# How does the presence of HOV lanes affect plug-in electric vehicle adoption in California? A generalized propensity score approach

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**Abstract** Policymakers have sought to spur consumer adoption of advanced clean vehicles by granting them single-occupancy access to high-occupancy vehicle (HOV) lanes. We offer the first causal evaluation of these policies that accommodates geographic variability in the magnitude of this policy's treatment effect. Focusing on the outcome of plug-in electric vehicle (PEV) adoption in California, we employ a generalized propensity score matching approach that allows for continuous, rather than binary, treatment effects. We estimate a state-wide dose-response curve to show that access to 6, 20, and 100 miles of nearby HOV lanes leads to 1, 3, and 10 additional PEV registrations in a census tract. We predict that with a 95% confidence interval, roughly one quarter of California PEV registrations during 2010-2013 were a result of the HOV lane policy. We identify geographically-specific marginal policy effects that are smaller in Los Angeles, but relatively larger in San Diego and Sacramento.

**Keywords:** quasi-public goods; environmental subsidy; transportation policy

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# 1 Introduction

Policymakers commonly design policies with the goal of increasing consumers' adoption of newer, less-polluting technologies, including advanced clean vehicles.[1] A common policy approach has been to grant these advanced clean vehicles access to high occupancy vehicle (HOV) lanes in an effort to increase the utility that drivers derive from the use of these vehicles.[2] Historically, nine states adopted such policies for hybrid vehicles. Currently fourteen states have similar policies for plug-in electric and natural gas vehicles, with more states likely to offer future policies for hydrogen fuel cell vehicles (DeShazo et al., 2015).

In this paper we identify the causal impacts of such policies on the adoption of plug-in electric vehicles (PEVs) in the state of California between 2010 and 2013. Complicating the evaluation of this policy is the fact that HOV lanes are distributed unevenly throughout the state of California, as are prospective new car buyers who might adopt these vehicles. Researchers have shown that the average advanced vehicle owner is willing to pay a premium for access to HOV lanes in the case of both hybrid vehicles (Bento et al., 2014; Shewmake and Jarvis, 2014) and PEVs (Sheldon, DeShazo, and Carson, 2015). In light of this it is somewhat puzzling that several correlational studies have shown a weak relationship between hybrid sales and HOV lane access (Diamond, 2008; Gallagher and Muehlegger, 2011).[3] What has been missing in this literature, and what we estimate for PEVs, is the causal relationship between variation in geographic access to HOV lanes and geographic sales of advanced clean vehicles.

We use a generalized propensity score approach to estimate the impact of HOV lanes on PEV registrations, controlling for the probability of treatment (HOV lane density). Standard propensity score matching conditions on a binary variable, e.g., whether or not a census tract is near HOV lanes. However, we are interested in a continuous conditioning variable, namely, how many miles of HOV lanes a census tract is near. First, we estimate a generalized propensity score (GPS) for each census tract, which tells us the probability of treatment, based on a large set of demographics. Controlling for propensity score, we estimate a dose-response curve, which tells us how PEV registrations change as the number of nearby HOV lanes increases.

Few papers have employed the generalized propensity score methodology. This paper

[1] Other types of incentives in place to encourage PEV adoption include a federal rebate program, the California Clean Vehicle Rebate program, reduced electricity rates for PEVs and publicly subsidized refueling infrastructure.

[2] For a discussion of the social costs of these policies see Bento et al. (2014) and Shewmake and Jarvis (2014).

[3] One possible explanation is that supply was constrained in the early hybrid market, resulting in excess demand in every period regardless of policy.

is a novel application of GPS with several innovations. First, we use an unusual treatment variable, miles of HOV lanes within a thirty mile radius of the population centroid of a census tract. Our unit of analysis, the census tract, allows us to explore geographic heterogeneity by aggregating estimated effects at the metropolitan area level. Second, we use a Least Absolute Shrinkage and Selection Operator (Lasso) method to select first stage control variables, resulting in propensity scores that balance observables very well across census tracts with differing levels of treatment.

We offer the first causal estimate of the impact of California's HOV lane policy on PEV adoption, estimating that access to 6, 20, and 100 miles of nearby HOV lanes results 1, 3, and 10 additional PEV registrations in a census tract over the time period analyzed. To put this in perspective, the mean and median number of PEV registrations per census tract in this time period was 8.5 and 4, respectively. A back-of-the-envelope calculation in Section 5.3 predicts that with a 95% confidence interval, roughly one quarter of California PEV registrations during 2010-2013 were a result of the HOV lane policy.

## 2 Background

The primary purpose of high occupancy vehicle (HOV) lanes is to encourage carpooling in order to decrease congestion and local air pollution. Typically, only vehicles with two (sometimes three) or more occupants are able to utilize HOV lanes. The decision to designate or construct HOV lanes is made at the state level, and HOV lanes tend to be located in higher population density areas.

More recently, various clean vehicles have be granted single-occupant access to HOV lanes in California. Hybrid vehicles were granted access via a yellow decal program, which lasted from mid-2005 to mid-2011. Plug-in electric vehicles (PEVs) have free single-occupant access to HOV lanes through 2019. An unlimited number of white decals are available that allow battery electric vehicles (BEVs) access to HOV lanes. Plug-in hybrid electric vehciles (PHEVs) are granted HOV access via green decals. Originally, green decals were to be allocated to the first 40,000 applicants who purchased a "transitional zero emissions vehicle" (PHEV). In mid-2014 the green decal limit was increased to 55,000 and has subsequently been increased to 70,000. As of December 31, 2013, the end of our analysis period, 28,739 green decals had been issued and as such the decal cap was not binding.[4] While such programs are not expected to reduce congestion, they are intended to reduce greenhouse gas emissions and local air pollution.

Relative emissions from electric versus conventional internal combustion engine vehicles

[4]Details can be found at http://www.arb.ca.gov/msprog/carpool/carpool.htm.

depend on how the electricity fueling the PEV was generated. Electricity generation in California tends to be cleaner than other parts of the country. Archsmith, Kendall, and Rapson (2015) estimate that the benefit of greenhouse gas reductions per electric vehicle in western states is currently \$425. Holland et al. (2015) estimate that the total environmental benefit from an electric vehicle, including reduction in local air pollution, is \$3,025 in California.

According to the American Road and Transportation Builders Association, the cost of expanding a four-lane interstate highway to six lanes is approximately \$4 million per mile. However, in terms of HOV lane policies to incentivize PEVs, the policy question is typically not whether or not to construct new HOV lanes, but rather, whether to give PEVs access to existing HOV lanes. Thus capital and upfront costs of such policies tend to be low. Such policies may lead to an increase in the total number of vehicles on the highway, which would result in congestion costs. Bento et al. (2014) find evidence that the yellow decal program led to a net increase in congestion on the I-10W in the Los Angeles area and estimated the annual social costs of this congestion to be between \$0 and \$4,500 per additional hybrid vehicle depending on the time of day the vehicle is on the highway. Little is known about the heterogeneity of this congestion cost across locations.

Sheldon, DeShazo, and Carson (2015) find that the average new car buyer in California is willing to pay about \$900 for free single-occupant HOV lane access. Bento et al. (2014) estimate the average annual rent of a hybrid HOV sticker in southern California to be \$743, with a net present value of \$4,800. Shewmake and Jarvis (2014) estimate an average premium of \$3,200 for a hybrid with an HOV sticker, which translates into a yearly value of \$625. We offer the first causal evaluation of such incentives and find that roughly one quarter of California PEV registrations during 2010-2013 were a result of the HOV lane policy.

# 3 Methodology

In an ideal experimental setting, we would randomly assign households the right to utilize HOV lanes as single occupants of PEVs. We would compare subsequent PEV registrations of the treatment versus control group within a census tract and see how treatment effects vary across census tracts with access to differing quantities and qualities of HOV lanes.

Since we cannot manipulate California's HOV lane policy, we compare PEV registrations across census tracts with differential HOV lane access. PEV registrations are also influenced by household preferences, income, education, driving needs, and many other factors that vary across census tracts and could confound estimated effects of the HOV lane policy on PEV registrations. Potential identification strategies include 1) standard regression analysis controlling for all observables that may influence PEV registrations, 2) a discrete choice model of vehicle purchases, 3) a differences-in-differences framework, 4) a regression discontinuity framework, or 5) a generalized propensity score approach. There is almost no variation in HOV lane miles over time in California during the timeframe in quesion, thus we are limited to a cross sectional analysis.

Standard regression analysis is susceptible to selection on unobservables, since we are unlikely to control for every variable that influences PEV registrations. Furthermore, to achieve the same level of flexibility in model specification as a generalized propensity score approach requires a substantial reduction in power.

A discrete choice framework would model the consumer's vehicle choice problem, where a consumer chooses between vehicles with varying attributes, including HOV lane access. This would require registration data for all vehicle types, not only PEVs and hybrids, to which our data is limited.

A differences-in-differences framework would compare PEV registrations in census tracts with differing levels of treatment before and after the implementation of the HOV lane policy. We are not able to implement this strategy due to two reasons. First, we do not have BEV registration data prior to the implementation of the white sticker program and cannot construct a pre-period. Second, the green sticker program began concurrently with the release of several new PHEV models. Prior to the green sticker program, only one PHEV model was widely commercially available, and had not been so for long. Thus the pre-period for the green sticker program is limited to very early adopters of one model.

The concurrent release of many PHEV models and the beginning of the green sticker program rules out a regression discontinuity framework, which would attempt to identify a change in PEV registrations over a small window around the implementation of the policy. Furthermore, vehicle purchase decisions may lag such a policy announcement.

Propensity score matching is a technique to remove biases in the comparison of treatment groups such that the effectiveness of treatment can be estimated. Standard propensity score matching conditions on a binary treatment variable; however, we are interested in evaluating the effect of a continuous treatment, i.e., HOV lane density. Therefore we follow the generalized propensity score (GPS) approach as detailed by Hirano and Imbens (2005) to evaluate the effect of HOV lanes on our outcome variable, PEV registrations. According to Angrist and Piscke (2008), a propensity score approach is preferred to a standard regression approach when it is easier to model treatment than outcome. This tends to be the case when treatment is a result of government policy. Indeed, the state government decides where to build HOV lanes, typically in more congested locations. In Section 5.1.2 we estimate the generalized propensity score (GPS) as a function of demographics, including population density and commuting patterns. In Section 5.1.4 we find compelling evidence that controlling for the propensity score nearly eliminates all differences in observables across census tracts with different levels of treatment (HOV "lane-miles").

