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Effectiveness of electric vehicle incentives in the United States

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ABSTRACT

Transportation accounts for 28% of total energy use and 26% of carbon emissions in the US, and battery electric and plug-in hybrid electric vehicles are promising options to decarbonize transportation. Federal and state governments, electric utility operators, and a number of other entities have provided support to accelerate electric vehicle purchases via monetary and non-monetary incentives. In this paper, we evaluate the effect of these incentives on the adoption of electric vehicles. We find that every $1000 offered as a rebate or tax credit increases average sales of electric vehicles by 2.6%. We also find that HOV lane access is a significant contributor to adoption, the effect is a 4.7% increase corresponding to density of HOV lanes (every 100 vehicles per hour). In addition, we introduce a novel variable to capture consumer knowledge of EVs and associated incentives in our model to help explain the state level heterogeneity in response to incentives and find that raising consumer awareness is critical to the success of EV incentive programs.

1. Introduction

The development and adoption of electric vehicles (EVs) has been increasing in sales and model availability over the last decade as a potential mitigation method to reduce greenhouse gas emissions in the transportation sector. Since the introduction of electric vehicles, various entities such as federal governments, state governments, and electric utilities across the United States have offered incentives in an effort to promote their adoption (e.g. IRS 30D, the federal Plug-in Electric Drive Vehicle Credit). These incentives vary in design (monetary credits and rebates, carpool lane access, toll and registration exemptions, etc.), scope (federal, state, and local regions as well as by vehicle type, battery size/range), and magnitude (ranging from hundreds to several thousands of dollars for monetary incentives). We have developed a comprehensive dataset of nearly 200 incentives offered throughout the United States for electric vehicles and the purpose of this work is to understand the effects of the different incentives and what conditions affect their efficacy.

While electric vehicle technology has existed throughout the passenger fleet for many decades, their widespread commercial viability was not realized until the end of 2010 with the release of the Chevrolet Volt (a plug-in hybrid electric vehicle, PHEV) and the Nissan Leaf (a full battery electric vehicle, BEV). The rapid growth of electric vehicle sales (see Fig. 1) corresponds to a swath of incentives for both purchase and usage of EVs. This provides an ideal environment to conduct an econometric analysis of EV sales employing a detailed dataset (described in Section 3). The remainder of the paper is organized as follows: Section 2 provides a comprehensive literature review of incentive efficiency starting from hybrid technologies to more recent electric vehicle incentives, Sections 3 and 4 outlines the data used for modeling and the methods of our empirical analysis, Section 5 details the results of our analysis, and Section 6 concludes the paper with a discussion of the importance of our results.

2. Literature review

The study of vehicle incentives has a rich history for the hybrid electric vehicle (HEV) technology that was first introduced to the US in 2000. One of the earliest studies was conducted by Diamond (2009) who examined sales for the Honda Civic Hybrid, Toyota Prius, and Ford Escape Hybrid at a state level from 2001 through 2006. Diamond employs an econometric approach on a number of control variables, including a "green planning capacity" index: a proxy measure of energy and environmental conservation. Unfortunately, the author consistently finds that the presence of the incentive actually leads to a decrease in the market share of HEVs across all three models. Chandra et al. (2010) is another early look at incentives but in Canadian states and by market share over different vehicle segments. Their results indicate that the presence of a $1000 incentive leads to an increase of the market share of hybrids by more than 30%. In Sallee (2011), the author demonstrates

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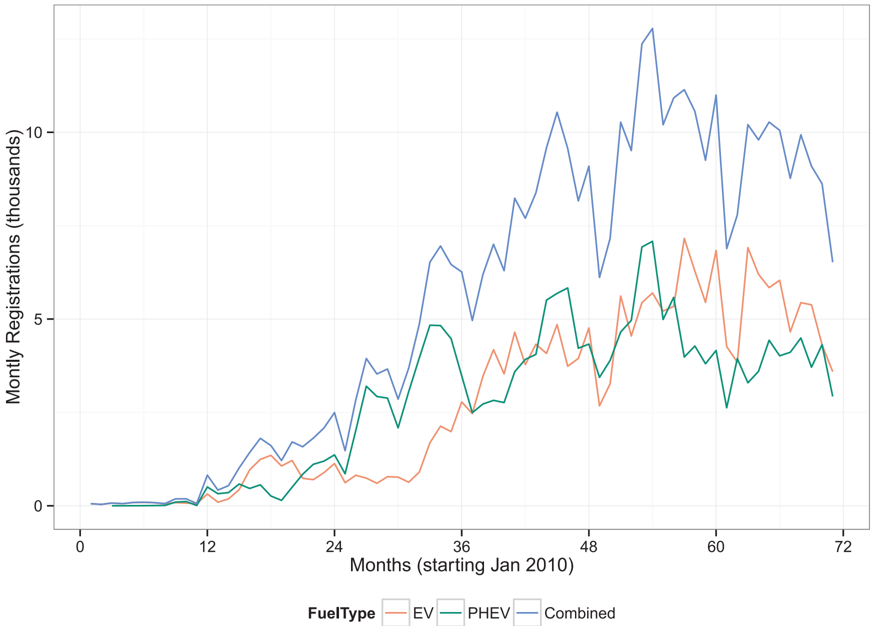

