Plug-in Electric Vehicle Diffusion in California: Role of Exposure to New Technology at Home and Work

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16. Abstract
The market for plug-in electric vehicles (PEVs) that primarily include battery electric vehicles (BEVs) and plug-in hybrid vehicles (PHEVs) has been rapidly growing in California for the past few years. Given the targets for PEV penetration in the state, it is important to have a better understanding of the pattern of technology diffusion and the factors that are driving the process. Using spatial analysis and Poisson count models, the researchers identify the importance of a neighborhood effect (at home locations) and a workplace effect (at commute destinations) in supporting the diffusion of PEV technology in California. In the case of new BEV sales, they found that exposure to one additional BEV or PHEV within a 1-mile radius of a block group centroid is associated with a 0.2% increase in BEV sales in the block group. Interestingly, for new PHEV sales, the neighborhood effect of BEV sales is negative, suggesting that enhanced exposure to this type of technology (which is differentiated in distinctive ways from PHEVs) may impact new PHEV sales through a substitution effect. Specifically, higher BEV concentration in an area can have an overall negative effect on new PHEV sales. While the neighborhood effect at residential locations is important, workplace effect also have a notably important effect on new PEV sales. Both effects work in combination with socioeconomic, demographic, policy, and built environment factors in encouraging PEV adoption. These results suggest that policymakers should consider targeted programs and investments that can boost the impact of neighborhood and peer effects on PEV sales

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EXECUTIVE SUMMARY

The purpose of this research is to make advances in understanding and modeling dynamic processes that occur as part of the creation of new markets and/or the penetration of new technologies into existing markets with incumbent, legacy technologies. The specific case considered here is the introduction and penetration of zero-emission vehicles (ZEVs) in the state of California. A variety of programs and policies exist that are intended to support, promote, and accelerate the penetration of ZEVs. The efficacy of these programs will depend at least in part on how they interact with these dynamic processes, so a better understanding of these interactions can lead to improved projections of the impact of existing programs, and improved design of future programs.

Existing programs already incorporate premises about a variety of dynamic effects. For example, subsidizing sales of new ZEVs leads to increased cumulative sales that can contribute to lower manufacturing costs and improve performance characteristics (e.g., increased range) due to learning effects. Similarly, it is widely assumed that increasing the number of publicly available recharging stations will lower perceived obstacles to purchasing PEVs (e.g., range anxiety), which would also contribute to accelerating cumulative sales. Diffusion of innovation theory suggests a variety of possible effects related to consumer perceptions and behavior. Increased numbers of vehicles on the road contribute to increasing awareness and knowledge levels on the part of the general population, and the longer this continues, the more "legitimized" the new technologies will be in the minds of consumers. These effects require some type of "proximity" and interaction within groups of consumers (either geographically or "socially") so the focus in the literature had been on so-called "peer effects" that produce a type of contagion dynamic that expands both geographically and temporally. While initial purchases might occur among so-called "innovators" or "early adopters," the effect eventually spreads to mainstream consumers. Another important dimension as the market evolves is the increased availability of new makes and models of vehicles, especially across a wider variety of vehicle classes (e.g., minivans, SUVs, etc., rather than just mid-sized and small cars).

The methodological approach proposed for this research was to (1) combine multiple (pre-existing, readily available) data sets containing different types of information in ways that would support the econometric identification of the dynamic effects of interest, and (2) apply advanced consumer modeling methodologies to estimate the effects. The original proposal identified a variety of such data sets, many involving survey data on ZEV buyers collected at multiple points in time over the period 2015-2018 by researchers at the UC Davis Plug-in Hybrid Electric Vehicle (PHEV) Center, as well as data sets from other surveys we had been involved in. In addition, we anticipated combining these data with some type of "administrative data" on aggregate vehicle sales from a source such as the Department of Motor Vehicles (DMV).

While these original ideas are still part of our ongoing research agenda, once the project was funded and work began, we gained access to an unanticipated data source: DMV vehicle registrations data over multiple years at the individual vehicle level (including VIN information). While much of the identifying information was removed for privacy reasons, records for the most critical years (2014-2017) were geocoded at the Census Block Group level, including variables for identifying specific dates of new vehicle transactions. These data were merged with various other data sets (via VIN prefixes and Census Block Group ID) to incorporate information on vehicle technology (DataOne Software), household demographics and socio-economic factors (American Community Survey), origin-destination commute patterns (LODES data), public charger location data (Alternative Fuel Data Center), transit accessibility (EPA Smart Location tool), land use type (*1*), and State of California vehicle incentive programs. Spatial and temporal patterns of PEV adoption were explored using GIS approaches and quantitative behavioral models of vehicle purchase counts incorporating "*neighborhood*" and "*workplace effects*", collectively referred to as *"peer*" effects, demographic, socio-economic, built environment, and policy factors were estimated using quarterly new vehicle sales for the years 2015-2016.

Our results confirm that peer effects in combination with socioeconomic, demographic characteristics and PEV-friendly policies can play an important role in the market penetration dynamics for PEVs. Exposure to new technology encompasses both physical exposure (i.e., seeing electric vehicles on the road or in a parking lot), and social exposure (i.e., talking with friends, colleagues, and family members about the topic). Estimating the impact of such physical and social exposure at home (neighborhood effect) and commute locations (workplace effect) on PEV adoption is important for estimating impact on the spatial distribution of new PEV buyers, as well as the derived demand for charging and thereby the derived demand for electricity. Moreover, peer effect at the commute destination can be an important factor in accelerating PEV market growth in disadvantaged communities with a low local concentration of PEVs in the immediate neighborhood. Residents of areas who may not experience neighborhood effects can still be exposed to PEV technology when they commute to work locations. Thereby, policies or infrastructure support that encourages commuters to drive their PEVs to work can play an important role in the diffusion process.

This study focuses on new PEV sales in California; however, past studies have shown that areas with low- and middle-income households are more likely to participate in the used PEV market. In this regard, targeted policies/programs and peer effects might also influence market penetration through the purchase of used PEVs trickling down to lower-income households and communities with low adoption of new vehicles. This is a possible area for additional research to gain an increased understanding of what role this might play in the overall evolution of PEV adoption. In any case, these results suggest that policymakers should consider measures that might more effectively leverage neighborhood and peer effects on PEV market growth. In addition, they should consider targeted programs and investments that will compensate for the lack of neighborhood effects in some communities (e.g., the Clean Car 4 All program).

Introduction

The contribution of any new technology to society can only be realized if the technology is widely diffused and used. For example, plug-in electric vehicles (PEVs), the technology solution proposed by most policymakers and researchers to reduce pollution from the transportation sector, will only have the desired effect when they successfully penetrate the market and are adopted by more and more vehicle owners. Over the past decade, policymakers have implemented various policies and programs to promote the adoption of vehicles with alternative fuel technologies. These include tax credits and subsidies for new plug-in vehicle purchases, investment in charging infrastructure, use-based incentives like High-Occupancy Vehicle (HOV) lane access, parking benefits, etc. Part of the logic is that various dynamic effects known to occur as part of the innovation diffusion process will accelerate in response to such promotion, impacting both the demand- and supply-side of the market.

On the supply-side, increasing sales volumes can result in lower manufacturing costs due to learning effects and economies of scale. Additionally, as the market starts to get larger a more diverse set of vehicle types and brands can be offered. These dynamics can lead to lower prices and more diverse offerings, that in turn lead to more demand.

On the demand-side, a critically important factor is for vehicle owners to become more aware and knowledgeable about the new technology offerings as a prerequisite for consideration. Beyond that, the diffusion process must proceed until new technologies are "legitimized" and considered less risky by mainstream market segments.

In the case of PEVs, globally, the diffusion process appears to be underway with the sale of PEVs crossing the two million mark in 2019 (*2*, *3*). However, the technology diffusion curve in most places is still in the early adoption stage with high regional disparities globally as well as within a country (*4*). California, accounting for usually 47%-50% of the new PEV sales in the United States has a target of 5 million zero-emission vehicles (PEVs and fuel cell electric vehicles) by 2030[1]. Moreover, recently the state government proposed ending gasoline vehicle sales beyond 2035 (*5*). Even though the year-on-year sales of PEVs have grown by approximately 56% in the past couple of years, in 2018, PEVs still constituted only 7.8% of California's new vehicle sales.[2] Therefore, policymakers continue to wonder how much promotion and government support might be necessary to achieve the 5 million target, and for how long. To help answer these questions, an improved understanding of the factors determining market dynamics is key.

Consistent with expectations, early adopters of PEVs generally fit a known profile and can be targeted accordingly for policy purposes. However, it is important to understand that their behavior can have an impact on the adoption behavior of the more general population as factors related to awareness, knowledge, consideration, and legitimization of the new technologies are known to be important (*6*, *7*). This article examines the adoption of PEVs in California over the period 2014 to 2016 in terms of diffusion patterns, both spatially and

[1] https://evadoption.com/ev-market-share/ev-market-share-state/
[2] https://evadoption.com/ev-market-share/ev-market-share-california/

temporally. The goal is to gain a better understanding of the diffusion process and its drivers, controlling for all the factors that can impact vehicle choice and particularly PEV adoption in the state. We first explore patterns of diffusion using geostatistical approaches and heat maps for two points in time (2014 and 2016). These readily demonstrate expected spatial distributions related to, e.g., household income. However, diffusion over time relative to the initial "clusters" of adoption is also observed, suggestive of the so-called contagion (peer) effects discussed and modeled in the technology diffusion literature. We then provide a quantitative model to identify and analyze these effects on PEV adoption, using cross-sectional panel data that controls for a full range of factors, including demographics and socioeconomic factors, incentive programs, and built environment variables. Unlike other new technologies like photovoltaic cells, the contagion effects for PEVs are not confined to the residential location. Since vehicles are mobile it is essential to not only consider peer effects at the residential location, referred to as *neighborhood effects,* but also peer effects at commute destinations[3], referred to as *"workplace effects*". We combine data from multiple sources to identify both the workplace and neighborhood effects. The results of the spatial analysis of the diffusion pattern and the econometric model help us address key questions related to the importance of exposure to technology on the PEV diffusion process as well as the effect of some pilot programs to encourage PEV adoption. The findings have policy implications for the planning of infrastructure as well as targeting incentive programs.