This methodology has several advantages. First, we reduce the dimensionality of our control variables from hundreds to one, the generalized propensity score (GPS). If the assumptions of the framework hold, the propensity score controls for all observable and non-observable differences across census tracts. Thus, in order to estimate treatment effects, we need only control for propensity score. Second, we can estimate marginal effectiveness of treatment at different treatment levels rather than estimating the average effect of treatment. This allows us to better understand heterogeneity across treatment groups. Third, this approach is flexible. For example, we assume that controlling for covariates, treatment follows a lognormal distribution. The GPS is a measure of how likely a census tract is to have a certain number of HOV lane-miles, given its covariates and assuming a lognormal distribution. Such assumptions would not be possible using standard regression techniques.

## 3.1 The Generalized Propensity Score Approach

### 3.1.1 First Stage

In regular propensity score matching, the first stage involves a probit or logit regression[5] of the binary treatment variable on a vector of variables that predict treatment. The propensity scores are the predicted values of this regression and are the probability that a unit is treated.

With a continuous treatment, the first stage involves fitting a distribution, often normal, to the treatment variable, controlling for a vector of variables that predict treatment. The generalized propensity score, or GPS, is the probability distribution function (or probability mass function) evaluated at the level of treatment using the predicted distributional parameters. Thus the GPS is a measure of the probability that a unit receives its level of treatment, given its characteristics.

The goal of the first stage is not to establish a causal relationship between predictive covariates and treatments. Rather, the goal is to estimate propensity scores that best control for observed differences in treatment groups. Here, this involves two key decisions. The first is the choice of predictive covariates to include, and the second is the choice of distribution to fit. We discuss these decisions in Sections 5.1.1 and 5.1.2. In our preferred specification, we assume that treatment, $N_i$, is lognormally distributed given covariates, $X_i$:

$$N_i|X_i \sim \; ln\, \mathcal{N}(\mu, \sigma^2). \tag{1}$$

[5] Any standard probability model can be used. Since the outcome variable should be between 0 and 1, probit and logit models are commonly used.

One of our two key assumptions is weak unconfoundedness, or independence of treatment given covariates, $Y_i(n) \perp N|X$, where $Y_i(n)$ is our outcome variable, PEV registrations. In other words, we assume that after controlling for a rich set of census tract characteristics, assignment of HOV lanes is independent of PEV registrations.[6]

We estimate the parameters of the distribution $(\hat{\mu}, \hat{\sigma^2})$ using maximum likelihood estimation. We refer to this as the "first estimation stage." We then calculate the estimated GPS, $\hat{R}_i$ for each census tract $i$:

$$\hat{R}_i = \frac{1}{N_i \hat{\sigma} \sqrt{2\pi}} exp\left(-\frac{(ln(N_i) - \hat{\mu})^2}{2\hat{\sigma^2}}\right). \tag{2}$$

### 3.1.2 Second Stage

In regular propensity score matching the second stage is to estimate the average effect of treatment on the treated (ATT). Ideally one could calculate the difference in outcome between two units, one with treatment and one without, which have the identical propensity score. In practice, two observational units rarely have an identical propensity score, so researchers employ different matching techniques, such as nearest neighbor matching, kernel matching, and inverse probability weighting to decide which treated units to compare to which untreated units.

When treatment is continuous, we must estimate the average conditional expectation of outcome given treatment and propensity score. Since treatment is not binary we cannot use a matching method and compare outcomes of treated versus non-treated groups. Each observation has a different level of treatment. Instead, we model conditional expectation as a flexible function of treatment and GPS. In regular propensity score matching it is important to show that the ATT is robust to alternative matching techniques. Analogously, we show that our conditional expectation of PEV registrations given HOV lane-miles is robust to alternative second stage functional forms.

If we assumed a quadratic functional form, we would estimate the following equation in the "second estimation stage:"

[6]The weak unconfoundedness assumption is not statistically testable. Reverse causality is one potential violation of this assumption. We cannot rule out the possibility that it is PEV registrations driving HOV lane construction decisions, however, we find this unlikely to be the case. Another potential violation of this assumption is correlation between the error terms of the HOV lane variable and PEV registrations, which would occur if an omitted variable affected both HOV lanes and PEV registrations. We also find this to be unlikely as the decision to construct HOV lanes is made at the state level and affects many local jurisdictions. It is unlikely, though not impossible, that a census tract with a local government keen on promoting local PEV registrations influences HOV lane decisions. Figure 1 in Section 4 shows that PEV registrations appear to be uncorrelated with HOV lane density.

$$E[Y_i|N_i, \hat{R}_i] = \alpha_0 + \alpha_1 N_i + \alpha_2 N_i^2 + \alpha_3 \hat{R}_i + \alpha_4 \hat{R}_i^2 + \alpha_5 N_i \hat{R}_i. \tag{3}$$

The second key assumption is that the set of covariates is orthogonal to treatment status given GPS, i.e., $X \perp 1\{N = n\}|r(n, X)$. That is, we assume that controlling for GPS removes biases in comparisons across treatment statuses. In Section 5.1.4 we find support for this assumption and discuss possible threats to identification. This assumption, together with the weak unconfoundedness assumption, implies that treatment is uncounfounded given GPS. In other words, if our two key assumptions hold, then we remove biases associated with differences in covariates and can compare treatment groups to estimate the causal effect of treatment.

Finally we would calculate the estimated average potential outcome at treatment level $n$ as (using the quadratic example):

$$E[\hat{Y(n)}] = \frac{1}{M} \sum_{i=1}^{M} (\hat{\alpha}_0 + \hat{\alpha}_1 n + \hat{\alpha}_2 n^2 + \hat{\alpha}_3 \hat{r}(n, X_i) + \hat{\alpha}_4 \hat{r}(n, X_i)^2 + \hat{\alpha}_5 n \hat{r}(n, X_i)), \tag{4}$$

where $\hat{r}$ is the GPS recalculated for each $n$ using the first estimation stage, $\hat{\alpha}_1$ through $\hat{\alpha}_5$ are the coefficients estimated from the second estimation stage, and $M$ is the total number of census tracts in California.

We calculate the estimated average potential outcome (PEV registrations) for each level of treatment $n$ (number of HOV lane-miles) in order to estimate an entire dose-response curve.[7] The dose-response curve shows how a marginal increase in treatment, i.e., an increase in nearby HOV lanes, impacts PEV registrations. We bootstrap the standard errors and cluster the standard errors at the county level.

The GPS technique is fairly new and has been used relatively infrequently in the economic literature. Hirano and Imbens (2005) apply the methodology to estimate the effect of lottery prize size on winners' subsequent labor earnings. Other studies estimate the effect of duration and quality of training programs (Flores et al., 2012; Kluve et al., 2012; Dammert and Galdo, 2013). There have also been studies in the medical and healthcare literature using GPS (Moodie, Pai, and Klein, 2009; Slavov, 2010; Jiang and Foster, 2013). This paper is a novel application of GPS with several innovations. First, we use an unusual treatment variable, miles of HOV lanes within a thirty mile radius of the population centroid of a census

[7]The dose response curve shows how a marginal increase in HOV lane-miles increases PEV registrations in an average census tract. Ideally we would weight Equation 4 by total new vehicle registrations in each census tract. Lacking this data and believing other variables to be poor proxies for new vehicle registrations, we weight each census tract equally.

tract. Our unit of analysis, the census tract, allows us to explore geographic heterogeneity by aggregating estimated effects at the metropolitan area level. Second, we use a Lasso methodology to select first stage control variables, resulting in propensity scores that balance observables very well across census tracts with differing levels of treatment.

# 4 Data

PEV and hybrid vehicle registration data were purchased from R.L. Polk & Company and include PEV and hybrid vehicle registrations by month and by census tract for the state of California during the period of February 2010 through December 2013. The resolution of this data is by vehicle model type. Each model is classified as a hybrid vehicle, a battery electric vehicle (BEV), which has only an electric engine, or a plug-in hybrid electric vehicle (PHEV), which has both an electric engine and an internal combustion engine. In this analysis we use cumulative retail PEV registrations as of December 2013 by census tract as the outcome variable and hybrid vehicle registrations as a control variable.[8,9]

The treatment variable is the number of miles of HOV lanes ("lane-miles") within a 30-mile radius of the population centroid of a census tract as of December 2013.[10,11] There is almost no variation in HOV lane miles over time in California during our PEV registration data sample, thus we are limited to a cross sectional analysis. The data on geographical locations of HOV lanes in California are collected by Caltrans and made public on the Caltrans website. Figure 1 shows HOV lane density and PEV registration density in the county of Los Angeles. Figure 1a shows that HOV lane density is highly correlated with urban areas. PEV density, as shown in Figure 1b, appears to be uncorrelated with HOV lanes.[12] Instead, greater PEV density is found in more affluent and coastal areas. Some PEV-dense census tracts have high HOV lane density, and other PEV-dense census tracts

[8]Our analysis implicitly assumes a uniform distribution of PEV supply at dealerships across California. While there may be heterogeneity in dealers' understanding and ability to educate prospective buyers, availability of vehicles across dealerships is likely uniform across dealers due to their ability to trade vehicles across dealerships. In other words, if a customer would like to purchase a PEV from a dealership that is out of stock, the dealership can transfer the PEV from another dealership.

[9]PEV registrations include both PHEV and BEV registrations. We exclude fleet registrations and neighborhood electric vehicles, or NEVs, which are not allowed on highways.

[10]The average length of weekday home to work trips in California is 26 miles (Caltrans, 2013). A 30-mile radius is large enough to encapsulate most commuters' daily commutes but small enough to retain variation across census tracts.

[11]While density of HOV lane-miles is not a perfect measure of HOV access, it is a good proxy for HOV lane access. HOV lane-mile density is highly correlated with being in an urban area, as is HOV lane access, i.e., the distance of a census tract from a highway entrance ramp with an HOV lane. Provision of these entrance ramps by Caltrans is generally in response to growing population density.

[12]This supports the first key assumption from Section 3.1.1 that assignment of HOV lanes is independent of PEV registrations.

have low HOV lane density.