Fig. 1. Monthly sales of electric vehicles in the United States from January 2010 through November 2015. The sales of BEVs (red) are relatively comparable to the sales of PHEVs (green), the sum of the two comprise the combined totals of EVs (blue). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.).

that consumers are the ones capturing the majority of benefits from tax subsidies (not manufacturers or dealers). This effect was demonstrated by closely examining the market for Toyota Priuses and associated changes (or non-changes) in price accompanying shifts in HEV incentive amounts. Contrary to Diamond's earlier findings, more recent studies conducted in the US have found a positive impact of incentives on the adoption of HEVs. One such study on the national sales of HEVs demonstrated consistent increases in per-capita sales in response to state level tax incentives. The authors importantly investigated the effect of different types of incentives as well as the effects from how the incentives were obtained (credits versus waivers) and found that waivers tended to be the most effective (Gallagher and Muehlegger, 2011). In Jenn et al. (2013), the authors also take an empirical econometric approach using lagged dependent variables to approximate natural growth of the technology. Their results indicate that literature values tend to overestimate incentive effects but nonetheless the effects are positive and consistent.

More recently there have been a number of studies that have begun to examine the incentives offered for both BEVs and PHEVs. In an effort to identify the largest barriers to the adoption of EVs, Egbue and Long (2012) conducted a survey to identify the primary concerns about the new technology. The largest concerns were that of battery range and cost, the latter being a critical factor that can potentially be alleviated by the presence of monetary incentives. However, Skerlos and Winebrake (2010) argue that the structure of the federal incentives introduced in 2009 would have higher social benefit if the subsidy policies were varied across income. Additionally, Dumortier et al. (2015) examine how the presentation of cost information, specifically regarding total cost of ownership can actually increase the probability that electric vehicles are selected. This can have important implications for providing price information to consumers for monetary incentives as well. An overview of different policy mechanisms is provided by Zhang et al. (2014). While their analysis is primarily qualitative, they supply a thorough summary of different incentives, particularly in the United States. In terms of the effect of incentives, there are a number of studies that estimate the influence of incentives on adoption of electric vehicles via empirical sales data (Sierzchula et al., 2014; Silvia and Krause, 2016; Vergis and Chen, 2015) and via survey-based data (Krause et al., 2013; Helveston et al., 2015; DeShazo et al., 2017; Tal and Nicholas, 2016).

Additionally there are a number of studies concentrated in Scandinavian countries due to EV popularity and relatively successful integration into the auto market. Langbroek et al. (2015) examine the effect of policy incentives but use a stated-choice experiment in Sweden rather than an econometric approach. With this approach, they are able to not only examine monetary incentives but a number of other incentives such as parking discounts, access to bus lanes, and charging discounts. The authors find relatively low price-sensitivity, particularly for individuals who are in an “advanced stage-of-change” (accepting of EVs). Therefore the behavioral component of acceptance of EV use is critical to the success of incentives. Mersky et al. (2016) study the effectiveness of incentives in Norway. The authors argue that the creation or increase of price incentives for EVs are more important than the provision of toll exemptions or bus lane access for increasing adoption. Bjerkan et al. (2016) use a large survey while Aasness and Odeck (2015) use empirical data to elicit the importance of the various incentives for EV owners in Norway. Both studies find that the purchase tax exemption and value added tax exemption are the most important drivers for adoption. However, the high relative success of Norwegian EV adoption has led Holtsmark and Skonhoft (2014) to question the benefits of high adoption rates. The authors argue that from a carbon perspective, the incentives actually motivate households to increase average household vehicle ownership and simultaneously detract from using public transit and cycling. In addition, they point out that the effective carbon price for the monetary policy amounts to around \$13,500 per ton of CO_2. Finally, Figenbaum offers a very detailed perspective on the Norwegian EV market based on a technological innovation model and his investigation on various driving factors of adoption. His framework of analysis outlines the dynamics of the policy framework for BEVs (Figenbaum, 2016; Figenbaum et al., 2015).

Beyond the research focused on monetary incentives on the purchase of electric vehicles, a number of studies have been released examining other mechanisms of incentivizing such as high-occupancy vehicle (HOV) lane access, infrastructure subsidies, time-of-use rates, parking benefits, and others. An earlier study by Shewmake and Jarvis (2014) examined the California Clean Air Access Stickers provided for HOV lane access and derived their value by investigating the used car market for hybrids. The authors found the worth of the stickers to be approximately \$5800. There are a number of other studies that examine other non-monetary incentives such as the importance of work based charging (Adepetu et al., 2016), parking and charging access (Ajanovic and Haas, 2016; Bakker and Trip, 2013; Hackbarth and Madlener,

Table 1
Summary of literature review.