[3] There is a variety of terminology used in the innovation diffusion literature when modeling contagion-related effects. In what follows, we endeavor to consistently use the term "neighborhood effect" when referring to effects associated with individuals observing PEVs in their neighborhood (or otherwise interacting with the owners of such vehicles). In some papers this may also be called an *installed base* effect. "Workplace effect" refers to the effects associated with individuals observing PEVs at their commute destination (or otherwise interacting with colleagues owning such vehicles) We reserve the term "peer effect" to encompass the effects associated with exposure to PEVs both in the neighborhood and at commute destinations.

Literature Review

The International Energy Agency (IEA) in their annual publication on the PEV market made projections that if by 2030 global policy ambitions are met, global electric car sales will reach 23 million and the stock will exceed 140 million vehicles (excluding two/three-wheelers) (*2*). Multiple other organizations have such market forecasts and projections based on different policy scenarios, with some recent studies accounting for the effect of the COVID 19 pandemic on vehicle sales (*8*, *9*). While most of these forecasts are simply an aggregate market share projection for a country or a state, they illustrate the rapid growth of the PEV market globally and the urgent need to understand the diffusion pattern of the technology to enable better policy and more efficient infrastructure investment (*4*). Past studies have shown that the market growth of PEVs will depend not just on policy commitments and incentives offered by governments but also on the efficiency of charging infrastructure and the electricity grid that will support the growth of the PEV market (*10*–*16*). To enable better infrastructure and grid planning, it is essential to build an understanding of the spatial pattern of technology diffusion, which neighborhoods or households are more likely to own these vehicles. In addition to infrastructure planning, the ability to predict or explain the spatial pattern of penetration of PEVs will enable more targeted policy implementation to encourage further growth in the PEV market.

There is extensive literature on the diffusion of green technologies like the photovoltaic cell and PEVs. Though the studies on technology penetration often differ in terms of the studied region (country/state/city), influencing parameters, and the methodology, the analytical models can be broadly classified as either predictive or explanatory. The predictive models aim to estimate the likelihood of the geographical areas where the technology will penetrate and the timeline of the diffusion process. Explanatory models on the other hand primarily focus on identifying and estimating the influence of factors that can drive the diffusion process in an area. Considering past research focusing on PEVs, system-dynamic models, agent-based models, and discrete choice models are commonly used for explaining and predicting the diffusion of battery electric (BEV) and plug-in hybrid electric vehicles (PHEVs). System dynamic or simulation-based models also allow the researcher to account for policy feedback and dynamic preferences that are difficult to consider in choice models and thereby often ignored (*17*, *18*). On the other hand, based on disaggregated data, discrete choice models allow researchers to identify and analyze the factors that drive vehicle purchase behavior at the individual- or household-level and subsequently predict the market share of the alternative fuel technologies based on well-grounded consumer behavior theories (*19*–*21*). A vast majority of these studies focus on the role of policy, demographic characteristics, political affiliation, environmental attitude, user experience, and vehicle characteristics in the diffusion process (*17*, *22*–*26*). Studies by Rezvani et al., (*27*), Coffman et al. (*28*), Jochem et al., (*29*), and Hardman, S. (*30*) offer a thorough review of the literature on PEV adoption and the methodology used in the studies. Though bottom-up models like the choice models (multinomial logistic regression, nested logit, or the hybrid choice models) are based on strong theoretical backgrounds, the need for detailed disaggregated data is challenging. Moreover, these models are appropriate for snapshot analysis of the dynamics in the market for alternative vehicle technologies (*29*).

Due to these limitations, when the objective is to forecast market penetration over a longer time horizon, multiple studies have built and analyzed PEV diffusion using aggregated time-series data and the Bass diffusion model (*31*, *32*). Overall, despite this rapidly growing literature in the field of alternative fuel vehicles, it is surprising that a good understanding of the role of social influence or peer effect on PEV adoption is not as well-developed. In their meta-study of PEV diffusion models developed globally, Gnann et al., (*33*) note that almost two-thirds of the models do not account for the effect of social interactions on PEV penetration.

The effects of social interactions on technology adoption, referred to as peer effects , has been extensively studied in relation to other technologies and innovations like cell phones, computer software, and more recently photovoltaic cells (*34*–*38*). Incorporation of the influence of social interaction and spatial effects on PEV diffusion is important because the initial distribution of the PEVs, along with the factors identified by past studies, can play an important role in defining the lead and the laggard markets in a region. As Axsen and Kurani (*6*) point out, transportation researchers are only starting to explore social influence as a driver of adoption even though most households in their demonstration project setting ranked at least one social interaction as being highly influential in their assessment of alternative fuel vehicles. The limited number of studies that have analyzed the role of social interactions and estimated the neighborhood or peer effect on PEV adoption have found that it plays an important role in market penetration (*39*–*43*). In the context of UK and the US market, both Morton et al. (*40*) and Chen et al. (*43*) respectively find that in addition to demographic, economic, policy, and built environment factors, neighborhood effects arising from heterogeneity in the spatial distribution of PEVs influence technology penetration. Analyzing the effect of social interactions on the PEV adoption rate in Sweden, Jansson et al. (*42*) mention that interpersonal influence on PEV adoption can originate from different social domains like neighbors, family, and co-workers. The authors find that even though all three sources of interaction are important, neighborhood effect at the residential location has the strongest influence on PEV adoption decision.

The current study adds to the research on the role of peer effects in the PEV diffusion process by examining the impact of exposure to technology in the neighborhood and at the commute location while controlling for the effects of demographic, built environment characteristics at the census block group level, and policy impacts. It is important to account for demographic characteristics, built environment features, and the role of institutional settings in the analysis of diffusion patterns since all these factors have been identified as important drivers of vehicle choice and particularly PEV adoption. For example, income distribution and education play a role in determining risk aversion and a positive attitude towards technology. In terms of built environment features, low residential density has been found to encourage vehicle usage and the choice of less fuel-efficient vehicles (*44*). Considering features specific to the PEV market, previous studies have found that a denser distribution of PEV charging stations has a positive impact on adoption (*25*, *45*). Based on quarterly EV sales and charging station deployment in 353 metro areas in the US, the authors find evidence of indirect network effects on both sides of the market or a feedback loop between PEV adoption and investment in charging infrastructure, with the positive impact on the PEV demand side being stronger (*45*). Finally, while incentives like the federal tax credit or the state rebates offered to PEV buyers have a positive impact on overall PEV sales growth (*22*, *30*, *46*), more targeted policies undertaken by the California government like the “Enhanced Fleet Modernization Program” can impact the technology diffusion pattern in the state (*47–49*). Analyzing the impact of the program, Muehlegger and Rapson (*47*) find that it has a muted but positive effect on the adoption of fuel-efficient vehicles among low- and middle-income vehicle buyers. The econometric model presented in this explanatory study aims to extend the current understanding of the spatial diffusion of PEVs in California by determining the degree to which neighborhood/peer effects, socio-economic, demographic characteristics, targeted policies, and built environment characteristics can explain the spatial variation in EV diffusion.

Data Description

To study the drivers and spatial-temporal patterns of PEV adoption in California, we rely on several sources of data as described in this section. We focus our data collection and analysis efforts at the Census block group level as defined by the 2010 Census boundaries since this is the most disaggregated level for which data on key variables (such as median household income or distribution of dwelling types) are available.

Data on new vehicle purchases and vehicle stock

We use vehicle registration data from the California Department of Motor Vehicles (DMV) for the period October-2014 to December-2016 to obtain counts of BEVs, PHEVs, and vehicles of other fuel types in the state. In California, every vehicle must be registered annually. Each record includes a 17-digit vehicle identification number (VIN) that uniquely identifies the vehicle, the most recent registration date, the date when the vehicle was last sold, and other vehicle purchase/transfer related information. Basic vehicle attributes (e.g., horsepower, fuel type, etc.) are obtained using a VIN decoder purchased from DataOne Software. Results from the VIN decoder is used in combination with the DMV data to obtain vehicle counts for different fuel technology types at the block group level. To construct block-group-level panel data of new vehicle sales and total vehicle stock by fuel type, we split the years for which DMV data are available into quarters. New vehicle sales are identified using the following information available in the DMV data: registration date, model year, the year the vehicle is first sold, and absence of transfer date. The vehicle stock is calculated using data on the last ownership date of the vehicle, which considers the day when the vehicle buyer took ownership of the title. Therefore, if the vehicle was transferred to another individual, the last ownership date gives the day the title of the vehicle was transferred. Based on the California DMV data, Figure 1 and Figure 2 represent the total number of the new light-duty vehicle (LDV) sales and the total stock of LDVs in California for the four fuel/powertrain types during the study period (Q4 2014-Q4 2016). Other fuel types not shown in the figures are diesel, diesel hybrid, flex-fuel, natural gas, propane, and hydrogen fuel cell. As the two figures show, the sales of new BEVs and PHEVs were consistent through the years 2015 and 2016 and the stock of the alternative fuel technology vehicles grew steadily. On the other hand, the number of new conventional hybrid vehicles sold went down during the period, potentially losing market share to BEVs and PHEVs.

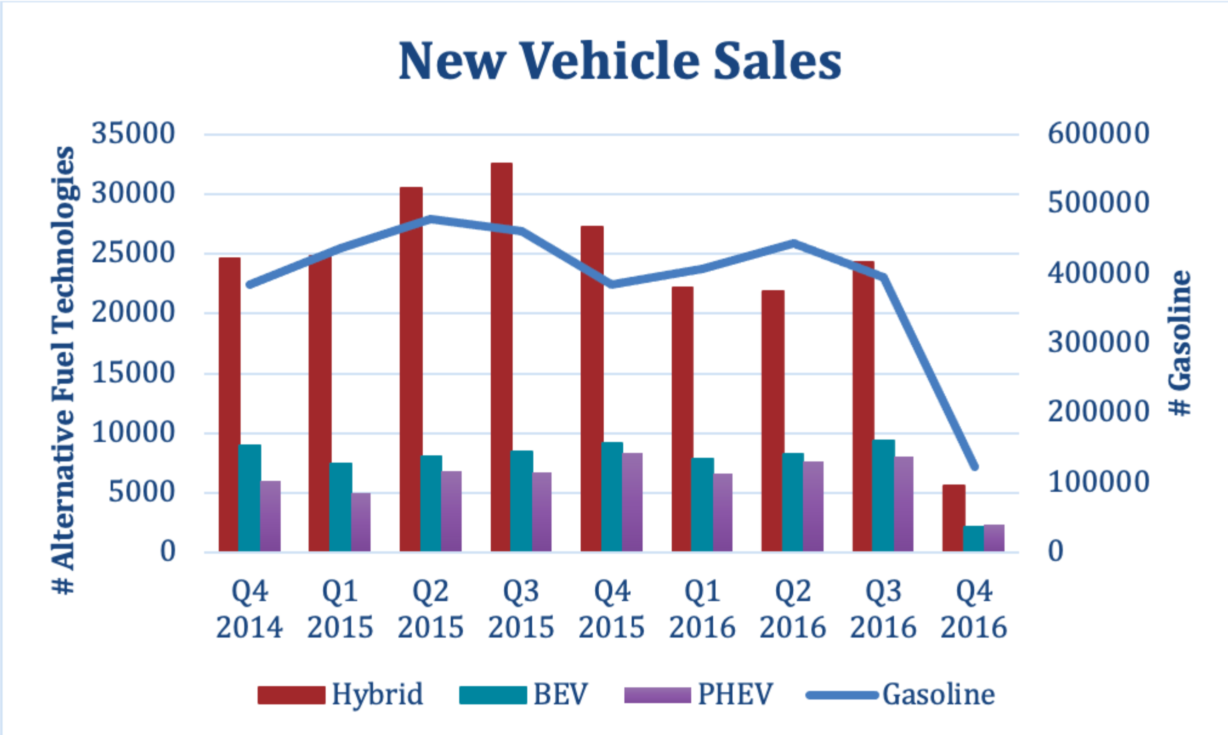

Figure 1. Total New Sales in California by Fuel Type (October 2014-December 2016)