Most of the covariates are socio-demographic variables from the U.S. Census Bureau's 5-year 2008-2012 American Community Survey (ACS). We also use the share of a voting district voting "yes" on California Proposition 23 as a measure of its green propensity. California Proposition 23 was a 2010 ballot measure to suspend AB 32, the "Global Warming Solutions Act of 2006." A higher proportion of "yes" votes should correlate to a lower green propensity. Average gasoline prices in December 2013 by census tract were obtained from Gas Buddy Organization Inc. Average overnight electricity rates in December 2013 by census tract were obtained directly from utilities' rate schedules. Lastly, publicly-available PEV charger density (Level 1 Chargers, Level 2 Chargers, and DC Fast Chargers within a 5-mile, 20-mile, and 30-mile radius of the population centroid of each census tract) as of December 2013 were obtained from the U.S. Department of Energy's Alternative Fuels Data Center. PEV charger density is a measure of amenability of the built environment to PEV ownership.

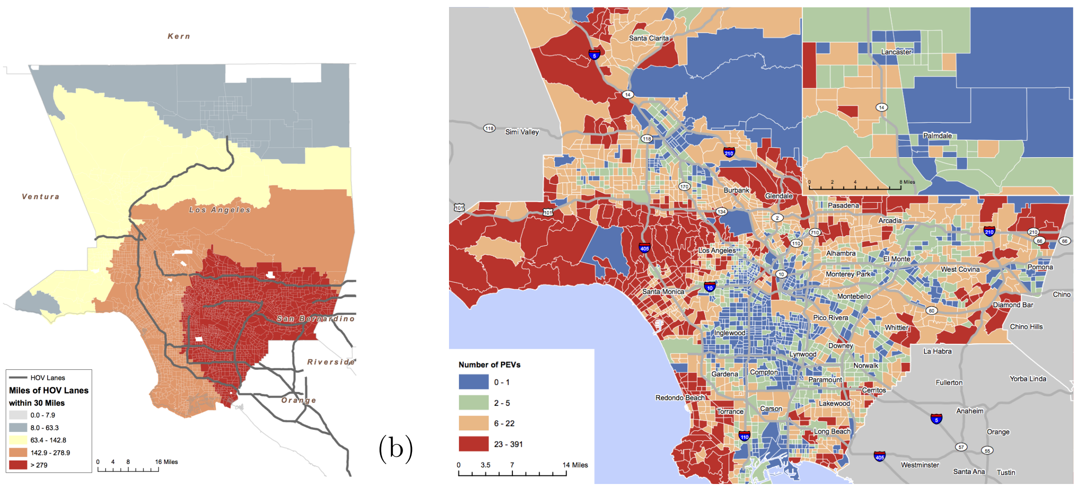
Finally, we obtain proxies for congestion from Caltrans. The first variable is number of traffic bottlenecks in each census tract in 2012, where a bottleneck represents a segment of heavy congestion during peak morning and/or evening periods. Bottlenecks are a good predictor of HOV lane-miles in the first stage. The second variable is annual average daily traffic volume by census tract in 2012, which is the total volume for the year divided by 365 days. Because traffic volumes are monitored in less than half the census tracts in California, we do not use this variable in the first stage. However, we do check the balance of this variable across census tracts in Section 5.1.4.

Table A.1 in the Appendix shows average covariate levels for census tracts in the bottom, middle, and top third of the HOV lane distribution. The group with the fewest HOV lane-miles has an average of 10 miles of HOV lanes within a 30-mile radius. The middle group has an average of 116 miles, and the top group has an average of 287 miles.[13] Census tracts with more HOV lane-miles tend to be more urban, with greater population density, have a lower percent of "yes" votes on Proposition 23, higher gas prices, higher median home values, and more workers with medium to long commutes by automobile. Census tracts with more HOV lane-miles also have less agricultural industry, which is likely because urban areas tend to have more HOV lanes than rural areas. Census tracts that have more HOV lane-miles have more households without heat, which may be correlated with coastal locations. Areas with more HOV lane-miles have more racial diversity, also a likely proxy for urban areas. Employment, income, sex, and age do not appear to be substantially different across the groups.

[13]Note that one mile of six-lane highway with two HOV lanes in both directions would count as 4 miles of HOV lanes.

Figure 1: HOV Lane and PEV Registration Density in Los Angeles County

(a) (b)




# 5 Results

## 5.1 First Stage

The goal of the first stage is not to establish a causal relationship between predictive covariates and treatments. Rather, the goal is to estimate propensity scores that best control for observed differences in treatment groups. The GPS is the probability distribution function (or probability mass function) evaluated at the level of treatment using the predicted distributional parameters. Thus the GPS is a measure of the probability that a unit receives its level of treatment, given its characteristics. The first key decision to estimate GPS is the choice of predictive covariates to include, and the second is the choice of distribution to fit. We use various statistical measures to guide these decisions. After estimating GPS, we perform two checks that help inform which measure of GPS to use in the second stage. The first is common support, where we ensure that there is overlap in the covariate distributions between units with different levels of treatment. The second is balance of covariates, which is a measure of how well controlling for GPS eliminates observable differences between treatment groups.

### 5.1.1 Covariate Selection

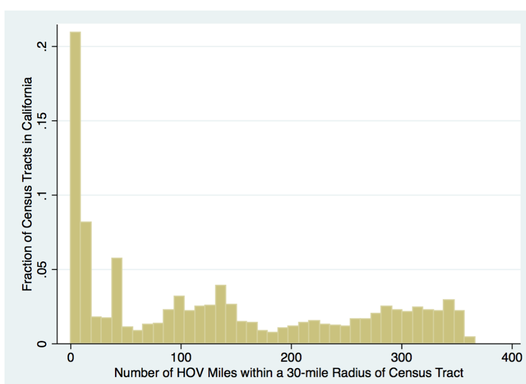
We cannot include all of the nearly 200 covariates due to power and collinearity issues. In such cases researchers typically select covariates according to economic intuition. As a robustness check, we select an“intuitive” set of covariates. For our main specification, we use a Least Absolute Shrinkage and Selection Operator (Lasso) method, a more robust and systematic method of covariate selection. Table A.2 in the Appendix shows the covariate sets as selected by Lasso and intuition.

Lasso is a model selection procedure that solves the ordinary least square objective function with a penalty for adding variables with small coefficients. Specifically, we use the Lasso procedure developed by Belloni et al. (2012) in the context of instrumental variables for estimating the first stage regression of an endogenous variable on instruments. This is a similar context as ours, where we are selecting which variables to include in our first stage estimation of an endogenous variable, HOV lane-miles.

### 5.1.2 Distributional Assumption

Figure 2 shows the distribution of HOV lane-miles across census tracts. Figure 2 suggests that a lognormal, Poisson, or negative binomial distribution may fit the data well. Table A.2 in the Appendix shows the results of a lognormal, Poisson, and negative binomial regression of HOV lane-miles on each of the two sets of covariates. The lognormal specification has the greatest log-likelihood and the lowest Akaike and Bayesian information criteria (AIC and BIC), suggesting it is the best fit, followed by the negative binomial specification. Since the negative binomial specification leads to computational difficulties,[14] we use the lognormal distribution as our preferred specification and the Poisson distribution as a robustness check.

Figure 2: HOV Lane Frequency




[14]To calculate the GPS we must calculate the probability mass function of the negative binomial distribution, which involves taking a factorial of N, the number of HOV lane-miles in a census tract. In many cases N is greater than 150, up to 366. Standard software cannot evaluate the factorial of such large numbers. This problem can be mitigated by setting treatment equal to $\tilde{N} = \frac{N}{10}$, however, $\tilde{N}$ must be truncated and input into the probability mass function as an integer, which results in a significant loss in variation of treatment.

### 5.1.3 Common Support

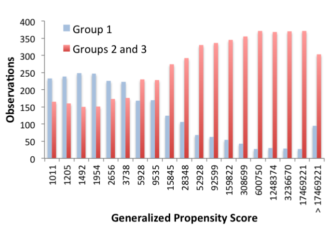
Common support is necessary for propensity score matching to ensure sufficiency of comparison groups. Common support requires that there is overlap in the covariate distributions between the treated and untreated populations. For the binary case, one typically compares the propensity score distribution of the treated group with that of the non-treated group and removes observations from either distribution without overlap. For continuous treatment, we can test for common support following the approach of Flores et al. (2012).

We divide observations into three groups of approximately equal size according to treatment level. We evaluate the GPS for all observations at the median treatment of the first group and compare the distribution of this GPS for the first group to the distributions of the other groups. We then evaluate the GPS at the median treatment levels of the second and third groups and repeat the analogous comparison of distributions.

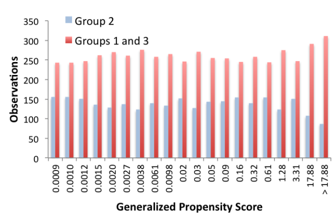
For each covariate set-distribution pair except the Poisson distribution (which we do not use for the second stage) using the Lasso-selected covariates, we find sufficient overlap in the covariate distributions. Figure 3 shows the covariate overlap using the Lasso-selected covariates and a lognormal distribution. Typically, researchers remove any observations that lack common support before moving on to the second stage. Since we have common support across all treatment levels, we do not trim the data as we have confirmed that each census tract can be compared to another census tract with a similar GPS but different level of treatment.

Figure 3: Common Support

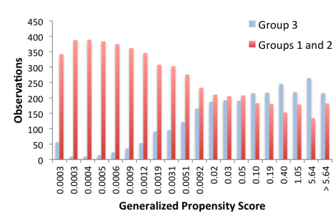
(a)




(b)




(c)




### 5.1.4 Balancing of Covariates

We also test for balancing of the covariates, i.e., that controlling for GPS sufficiently removes biases in covariates. In the binary case we would simply compare the covariate means between the treated and untreated groups before and after matching. In our continuous treatment case, we follow Hirano and Imbens (2005) and use a "blocking on the score" approach. We divide the sample into three intervals according to treatment. Within each interval, we compute the GPS for all observations at the median of the treatment interval. We divide each treatment interval into thirty blocks by GPS evaluated at the median of the treatment interval. Then we compare the means of a covariate between a given block and observations from different treatment intervals with similar GPS. Lastly we calculate a weighted average over the thirty blocks of each treatment interval and use a t-test to determine if the difference in covariate means is significant. We repeat this for every treatment interval and for every covariate. If GPS perfectly balances the covariates, the differences in covariate means should not be statistically different from zero.