Authors	Method	Vehicle Type	Region	Incentive Type
(Diamond, 2009)	Hedonic regression	HEV	USA	Tax credits
(Chandra, Gulati, and Kandlikar, 2010)	Hedonic regression	HEV	USA	Tax credits
(Sallee, 2011)	Incidence analysis	Prius	USA	Tax credits
(Gallagher and Muehlegger, 2011)	Hedonic regression	HEV	USA	Tax credits and HOV lanes
(Jenn et al., 2013)	Hedonic regression	HEV	USA	Tax credits
(Egbue and Long, 2012)	Survey analysis	EV	USA	n/a
(Skerlos and Winebrake, 2010)	Qualitative discussion	PHEV	USA	Tax credits
(Dumortier et al., 2015)	Total cost of ownership/survey	EV	USA	n/a
(Zhang et al., 2014)	Qualitative discussion	EV	USA	n/a
(Sierzchula et al., 2014)	Hedonic regression	EV	Intl	Financial
(Silvia and Krause, 2016)	Agent-based model	BEV	USA	Financial
(Vergis and Chen, 2015)	Hedonic regression	EV	USA	Financial and non-monetary
(Krause et al., 2013)	Survey analysis	EV	USA	Financial and non-monetary
(Helveston et al., 2015)	Survey analysis	EV	USA and China	Financial and non-monetary
(DeShazo et al., 2017)	Survey analysis	EV	California	CVRP
(Tal and Nicholas, 2016)	Multinomial logit model	EV	USA	Federal tax credit
(Langbroek et al., 2015)	Survey analysis	EV	Stockholm	Financial and non-monetary
(Mersky et al., 2016)	Hedonic regression	EV	Norway	Financial and non-monetary
(Bjerkan et al., 2016)	Survey analysis	EV	Norway	Financial and non-monetary
(Aasness and Odeck, 2015)	Qualitative discussion	EV	Oslo	Financial
(Holtsmark and Skonhoft, 2014)	Qualitative discussion	EV	Norway	Financial and non-monetary
(Figenbaum, 2016)	Multilevel Perspective Framework	EV	Norway	Financial and non-monetary
(Figenbaum et al., 2015)	Qualitative discussion	EV	Norway and Austria	Financial and non-monetary
(Shewmake and Jarvis, 2014)	Hedonic regression	HEV	USA	HOV lanes
(Adepetu et al., 2016)	Agent-based model	EV	San Francisco	Financial and non-monetary
(Ajanovic and Haas, 2016)	Qualitative discussion	EV	Intl Cities	Financial and non-monetary
(Javid and Nejat, 2017)	Multinomial logit model	EV	California	Financial and non-monetary
(Hackbarth and Madlener, 2013)	Discrete choice analysis	EV	Germany	Financial and non-monetary
(Bakker and Trip, 2013)	Qualitative discussion	EV	n/a	Financial and non-monetary

2013), and infrastructure availability (Javid and Nejat, 2017). Please refer to Table 1 for an overview of electric vehicle incentive literature.

Our work contributes to the growing body of literature with a focus on the US EV market. We introduce several novel aspects in this our research: from a data perspective we are able to take advantage of a much higher resolution dataset of all vehicle sales by model, state, and month from the beginning of 2010 through the end of 2016. Previous studies rely on aggregate sales that detract from the ability of analysis to incorporate state-level differences in incentives. Methodologically, we employ a unique technique (described in Sections 3.2 and 4.2) in order to capture consumer awareness of electric vehicles and associated incentives, a first among the reviewed literature. The consumer awareness allows us to measure the heterogeneity in state-level monetary incentives, an issue that remains entirely unaddressed in the current research landscape. Lastly, our work addresses critical issues of endogeneity which additionally provides robustness to our general results.

3. Data

Our approach examines empirical data in order to estimate the effects of different variables on the adoption of electric vehicles. The primary source of data used in the model comes from vehicle registration data from R.L. Polk/IHS Automotive in collaboration with the National Renewable Energy Laboratory. The dataset contains all new vehicle registrations at the vehicle model level, by month, and by state across all 50 states of the US from January 2010 through November of 2015.

As the data are also categorized spatially by US state, we are able to observe the regional differentiation in vehicle registrations from state to state. As the electric vehicle market grows, we are able to observe nuances of the market, including regional differentiation in EV sales. For example, the market share of electric vehicles in 2015 is shown in Fig. 2. Asides from population, one potential reason for large differences in EV markets between states is regulatory policy that requires automakers to sell EVs in certain states. There are a total of ten states that have a Zero Emission Vehicle (ZEV) mandate that requires the sales of electric vehicles (although credits can be transferred between states). These states include California, Oregon, Maine, Vermont, New York, New Jersey, Massachusetts, Rhode Island, Connecticut, and Maryland. However, a number of other states have relatively high EV sales as well: Washington, Texas, Illinois, Michigan, Georgia, and Florida.