As evident from Figure 1, there are some issues with the DMV data that one needs to keep in mind while interpreting the results of the analysis below. First, the California DMV data is obtained in the form of a “snapshot” taken in October 2014, 2015, and 2016. There is a 6-month to a year lag in the number of registrations in each quarter that show up in the data. Though the 2017 DMV data was used to fill in the vehicle registration data for Q4 2016, we undercount the numbers for all the fuel types. Second, the DMV data does not provide the block group information of vehicles that are registered in areas with less than 100 vehicles due to privacy concerns. As a result, the number of luxury vehicles is probably underestimated in the DMV data. In the case of BEVs, the problem mainly exists for Tesla models. The DMV data reports block group information for 68.7% of the Tesla registered in California.[4] The rest of the Tesla models were not identified in the DMV data shared with us due to privacy concerns. Due to the missing Tesla vehicles in these data, we can expect that the estimate of the average neighborhood effect, as well as workplace effect, to be downward biased. The results of the econometric models estimated in this study should be interpreted keeping this caveat in mind.

[4] Information shared by staff from California Air Resource Board (personal communication). The information pertains to the DMV file offering a snapshot of the vehicles registered in California in October 2015.

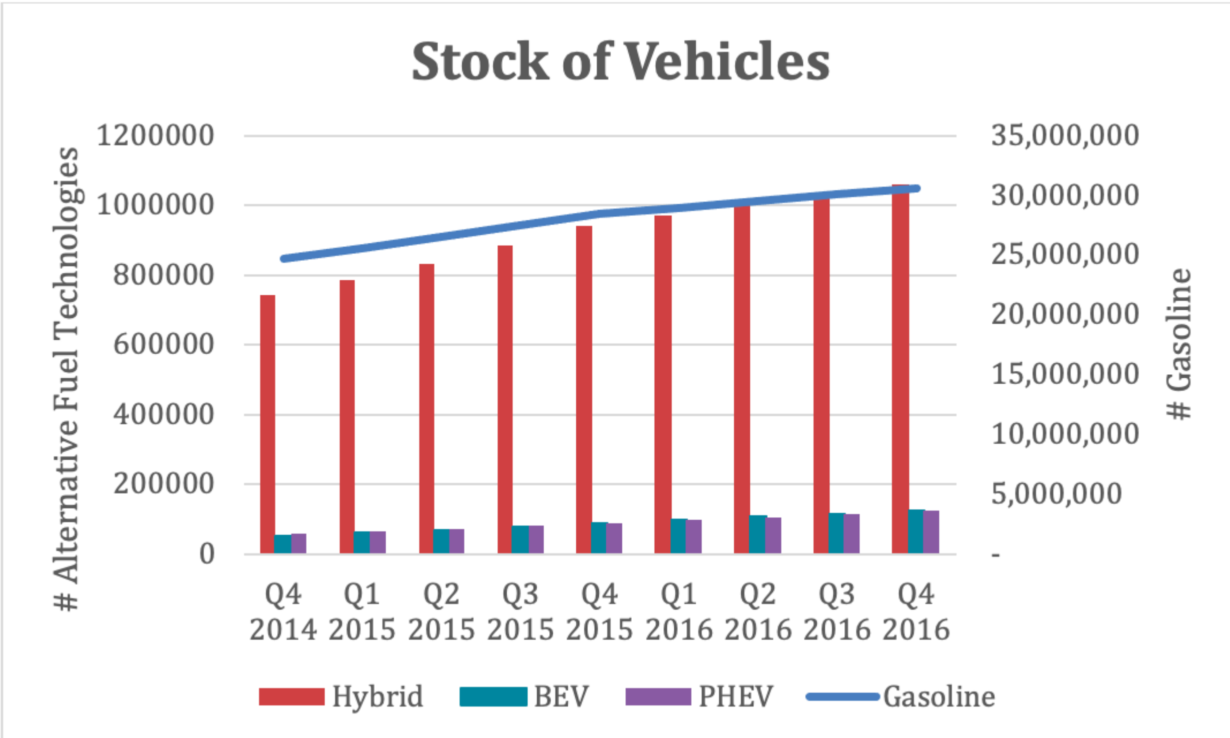

Figure 2. Total Vehicles in California by Fuel Type (October 2014- December 2016)

Past studies have shown that there is spatial variation in awareness of alternative fuel technology vehicles as well availability of infrastructure (*50*). Theory and evidence from analogous product categories suggest that one of the major factors driving this variation in awareness is exposure to these new technology vehicles through contact with other individuals who have already purchased them, either through geographic proximity or social interaction (or a combination). Consumers with higher awareness of PEVs are more likely to consider them when time comes to make a new purchase. Table 1 gives the share of block groups in California with positive numbers of BEV and PHEV sales, and stock in each quarter of the period of analysis. Between Q4 2014 and Q4 2016, new PEV sales in each quarter were identified in 20% of the block groups (on average) in California. In terms of vehicle stock, though on average 58% (65%) of the block groups had positive number of BEVs (PHEVs) in Q4 2014, only 18% (19%) of these block groups had more than five BEVs (PHEVs) in Q4 2014. As the number of block groups with non-zero PEVs stock grew over the period of analysis, as observed in Table 1, the share of block groups with more than 5 BEVs or PHEVs also increased. The observed pattern related to new PEV sales and PEV stock indicates that neighborhood and workplace effects may play a role in the expansion of the PEV market from initial agglomeration centers.

Table 1. Percentage of block groups with positive PEV sales and stock between Q4 2014-Q4 2016

Quarters	Q4 2014	Q1 2015	Q2 2015	Q3 2015	Q4 2015	Q1 2016	Q2 2016	Q3 2016	Q4 2016
PEV sales[5]									
Non-zero BEV sales	23	20	23	22	21	19	20	21	4
Non-zero PHEV sales	19	16	20	20	22	19	21	22	5
PEV Stock									
Non-zero BEV stock	57.8	61.6	64.4	67.6	70.2	71.6	72.3	74	74.9
Non-zero PHEV stock	64.6	67.3	69.5	72.2	74.5	76	77.2	78.6	79.8

Spatial data for the analysis of PEV adoption patterns

The neighborhood effect at the residential location is analyzed using the buffer-ring method. To create the spatiotemporal variable, we consider the centroid of each block group and define a buffer-ring around it at a 1-mile radius. Subsequently, we count the number of PEVs registered within the 1-mile radius. Therefore, for each block group *'i'*, we count the number of PEVs in each block group *'j'* such that:

$$(c_i - c_j) \leq D, j \neq i \; and \; D = 1 \; mile \quad (1)$$

Where, c_i and c_j are the centroids of the block group *'i'* and block group *'j'* respectively. There can be multiple block groups within the 1-mile ring drawn about the centroid of the block group *'i'*. However, in the case of block groups with larger areas, there may be no other block groups within a mile at least in one of the directions. In this scenario, only the stock of PEVs registered in block group '*i*' is counted in the PEV exposure variable representing the *neighborhood effect*.

Figure 3 and Figure 4 show the distribution of the stock of BEVs and PHEVs, respectively within a 1-mile radius of a block group in California. Like PEV sales (Table 1), the stock of PEVs is also concentrated in a few block groups with the distribution being positively skewed. In other words, on average the stock of PEVs surrounding a block group is low (mostly zero) with only a few block groups having a high stock of PEVs in their neighborhoods.

[5] Majority of the block groups with non-zero PEV sales had 1 PEV sale in a quarter. 15.4% (13.8%) block groups had 1 BEV sale in Q4 2014 (Q4 2016). Similarly, in the case of PHEVs, 14.5% (15.9%) block groups had 1 PHEV sale in Q4 2014 (Q4 2016).

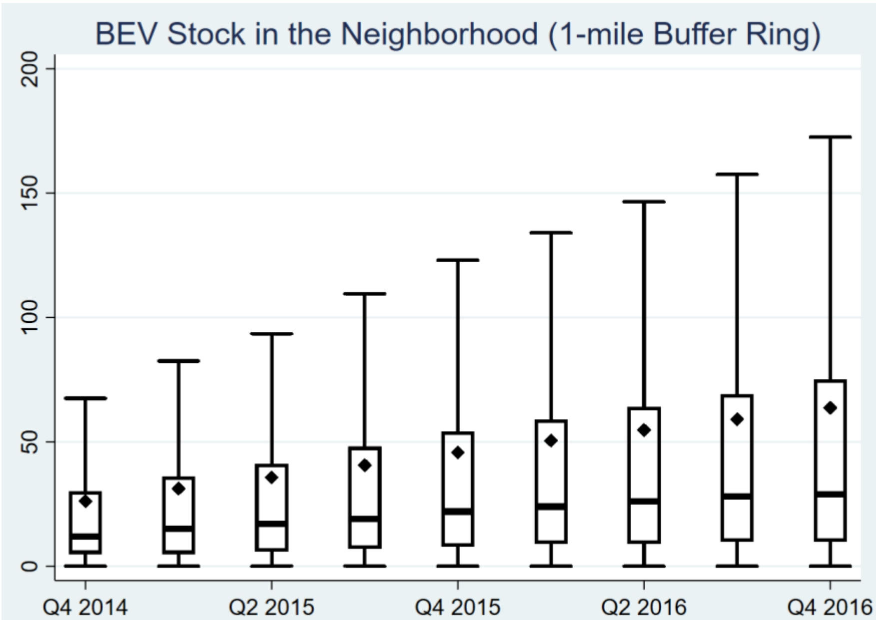

Figure 3. Average, Median, and Inter-quartile range of BEV stock within 1-mile of a California block group by quarter. (The average is represented by the ◆ symbol in the box plot.)