The results of the blocking on the score methodology for testing the balancing property of the GPS are shown in Table 1. Note that we perform the balancing test for all 200 variables in our data (i.e., all observables), not only the covariates used in the first stage. Before adjusting for GPS, the t-statistics for less than 16% of variables fail to reject the null hypothesis of equality of means at the 5% significance level. In other words, before adjusting for the GPS, census tracts with different levels of treatment exhibit different characteristics. After adjusting for GPS, however, the t-statistics for the majority of variables fail to reject the null hypothesis at the 5% significance level. Using the Lasso-selected covariates and a lognormal distribution of treatment results in the best covariate balance. We consider this our preferred first stage specification and use it in the second stage estimation. In this specification, after controlling for GPS, 95% of approximately 200 observable characteristics are statistically indistinguishable across census tracts with different levels of treatment.[15] This is the same level of balance achieved by Hirano and Imbens (2005). Table A.3 in the Appendix shows the detailed results of the balancing tests for the preferred specification.

Table 1: Balancing Tests of Alternative Specifications

| Covariates | Distribution | Unadjusted[1] | Adjusted[2] |
|---|---|---|---|
| Lasso | lognormal | 15.8% | 94.8% |
| Intuitive | lognormal | 15.8% | 93.3% |
| Lasso | Poisson | 13.8% | 93.1% |
| Intuitive | Poisson | 4.6% | 86.5% |

[1] Percent of covariates with t-statistics that fail to reject the null hypothesis of equality of means at the 5% significance level *before* adjusting for GPS

[2] Percent of covariates with t-statistics that fail to reject the null hypothesis of equality of means at the 5% significance level *after* adjusting for GPS

[15] The remaining 5% of variables are not necessarily unbalanced. Since no two census tracts have an identical GPS, we compare variable means between census tracts with different levels of treatment and *similar* GPS. Remaining differences in variable means could result from the same source as differences in GPS.

**Threats to Identification**

As mentioned in Section 3, when using the GPS methodology, there are two assumptions that must hold in order to causally identify treatment effects.

The first assumption is that after controlling for a rich set of census tract characteristics, assignment of HOV lanes is independent of PEV registrations.[16] The second assumption is that the set of covariates is orthogonal to treatment status given GPS, i.e., controlling for GPS removes biases in comparisons across treatment statuses. The GPS methodology essentially identifies the effect of treatment (HOV lane-miles) on outcome (PEV registrations) conditional on treatment probability (GPS). Note that unobservables that influence PEV registrations, such as green preferences or early adoption proclivity, are *not* a threat to identification in this framework except to the extent that they covary with treatment status.

Section 5.1.4 shows that observable characteristics of different treatment groups are nearly indistinguishable after controlling for GPS, which supports the second assumption. However, we cannot test that controlling for GPS removes differences in unobservable characteristics that may influence treatment status (HOV lane-miles). Unobservables that may covary with treatment include local PEV incentives and vehicle preferences.

Most PEV incentives in California are state-wide or federal, including rebates and tax credits. However, there are various local incentives including preferential parking and public charging stations that may or may not be subsidized. There does not appear to be a consistent data source for these local incentives. However, we do control for publicly available charging stations, which is likely a good proxy for local incentives. Additionally, we control for hybrid vehicle registrations, which may covary with local incentives. Note that adjusting for GPS removes observable differences in hybrid registrations and publicly available charging stations, as shown in Table A.3 in the Appendix.

Vehicle preferences may covary with treatment if, for example, more urban areas (with greater HOV lane access) prefer smaller vehicles, since most PEV models are small sedans and hatchbacks. If we had vehicle registration data for internal combustion engine vehicles we could control for how vehicle preferences vary across census tracts. Hybrid vehicle registrations, which we control for, may also be a proxy for vehicle preferences.

## 5.2 Second Stage

When treatment is continuous, we must estimate the average conditional expectation of outcome given treatment and propensity score. Since treatment is not binary we cannot use a matching method and compare outcomes of treated versus non-treated groups. Each

[16] As mentioned in Section 3.1.1, we believe this assumption is not an issue as the decision to construct HOV lanes is made at the state level and affects many local jurisdictions.

observation has a different level of treatment. Instead, we model conditional expectation as a flexible function of treatment and propensity score. In regular propensity score matching it is important to show that the ATT is robust to alternative matching techniques. Analogously, we show that our conditional expectation of PEV registrations given HOV lane-miles is robust to alternative second stage functional forms.

Most previous studies have assumed a low order polynomial. Lower order polynomials are limited in their curvature, while higher order polynomials may fit poorly at extreme covariate values. Fractional polynomials, which allow for both integer and non-integer value polynomials as well as natural logs, are more flexible than standard polynomials (Royston and Altman, 1994). We utilize an algorithm by Royston and Ambler (1998) for model selection, which selects the multivariable fractional polynomial (MFP) that best predicts the outcome from the right hand side variables based on goodness of fit statistical tests. We also fit a quadratic and cubic specification. Table 2 shows the results of the second estimation stage, regression of PEV registrations on the specified function of treatment and GPS. The cubic specification has the best model fit, with the lowest AIC and BIC, therefore it is our preferred specification. Table A.4 in the Appendix shows the second stage estimation results by vehicle technology.

**Comparison with OLS**

Table A.5 in the Appendix shows the results from an OLS regression of the outcome variable, PEV registrations, on the two sets of control variables. In both specifications, the coefficient on HOV lane-miles is close to zero. Using the larger set of Lasso-selected covariates, this coefficient is not statistically significant, and using the smaller set of intuition-selected covariates, this coefficient is statistically significant at the 10% level. This suggests that a one-mile increase in HOV lanes has, if anything, a negative effect on PEV registrations. Not only is this approach less flexible than the GPS approach, but it is also more susceptible to omitted variable bias. Unlike the GPS approach, controlling for a set of covariates does not necessarily lead to observables being balanced across treatment groups.

**Falsification Test**

As a robustness check for estimating causal effect of a treatment, Imbens and Wooldridge (2009) recommend a falsification test. The researcher can estimate a "pseudo" average treatment effect by assuming one of the control groups was treated and testing if the pseudo average treatment effect is zero as expected. In our context, this is analogous to randomly assigning census tracts a different level of treatment and ensuring that we find no effect of this falsified treatment.

PEV sales in a census tract should not be a function of HOV lane-miles in a different census tract more than 30 miles away (i.e., without overlapping HOV lane-miles). To implement

Table 2: Second Stage Results

| | (1) Quadratic | (2) Cubic | (3) MFP |
|---|---|---|---|
| N | 0.179*** | 0.365*** | |
| | (0.011) | (0.036) | |
| $N^2$ | -0.0003*** | -0.001*** | |
| | (2e-05) | (0.0001) | |
| $N^3$ | | 8e-07*** | |
| | | (2e-07) | |
| lnGPS | -0.214*** | -0.137*** | |
| | (0.039) | (0.048) | |
| $lnGPS^2$ | -0.010** | -0.036*** | |
| | (0.004) | (0.009) | |
| $lnGPS^3$ | | -0.0006*** | |
| | | (0.0002) | |
| N*lnGPS | 0.008*** | 0.032*** | |
| | (0.001) | (0.007) | |
| $N^2$*lnGPS | | -6e-05*** | |
| | | (1e-05) | |
| N*$lnGPS^2$ | | 0.0008*** | |
| | | (0.0002) | |
| $\widetilde{N_1}$ | | | 31.030*** |
| | | | (2.116) |
| $\widetilde{N_2}$ | | | -5.766*** |
| | | | (0.397) |
| $\widetilde{lnGPS}$ | | | -0.190*** |
| | | | (0.058) |
| $N * \widetilde{lnGPS}_1$ | | | -16.650*** |
| | | | (4.206) |
| $N * \widetilde{lnGPS}_2$ | | | 4.590*** |
| | | | (0.713) |
| Constant | 3.276*** | 3.120*** | 13.041 |
| | (0.205) | (0.288) | (0.307) |
| Observations | 7,772 | 7,772 | 7,772 |
| $R^2$ | 0.098 | 0.105 | 0.102 |
| Log Likelihood | -31,362 | -31,330 | -31,344 |
| AIC | 62,736 | 62,679 | 62,700 |
| BIC | 62,778 | 62,749 | 62,741 |

where $\widetilde{N_1} = \left(\frac{Treatment}{100}\right) - 1.3$

$$\widetilde{N_2} = \left(\frac{Treatment}{100}\right)^2 - 1.8$$

$$\widetilde{lnGPS} = ln(GPS) + 5.3$$

$$N * \widetilde{lnGPS}_1 = \frac{Treatment * ln(GPS) + 4751}{1000} - 3.8$$

$$N * \widetilde{lnGPS}_2 = \left(\frac{Treatment * ln(GPS) + 4751}{1000}\right)^2 - 14.2$$

Standard errors in parentheses are clustered at the county level.

*** p<0.01, ** p<0.05, * p<0.1

Table 3: Second Stage Pseudo Outcome Results

| | PEV Registrations |
|---|---|
| N | -0.008 |
| | (0.010) |
| $N^2$ | 7e-05 |
| | (9e-05) |
| $N^3$ | -1e-07 |
| | (2e-07) |
| lnGPS | -0.934*** |
| | (0.046) |
| $lnGPS^2$ | -0.078*** |
| | (0.008) |
| $lnGPS^3$ | -0.001*** |
| | (0.0002) |
| N*lnGPS | -0.0004 |
| | (0.0007) |
| $N^2$*lnGPS | -1e-07 |
| | (2e-06) |
| N*$lnGPS^2$ | -1e-05 |
| | (2e-05) |
| Constant | 6.351*** |
| | (0.295) |
| Observations | 7,772 |
| $R^2$ | 0.037 |
| Log Likelihood | -31,615 |
| AIC | 63,251 |
| BIC | 63,321 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

such a falsification test, we randomly assign each census tract the treatment, or number of HOV lane-miles, of a census tract from another county. We re-estimate the second stage using actual outcome (PEV registrations), actual GPS, and the assigned falsified level of treatment. Table 3 shows the results. None of the coefficients on treatment variables (N, $N^2$, $N^3$, and interactions with GPS) are statistically significant or different from zero. We conclude the pseudo average treatment effect is zero, as we would expect if our methodology successfully identifies causal effects of HOV lane-miles on PEV registrations.