3.1. Electric vehicle incentives

There are a large number of incentives available, not only for the purchase of electric vehicles but additional benefits such as HOV lane access (carpool lanes) and charging infrastructure subsidies. We compiled a database of 198 incentives across all 50 states and categorized them as follows:

Individual credit: Tax credit or rebate received upon purchasing the vehicle. The credit amount varies from state to state and can be flat, a function of the vehicle technology, the battery size, the vehicle model, the manufacturer's suggested retail price (MSRP) of the vehicle, and additionally the incentives typically vary over time. The highest credit amount over the period of observation is offered is $7000 at the state level (federal credits range in amount up to $7500).

Fleet credit: Similar to the individual credit but only offered to larger entities such as businesses, government, or universities. The credit amount can often be larger but with limits imposed on the number of vehicles that any single entity can take advantage of. Limited in scope with very few offering entities in comparison to individual credit opportunities.

HOV lane access: Electric vehicles can be qualified to receive an allowance sticker that provides them with the ability to drive in carpool lanes even if they don't meet the required minimum number of passengers.

Inspection Exemption: Electric vehicles are exempt from having to undergo annual or biannual (depending on the state) emissions inspections.

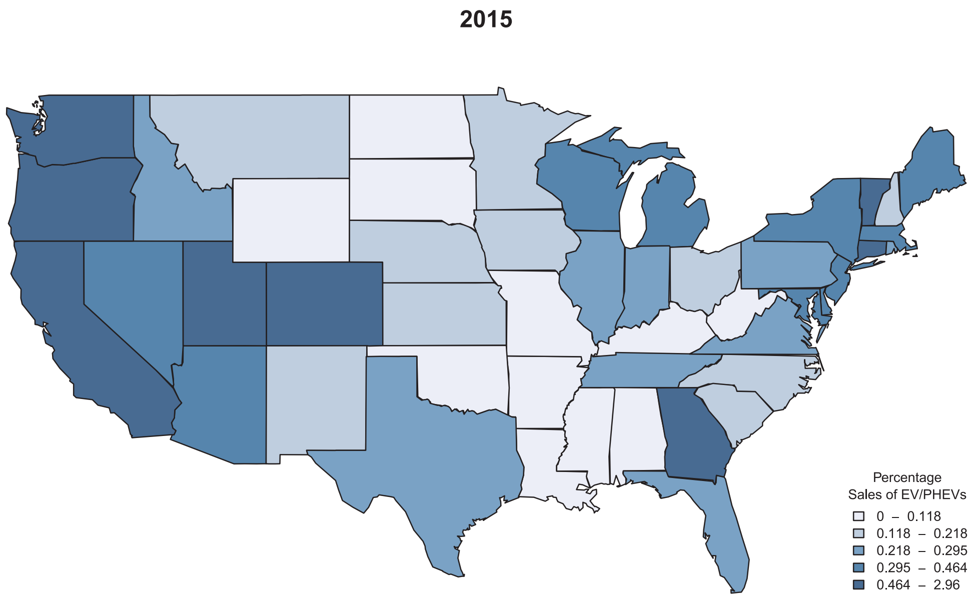

Fig. 2. Market share of electric vehicles by state in 2015.

Registration fee reduction: Annual/biannual (depending on the state) vehicle registration fees are reduced or eliminated.

Time of Use (TOU) rate: Reduced electricity rates based on the time of day, which can allow customers for large savings on their electricity bill. These rates are most often offered by electric utility companies in an attempt to promote electric vehicle charging (and general electricity usage) during non-peak hours (times when electricity demand is relatively low). These incentives do not correspond to state-level regions but rather to utility-level regions.

EVSE (home and public): Subsidies for electric vehicle charging infrastructure that is to be installed at the customer's place of residence or in public areas/businesses. The incentives can vary in structure (rebates, grants, loans) and by charger type.

Not all incentives are covered in our analysis: we omit fleet credits, inspection exemptions, registration fee reductions, and time of use (TOU) subsidies for a number of reasons. The fleet credits are much more limited in scope and differ substantially from each other depending on the entity offering the incentive (e.g. some are grants versus loans). In addition, there are often significant offering limitations (such as a maximum of six available claims per business) that make the fleet incentive impossible to track with aggregated registration data. The inspection waiver and registration fees are too small to be considered a "purchase" incentive and are often collinear with other variables. Lastly, the TOU rates are at much smaller levels of resolution than state level and therefore are unable to be measured with our data. (Table 2).

Table 2
Summary statistics for IHS vehicle registration dataset.

Variable	Description			
Observed time period	Jan 2010-Nov 2015			
Total registrations	83,026,589			
Vehicle fuel types	Gasoline, Diesel, Flex Fuel, Hybrid, Compressed Natural Gas, Battery Electric Vehicle, Plug-in Hybrid Electric Vehicle			
Number of Models	549			
Number of Manufacturers	104			
	Mean	Std Dev	Min	Max
Annual registrations	13,837,765	1917,111	10,928,600	16,030,901
Annual state-level registrations	271,328.7	317,073.2	15,783	1882,429

In our analysis, we weight the HOV lane access by the density of traffic (vehicles per lane per hour) based on data from the Office of Highway Policy Information. This allows us to capture the importance of HOV lane usage since the presence of the special lane does not translate to importance of access (as areas with less traffic will not employ HOV access to the same extent). The densities are provided on a state level and allow us to differentiate the importance of HOV access based on the intensity of use of the carpool lanes. The summary statistics of the incentives in our analysis can be found in Table 3.