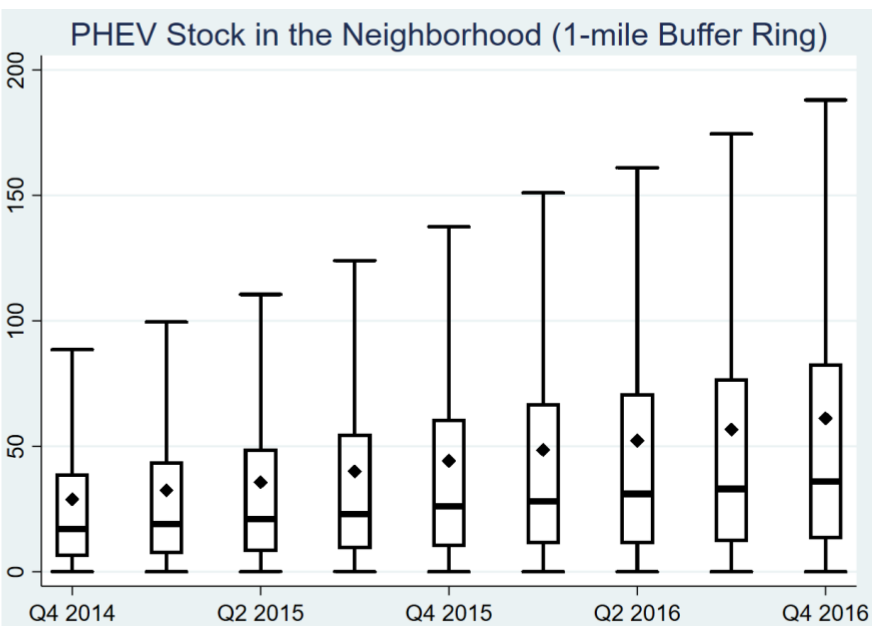

Figure 4. Average, Median, and Inter-quartile range of PHEV stock within 1-mile of a California block group by quarter. (The average is represented by the ◆ symbol in the box plot.)

One can hypothesize that a vehicle purchase decision is formulated over a relatively long period of time, and the type of vehicles observed in the previous quarter (or perhaps earlier) will affect one's adoption decision. In our model, we use the total PEV stock in the previous quarter to construct the explanatory variables representing neighborhood effect. This approach also has the desirable feature of reducing the likelihood of a known econometric issue: the simultaneity or reflection problem (*38*).

Topologically Integrated Geographic Encoding and Referencing (TIGER) shapefiles for California block groups are used to identify the adjoining block groups within a 1-mile radius. Moreover, to better understand the spatial pattern of the PEV adoption in California, heat maps using the TIGER shapefiles for California are created. The heat maps are created with shapefiles at the census tract level as the PEV distribution is sparse in the majority of the 23,000 plus block groups in California and heavily concentrated in some areas. For the graphical representation, the TIGER census tract shapefiles were merged with the DMV, American Community Survey (ACS), and the Longitudinal Employer-Household Dynamics (LODES) data. Several landscape shapefiles from the North American Cartographic Information Society (NACIS) have been used to make ocean and land backgrounds for the maps.

Data on commute pattern and calculation of expected PEV exposure at work

To model the effect of PEV exposure at the commute location (which we refer to as a 'workplace effect') we obtain data on the number of jobs, the number of commuters, and the origin-destination of commutes for each block group from the Longitudinal Employer-Household Dynamics Origin-Destination Employment Statistics (LODES) database. The job location data are used to map the commute patterns from each block group in California. Consequently, using the cumulative count of PEVs in each block group, we estimate the expected number of PEVs a commuter from each block group is exposed to at the workplace during each quarter. Workers can either have jobs in their own block group or travel to other block groups for work. Therefore, the expected exposure count in a particular block group is cumulative of all the PEVs that commuters working in that block group get exposed to as well as the expected number of PEVs seen by commuters traveling to other block groups. Similar to the variable measuring neighborhood effect, to avoid the issue of simultaneity, the workplace effect is the expected PEV exposure for commuters in block group '*i*' during the previous quarter.

The expected PEV exposure (workplace effect) for commuters from block group '*i*' in quarter '*q*' is estimated as (unit of the variable is the number of PEVs a commuter is exposed to at the workplace):

$$Expected\ Workplace\ Exposure\ (workplace\ Effect)_{\ iq} = \sum_{k=1}^{K} Expected\ number\ of\ commuter\ with\ cars\ traveling\ to\ `k'_{i,q-1} \times \#\ PEVs_{k,q-1} + (Expected\ number\ of\ commuters\ with\ cars_{i,q-1} \times \#\ PEVs_{i,q-1}) \quad (2)$$

Where, $k \neq i$ and k represents all the destination block groups for commuters from '*i*'.

The descriptive distribution of the PEV exposure variable is given in Figure 5 below. As the stock of PEVs builds up with time, the average as well as the median number (expected) of PEVs a commuter from a given block group is exposed to increases. However, similar to the variables representing neighborhood effect, the distribution is skewed to the right.

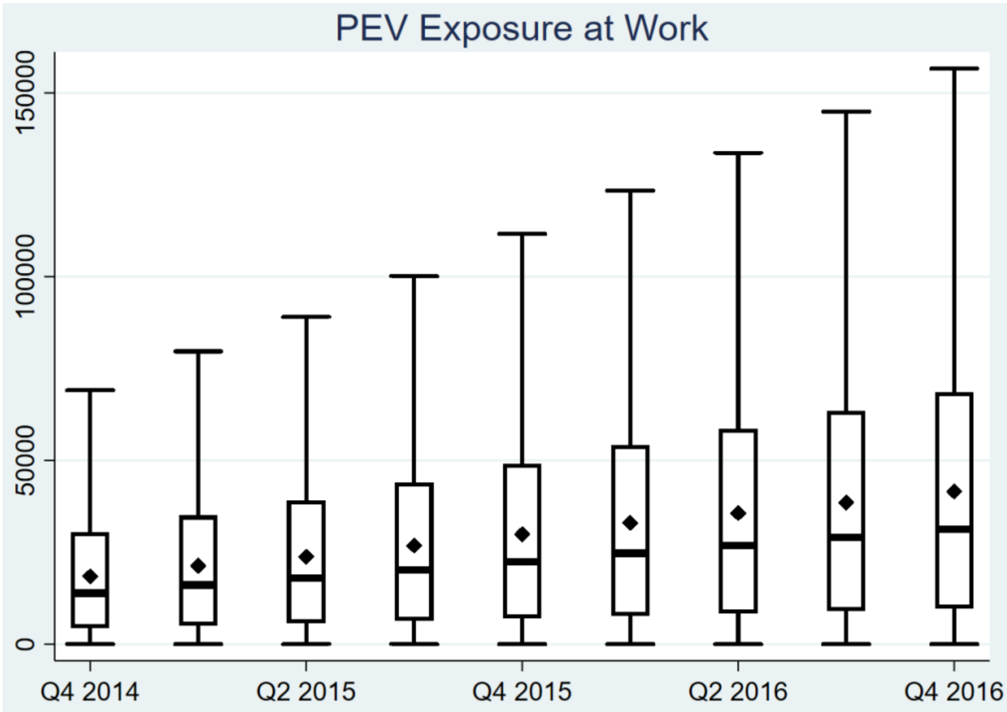

Figure 5. Average, Median, and Inter-quartile range of the expected number of PEVs a commuter from a California block group is exposed to at the workplace by quarter. (The average is represented by the ◆ symbol in the box plot.)

A thing to note, while the "workplace effect" estimated here using the LODES data approach would capture expected exposure at the commute location, it does not account for exposure created by commuters on their way to the commute destination or while stopping for errands in stores, etc.).

Demographic, socio-economic, and built environment data

We use the 2012-2017 US Decennial Census waves of the ACS (*51*) for data on demographics at the block group level. There are over 23,000 block groups in California. We drop ocean block groups and those that were inland but had zero population. We also truncated the data to only include block groups with the number of housing units within the 5th and 95th percentile of the distribution. Therefore, we have block groups with total housing units ranging from 221 units to 1090 units. The truncation was done to avoid the impact of extreme values on the model estimation. Specifically, the truncation helps in dealing with the challenge of overdispersion in the count variable that can affect the estimates of the Poisson count model used in the next section. We retained 20,560 block groups in the data used for analysis. Data on demographics and socio-economic factors like total population, median age, median household income, gender distribution in the population, number of occupied housing units, types of families in a housing unit, the share of detached homes, and the share of renters were obtained from the ACS database.