**HOV Lane Quality**

In our main specification we estimate the average potential outcome for additional HOV lane-miles, holding all else constant. Impacts of the HOV lane policy likely depend on potential travel time savings from utilizing HOV lanes. Travel time savings depend not only on the quantity of HOV lanes a driver has access to, but also the quality of those lanes, i.e., congestion of the HOV lanes relative to regular lanes. With a measure of HOV lane quality, we could construct a treatment variable that is a function of both quantity and quality of HOV lanes that would enable us to better estimate heterogeneity of impacts of the HOV lane policy across locations. An ideal measure of HOV lane quality would be predicted travel time savings for each HOV lane-mile. This would require data on traffic flows in HOV lanes and regular lanes throughout the day, a measure of direction of traffic at these locations during peak travel times, as well as an idea of net directional commuting flows across census tracts for the state of California. Lacking this data, estimating impacts of the HOV lane policy as a function of both quantity and quality of HOV lanes is outside the scope of this paper.

As shown in Table A.3 in the Appendix, after controlling for GPS, we cannot reject the null hypothesis that the number of bottlenecks and annual average daily traffic volume, our measures of congestion, are equal across census tracts with differing numbers of HOV lane-miles. Therefore marginal impacts of HOV lane-miles estimated in the second stage are average impacts after controlling for congestion.

### 5.3 Dose-Response Curves

We construct a dose-response curve by recalculating the GPS at each level of potential treatment and using the second stage results to predict the average potential outcome, as explained in Section 3.1.2. Figure 4 shows the resulting dose-response curves. The dose-response curves isolate the effects of changes in HOV lane-miles on PEV registrations and are effectively a series of marginal effects. This allows us to predict marginal changes in PEV registrations as a function of marginal changes in HOV lane-miles. While the shape of the dose-response curves contains useful information, such as exhibition of decreasing marginal returns, we must use caution in our extrapolations from the dose-response curves.[17]

Figure 4b, our preferred specification, suggests that nearby HOV lane-miles have a statistically significant impact on PEV registrations, with the first six HOV lane-miles within a 30-mile radius resulting in one additional cumulative PEV registration and the next six miles resulting in a second additional PEV registration. As the number of HOV lane-miles increases further, the slope gradually decreases, eventually flattening out around 100 HOV lane-miles at just over 12 cumulative PEV registrations, suggesting that 100 or more HOV

[17] The intercept of the dose-response curve is not estimated separately for each census tract but rather represents the average number of PEV registrations to expect in a census tract with average covariate values and no access to HOV lanes. Therefore, our analysis does not allow us to compare PEV registrations across different census tracts in the absence of an HOV lane policy.

lane-miles results in a total of more than 10 additional PEV registrations. These are substantial effects, especially considering that census tracts are generally only a few square miles in area, meaning that an HOV lane-mile could be in the 30-mile radius of many census tracts. To put this in perspective, the mean and median number of PEV registrations in this time period was 8.5 and 4, respectively. Figures 4a and 4c show that the dose-response curve is robust to alternative second stage specifications. The quadratic and cubic specifications also flatten out around 100 miles, though at a lower level, suggesting a somewhat smaller, though still significant, causal impact of HOV lane-miles on PEV registrations.

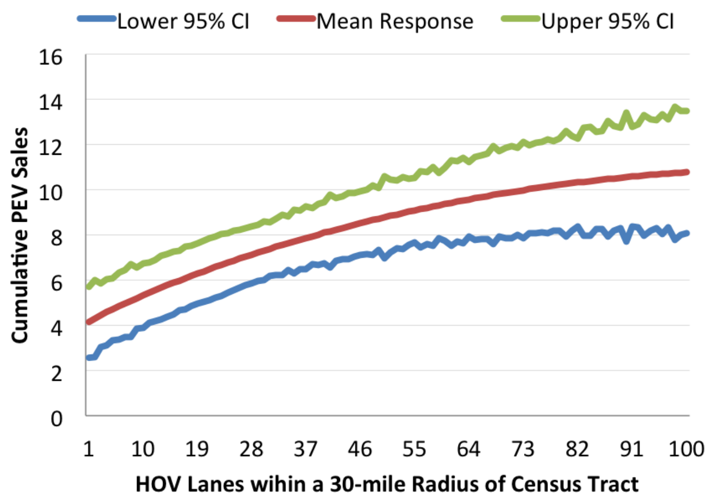
Figures 5b and 5c show the separate dose-response curves for PHEVs and BEVs, respectively, with the PEV dose-response curve for comparison. These two dose-response curves have very similar intercepts and and similar shapes, both flattening out around 100 miles. This suggests that the impact of the HOV lane policy is similar across vehicle technologies, and one technology type or model does not appear to drive the main result in Figure 5a.

Although the dose-response curve is a series of marginal effects, we can cautiously interpret the intercept as the number of PEVs that would have been purchased in the absence of the HOV policy for the *average* census tract with *average* covariate values. In our sample, 66,728 PEVs were purchased between 2010 and 2013. For each census tract, we use the second stage estimation results to predict PEV registrations given GPS, assuming the number of HOV lane-miles is zero. Integrating across census tracts, we predict 19,374 PEV registrations in the absence of the HOV policy, with a standard error of 14,995. The confidence interval is large due to the accumulation of standard errors from the marginal effects. Nevertheless, with upper bound of 49,363, these predictions suggest that with 95% confidence, at least 26% of PEV registrations in California between 2010-2013 were a result of the HOV lane policy.

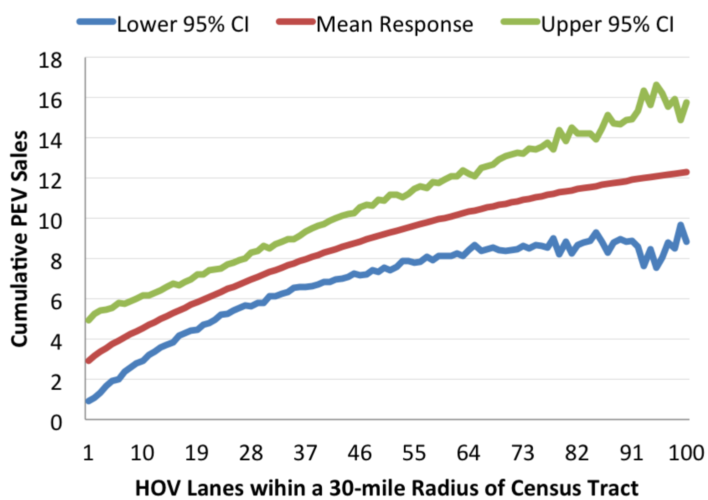
## 5.4 Simulations

The second stage estimation results in Table 2 show that more HOV lane-miles (that is, a higher level of treatment) are associated with higher PEV registrations, with the negative quadratic term suggesting decreasing marginal returns to treatment. Table 4 shows average HOV lane-miles, PEV registrations, and selected socio-demographics for California's largest metropolitan areas.

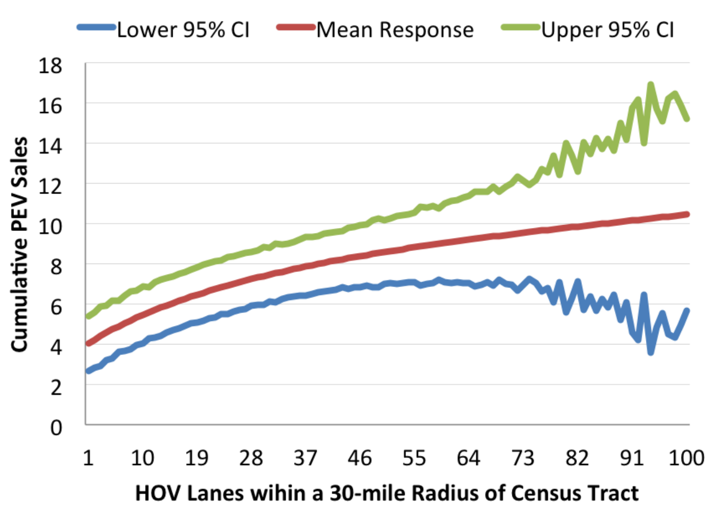
Figure 4: Dose-Response Curves by Second Stage Specification




(a) Quadratic

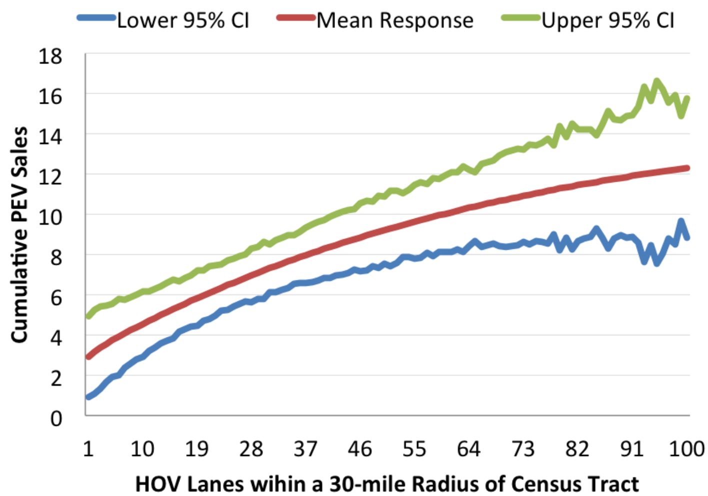



(b) Cubic

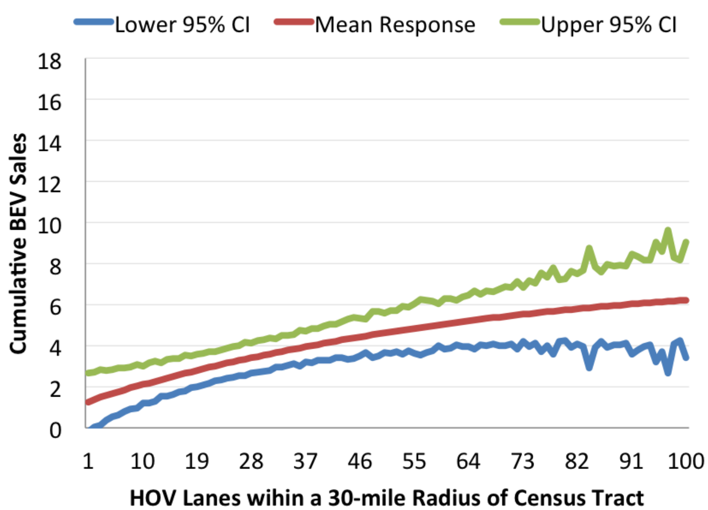



(c) MFP

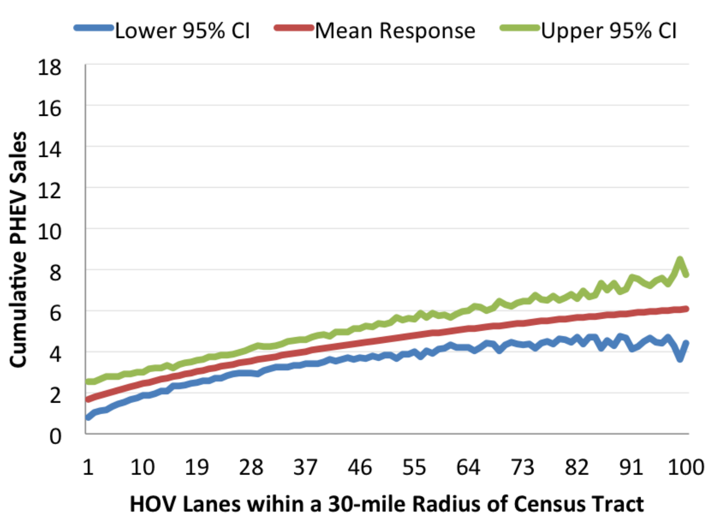
Figure 5: Dose-Response Curves by Technology (Cubic Specification)