One of the ideal aspects of the incentive data are the discontinuities that occur both over time and region. While some incentives have been in place since the introduction of EVs on the commercial market, many more have either expired or have been introduced heterogeneously throughout the different incentive types. The regional and temporal differences in incentives and incentive types offer rich variation upon which we can conduct our econometric analysis. Additionally, there is variation across both vehicle technologies and through different vehicle models.

3.2. Knowledge of incentives

Our analysis also seeks to incorporate the role of consumer awareness of EVs and EV incentives as method to model the heterogeneity of incentive effectiveness between states. In our data, we observe that even in states with similar incentive programs, the per capita sales of EVs can differ quite drastically. One potential reason for this discrepancy is that even if electric vehicles are available in the market, the perceived vehicle price to the consumer may not reflect the true price to consumers if they are not aware of the incentive programs available to them. This factor contributes to the variation of EV adoption between two different states with similar incentive programs. We employ a novel metric in an attempt to proxy for the consumer awareness of the

Table 3
Summary statistics of EV incentives.

Variable	Mean	Std Dev	Min	Max
Individual Credit ($)	526	1250	0	7000
HOV Lane Density (vehicles per lane per hour)	388	407	0	1087
EVSE Home ($)	167	521	0	2500
N	18,644			

incentives using a database consisting of classifiers trained using the Stanford Natural Language Processing Group on a comprehensive set of newspaper articles from Lexis-Nexis related to electric vehicles as demonstrated in Kessler (2015). The articles are sorted into specific Technology Innovation System (TIS) Functions (categorization of articles via machine learning algorithms) of which we select those that are appropriately associated with incentives:

- Resource mobilization of government subsidies
- Market formation of the product through government incentives
- Influence on the direction of search highlighting policy incentives that have positive or negative commercial outcomes

The article counts are organized by state-level regions based on the readership of articles (both in-print and online) about electric vehicles and their associated incentives. This method allows for widely available news sources (such as *The New York Times*) to be counted in multiple states. In our final analysis, we combine the knowledge indexes into a single variable representing the cumulative sum of knowledge.

4. Methods

We produce three different generalized models to investigate different aspects of incentive efficacy. The three groups of specifications are: generalized model, knowledge model, and lagged-dependent model. The generalized model provides insight into the average effect of incentives across the country, the knowledge model incorporates consumer awareness and knowledge of incentives to measure the heterogeneity of incentive efficacy across different states, and the lagged-dependent model addresses important issues of endogeneity in the econometric models.

4.1. General model specification

Our detailed dataset allows us to examine variance across models, states, and time (on a monthly basis), which aids in overcoming many limitations of traditional annual, national level sales. Variation in incentives occurs across all three factors, allowing our approach to isolate the effect of the incentives. We model new vehicle registrations, R, across the set of vehicle models i, monthly time periods t, and state level regions r. The registrations are a function of a set of incentives X, a set of macroeconomic variables Y, and fixed effects for model specific factors η, time varying factors ν, and state regional factors γ:

$$R_{itr} = f(X_{itr}, Y_{tr}, \eta_i, \nu_t, \gamma_r) \tag{1}$$

The fixed effect factors across models, state, and time allow the models to capture unobserved characteristics implicit in each of the factors. We employ clustered standard errors across the different factors to account for serial correlation in the data. Our general specification describes vehicle registrations as a function of available incentives, macroeconomic controls, and fixed effects controlling for vehicle attributes, region specific attributes, and variation across time:

$$\log R_{itr} = \alpha + \sum_{X \in I} \beta_I X_{itr} + \sum_{Y \in M} \delta_M Y_{tr} + \eta_i + \nu_t + \gamma_r + \varepsilon_{itr} \tag{2}$$

where I represents the set of available incentives associated with electric vehicles. This includes individual tax credits at both the state and federal level, access to HOV lanes weighted by traffic density in those lanes, and EVSE subsidies. The set of macroeconomic controls, M, includes state-level GDP, gas prices, and unemployment. GDP is obtained from the Bureau of Economic Analysis at a quarterly period for every state. Gas prices are obtained from the Energy Information Agency and are monthly by region. Lastly, unemployment data are provided by the Bureau of Labor Statistics at a state and monthly level. We estimate this equation using a standard fixed effects regression model.