In terms of built environment variables, the first factor we control for is the stock of Level 2 public chargers in a block group. Data on the total number (stock) of Level 2 public chargers in each block group is obtained using a database that combined the charger location data maintained by the Alternative Fuel Data Center (AFDC) of the U.S. Department of Energy with PlugShare data. Along with the data from AFDC and PlugShare, the combined database also used charger location information collected through a multi-year cohort survey of PEV owners administered by the Plug-in Hybrid & Electric Vehicle (PH&EV) Research Center, University of California Davis. Details on how the charger location data from the three sources have been combined are discussed in the study by Xu et al. (*52*). Second, the type of neighborhood (e.g., urban or suburban) can play an important role in vehicle choice. Each block group in the data is characterized as *urban or central city, suburban, rural-in-urban, or urban neighborhood* based on the classifications developed in Salon (*1*). As the neighborhood type classifications in Salon (*1*) were at the census tract level, multiple block groups located within the same tract will have the same classification in our data. The extent of vehicle usage and thereby PEV exposure can also depend on whether a neighborhood has mixed development and on access to public transit. The EPA Smart Location Mapping - Access to Jobs and Workers Via Transit Tool provides an index of the relative accessibility of a block group compared to other block groups within the same metropolitan region, as measured by travel time for the working-age population via transit. Values closer to 1 represent greater transit accessibility. We use this index to control for the effect of transit accessibility on PEV sales (*53*). The EPA Smart Location Mapping- National Walkability Index tool gives an index measuring the diversity of development within a block group. A block group with a diverse set of employment types (such as office, retail, and service) plus a large number of occupied housing units will have a relatively higher value that correlates with more walk trips and less vehicle use. We use this index to map the effect of mixed development on PEV sales (*54*). Finally, PEV owners get access to High Occupancy Vehicle (HOV) lanes even as a single driver. Past research has shown that this incentive has an important effect on the decision to purchase PEVs, particularly when an individual commutes on a congested route and their commute route has an HOV lane (*55*–*57*). Using the LODES data on commute patterns we estimate the fraction of total commuters within a block group whose commutes include any distance on roads with HOV/carpool lanes. The variable *'Share with HOV lane use'* is calculated as (for block group '*i*'):

$$Share\ of\ HOV\ lane\ use_i = Prob.of\ commute\ route\ with\ HOV\ lane_i \times Prob.of\ commute\ with\ car_i \tag{3}$$

This variable allows us to control for the effect of the relative importance of the HOV lane incentive on PEV adoption at the block group level. We assume that the share of commuters with HOV lane usage in a block group does not change in the period of analysis. In Table 2, we summarize descriptive statistics for the demographic, socio-economic, and built environment variables in our dataset. Except *total population, total occupied housing units, median age, median income, share of commuters with HOV lane use, and the indices representing mixed development and transit access*, all other variables are represented as 'per capita' (total count/total housings units in a block group).

Table 2. Descriptive statistics of demographic, socio-economic, and built environment variables across included census blocks *(n=185,040)*

Variable	Mean	Std. Dev.
Demographic/Socioeconomic		
Total population	1602.4 (Min= 319; Max=18,959	701.2
# Occupied housing units	528.8 (Min=221; Max=1,090)	204.8
Male population per capita	1.53	0.53
# Renter occupied housing per capita	0.44	0.27
# Identify as White per capita	1.86	0.75
# Identify as African American per capita	0.179	0.33
# Identify as Asian per capita	0.41	0.55
Median Age	38.6 (Min=15; Max=84)	9.1
Median Annual Household Income ($)	76,007 (Min= 4,747; Max=250,001)	40,535
#At least bachelor's degree per capita	0.63	0.42
# Couple with kids per capita	0.24	0.12
# Couple with no kids per capita	0.26	0.13
# One adult alone per capita	0.23	0.14
# Single parents per capita	0.12	0.10
# Others with kids per capita	0.002	0.01
# Other no kids per capita	0.15	0.09
Built Environment		
Index Mixed Development	0.46 (Min=-0; Max=1)	0.21
# Commuters per capita	1.10	0.56
Share with HOV lane use	0.33	0.27
# Level 2 chargers per capita	0.003	0.03
Index Transit Access	0.09 (Min=-0; Max=1)	0.13

Policy controls

In addition to the demographic, socioeconomic, and built environment variables we control for the effect of the Clean Cars 4 All (CC4A) program (formerly known as the Enhanced Fleet Modernization Plus-Up Program) on PEV sales. The CC4A is a vehicle incentive program that provides subsidies to low- and middle-income households to scrap old vehicles for newer (used vehicles allowed) and more fuel-efficient vehicles. The program was first introduced as a pilot in July 2015 in two Air Quality Management Districts (AQMD), namely the San Joaquin Valley Air Pollution Control District (called the Drive Clean program) and the South Coast Air Quality Management District (called the Replace Your Ride Program).

The CC4A was initially designed as a retire-and-replace program along the lines of cash-for-clunkers. However, in April 2015, the program was redesigned to combine features of a retire-and-replace program with an incentive program for the purchase of high fuel-economy vehicles (including conventional hybrids and PEVs), targeting low- and middle-income consumers residing in the AQMDs. Eligibility and the incentive amount depend on the household income, whether the household resides in a census tract designated as a Disadvantaged Community (DAC), and the type of replacement vehicle chosen. First, households below 225% of the federal poverty line (FPL) are eligible for $5,000. As household income rises, subsidy generosity declines until a household is no longer eligible for the program above 400% of the FPL. Second, when a household resides in a DAC within the AQMD, it is eligible for a higher incentive amount. Third, the design of the program in terms of the incentive amount for different fuel types varies across the two AQMDs. While BEVs received higher incentives than PHEVs in the San Joaquin APCD, the amount was the same for the two powertrains as well as conventional hybrids in the South Coast AQMD. Finally, once a household's eligibility is proven, the buyer can go to an authorized dealer in the AQMD for the purchase. The incentive amount offered by the CC4A program is in addition to the rebate offered by the California Clean Vehicle Rebate Program (CVRP) to qualifying PEV buyers.

In the analysis here, we control for the level effect of the program in the two AQMDs using two dummy variables. Models controlling for both the level and lag effect of the policy were also estimated. However, based on the model fit estimates we chose the model with only the level effect.

Spatial Pattern of PEV Adoption in California

The number of PEVs have increased exponentially within the past few years in California. The expansion of the PEV market can be observed in Figure 6, especially in the coastal counties of California. As the two major PEV clusters or agglomeration centers in California, census tracts in the Bay Area and those around Los Angeles may have played vital roles in the diffusion of PEVs to the nearby census tracts. As an illustration, in the study year of 2014, most of the PEVs could only be observed around San Jose in North California. However, in 2016 we observe that the PEV market has expanded to Sacramento, and several PEVs are also seen in Santa Rosa, north of San Francisco. We see several PEV clusters in the Central Valley at Bakersfield and Fresno in 2016, which also illustrates the progress of PEV adoption in California over the years.

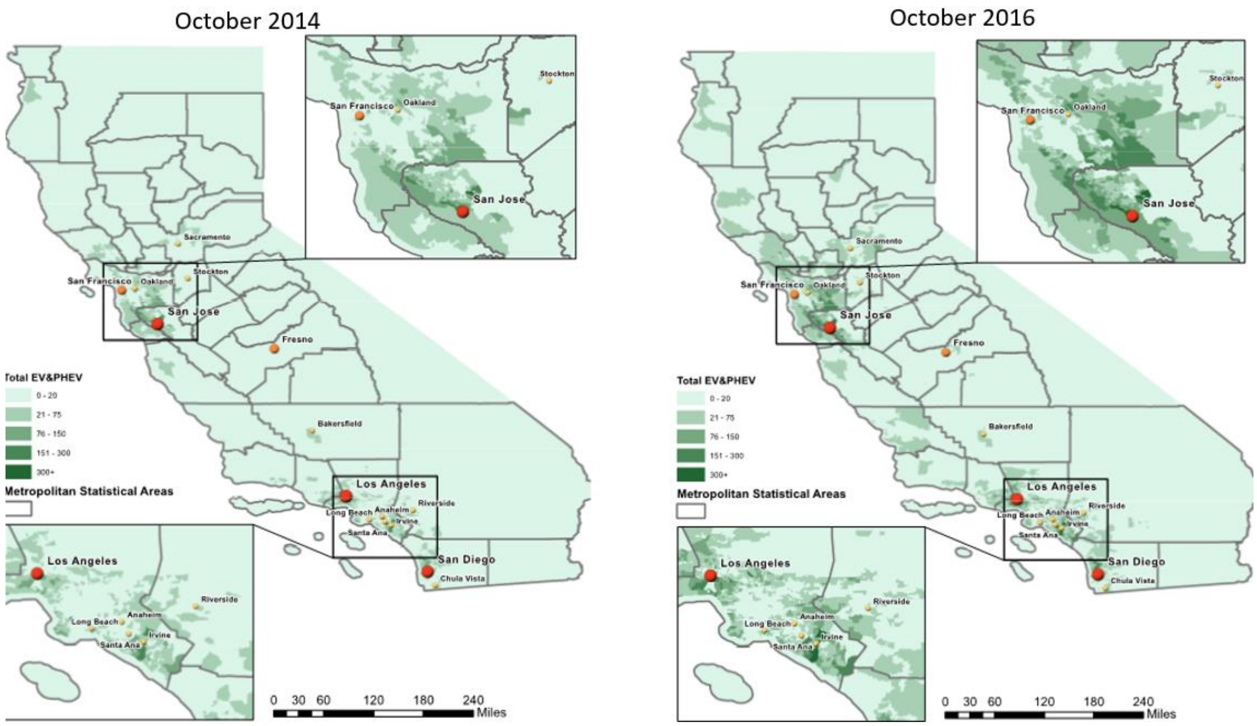

Figure 6. The progress of PEV adoption in California from 2014 to 2016, with market expansion to the Sacramento, Santa Rosa, Bakersfield, and Fresno areas.

Historically, major agglomeration centers of any new technology adoption have been high-income neighborhoods. Past studies exploring the demographic characteristics of PEV adopters from 2012 to 2017 have found that 49% of PEV buyers belonged to high-income families (*32*). Therefore, as expected, in 2014 when the PEV market was starting to grow, most of the agglomeration centers are observed in high-income neighborhoods in the Bay area and the coastal region of southern California. Over time, while diffusion of technology continues to happen around these initial agglomeration center, new clusters have emerged in census tracts that are not considered high-income. Figure 7 below demonstrates the spatial relationship between household income and PEV adoption rate in California for the year 2016.

