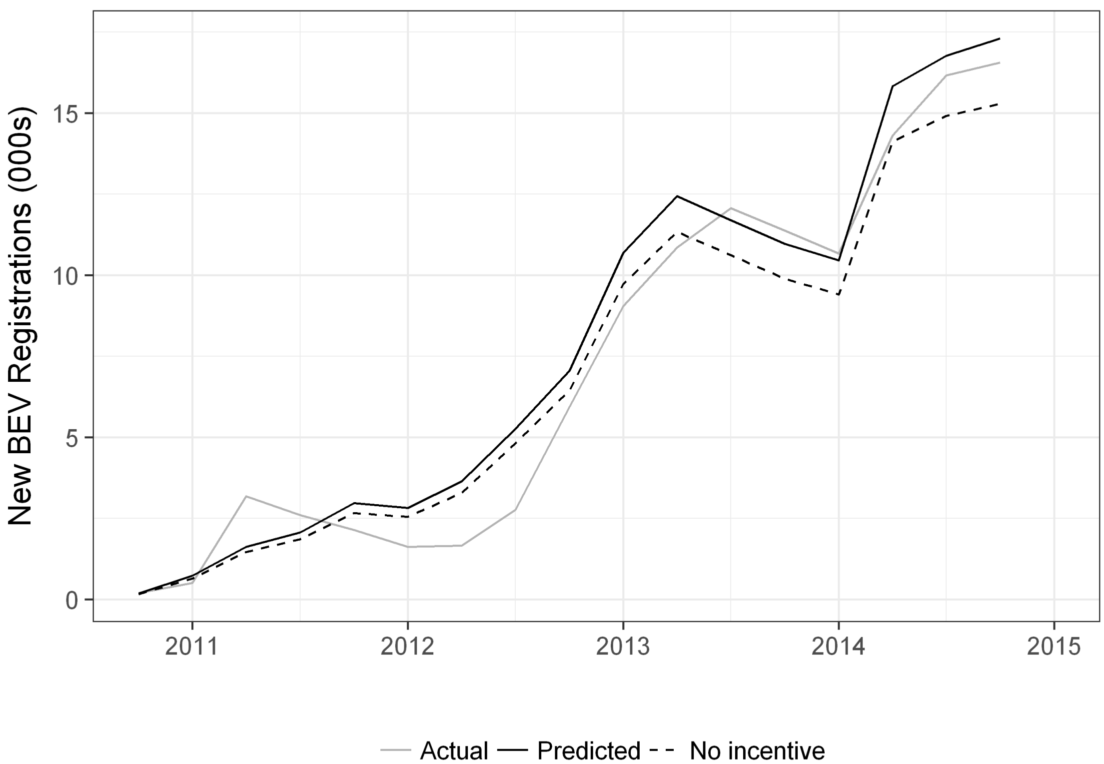
Figure 6: Illustrative State-level Market for BEVs



(a) $\text{Emissions}_{Elec} < \text{Emissions}_{Gas}$

(b) $\text{Emissions}_{Elec} > \text{Emissions}_{Gas}$

Figure 7: National BEV Registrations by Quarter



Notes: Predicted incentive effects are based on the specification presented in Table 4, column (4). Impacts are allowed to vary by incentive format. New BEV registrations in the absence of BEV subsidies assume rebate and tax credit values of zero for all incentive states.