(a) PEV




(b) BEV




(c) PHEV

Table 4: California Metropolitan Area Characteristics†

| | San Diego | Los Angeles | San Francisco | Sacramento |
|---|---|---|---|---|
| HOV Lane-Miles (30-mile radius) | 9.7 | 260.1 | 98.5 | 38.5 |
| Cumulative PEV Registrations | 9.0 | 7.8 | 8.1 | 4.1 |
| Cumulative BEV Registrations | 5.2 | 3.1 | 4.8 | 2.2 |
| Cumulative PHEV Registrations | 3.8 | 4.7 | 3.3 | 2.0 |
| Cumulative Hybrid Registrations | 39.8 | 35.7 | 42.4 | 20.7 |
| Population Density (per sq. mile) | 7,138 | 13,194 | 28,818 | 5,187 |
| Number of Bottlenecks | 0.6 | 0.9 | 0.2 | 0.2 |
| Level 2 Chargers (20-mile Radius) | 355.9 | 573.8 | 490.7 | 258.5 |
| Prop 23 Vote, % of District Voting "Yes" | 43% | 32% | 18% | 37% |
| Avg Gas Price ($) | 3.6 | 3.6 | 3.7 | 3.4 |
| Race: White (%) | 73% | 53% | 52% | 63% |
| Industry: Agriculture (%) | 0.5% | 0.3% | 0.1% | 0.4% |
| Industry: Public (%) | 3.1% | 1.9% | 2.3% | 6.3% |
| Median House Value ($10,000s) | 42.2 | 44.3 | 72.2 | 24.8 |
| Median Rent ($1,000s) | 1.4 | 1.3 | 1.5 | 1.1 |
| Commute: Public Transport (%) | 3% | 8% | 32% | 3% |
| Commute: 10-19 minutes (%) | 30% | 24% | 21% | 29% |
| Commute: 60-89 minutes (%) | 4% | 8% | 8% | 4% |
| Education: College or Some College (%) | 52% | 44% | 52% | 55% |
| Single House (%) | 68% | 63% | 40% | 78% |

†All characteristics shown are the mean across census tracts in each metropolitan area. PEV Registrations, PHEV Registrations, and BEV Registrations are cumulative between 2010 and 2013. HOV Miles, Average Gas Price, and Publicly Available Charging Stations are all as of December 2013.

Los Angeles has the highest average number of HOV lane-miles within a 30-mile radius of a census tract at 260 miles, followed by San Francisco (98), Sacramento (38), and San Diego (10). The level of actual treatment, or HOV lane-miles, determines where a census tract is located on the dose-response curve and which marginal effects are relevant. Census tracts with fewer than 100 HOV lane-miles will be located on the positively-sloped portion of the dose-response curve, while those with more than 100 HOV lane-miles will be located on the flat part of the dose-response curve. Therefore, we would expect areas with fewer HOV lane-miles, such as San Diego and Sacramento, to be responsive to marginal changes in HOV lane-miles, and we would expect areas with very many HOV lane-miles, such as Los Angeles, to be relatively unresponsive to marginal changes in HOV lane-miles.

We use our results to simulate how an increase or decrease in HOV lane-miles would affect PEV registrations in California's largest cities. For each census tract, we increase or decrease the number of HOV lane-miles by a given percent and predict the number of

Table 5: Simulation Results

| HOV Lanes, % of Actual | PEV Registrations (Feb 2010-Dec 2013), % of Actual California | San Diego | Los Angeles | San Francisco | Sacramento |
|---|---|---|---|---|---|
| 70% | 94.4% | 87.4% | 98.4% | 82.3% | 81.5% |
| 80% | 96.6% | 91.6% | 99.1% | 87.9% | 87.9% |
| 90% | 98.4% | 95.8% | 99.6% | 96.7% | 94.1% |
| 100% | 100.0% | 100.0% | 100.0% | 100.0% | 100.0% |
| 110% | 101.3% | 104.1% | 100.3% | 102.6% | 105.7% |
| 120% | 102.3% | 108.3% | 100.5% | 102.6% | 111.1% |
| 130% | 103.1% | 112.3% | 100.7% | 104.5% | 116.3% |

| HOV Lanes, % of Actual | PEV Registrations (Feb 2010-Dec 2013) California | San Diego | Los Angeles | San Francisco | Sacramento |
|---|---|---|---|---|---|
| 70% | 63,009 | 4,881 | 17,656 | 1,282 | 1,032 |
| 80% | 64,464 | 5,118 | 17,786 | 1,369 | 1,112 |
| 90% | 65,691 | 5,353 | 17,878 | 1,507 | 1,190 |
| 100% | 66,728 | 5,587 | 17,946 | 1,558 | 1,265 |
| 110% | 67,584 | 5,819 | 17,997 | 1,598 | 1,337 |
| 120% | 68,253 | 6,049 | 18,036 | 1,598 | 1,405 |
| 130% | 68,778 | 6,277 | 18,068 | 1,628 | 1,471 |

PEV registrations using the second stage estimation results. We are then able to integrate PEV registrations over all census tracts in a given city. Table 5 shows how cumulative PEV registrations are predicted to change, both in percentage terms and in terms of number of vehicles, if the number of miles of HOV lane-miles in a city increased or decreased.[18]

Los Angeles seems to be at the flat part of the dose-response curve, where HOV lane density is already high enough in most census tracts that additional HOV lane-miles do not further impact PEV registrations. Los Angeles has the most HOV lane-miles out of the four cities. This suggests the Los Angeles area is relatively saturated in HOV lanes, such that all consumers will be less responsive to further increases in HOV lane access. Notice that if there were 30% fewer HOV lane-miles in Los Angeles, it would still have more than any other city in California. Importantly, this finding does not mean that California's HOV lane policy has not induced PEV registrations in Los Angeles. Indeed, HOV lane access may have motivated a substantial number of PEV registrations in the area, but our analysis identifies only the marginal effects of changes in HOV lane access.

San Francisco and Sacramento PEV registrations are predicted to be more sensitive to changes in HOV lane density. A 10% decrease (increase) in HOV lane-miles is associated with a 3.3% decrease (2.6% increase) in PEV registrations in San Francisco and a 5.9% decrease

[18]The cumulative PEV registrations at 100% of current HOV lane-miles (i.e., no change) have been normalized to actual registrations for each city. Our empirical model identifies the incremental effect of HOV lane-miles on PEV registrations but does not estimate the intercept for each census tract.

(5.7% increase) in Sacramento. That PEV registrations are lower in these cities than San Diego and Los Angeles and also more sensitive to HOV lane density suggests that a larger proportion of marginal PEV registrations in San Francisco and Sacramento are motivated by drivers who are responsive to marginal increases in access to HOV lanes.

San Diego has more PEV registrations and the lowest number of HOV lane-miles out of all four metropolitan areas. That San Diego PEV registrations are so high suggests that factors other than HOV lane access are motivating San Diego drivers to adopt PEVs. Nevertheless, our simulations suggest PEV registrations in San Diego are still quite responsive to changes in HOV lane density. A 10% decrease (increase) in HOV lane-miles is associated with a 4.2% decrease (4.1% increase) in PEV registrations.

# 6 Caveats and Conclusion

We have developed an approach that identifies both state-wide average marginal effects of HOV lane access on PEV registrations and geographic-specific estimates that accommodate local variation on policy treatment. Our estimated treatment effects are conditioned on several factors. First, our estimated marginal effects are for a new product market and a policy that has been in place for four years. Therefore, we are measuring a treatment effect over a considerable period of time for early and middle-market adopters, who may be less responsive to the time and cost savings associated with increased HOV lane access than will be future PEV adopters. Our approach, when combined with a future discrete policy change, may allow future researchers to identify per year effects rather than cumulative effects. Second, the impacts of this policy may depend upon both other policies and market conditions that affect the total costs of owning PEVs. Changes in PEV market prices relative to conventional vehicle, gasoline and electricity prices, as well as vehicle purchase incentives and refueling infrastructure subsidies could affect our findings. Lastly, as congestion changes in existing HOV lanes, so too will drivers' willingness to pay to access these lanes.

We find evidence that California's policy to allow PEVs free single-occupant access to HOV lanes led to an increase in PEV registrations during 2010-2013. Although we estimate the impact of this policy on PEV registrations, our analysis offers little guidance in terms of the net effect of the HOV lane policy on welfare. The net effect of the on welfare depends on whether the environmental benefits from PEV adoption (which Holland et al. (2015) estimate to be $3,025 annually) outweigh any increase in congestion costs (which Bento et al. (2014) estimate to be between $0 and $4,500 annually). To perform such an analysis at a state-wide level would require more detailed data, particularly on traffic volumes on major highways throughout the state.