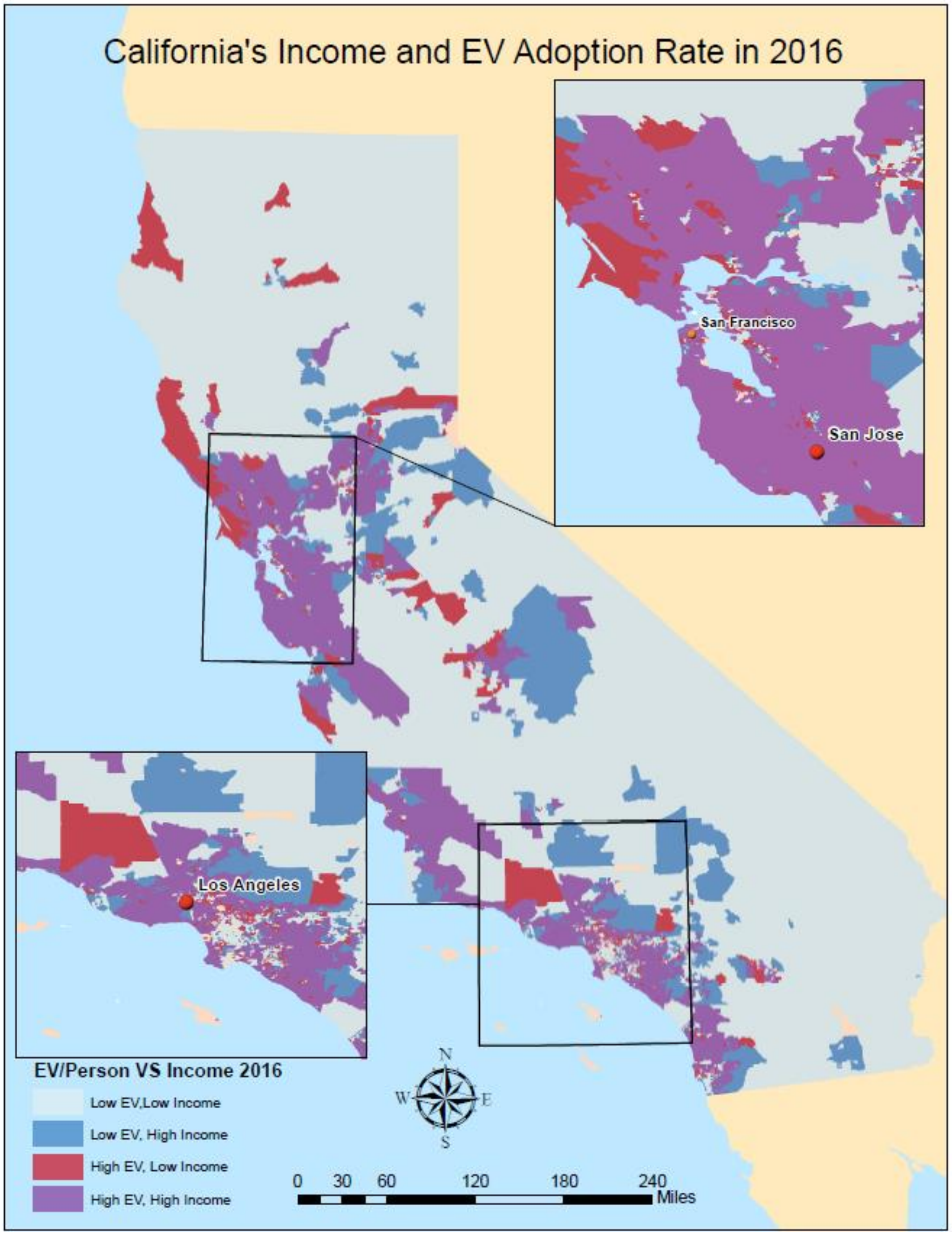

Figure 7. Contrast Map between PEV adoption rate and income level at the census tract level.

Census tracts are classified by their PEV adoption rate (PEVs per person) and median income. Census tracts in which the median income and PEV adoption rate are both higher than the statewide median values of income and PEV stock are shown in purple. This classification covers much of the Bay Area, as well as the high-income areas of Greater Los Angeles, Orange County, and San Diego County. The dark blue areas are those with income above the statewide median but EV adoption rates below the median for all tracts. Dark red zones correspond to tracts with below the statewide median income but higher EV adoption rates than most other tracts in California.

Why might we see the patterns in adoption rate whereby, some high-income areas have low PEV adoption rates while certain low-income regions have a high number of PEV adopters? The purchasing power of households in combination with other socio-demographic characteristics, built environment, and other institutional settings can provide a likely explanation. For example, the tracts marked dark blue are mostly located inland where issues like low charging infrastructure availability and limited range of the vehicles might be limiting the diffusion of PEVs. Moreover, they are relatively isolated from contact with the purple areas. On the other hand, the tracts that are marked with dark red often coincide with census tracts identified as DAC zones. Some of these zones may be responding to policies that target incentives for PEV adoption towards lower-income census tracts. These dark red zones are also mostly on the periphery of major PEV / high-income centers and could be subject to peer effects. Workplace effects are also possible if residents commute to areas with high PEV adoption. These examples show the limits of interpretation that are possible with maps alone. In the next section, we turn to an empirical model that will enable an in-depth exploration of the factors that can influence the diffusion patterns observed above.

Model Description

Model of new PEV sales in California

Based on the spatial patterns of PEV adoption observed in the previous section (heat maps), one might expect that neighborhood and workplace effects could be factors mediating the market penetration of PEVs in the state. To examine how the neighborhood and/or workplace effect influence PEV adoption, we model the new PEV sales in block group '*i*' for quarter '*q*' as a function of the spatiotemporal variables (neighborhood effects and workplace effects), controlling for the effect of demographic, socioeconomic, built environment factors, and policies related to PEV sales—see Table 2.

In much of the literature, household vehicle choice has typically used disaggregate data to model a variety of discrete choices related to either vehicle holdings (how many vehicles, and what types) or vehicle transactions (whether to transact, type of transaction, and what types of vehicles to dispose of and/or purchase). The role of demographic, socioeconomic, and built-environment variables on these different types of choices has been well explored. In many cases the same variable can affect more than one type of choice. When specifically considering vehicle type choice from among, e.g., competing vehicle fuel technologies, vehicle attributes such as purchase price, fuel cost, range, etc., also play a role (usually in the context of stated choice experiments). Our current goal is to estimate models using aggregate-level data on total, actual sales (revealed preference data) for an entire market (California) over a period when the market formation process is under way. Although we are working at a relatively detailed level (Census block groups), the dependent variables are aggregated new sales totals (counts) for block groups by quarter. Explanatory variables (other than neighborhood and workplace effects) take the form of summary statistics or measures for individual block groups, which in our case do not vary over the entire nine-quarter period.

For this paper we have elected to develop Poisson longitudinal count data models *(58)*. Specifically, we develop two independent models: one for BEVs, and one for PHEVs. Total demand for a specific powertrain type at any point in time can be viewed as coming from two effects -total vehicle demand and market share of the powertrain type; so, demand for two competing powertrain types is not strictly independent. In the absence of a more detailed vehicle/powertrain type choice model employing vehicle attributes, the total demand for a vehicle/powertrain type can be viewed as arising from multiple combined effects from the explanatory variables we have identified. Similar to random utility models, total demand can be modeled using linear in parameters index function of the form:

$$V_{iq} = X'_{iq}\beta + \delta_i + \gamma_q \tag{4}$$

where V_{iq} is the index value for block group *i* in quarter *q*, and X_{iq} is a collection of variables given by $X_{iq} = [N_{i,q-1}, P_{i,q-1}, D_i, B_i, C_i]$. The term $N_{i,q-1}$ represents the variables capturing neighborhood effect(s), e.g., the number of PEVs residents of block group '*i*' were exposed to in the previous quarter; $P_{i,q-1}$ represents the workplace effect experienced by commuters/workers of block group *'i'* in the previous quarter, D_i is a vector of demographic and socioeconomic variables; B_i includes built-environment variables (e.g. total chargers in block group *'i'*); and C_i represents policy control variables, namely the effect of the 'Clean Car 4 All' program in the San Joaquin and in the South Coast AQMD's. Vector D_i includes variables related to the family composition (e.g., couple with kids), number of housing units occupied by renters (per capita), number of residents in the population (per capita) who identify themselves as White, African American, or Asian (base is all other races), number of male residents (per capita) in the population, number of residents with an undergraduate degree and above (per capita), median income, and median age of residents. In equation (4), δ_i is an individual-specific effect for block group '*i*,' and γ_q is a fixed effect for quarter *q*. The quarter fixed effects γ_q allows control for broader trends in the vehicle market and potential seasonality in purchase behavior.

Here, new vehicle sales are represented as a Poisson process:

$$New\ PEV\ sales_{iq} \sim Poisson(\mu_{iq}) \tag{5}$$

where $New\ PEV\ sales_{iq}$ is the observed count of new PEV sales in block group *'i'* in quarter *'q'*. The expected PEV count (new sales) for each block group is then defined as:

$$E\left(New\ PEV\ sales_{iq} \middle| \alpha_i, X_{iq}, \gamma_q\right) = \mu_{iq} = \alpha_i \exp\left(X'_{iq}\beta + \gamma_q\right) = \exp\ (\delta_i + X'_{iq}\beta + \gamma_q) \tag{6}$$

where $\delta_i = \ln(\alpha_i)$. Due to a variety of factors (e.g., there are over 20,000 block groups, and most of the explanatory variables are non-time-varying), the individual block group effects δ_i are modeled as IID random effects. Because the δ_i term in equation (6) is unobserved and common across all quarters for block group '*i*,' estimation requires that it be integrated out to obtain the joint density of observations from block group *'i'* (conditional on $X'_{iq}\beta + \gamma_q$ and δ). Following *(58, pp 360-361)* we assume that the δ_i terms are IID such that $\alpha_i = \exp\ (\delta_i)$ has a gamma (δ, δ) distribution, so that $E[\alpha_i] = 1$ and $V[\alpha_i] = {}^{1}/_{\delta}$. These models can then be estimated using the Stata *xtpoisson* command (with random effects)[6].

Although the dependent variable in equation (5) is formally measured as raw counts, from a modeling perspective we would expect the fundamental quantity to be the *intensity* or *incidence rate* in units of sales per household (per block group-quarter), so that counts = (incidence rate) * (total households in block group). In this form, total household is denoted the *exposure* variable, which can be identified as such in estimation software. In this case, the model in, e.g., equation (6) is modified by including *ln (total households)* in X_{iq} with the associated β coefficient set to one.[7] Finally, the model form can be rearranged so that each estimated coefficient is expressed as an *incidence rate ratio (IRRs)*, which represents the

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[6] The notation here has (as noted) been adopted from (*58*), which is different than the Stata notation. Stata estimates a parameter it calls $\alpha = {}^{1}/_{\delta}$. It reports both $\frac{1}{ln(\alpha)}$ and α, and tests the null hypothesis that $\alpha = 0$.

[7] This use of the term 'exposure' should not be confused with discussion that appears elsewhere regarding neighborhood or peer effects from households being 'exposed' to varying numbers of PEVs.

percentage change in the incidence rate for a one-unit increase in the associated explanatory variable.