Tables

Table 1: Summary Statistics

Variable	N	Mean	Std. Dev.	Min	Max
Quarterly vehicle registrations[a]					
BEVs	3864	31	171	0	3020
BEVs per million residents	3864	3.07	12.24	0.00	299.09
BEVs per 10,000 new registrations	3864	0.34	1.42	0.00	32.67
Incentives[b]					
Rebate ($)	425	2912	787	500	4500
Tax credit ($)	510	3032	2073	605	6000
Controls					
Charging station installations (public)	763	151.9	333.4	0.0	3589.0
Charging station installations (private)	763	27.0	47.4	0.0	410.0
Dollars per mile (electricity)[c]	3864	0.04	0.02	0.02	0.21
Dollars per mile (gasoline)[c]	3864	0.17	0.02	0.12	0.25
Mean age	763	37.6	1.5	32.0	41.2
Percent female	763	50.9	0.8	48.4	52.5
Per capita income ($000)	763	43.577	6.512	31.855	63.185
Percent high school graduates	763	83.8	2.8	75.6	89.5
Percent college graduates	763	35.7	4.7	26.5	46.5
LCV environmentalism index	763	0.45	0.27	0.00	0.98

Notes: Variables reported on a year-quarter basis except where noted. [a]Vehicle registrations include personal BEVs only and are reported at the year-quarter-model level. [b]Rebate and tax credit values conditional on incentive availability. [c]Fuel costs in dollars per mile are reported at the year-quarter-model level.

Table 2: BEV Market Summary by State (2011-2014)

	BEV Registrations		Incentive details				
	Total	Share[a]	Value	Period	Eligibility		
Panel A: States offering direct vehicle rebates							
CA+	56,292	10.01	\$2,500	Q1 2010 –	All BEVs		
HI+	2,212	12.21	\$4,500	Q2 2010 – Q3 2013	All BEVs		
IL	2,485	1.28	\$4,000	Q2 2008 –	All BEVs		
MA	1,473	1.29	\$2,500	Q2 2014 –	Bat. cap. $\geq$ 10 kWh		
PA	1,356	0.61	\$2,000	Q1 2014 –	Bat. cap. $\geq$ 10 kWh		
			\$3,000	Q1 2013 – Q4 2013			
			\$3,500	Q3 2011 – Q2 2012			
			\$500	Q3 2007 – Q2 2011			
TN+	1,680	2.10	\$2,500	Q2 2011 – Q1 2013	Nissan LEAF only		
TX	4,474	1.00	\$2,500	Q2 2014 –	Bat. cap $\geq$ 4 kWh		
Panel B: States offering income tax credits						Carry-over	Refundable
CO	1,919	2.57	\$6,000	Q1 2010 –	All BEVs	No	Yes
GA+	14,792	10.64	\$5,000	Q1 2001 –	All BEVs	Yes	No
LA	162	0.22	\$3,000	Q3 2009 –	Bat. cap. $\geq$ 4 kWh	No	Yes
MD+	1,273	1.35	\$3,000	Q3 2014 –	Bat. cap. $\geq$ 24 kWh	No	Yes
			\$1,000	Q4 2010 – Q2 2014	Bat. cap. $\geq$ 15 kWh		
OR	3,326	7.10	\$750	Q1 1998 – Q4 2011	All BEVs	Yes	No
SC	360	0.53	\$1,500	Q1 2006 –	Bat. cap. $\geq$ 4 kWh	Yes	No
UT+	897	2.63	\$605	Q1 2009 – Q4 2014	All BEVs.	Yes	No
WV	44	0.14	\$7,500	Q1 2011 – Q2 2013	All BEVs.	Yes	No

Notes: [a]Number of BEV registrations per thousand new vehicle registrations. +indicates states offering single-occupant HOV lane access. AZ, FL, NJ, NY, NC, and VA offer HOV incentives only. Incentive begin and end dates include incentives active during the study time period (Q1 2011 through Q4 2014). See Table A1 in the appendix for battery capacities of BEVs in our sample. Vehicle residency requirements: CA, 36 months; IL, 60 months; OR, 12 months.