Our analysis does, however, shed light on relative policy effectiveness. During the time period under analysis, the state of California also offered rebates of $1,500 and $2,500 for PHEV and BEV purchases, respectively. DeShazo, Sheldon, and Carson (2015) find that most of these rebates were non-marginal in the sense that they were given to customers who would have purchased a PEV regardless of the rebate. They estimate the cost of the rebate policy per induced PEV purchase to be $30,000. We estimate roughly one quarter of California PEV registrations during 2010-2013 were a result of the HOV lane policy. The capital costs of this policy are approximately zero since the policy allowed PEVs to access HOV lanes that already existed, and congestion costs per additional PEV are likely well below $30,000. Therefore, we find California's PEV HOV lane policy to be considerably more cost effective than its rebate program.

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# A Appendix

Table A.1: Descriptive Statistics

| | HOV Lanes (30-mile radius) | | |
|---|---|---|---|
| Covariate | Bottom Third | Middle Third | Top Third |
| HOV Lanes within 30-mile Radius | 10 | 116 | 287 |
| Cumulative PEV Registrations | 4 | 14 | 8 |
| Cumulative PHEV Registrations | 2 | 7 | 5 |
| Cumulative BEV Registrations | 2 | 7 | 3 |
| Cumulative Hybrid Registrations | 25 | 42 | 36 |
| Population | 4,824 | 4,642 | 4,466 |
| Commuters | 1,974 | 2,117 | 2,015 |
| Area (Land, $mi^2$) | 48 | 4 | 1 |
| Population Density (per $mi^2$) | 4,306 | 8,660 | 12,660 |
| Prop 23 "Yes" Vote | 44% | 33% | 35% |
| Avg Gas Price ($) | 3.54 | 3.60 | 3.63 |
| Avg Electric Price (cents/kWh) | 10.5 | 11.3 | 10.3 |
| Industry: Construction | 4% | 4% | 3% |
| Industry: Transport | 2% | 3% | 3% |
| Industry: Manufacturing | 4% | 6% | 7% |
| Industry: Agriculture | 3% | 0% | 0% |
| Industry: Education | 11% | 13% | 12% |
| Industry: Wholesale | 2% | 2% | 2% |
| Industry: Management | 6% | 9% | 7% |
| Employed | 53% | 59% | 58% |
| Unemployed | 8% | 7% | 7% |
| Has Mortgage | 71% | 77% | 76% |
| Has 2nd Mortgage | 17% | 21% | 18% |
| Income: $10-$15k | 6% | 4% | 6% |
| Income: $20-$25k | 6% | 4% | 5% |
| Income: $25-$30k | 5% | 4% | 5% |
| Income: $30-$35k | 5% | 4% | 5% |
| Income: $35-$40k | 5% | 4% | 5% |
| Income: $45-$50k | 4% | 3% | 4% |
| Income: $50-$60k | 8% | 7% | 8% |
| Income: $125-$150k | 5% | 7% | 5% |
| Median Rent ($1,000s) | 1.2 | 1.5 | 1.3 |

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**Table A.1 – continued from previous page**

| | HOV Lanes (30-mile radius) | | |
|---|---|---|---|
| Covariate | Bottom Third | Middle Third | Top Third |
| Median House Value ($10,000s) | 29.9 | 50.0 | 44.8 |
| Poverty Rate | 16% | 11% | 15% |
| Heat: Solar | 0.1% | 0.1% | 0.1% |
| Heat: Oil | 1% | 0% | 0% |
| Heat: Electric | 26% | 23% | 23% |
| Heat: None | 2% | 2% | 6% |
| Race: Black | 5% | 7% | 7% |
| Race: White | 73% | 60% | 54% |
| Race: Asian | 7% | 18% | 15% |
| Single, Attached House | 6% | 9% | 8% |
| Single House | 84% | 74% | 63% |
| Mobile House | 8% | 3% | 2% |
| Houseunits: 3-4 | 6% | 6% | 7% |
| Houseunits: 10-19 | 4% | 5% | 8% |
| House Value: Under $20k | 3% | 1% | 1% |
| House Value: $100-$150k | 10% | 5% | 3% |
| House Value: $150-$300k | 33% | 19% | 21% |
| House Value: Over $1,000k | 4% | 11% | 7% |
| Male: 25-34 | 7% | 7% | 8% |
| Male: 45-54 | 7% | 7% | 7% |
| Male: 55-64 | 6% | 6% | 5% |
| Male: 75-84 | 2% | 2% | 2% |
| Female: 35-44 | 6% | 7% | 7% |
| Female: Over 85 | 1% | 1% | 1% |
| Age: 15-24 | 15% | 14% | 15% |
| Age: 35-44 | 13% | 14% | 15% |
| Age: 45-54 | 14% | 15% | 14% |
| Age: 65-74 | 7% | 7% | 6% |
| Foreign: Naturalized | 8% | 14% | 16% |
| Foreign, Entry: 1990-1999 | 24% | 25% | 25% |
| Moved, High School or Less | 40% | 33% | 44% |
| Moved, College | 47% | 48% | 43% |
| Moved from Other State | 11% | 5% | 5% |
| Commute: Walk | 3% | 3% | 3% |
| Commute: Public Transport | 2% | 8% | 7% |

Continued on next page

**Table A.1 – continued from previous page**

| | HOV Lanes (30-mile radius) | | |
|---|---|---|---|
| Covariate | Bottom Third | Middle Third | Top Third |
| Commute: Motorcycle | 0% | 0% | 0% |
| Commute by Auto: Under 15min | 28% | 19% | 17% |
| Commute by Auto: 30-60min | 21% | 26% | 30% |
| Commute by Auto: Over 60min | 7% | 9% | 8% |
| Leave Home 7-8am | 26% | 25% | 24% |
| Leave Home 9-10am | 6% | 9% | 9% |
| Leave Home 10am-noon | 5% | 5% | 5% |
| Education: High School | 23% | 19% | 21% |
| Education: Some College | 34% | 28% | 27% |
| Education: College | 49% | 51% | 45% |
| Education: MA | 6% | 10% | 6% |
| Education: Professional Degree | 2% | 3% | 2% |
| Level 1 Chargers (5-mile Radius) | 2 | 17 | 8 |
| Level 2 Chargers (5-mile Radius) | 21 | 54 | 57 |
| DC Chargers (5-mile Radius) | 0.2 | 1.0 | 0.7 |

Table A.2: First Stage Results

| | Lasso-Selected | | | Intuition-Selected | | |
|---|---|---|---|---|---|---|
| | Lognormal | Negative Binomial | Poisson | Lognormal | Negative Binomial | Poisson |
| Cumulative Hybrid | 0.120*** | 0.065*** | 0.032*** | | | |
| Registrations | (-0.015) | (-0.007) | (-0.0004) | | | |
| Level 2 Chargers (5-mi Radius) | 0.007*** | 0.0005 | 0.0006*** | 0.007*** | 0.00005 | -0.0002*** |
| | (-0.0008) | (-0.0003) | (-0.00003) | (-0.0009) | (-0.0004) | (-0.00002) |
| Level 1 Chargers (20-mi Radius) | 0.014*** | 0.010*** | 0.006*** | | | |
| | (-0.001) | (-0.0005) | (-0.00003) | | | |
| Level 2 Chargers (20-mi Radius) | 0.003*** | 0.0005*** | 0.0009*** | | | |
| | (-0.0003) | (-0.0001) | (-0.000009) | | | |
| DC Chargers (20-mi Radius) | -0.074*** | -0.023*** | -0.030*** | | | |
| | (-0.009) | (-0.003) | (-0.0003) | | | |
| Prop 23 Vote, % of District | -0.735 | 0.239 | 2.054*** | -6.819*** | -1.365*** | -0.362*** |
| Voting "Yes" | (-0.482) | (-0.185) | (-0.018) | (-0.475) | (-0.185) | (-0.013) |
| Avg Gas Price ($) | 0.112 | 0.692*** | 0.463*** | -0.076 | 1.291*** | 0.383*** |
| | (-0.293) | (-0.136) | (-0.010) | (-0.326) | (-0.184) | (-0.008) |
| Population Density | 1.41e-05*** | 1.32e-05*** | 8.38e-06*** | 5.40e-05*** | 3.21e-05*** | 1.38e-05*** |
| (per sq. mile) | (-6e-6) | (-2e-6) | (-2e-7) | (-6e-6) | (-3e-6) | (-1e-7) |
| Number of Bottlenecks | 0.0857*** | 0.041*** | 0.021*** | 0.253*** | 0.104*** | 0.061*** |
| | (-0.021) | (-0.009) | (-0.0005) | (-0.024) | (-0.010) | (-0.0005) |
| Race: White (%) | 0.357 | -0.111 | -0.314*** | | | |
| | (-0.279) | (-0.109) | (-0.008) | | | |
| Race: Hawaiian (%) | 1.30 | -1.067 | -2.634*** | | | |
| | (-2.923) | (-1.191) | (-0.097) | | | |
| Race: Other (%) | 0.103 | 1.173*** | 0.463*** | | | |
| | (-0.403) | (-0.164) | (-0.012) | | | |
| Race: Two or More (%) | 1.961 | 0.212 | -0.949*** | | | |

Standard errors in parentheses are clustered at the county level.

*** p<0.01, ** p<0.05, * p<0.1

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**Table A.2 – continued from previous page**

| | Lasso-Selected | | | Intuition-Selected | | |
|---|---|---|---|---|---|---|
| | Lognormal | Negative Binomial | Poisson | Lognormal | Negative Binomial | Poisson |
| | (-1.243) | (-0.487) | (-0.043) | | | |
| Industry: Agriculture (%) | -33.810*** | -17.400*** | -16.480*** | -48.920*** | -24.190*** | -32.710*** |
| | (-1.135) | (-0.560) | (-0.127) | (-1.162) | (-0.565) | (-0.135) |
| Industry: Construction (%) | 5.878*** | -0.081 | -1.109*** | | | |
| | (-1.603) | (-0.663) | (-0.053) | | | |
| Industry: Manufacturing (%) | 10.490*** | 3.919*** | 1.819*** | | | |
| | (-1.048) | (-0.425) | (-0.032) | | | |
| Industry: Wholesale (%) | 4.774** | 3.581*** | 4.572*** | | | |
| | (-2.369) | (-0.979) | (-0.070) | | | |
| Industry: Transport (%) | 7.358*** | 4.390*** | 2.508*** | | | |
| | (-1.883) | (-0.744) | (-0.0595) | | | |
| Industry: Information (%) | -4.365** | 1.519* | 1.880*** | | | |
| | (-1.965) | (-0.785) | (-0.057) | | | |
| Industry: Professional (%) | 3.475*** | -0.232 | -0.152*** | | | |
| | (-1.080) | (-0.433) | (-0.035) | | | |
| Industry: Public (%) | -3.144* | -2.675*** | -3.910*** | | | |
| | (-1.649) | (-0.651) | (-0.070) | | | |
| Households: With interest, dividends, | -1.970*** | -0.720*** | -0.929*** | | | |
| or net rental income (%) | (-0.428) | (-0.172) | (-0.015) | | | |
| Houseunits: 2 (%) | -6.465*** | -2.080*** | -1.210*** | | | |
| | (-0.827) | (-0.312) | (-0.030) | | | |
| Houseunits: 3-4 (%) | 0.213 | 0.905*** | 0.428*** | | | |
| | (-0.505) | (-0.204) | (-0.016) | | | |
| Primary heat source: Electric (%) | -0.453* | -0.617*** | -0.532*** | | | |
| | (-0.262) | (-0.102) | (-0.009) | | | |
| Primary heat source: Coal (%) | -10.910*** | -4.742*** | -5.893*** | | | |

Standard errors in parentheses are clustered at the county level.