Other details about these models require additional discussion. When trying to identify neighborhood or workplace effects using these types of models, there are a number of potential concerns: homophily or self-selection of peers, correlated unobservable effects, simultaneity, and the effect of exposure time (e.g., need to control for the effect of driving license ownership period on insurance claim count) or exposure to geography/space-related factors (e.g., population of a region, or area of a region) on the rate of occurrence of any event (Note: in this context, 'exposure' is a technical term associated with count data models and does not refer to, e.g., PEV exposure (*58*)). Homophily can bias the estimate of the spatial peer (neighborhood or workplace) effect upward if residents with similar views and attitude towards new technology live nearby because these same views/attitudes have affected their choice of residence location. In this scenario, the coefficient on the neighborhood effect would simply capture common preferences rather than an actual neighborhood effect. Correlated unobservables, such as an unaccounted-for policy implementation specific to a block group would pose endogeneity concerns and finally, simultaneity could bias estimates to the extent that a peer effect works in both directions (a person is affected by neighbors/peers, but the person also affects them as well).

In our model specification, first, we attempt to address the homophily issue by including many demographic and socioeconomic variables that could explain both neighborhood selection and the inclination to purchase PEVs. We also include a randomly distributed block-group-level-specific effect that captures heterogeneity at the block group level and would persist over time. Second, to control for the possibility of time-varying correlated unobservable, we include quarter fixed effects as well as indicators for the introduction of the 'Clean Car 4 All' program in two AQMDs starting in July 2015. Potentially, there can still be unobservable factors in the error component leading to issues of serial correlation. To check for such a problem, we estimated the population-averaged Poisson model with first-order autocorrelation.[8] The estimated AR (1) coefficients were very small (less than 0.13) suggesting that serial correlation may not be a major problem here. Moreover, the coefficients of the population-averaged Poisson regression models and the random-effect Poisson regression models are similar. Third, we avoid the problem of simultaneity by only using one quarter lagged values of PEV counts in the 1-mile buffer ring and expected workplace exposure to PEVs. Finally, it is unlikely that the rate of new PEV sales will be the same across block groups. Population in an area and the number of housing units would influence the number of vehicles sold. To control for the implicit variation in the probability of the event occurring (new PEV sales in this case) across block groups we use total housing units in a block group as the 'exposure variable'.

The Poisson count model makes some structural assumptions about the mean and variance of the distribution of the count variable, namely the equidispersion (conditional mean =

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[8] Two separate population-averaged Poisson models were estimated with the number of new BEVs ad PHEVs registered in a quarter as the dependent variable, similar to the main random effect models discussed here.

conditional variance of the distribution) property. However, in most applied work the equidispersion property is violated due to potential heterogeneity. The usual way to deal with the problem is to fit a negative binomial model that explicitly addresses the problem of overdispersion. However, because we are using a Poisson random effects model that considers heterogeneity, the assumption of equidispersion is relaxed. The assumptions described above yield a model with a similar form to the negative binomial that directly addresses overdispersion.

Finally, although the focus of this study is on the diffusion pattern of PEVs in California, the sales are taking place within the larger context of the new vehicle market. Thereby, there are many possible modeling options (e.g., multivariate count models) and issues that could be considered instead of the simple Poisson regression model analyzed in this study. For example, PEVs comprise both BEVs and PHEVs with different operating characteristics, and the factors determining which powertrain is chosen at the vehicle market-level or the interactions between the two powertrain types is a topic of interest that need to be explored in future studies. This study represents an initial effort where we focus exclusively on the number of new BEVs and PHEVs registered in a quarter (two separate dependent variables) and the impact of the changing stock of PEVs in each block group on future sales. Here, the only interaction between the two types of powertrains considered is through the neighborhood effect and the workplace effect.

Result

The results of the Poisson count model for new BEV sales and new PHEV sales are given in Table 3 andTable 4**,** respectively. As described earlier, the models are estimated using the incidence rate ratio (IRR) form. The coefficients of the usual Poisson regression model generally give the change in ln (*New PEV Sales*) due to a 1 unit increase in an independent variable. To obtain the incidence rate ratio of new PEV sales per household (in a block group) the coefficients are exponentiated (exp^{β}). This IRR represents the *percentage* change in the count rate for a one unit increase in the explanatory variable. The results in Table 3 and Table 4 report tail probability values for z-statistic under the null hypothesis that IRR = 1 (i.e., no change). Specifically, if IRR = 1 then the associated variable has no effect on the rate of PEV sales, and if IRR>1 (<1) the associated variable has a positive (negative) effect. Lastly, when estimating the Poisson count model with an 'exposure' variable (here the 'exposure' variable is total household units), Ln (total household units) is included in the model as an explanatory variable with the coefficient constrained to 1.

Table 3. Poisson Count model for New BEV Sales

Dep. Var: New BEV Sales	IRR	Robust Stnd. Error	P-value*
# BEVs in One mile	1.0016	0.0003	0.000
# PHEVs in One mile	1.0018	0.0004	0.000
Prob. Workplace exposure	1.1832	0.0244	0.000
Total Level 2 chargers X Total Renters per HHS	1.0149	0.0030	0.000
Male per HHS	1.1512	0.0407	0.000
Couple with Kids per capita	1.1255	0.1303	0.307
Couple No Kids per capita	1.0918	0.1322	0.468
One Adult Alone per capita	1.8912	0.2668	0.000
Single Parent with Kids per capita	0.8141	0.1257	0.183
Other with Kids per capita	0.7149	0.5567	0.666
# of renters per capita	0.7045	0.0368	0.000
# of bachelor degree holders per capita	3.2741	0.1445	0.000
# of White households per capita	0.9704	0.0259	0.259
# of African American households per capita	0.8336	0.0409	0.000
# of Asian households per capita	1.0530	0.0285	0.056
Median Income	1.0062	0.0003	0.000
Median age	1.0149	0.0015	0.000
Clean Car For all (Yes=1) X San Joaquin	1.1658	0.0586	0.002
Clean Car For all (Yes=1) X South Coast	1.0089	0.0224	0.689
Residence Neighborhood (Base: Rural)			
Urban/Central City	1.0602	0.0383	0.106
Sub-urban	1.0376	0.0290	0.187
Rural -in-Urban	0.9308	0.0324	0.039
Share of commuters with any commute on HOV lane	1.3458	0.0471	0.000
Mixed Development (Index)	1.7416	0.0687	0.000
Transit Access Working Population (Index)	0.4037	0.0358	0.000
Q1 2015	0.8202	0.0146	0.000
Q2 2015	0.8704	0.0153	0.000
Q3 2015	0.8523	0.0157	0.000
Q4 2015	0.8153	0.0157	0.000
Q1 2016	0.6795	0.0141	0.000
Q2 2016	0.6803	0.0179	0.000
Q3 2016	0.7073	0.0157	0.000
Q4 2016	0.0883	0.0065	0.000
Constant	0.0000	0.0000	0.000
Ln (Total Households)	1.0000	(exposure)	
Ln (Alpha)	-1.1276	0.3215	
Alpha	0.3238	0.1041	

* P-value for the null hypothesis that IRR = 1

Table 4. Poisson Count model for New PHEV Sales

Dep. Var: New PHEV Sales	IRR	Robust Std. Error	P-value*
# BEVs in One mile	0.9984	0.0002	0.000
# PHEVs in One mile	1.0052	0.0004	0.000
Prob. Workplace exposure	1.0849	0.0168	0.000
Total Level 2 chargers X Total Renters per HHS	1.0133	0.0037	0.000
Male per HHS	1.0087	0.0352	0.805
Couple with Kids per capita	0.9185	0.1141	0.494
Couple No Kids per capita	0.9808	0.1158	0.869
One Adult Alone per capita	1.2023	0.1521	0.145
Single Parent with Kids per capita	0.7135	0.1179	0.041
Other with Kids per capita	0.2131	0.1640	0.045
# of renters per capita	0.5361	0.0305	0.000
# of bachelor degree holders per capita	2.4858	0.0974	0.000
# of White households per capita	1.0382	0.0268	0.147
# of African American households per capita	0.9434	0.0467	0.239
# of Asian households per capita	0.9435	0.0252	0.030
Median Income	1.0043	0.0004	0.000
Median age	1.0071	0.0014	0.000
Clean Car For all (Yes=1) X San Joaquin	0.5932	0.0460	0.000
Clean Car For all (Yes=1) X South Coast	1.1465	0.0241	0.000
Residence Neighborhood (Base: Rural)			
Urban/Central City	1.0825	0.0479	0.074
Sub-urban	1.0340	0.0321	0.280
Rural -in-Urban	0.9713	0.0393	0.471
Share of commuters with any commute on HOV lane	1.5602	0.0690	0.000
Mixed Development (Index)	1.5953	0.0642	0.000
Transit Access Working Population (Index)	0.4519	0.0369	0.000
Q1 2015	0.7943	0.0173	0.000
Q2 2015	1.0900	0.0250	0.000
Q3 2015	0.9992	0.0211	0.969
Q4 2015	1.1490	0.0245	0.000
Q1 2016	0.8867	0.0212	0.000
Q2 2016	0.9815	0.0229	0.425
Q3 2016	0.9793	0.0238	0.390
Q4 2016	0.1694	0.0091	0.000
Constant	0.0001	0.0000	0.000
Ln (Total Households)	1	(exposure)	
Ln (Alpha)	-1.30349	0.546078	
Alpha	0.271584	0.148306	

* P-value for the null hypothesis that IRR = 1

Before exploring neighborhood and workplace effects, we first consider the impact of sociodemographic characteristics, built environment factors, and the effect of targeted policies on PEV sales. The coefficients for the demographic and socioeconomic variables capture factors that are already well known in the literature for their potential effect on PEV purchases. As expected, both BEV and PHEV sales are positively related to median income, median age, and higher share of bachelor's degree holders in a block group. Given the high purchase cost of these vehicles, it is likely higher-income families (which are also correlated with age) have the resources to adopt the technology. The presence of a bachelor's degree is frequently associated with a higher level of "innovativeness" and a willingness to adopt new technologies. The coefficients on these are larger in the BEV model than in the PHEV model. On the other hand, as the share of renters in a block group goes up it has a negative effect on both BEV and PHEV sales. This result may be due to the difficulty of installing home chargers for renters[9].

Past studies have shown a gender difference in preference for technology, with women being more risk-averse about the adoption of new technology (*59*). In the models for new BEV and PHEV sales, we observe that each additional male per household multiplies the rate of BEV sales in a block group by 1.15 and PHEV sales by a factor of 1.008. Family composition generally does not have a significant effect on new PEV sales in a block group. The two cases where we observe a negative but significant effect on the rate of PEV sales are block groups with a higher share of single parents with kids and those with a higher share of households with multiple adults and kids. In both scenarios, the negative relationship could be due to a correlation with low income and thereby a lower likelihood of buying new vehicles. The racial composition of a block group also tends to not matter except in areas with a higher share of African American and Asian households. The rate of new BEV sales tends to be lower in block groups with a higher share of African American households. In the case of PHEVs, a 1% increase in the share of Asian households reduces the rate of new PHEV sales by 6%.