4.2. Knowledge model specification

While the regression model in Eq. (2) provides an adequate estimate of the average effect of incentives, we also attempt to capture the heterogeneity of the incentive effect across different states by implementing a "consumer awareness" variable as described in Section 3.2. The count of articles related to EV incentives from the NLP process is used as a proxy for awareness of the incentives. Unfortunately, the number of articles are not weighted by readership of a specific source. Nevertheless, if the number of articles written represent the general interest in a subject, our approach still captures the relative knowledge of incentives amongst the populace. The monetary incentives are interacted with the knowledge variable, K, to weight the effect of the incentives by state. This term designates a higher significance towards incentives that are both large in magnitude and well-known by consumers in the state of purchase. However, there is an endogeneity issue: higher sales of electric vehicles may lead to more articles about electric vehicle incentives. Therefore, we instrument on the count of all articles absent articles about electric vehicles Z. The overall article count is correlated with the count of articles on EV incentives, particularly across different regions. However, we do not find it plausible that electric vehicle registrations correlate with the total article counts, particularly because the articles relating to electric vehicles are subtracted away. The 2SLS first-stage is seen in Eq. (3) with ζ_{itr} representing the random error term of the first-stage equation. The second-stage main equation is described in Eq. (4).

$$K_{tr} = Z_{tr} + \zeta_{itr} \tag{3}$$

$$\log R_{itr} = \alpha + \sum_{X \in I} \rho_I (X_{itr} \cdot \hat{K}_{tr}) + \sum_{Y \in M} \delta_M Y_{tr} + \eta_i + \nu_t + \gamma_r + \varepsilon_{itr} \tag{4}$$

4.3. Lagged-dependent model specification

One potential concern in the general model described in Eq. (2) is simultaneity endogeneity. The idea behind this endogeneity issue is that states that have higher demand for electric vehicles are then motivated to create policy incentives for the vehicles, in other words the vehicle registrations lead to incentives rather than the other way around. However, there is a relatively low correlation between incentives and registrations (correlation coefficient of 0.11). Furthermore, there are a number of states with relatively high EV registrations yet whose incentives are not offered nearly to the same extent as major incentive states such as California or Georgia (these include Oregon, Washington, Texas, and Florida). Nevertheless, we attempt to address this issue by specifying a model focused on addressing the endogeneity in Eq. (5).

$$\log R_{itr} = \alpha + \pi \log R_{i,t-1,r} + \sum_{X \in I} \beta_I X_{itr} + \sum_{Y \in M} \delta_M Y_{tr} + \eta_i + \nu_t + \gamma_r + \varepsilon_{itr} \tag{5}$$

We introduce a lagged-dependent variable (LDV) term, $R_{i,t-1,r}$, representing the registrations that happened in the previous time period. The LDV addresses simultaneity since it operates under the assumption that future events do not influence past events. However, the inclusion of the LDV violates strict exogeneity and we therefore follow Arellano and Bond (1991) using a generalized method of moments estimator to estimate the fixed effects equation in (5). We instrument previous lags on different lags of the registration and use the J Hansen statistic to test for over-specification.

5. Results

5.1. Regression analysis

Table 4 displays the primary results of our regression models across

Table 4
Regression results on Log(Registrations).

	(1) General Model	(2)	(3) Knowledge Model	(4)	(5) LDV Model	(6)
Tax credit ($1000)	0.0441*** (4.94)	0.0259*** (3.83)	–	–	0.00891** (2.6)	0.0125*** (4.38)
Tax credit* Knowledge	–	–	1.94e-08*** (3.3)	3.23e-08*** (3.87)	–	–
HOV Access* HOV Density	0.000912** (3.12)	0.000473* (2.42)	0.000738** (2.99)	0.000562* (2.56)	− 0.0000689* (2.49)	− 0.0000301 (0.88)
EVSE credit ($1000)	− 0.101 (−1.83)	0.0196 (0.72)	− 0.0448 (−1.13)	− 0.0334 (−0.90)	− 0.00654 (−0.57)	− 0.0321* (−2.04)
L.log($R_{i,t-1,r}$)	–	–	–	–	0.760*** (26.45)	0.751*** (24.76)
Constant	1.086*** (10.32)	− 0.148 (−0.21)	–	–	–	–
Macro Controls		✓		✓		✓
Fixed Effects	✓	✓	✓	✓	✓	✓
Cluster	✓	✓	✓	✓	✓	✓
Instruments	–	–	All article count	All article count	L(2–4). *R*	L(2–4). *R*
rk LM Stat	–	–	8.091	8.991	5.317	5.603
rk LM Prob	–	–	0.00445	0.00271	0.0701	0.0607
Adj R-square	0.0116	0.0665	0.0182	0.0502	0.112	0.129
N	18,644	18,644	18,473	18,473	11,296	11,296

t statistics in parentheses.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

a variety of scenarios. Results (1) and (2) are results for the general model, results (3) and (4) are results for the knowledge model, and results (5) and (6) are results for the lagged-dependent variable model. Each pair of results represents a model with and without macroeconomic controls, we omit the controls to observe the consistency in results for incentives which may be weakly correlated with these controls. We begin our interpretation of the results for the three incentives measured in our model. Across all models, we find that the monetary incentives are consistently positive and statistically significant, providing robustness to the effect of the policy. The high-occupancy lane access weighted by density of traffic in those lanes is also found to be positive and significant in the general and knowledge models but is not significant in the LDV model. Lastly, the EVSE credits do not appear to have any significant effect on the adoption of electric vehicles in any of the regression models. Focusing specifically on our general model, the results from (2) (which include the macroeconomic controls) has a coefficient of 0.0259 for the tax credit incentive. This indicates an average increase in EV registrations of about 26% for a $10,000 incentive (the total credit amount in California). These results closely match a survey-based method conducted by Tal and Nicolas (2016) that attribute approximately 30% increase to the incentive. Similarly, the weighted HOV lane access has a coefficient of 0.000473, resulting in a 0.04% increase in registrations when HOV lane access is granted per average vehicle density. As an example, in California the average vehicle density is 983 vehicles per HOV lane per hour, resulting in approximately a 46% increase in registrations on average attributable to the HOV access pass.