Table 3: Effect of Financial Incentives on Per Capita BEV Registrations

	(1)	(2)	(3)	(4)
Incentive ($000)	0.076**	0.075**	0.078**	0.069**
	(0.036)	(0.032)	(0.032)	(0.028)
Charging stations (public)		0.098	0.099	0.101
		(0.076)	(0.077)	(0.070)
Charging stations (private)		0.131**	0.129**	0.143**
		(0.062)	(0.063)	(0.061)
Dollars per mile (gasoline)			0.983	−0.005
			(2.409)	(2.258)
Dollars per mile (electric)			−3.080	−0.959
			(5.945)	(5.352)
Average age				0.072
				(0.075)
Percent female				0.132*
				(0.071)
Ln(per capita income)				0.812
				(2.662)
Percent high school graduates				0.014
				(0.022)
Percent college graduates				0.035*
				(0.019)
Ln(Environmentalism)				0.176*
				(0.093)
Observations	3,864	3,864	3,864	3,864
Adjusted R^2	0.734	0.737	0.736	0.738

Notes: *p<0.1; **p<0.05; ***p<0.01. Dependent variable is log of BEV registrations per million residents. All specifications include model-time and state-model fixed effects. Standard errors clustered at the state level.

Table 4: Effect of Financial Incentives on Per Capita BEV Registrations by Incentive Type

	(1)	(2)	(3)	(4)
Rebate ($000)	0.081^{**}	0.082^{**}	0.085^{***}	0.078^{***}
	(0.037)	(0.032)	(0.032)	(0.027)
Tax credit ($000)	0.0002	−0.021	−0.022	−0.055
	(0.068)	(0.040)	(0.041)	(0.040)
Charging stations (public)		0.097	0.098	0.099
		(0.076)	(0.077)	(0.069)
Charging stations (private)		0.133^{**}	0.131^{**}	0.146^{**}
		(0.062)	(0.063)	(0.061)
Dollars per mile (gasoline)			0.953	−0.027
			(2.396)	(2.241)
Dollars per mile (electric)			−3.543	−1.394
			(5.945)	(5.347)
Average age				0.079
				(0.074)
Percent female				0.135^{*}
				(0.071)
Ln(per capita income)				0.589
				(2.696)
Percent high school graduates				0.017
				(0.022)
Percent college graduates				0.035^{*}
				(0.019)
Ln(Environmentalism)				0.176^{*}
				(0.094)
Observations	3,864	3,864	3,864	3,864
Adjusted R^2	0.734	0.737	0.736	0.738

Notes: *p<0.1; **p<0.05; ***p<0.01. Dependent variable is log of BEV registrations per million residents. All specifications include model-time and state-model fixed effects. Standard errors clustered at the state level.

Table 5: Estimates of Incentive Effects by Type of Policy Change

	Enacted (1)	Expiring (2)
Rebate ($000)	0.102***	0.080*
	(0.034)	(0.044)
Tax credit ($000)		0.101
		(0.374)
Charging stations (public)	0.050	0.315**
	(0.066)	(0.137)
Charging stations (private)	0.227***	0.034
	(0.057)	(0.155)
Dollars per mile (gasoline)	0.548	−2.030
	(2.756)	(5.122)
Dollars per mile (electric)	6.182	−12.540
	(6.747)	(14.757)
Average age	−0.0001	0.301***
	(0.082)	(0.109)
Percent female	0.059	0.332***
	(0.072)	(0.067)
Ln(per capita income)	−2.274	0.052
	(2.500)	(3.043)
Percent high school graduates	0.012	−0.076*
	(0.025)	(0.045)
Percent college graduates	0.019	0.127***
	(0.021)	(0.044)
Ln(Environmentalism)	0.145	0.115
	(0.090)	(0.426)
Control state incentives	None	Full
Observations	2,749	866
Adjusted R^2	0.694	0.846

Notes: *p<0.1; **p<0.05; ***p<0.01. Dependent variable is log of BEV registrations per million residents. No tax credits were enacted within the period of study. The control group for states with enacted incentives are states without BEV incentives at any point during the study period. The control group for states with expiring incentives is composed of states with incentives available over the full time period. All specifications include model-time and state-model fixed effects. Standard errors clustered at the state level.