Considering built environment factors like the interaction between the share of renters in a block group and the number of Level 2 chargers, we observe that for a given share of renters, an additional Level 2 public charger is associated with a 1.5% increase in BEV adoption. The effect on PHEV sales is weaker with an additional Level 2 charger being associated with only a 1.3% increase. These results should be interpreted with some caution. As past studies have pointed out, there is a strong correlation between the number of PEVs in a block group and the number of chargers and vice versa. Also, there may be endogeneity issues associated with this variable. Nevertheless, though we cannot be certain about the quantitative effect of PEV chargers on adoption, we can comment that it has a positive impact on PEV adoption in an area, particularly where there is a large share of renters.

Other built environment factors like the extent of mixed development in an area (locations with both residential and commercial spaces) and transit access have the expected effect on new BEV and PHEV sales. Mixed development in an area can imply more charging opportunities due

[9] In this case, the negative effect is larger for PHEV sales rates, perhaps the opposite of what would be expected. However, this variable is also associated with an interaction effect, complicating the interpretation.

to a denser network of public chargers, thereby promoting PEV sales. On the other hand, good transit access for commuters can imply lower dependence on vehicles for travel needs. Therefore, higher transit access in a block group has a negative effect on the rate of new BEV and PHEV sales. The type of neighborhood generally does not appear to have a significant effect, perhaps because the previously discussed variables have been considered. Lastly, block groups with a higher share of commuters who have access to the HOV lane in their commute route tend to have a higher rate of BEV and PHEV sales. A unit increase in the share of commuters with access to HOV lanes is associated with an approximately 34.5% (56%) increase in the rate of new BEV (PHEV) sales. This result conforms to the findings of past studies that the HOV lane incentive has a positive effect on PEV adoption (*55–57*) . Moreover, the stronger effect on PHEV sales compared to BEVs has policy consequences in terms of how the incentive affects the sale of BEVs and PHEVs in California and their impact on carbon emissions at the fleet-level.

The Enhanced Fleet Modernization Program (subsequently called Clean Car 4 All) was designed to help lower-income households shift to fuel-efficient vehicles. We observe that the policy has a positive significant effect on the rate of BEV sales in the San Joaquin AQMD but not in the South Coast AQMD. On the other hand, the program had a negative effect on the PHEV sales in the San Joaquin AQMD but a positive significant effect on the PHEV sales in the South Coast AQMD. These differences may be caused by the San Joaquin AQMD offering $1000 more for BEV purchase than for a PHEV while the South Coast AQMD gave the same incentive amount for both BEV and PHEV purchases. However, there are some other factors not controlled for in our model specification that could moderate the effect of the Clean Car 4 all program on BEV and PHEV sales. First, the success of the program and the effect on sales can depend on the outreach efforts of the AQMD. Second, since a qualifying household could take advantage of the program only at certain pre-approved dealerships, the effect of the program on BEV or PHEV sales can depend on the stock of vehicles available at the approved dealerships in the area.

The results discussed thus far are generally consistent with other studies in the literature. However, we are particularly concerned with identifying dynamic effects related to the market penetration process. For the type of model used here, it was important to consider potential effects due to unobserved factors both spatially and temporally. To take into account block-group-specific heterogeneity, we included random effects using the specification discussed previously. The parameter reported as “Alpha” in Table 3 and Table 4 capture the amount of variation in observed count rates due to random effects. The estimate is larger for the BEV model than for the PHEV model.

Dynamic effects in the models are captured by the effect of past PEV exposures on new sale rates. For the BEV model the IRR estimates for the neighborhood effects show that one more BEV or PHEV within a 1-mile radius (during the previous quarter) of a block group is associated with ~ 0.2% increase in BEV sales in the block group. Unlike the neighborhood effect on the rate of BEV sales, in the case of PHEVs, an additional BEV within 1-mile is associated with a 0.2%

decrease in new PHEV sales. Exposure to PHEVs however has a positive effect, where one additional PHEV within 1-mile raises the rate of PHEV sales by 0.5%.

As with other new technologies like the photovoltaic cell, positive neighborhood effects are generally interpreted as a contagion effect whereby households notice the vehicles or lifestyle of their immediate neighbors, gaining awareness (and perhaps increased knowledge) about these technologies, which in turn provides assurance of their legitimacy. This narrative is consistent with the results of the BEV model. However, the situation with PHEVs appears to be more complicated. Although the sales rate of PHEVs increases with prior PHEV exposure, the effect of BEV exposure is negative. However, it is important to note that these count data models are actually capturing two effects simultaneously: the effect on total sales, and the decision of which fuel technology to buy. In other words, there are both purchase share effects and total demand effects. In contrast to earlier work of this type that focused exclusively on, e.g., hybrid electric vehicle (HEV) penetration, there are potentially important substitution effects from competition between BEVs versus PHEVs, two new (but, in some ways, similar) fuel technology types that were both introduced in the market at a similar time (2010-2011). Both can be viewed as undergoing a market penetration process; however, there are some potentially important differences between the two. BEVs are generally more distinctive than PHEVs, and also 'riskier' due to exclusive reliance on electricity. In particular, during the period of this analysis many of the BEVs being sold are Tesla models, which could be viewed as sending multiple possible 'signals' about the owner (status, innovativeness, and 'greenness'). So, additional exposure to BEVs in a block group may lend not only legitimacy to the technology but also a combination of signals that differentiate BEVs from PHEVs. In this way, greater exposure to BEVs could have the effect of drawing market share away from PHEVs among those buyers ready to adopt new technologies.

In addition to the neighborhood effect at the residential location, the model confirms that there is a clear positive effect from increased exposure by individuals to PEV technology at the workplace (e.g., talking with their colleagues or interacting with fellow workers in the parking lot). Similar to positive neighborhood effect, this exposure could raise awareness and knowledge about the new technology, which in turn could affect the attitudes of non-PEV users and increase their likelihood of considering and adopting a PEV. In the current models, exposure to an additional PEV at a commute location yields an 18% (8.5%) increase in BEV (PHEV) sales in a block group.

Discussion and Conclusion

The spatial analysis of the PEV market in California as well as the results of the Poisson count models indicate that neighborhood and workplace effects in combination with socioeconomic, demographic characteristics and PEV-friendly policies can play an important role in the market penetration dynamics for PEVs. Exposure to new technology encompasses both physical exposure (i.e., seeing electric vehicles on the road or in a parking lot), and social exposure (i.e., talking with friends, colleagues, and family members about the topic). Estimating the impact of such social interactions at home (neighborhood effect) and commute locations (workplace effect) on PEV adoption is important for estimating impact on the spatial distribution of new PEV buyers. Peer effects (neighborhood and workplace) are also important for estimating the derived demand for charging and thereby the derived demand for electricity. Moreover, the workplace effect can be an important factor in accelerating the market growth in disadvantaged communities with a low local concentration of PEVs in the immediate neighborhood. Residents of areas who may not experience neighborhood effects can still get exposed to PEV technology when they commute to locations with PEV owners. Thereby, policies or infrastructure support that encourage commuters to drive their PEVs to work can play an important role in the diffusion process.

The results of the count models suggest that the availability of Level 2 charging infrastructure has a strong positive effect on PEV sales in an area. Though in our analysis we cannot separate pure public chargers from those that are dedicated for employee use, the location of chargers at commute locations may have a strong effect in terms of exposure to PEVs for all employees. When workplace chargers are in high visibility locations, it can play an important role in generating PEV exposure at commute locations and consequently a significant effect on PEV adoption.

Analyzing the neighborhood and workplace effects in combination with the demographic and socioeconomic factors derived from the census data allow us to account for factors other than exposure to technology. Accounting for sociodemographic factors in the count model also improves our ability to use it for generalization and prediction for current and future populations. After controlling for demographic, socio economic, and policy factors our results show that lack of neighborhood and workplace effects may delay the diffusion of PEVs in communities with low initial penetration even when PEV prices falls, and market supplies grow. In other words, to grow the market in disadvantaged communities and those with low initial penetration of PEVs, additional awareness campaigns to foster the neighborhood/workplace effect, targeted incentives, and infrastructure are needed to push electrification in these areas.

This study only focuses on new PEV sales in California. Past studies have shown that areas with low- and middle-income households are more likely to participate in the used PEV market (*60*). In this regard, the targeted policies/programs and neighborhood/workplace effect can also influence market penetration, with the used PEVs trickling down to lower-income households and communities with low adoption of new vehicles. Therefore, like new PEV sales, it is equally important to analyze how the factors discussed here like the neighborhood or workplace effect may impact used PEV adoption. Overall, we suggest that the policymakers should consider measures to leverage peer effects to grow the PEV market. In addition, they should consider targeted programs and investments that will compensate for the lack of neighborhood effect in some communities (E.g., the Clean Car 4 All).

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Data Management

Products of Research

The project has used existing proprietary data on vehicle registration and survey data collected by the PH&EV center for electric vehicle use. In addition, the analysis involved use of public data like the LODES data and American Community Survey data. No new data was collected under this project. All the existing data were managed by researchers at the PH&EV center in UC Davis. The final dataset was uploaded on Dryad (Cite: Chakraborty, Debapriya; Bunch, David (2021), Modeling Dynamic Processes in the California ZEV Market (2014-2016), Dryad, Dataset, https://doi.org/10.25338/B8RK86)

Data Format and Content

Anonymized data post analysis will be stored in a variety of formats: Excel, STATA, and SPSS files. All formats can be easily converted to Excel/CSV file

Data Access and Sharing

The data has been anonymized (VIN-level information removed through aggregation) before analysis and storage. No personal information has been retained in the data used for analysis. The final data (variables used in the analysis and the block group id) is shared on DRYAD.

Reuse and Redistribution

The PH&EV Center has the right to manage the raw DMV data. The aggregated data used for analysis (e.g., demographics, built environment variables, vehicle sales and total count data at the block group level) will be uploaded on DRYAD for reuse and redistribution (Cite: Chakraborty, Debapriya; Bunch, David (2021), Modeling Dynamic Processes in the California ZEV Market (2014-2016), Dryad, Dataset, https://doi.org/10.25338/B8RK86). Intellectual property rights of the raw data will not be transferred.