The individual tax credit weighted by consumer awareness (by article count using TIS functions) requires a slightly different interpretation. Fig. 3 displays the results of the knowledge model broken down by state based on consumer awareness of EV monetary incentives at the end of 2015. The variation in increase is not only a result of different incentives being offered but also due to differences in consumer awareness. While the average effect of the incentives is found to be 2.6% per $1000, in practice the knowledge model reveals the heterogeneity in states can vary as much as 62% on average in California (with approximately an average $8900 in incentives) down to 0% in states such as Montana or the Dakotas. A comparison of the effect of monetary incentives with knowledge incorporated and HOV lane access weighted by HOV density is shown in Fig. 4.

The lagged dependent variable model still maintains significance for the tax credit, albeit with a slightly smaller impact (1.3% increase corresponding to a $1000 monetary incentive). The potential endogeneity issue is directly addressed because the use of the LDV represents the incentive, which cannot plausibly be affected by future sales of electric vehicles. It should be noted that under the LDV model, the HOV access incentive loses significance. Nevertheless, the consistency in significance and the similarity in magnitude of the monetary incentives even across a number of different specifications lead us to conclude that the results of the model are robust. Offering monetary incentives for the purchase of electric vehicles has increased the adoption of the technology by double-digit percentage points across the United States.

6. Conclusion

We are able to conduct a thorough investigation of incentives by taking advantage of our high-resolution dataset, which allows us to take advantage of variance across a number of factors: spatially, temporally, and by vehicle model. Previous studies in the literature have not studied the breadth of incentives across all the US states and thus the conclusions of our studies provides a wider base upon which to evaluate the numerous incentive programs in the United States, particularly monetary credit or rebate incentives. In addition, we are able to address important issues of endogeneity that are often present in other works: the fact that incentive programs may be developed as a response to relatively stronger EV markets in the United States. By including a model that employs a lagged-dependent variable, we are able to break the issue of simultaneity and demonstrate consistency throughout our models.

Despite the higher resolution of our analysis, more in-depth studies are necessary to understand more local factors than state-level data are able to observe. For example, the time-of-use incentives offered by utilities across the country are quite prevalent but operate at sub-state level regions and therefore are not captured in our analysis. Whether or not more localized incentives are significant drivers of electric vehicle adoption is a question that can only be answered in future work that operates in greater spatial detail. Another concern is whether the future market of consumers will respond differently to the offering of incentives. The current electric vehicle market is less than 1% of total sales and as EVs move into more mainstream consumer markets in the future, response to the incentives may not reflect those found in our analysis. Lastly, the incentives themselves are rapidly changing with dozens of new incentives already being offered since the end period of our analysis (end of 2015). Studies that examine the effects of these new incentives may provide additional robustness to our results. In addition, to these incentives, we note that our study does not explicitly account for charging infrastructure as a variable in our model specifications. We

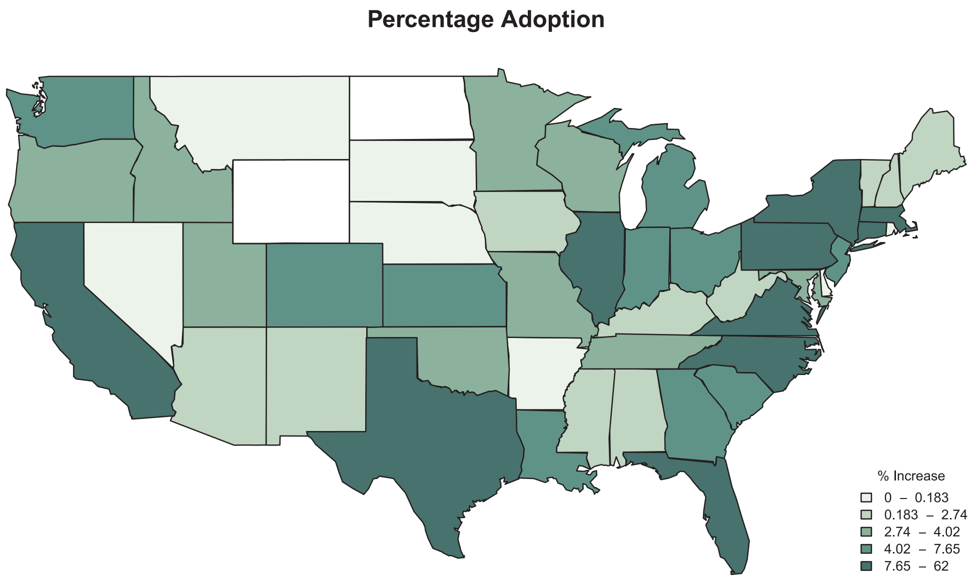

Fig. 3. Percentage increase in EV sales attributable to monetary incentives by state at the end of 2015. Heterogeneity in increases are due to slight differences in incentives being offered as well as variation in consumer awareness of incentives between states.