Table 6: Effect of Financial Incentives on Per Capita BEV Registrations by Vehicle Make

	(1)	(2)	(3)	(4)	(5)	(6)
Incentive (\$000)	0.069**	0.086***	0.087***			
	(0.028)	(0.022)	(0.020)			
Rebate (\$000)				0.078***	0.095***	0.097***
				(0.027)	(0.020)	(0.019)
Tax credit (\$000)				−0.055	−0.035	−0.044
				(0.040)	(0.061)	(0.069)
Charging stations (public)	0.101	0.101	0.090	0.099	0.099	0.087
	(0.070)	(0.070)	(0.112)	(0.069)	(0.069)	(0.111)
Charging stations (private)	0.143**	0.143**	0.126	0.146**	0.146**	0.130
	(0.061)	(0.061)	(0.085)	(0.061)	(0.061)	(0.084)
Dollars per mile (gasoline)	−0.005	−0.058	2.509	−0.027	−0.078	2.499
	(2.258)	(2.262)	(3.374)	(2.241)	(2.246)	(3.360)
Dollars per mile (electric)	−0.959	−1.224	−3.784	−1.394	−1.641	−4.270
	(5.352)	(5.359)	(6.566)	(5.347)	(5.350)	(6.604)
Incentive (\$000) × Tesla		−0.064	−0.064			
		(0.049)	(0.055)			
Rebate (\$000) × Tesla					−0.062	−0.065
					(0.052)	(0.060)
Tax credit (\$000) × Tesla					−0.064	−0.035
					(0.088)	(0.115)
Charging stations (public) × Tesla			0.040			0.041
			(0.150)			(0.150)
Charging stations (private) × Tesla			0.049			0.048
			(0.109)			(0.108)
Dollars per mile (gasoline) × Tesla			−6.555			−6.576
			(4.403)			(4.396)
Dollars per mile (electric) × Tesla			9.317			9.525
			(11.250)			(11.344)
Interaction	None	Incentive	Full	None	Incentive	Full
Observations	3,864	3,864	3,864	3,864	3,864	3,864
Adjusted R^2	0.738	0.738	0.738	0.738	0.738	0.738

Notes: *p<0.1; **p<0.05; ***p<0.01. Dependent variable is log of BEV registrations per million residents. All specifications include model-time and state-model fixed effects and the full set of demographic controls. Standard errors clustered at the state level.

Table 7: Robustness Results

	BEVs per capita		BEV market share of new reg.			
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(Incentive)	0.031***				0.039***	
	(0.008)				(0.010)	
Ln(Rebate)		0.033***				0.038***
		(0.009)				(0.011)
Ln(Tax credit)		0.012				0.051*
		(0.020)				(0.029)
Incentive ($000)			0.077*			
			(0.043)			
Rebate ($000)				0.071		
				(0.046)		
Tax credit ($000)				0.161***		
				(0.058)		
Charging stations (public)	0.101	0.102	0.081	0.082	0.082	0.081
	(0.070)	(0.070)	(0.099)	(0.099)	(0.098)	(0.098)
Charging stations (private)	0.140**	0.142**	0.218**	0.216**	0.214**	0.213**
	(0.061)	(0.061)	(0.086)	(0.086)	(0.086)	(0.086)
Dollars per mile (gasoline)	−0.004	−0.111	1.710	1.725	1.727	1.794
	(2.299)	(2.313)	(3.826)	(3.835)	(3.825)	(3.888)
Dollars per mile (electric)	−1.301	−1.369	−1.464	−1.168	−2.164	−2.121
	(5.426)	(5.453)	(9.335)	(9.390)	(9.437)	(9.460)
Specification	log-log	log-log	log-level	log-level	log-log	log-log
Observations	3,864	3,864	3,864	3,864	3,864	3,864
Adjusted R^2	0.739	0.738	0.507	0.507	0.507	0.507

Notes: *p<0.1; **p<0.05; ***p<0.01. Dependent variable is as specified in column headings. All specifications include model-time and state-model fixed effects and the full set of demographic controls. Standard errors clustered at the state level.

Table 8: Estimated Program Impacts by State

State	ΔQ (No. BEVs)	Program cost ($000)	Env. benefits ($000)	ΔW ($000)
CA	10,032	160,029	19,693	-56,858
IL	670	11,916	-1,145	-7,252
TX	301	5,297	76	-2,420
PA	224	4,388	-459	-2,519
HI*	133	2,583	-	-
TN	116	1,963	-199	-1,130
MA	103	1,851	-143	-1,013
National	11,447	185,444	17,822	-71,192
Excl. CA	1,415	25,415	-1,871	-14,333

Notes: Holland et al. (2016) do not calculate environmental benefits from vehicle use for the state of Hawaii. Environmental benefits assume a 10 year vehicle lifetime, 11,000 vehicle miles traveled per year. Welfare change assumes a marginal excess burden of 0.4.

Table 9: Sensitivity of Welfare Results to Model Specifications

		Environmental Benefits			
		Life = 10		Life = 1	
		Mean	Max	Mean	Max
National		17,822	34,746	1,782	3,475
Excl. CA		-1,871	-151	-187	-15
		Welfare Benefits			
		Life = 10		Life = 1	
	Program cost	Mean	Max	Mean	Max
National					
$r = 100$	185,444	-71,192	-54,267	-87,232	-85,539
$r = 80$	148,355	-40,220	-23,296	-56,260	-54,568
$r = 50$	92,722	6,238	23,162	-9,802	-8,110
Excl. CA					
$r = 100$	25,415	-14,333	-12,614	-12,650	-12,478
$r = 80$	20,332	-10,255	-8,536	-8,571	-8,399
$r = 50$	12,707	-4,138	-2,418	-2,454	-2,282

Notes: Shaded cells correspond to results in Table 8. All values in thousands of dollars. Negative benefits values indicate negative externalities from electric vehicles exceed those of gasoline vehicles. Values of r represent incentive redemption levels (e.g., 80% redemption means 80% of respondents claim the full incentive amount). Mean, Median, Min, and Max headers refer to the environmental benefits methodology from Holland et al. (2016). Environmental benefits assume 11,000 annual vehicle miles traveled. Welfare change calculation assumes a marginal excess burden of 0.4.

Appendix

Table A1: BEV Battery Capacities for Models in Sample

Model year(s)	Make	Model	Min. battery capacity (kWh)	kWh/100 miles
2011-2012	Azure Dynamics	Transit Connect E	28	54
2014	BMW	i3	22	27
2011	BMW	Active E	32	33
2014-2015	Chevrolet	Spark EV	21	28
2013-2015	Fiat	500e	24	29
2012-2014	Ford	Focus Electric	23	32
2013-2014	Honda	Fit EV	20	29
2015	Kia	Soul EV	27	32
2014	Mercedes-Benz	B-Class Electric Drive	28	40
2012, 2014	Mitsubishi	i-MiEV	16	30
2014-2015	Nissan	LEAF	24	30
2013	Nissan	LEAF	24	29
2011-2012	Nissan	LEAF	24	34
2013-2015	Smart	Fortwo	17.6	32
2011	Smart	Fortwo	16.5	39
2013-2014	Tesla	Model S	60	35
2012	Tesla	Model S	40	38
2010-2011	Tesla	Roadster	53	30
2012-2014	Toyota	RAV4 EV	41.8	44
2015	Volkswagen	e-Golf	24.2	29

Notes: Battery capacity reports minimum battery capacity offered. Energy per mile values from fueleconomy.gov.

Table A2: State Weights for Synthetic Controls

(a) Massachusetts

State	Weight
NH	0.63
VT	0.14
CT	0.14
DC	0.03
NC	0.03
WA	0.02

(b) Texas

State	Weight
AZ	0.24
KS	0.21
ND	0.20
ID	0.15
CT	0.07
DC	0.05
AK	0.05
OK	0.02
WY	0.02

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