were unable to include a high-resolution view of the infrastructure due to a lack of a comprehensive database on state-level infrastructure with monthly updates. While our base results may be slightly positively biased due to omitted variable bias that would result in an increase in vehicle registrations, the lagged-dependent variable will likely account for relative differences in infrastructure across time and space. Since each R_{itr} term will inherently account for γ (state-level effects) in t and $t-1$, the changes in infrastructure development by region will be captured in the lagged-term. The inclusion of an infrastructure variable would therefore be unlikely to affect our LDV results.

A continuing limitation of this field of work, ours being no exception, is a lack of supply-side analysis. At a macro-level, policies such as the Zero Emissions Vehicle mandate are significant contributors to the availability of vehicles that enable the market to be initially developed, and may encourage automakers to advance the market for EVs as well. At a micro-level, the stock/availability of specific electric vehicles at dealerships is an important consideration that can have significant implications to demand side modeling. As an extreme example, if a dealer simply has no stock of a vehicle then no amount of incentive can induce a consumer to purchase the EV since the product is simply unavailable. Our work is unable to consider these factors due to data limitations but these issues should be considered when interpreting our work.

Nevertheless, our paper incorporates many novel elements into incentive efficacy studies: we use a higher level of detail in vehicle sales data than seen in contemporary studies, we capture consumer awareness/knowledge of incentives, and we account for endogeneity (specifically simultaneity issues) in our models. Our general results indicate

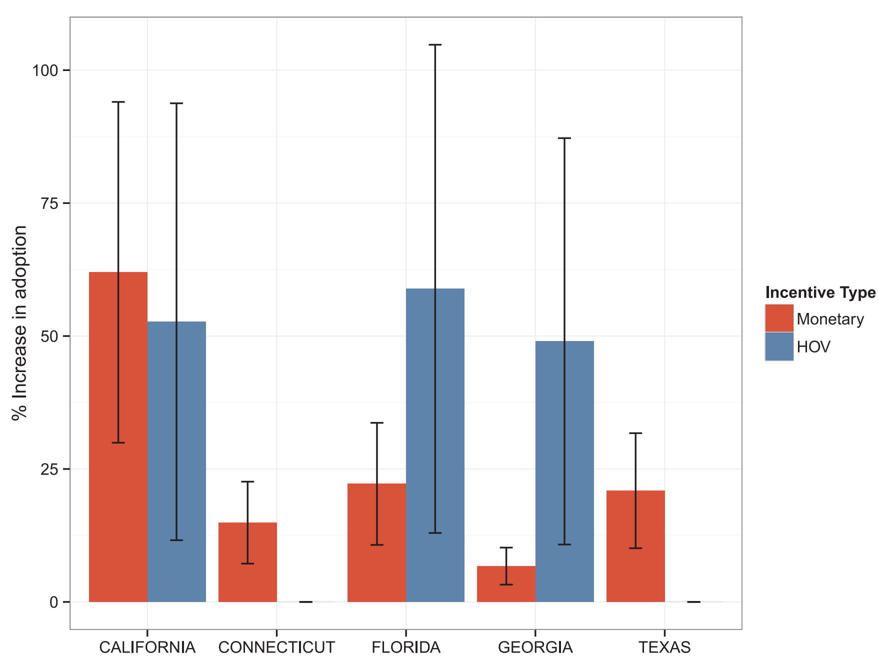

Fig. 4. Average effect of monetary incentives (incorporating heterogeneity in state knowledge of incentives) and HOV lane access weighted by density of traffic for five select states.

that an individual monetary incentive (as is the current most prevalent incentive) has a statistically significant effect averaging around 2.6% per $1000 offered throughout the US. However, we are able to additionally measure the heterogeneity in incentive effects across different states and find a much higher range for some states with greater volumes of EVs adopted. For policy-makers, our paper indicates that in addition to monetary incentives, other incentives such as HOV lane access can be important, particularly in states with a high density of traffic in carpool lanes. Similarly, increasing consumer awareness of incentives can be a very significant lever in which to increase the effectiveness of the monetary incentives themselves (see Fig. 3). We acknowledge the imperfections of our proxy and encourage future research to better capture metrics of awareness, perhaps through the integration of social media research or other means. Nevertheless, we find that in states where cumulative knowledge is high, there is a corresponding response seen in vehicle sales. Regional government agencies could stand to substantially improve the efficacy of their programs by shifting resources towards public awareness campaigns. Consumers may be unaware of the current benefits they may be able to accrue in the form of incentives and therefore have a perception that electric vehicles are more expensive than their true transaction price. Additionally, public information campaigns can have a secondary benefit in educating consumers on the new technology, either dispelling incorrect notions of the technology or revealing previously unknown benefits of the technology.

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