*** p<0.01, ** p<0.05, * p<0.1

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**Table A.2 – continued from previous page**

| | Lasso-Selected | | | Intuition-Selected | | |
|---|---|---|---|---|---|---|
| | Lognormal | Negative Binomial | Poisson | Lognormal | Negative Binomial | Poisson |
| | (-0.631) | (-0.288) | (-0.0687) | | | |
| Primary heat source: Solar (%) | -16.140* | -3.781 | -6.258*** | | | |
| | (-8.864) | (-3.738) | (-0.348) | | | |
| Primary heat source: Other (%) | -12.450*** | -2.376** | -4.494*** | | | |
| | (-2.595) | (-1.139) | (-0.169) | | | |
| Primary heat source: None (%) | -2.367*** | -0.199 | 0.262*** | | | |
| | (-0.727) | (-0.298) | (-0.019) | | | |
| House Value: $50-$100k (%) | -4.596*** | -2.145*** | -1.098*** | | | |
| | (-0.526) | (-0.187) | (-0.023) | | | |
| House Value: $100-$150k (%) | -1.427*** | -0.943*** | -1.150*** | | | |
| | (-0.488) | (-0.182) | (-0.021) | | | |
| House Value: $150-$300k (%) | -1.718*** | -0.733*** | -0.513*** | | | |
| | (-0.277) | (-0.111) | (-0.009) | | | |
| House Value: $300-$500k (%) | 0.556** | 0.177* | 0.085*** | | | |
| | (-0.232) | (-0.094) | (-0.008) | | | |
| House Value: $500-$750k (%) | 0.255 | 0.204* | 0.094*** | | | |
| | (-0.269) | (-0.109) | (-0.008) | | | |
| Commute: Public Transport (%) | -7.512*** | -4.166*** | -2.432*** | -2.140*** | -1.349*** | -1.419*** |
| | (-0.697) | (-0.281) | (-0.021) | (-0.667) | (-0.271) | (-0.016) |
| Commute: 10-19 minutes (%) | -2.334*** | -1.220*** | -0.376*** | | | |
| | (-0.568) | (-0.236) | (-0.023) | | | |
| Commute: 20-29 minutes (%) | 1.656** | -0.643** | -0.448*** | | | |
| | (-0.666) | (-0.272) | (-0.025) | | | |
| Commute: 30-39 minutes (%) | 7.419*** | 1.941*** | 0.817*** | | | |
| | (-0.626) | (-0.256) | (-0.023) | | | |
| Commute: 40-59 minutes (%) | 10.520*** | 2.145*** | 1.198*** | | | |

Standard errors in parentheses are clustered at the county level.
*** p<0.01, ** p<0.05, * p<0.1

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**Table A.2 – continued from previous page**

| | Lasso-Selected | | | Intuition-Selected | | |
|---|---|---|---|---|---|---|
| | Lognormal | Negative Binomial | Poisson | Lognormal | Negative Binomial | Poisson |
| | (-0.745) | (-0.306) | (-0.026) | | | |
| Commute: 60-89 minutes (%) | 17.380*** | 4.857*** | 2.316*** | | | |
| | (-0.859) | (-0.366) | (-0.030) | | | |
| Native-born (%) | -1.183* | -1.239*** | -0.770*** | | | |
| | (-0.618) | (-0.255) | (-0.020) | | | |
| Foreign Born: Naturalized | -3.152*** | -1.491*** | -1.092*** | | | |
| Citizen (%) | (-0.925) | (-0.376) | (-0.029) | | | |
| Year of Entry for the Foreign-Born | -0.681* | -0.245 | -0.162*** | | | |
| Population: 2000 to 2009 (%) | (-0.381) | (-0.158) | (-0.015) | | | |
| Year of Entry for the Foreign-Born | -0.881*** | 0.139 | 0.476*** | | | |
| Population: Before 1990 (%) | (-0.316) | (-0.129) | (-0.012) | | | |
| Commute by Carpool: | -0.0001 | -0.0004* | -0.0005*** | | | |
| Income \$35-\$75k (%) | (-0.0006) | (-0.0002) | (-0.00002) | | | |
| Commute by Carpool: | -0.002** | -0.002*** | -0.001*** | | | |
| Income >\$75k (%) | (-0.0010) | (-0.0004) | (-0.00003) | | | |
| Commute by Auto: | 0.001*** | 0.0003*** | 0.0002*** | -0.002*** | -0.001*** | -0.0005*** |
| 15-30min (%) | (-0.0002) | (-0.00007) | (-0.000006) | (-0.0001) | (-0.00005) | (-0.000004) |
| Leave Home 7-8am (%) | -0.002*** | -0.0007*** | -0.0003*** | | | |
| | (-0.0002) | (-0.00008) | (-0.000008) | | | |
| Median House Value (\$10,000s) | | | | 0.008*** | 0.010*** | 0.006*** |
| | | | | (-0.002) | (-0.0009) | (-0.00006) |
| Median Rent (\$1,000s) | | | | 1.553*** | 0.237*** | 0.0498*** |
| | | | | (-0.145) | (-0.054) | (-0.004) |
| Income: \$10-\$30k (%) | | | | -3.583*** | -1.669*** | -0.652*** |
| | | | | (-0.598) | (-0.233) | (-0.017) |
| Income: \$100-\$200k (%) | | | | 2.924*** | 1.130*** | 0.628*** |

Standard errors in parentheses are clustered at the county level.

*** p<0.01, ** p<0.05, * p<0.1

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**Table A.2 – continued from previous page**

| | Lasso-Selected | | | Intuition-Selected | | |
|---|---|---|---|---|---|---|
| | Lognormal | Negative Binomial | Poisson | Lognormal | Negative Binomial | Poisson |
| | | | | (-0.549) | (-0.222) | (-0.015) |
| Education: Some College (%) | | | | -7.425*** | -3.328*** | -2.714*** |
| | | | | (-0.359) | (-0.143) | (-0.010) |
| Commute by Auto: 30-60min (%) | | | | 0.005*** | 0.001*** | 0.0009*** |
| | | | | (-0.0001) | (-0.00007) | (-0.000004) |
| Single House (%) | | | | -1.216*** | -0.586*** | -0.445*** |
| | | | | (-0.106) | (-0.042) | (-0.004) |
| Constant | 0.276 | 2.352*** | 2.732*** | 6.744*** | 1.706** | 4.884*** |
| | (-1.345) | (-0.596) | (-0.046) | (-1.204) | (-0.669) | (-0.031) |
| Observations | 7,836 | 7,836 | 7,836 | 7,902 | 7,902 | 7,902 |
| Log-Likelihood | -38,885 | -41,346 | -180,753 | -40,653 | -43,050 | -317,021 |
| AIC | 77,870 | 82,792 | 361,603 | 81,340 | 86,134 | 634,074 |
| BIC | 78,218 | 83,140 | 361,944 | 81,459 | 86,252 | 634,185 |

Standard errors in parentheses are clustered at the county level.

*** p<0.01, ** p<0.05, * p<0.1

Table A.3: Number of HOV Miles: p-value of t-test of $H_0$ that populations are the same (reject H0 if p<5%)

| Covariate | G1 Adjusted | G1 Unadjusted | G2 Adjusted | G2 Unadjusted | G3 Adjusted | G3 Unadjusted |
|---|---|---|---|---|---|---|
| Cumulative Hybrid Registrations | 0.094 | 0.000 | 0.211 | 0.000 | 0.196 | 0.000 |
| Level 1 Chargers (5-mile Radius) | 0.054 | 0.000 | 0.049 | 0.000 | 0.133 | 0.720 |
| Level 2 Chargers (5-mile Radius) | 0.124 | 0.000 | 0.221 | 0.000 | 0.278 | 0.000 |
| DC Chargers (5-mile Radius) | 0.101 | 0.000 | 0.057 | 0.000 | 0.216 | 0.000 |
| Level 1 Chargers (10-mile Radius) | 0.012 | 0.000 | 0.004 | 0.000 | 0.053 | 0.000 |
| Level 2 Chargers (10-mile Radius) | 0.106 | 0.000 | 0.225 | 0.000 | 0.096 | 0.000 |
| DC Chargers (10-mile Radius) | 0.001 | 0.000 | 0.003 | 0.000 | 0.376 | 0.000 |
| Level 1 Chargers (20-mile Radius) | 0.000 | 0.000 | 0.000 | 0.000 | 0.073 | 0.000 |
| Level 2 Chargers (20-mile Radius) | 0.065 | 0.000 | 0.153 | 0.000 | 0.012 | 0.000 |
| DC Chargers (20-mile Radius) | 0.000 | 0.000 | 0.000 | 0.000 | 0.064 | 0.000 |
| Prop 23 Vote, % of District Voting "Yes" | 0.016 | 0.000 | 0.007 | 0.000 | 0.193 | 0.000 |
| Avg Electric Price (cents/kWh) | 0.077 | 0.000 | 0.010 | 0.000 | 0.231 | 0.000 |
| Avg Gas Price ($) | 0.144 | 0.000 | 0.229 | 0.000 | 0.034 | 0.000 |
| Population Density (per sq. mile) | 0.093 | 0.000 | 0.215 | 0.503 | 0.037 | 0.000 |
| Area (sq. miles) | 0.067 | 0.000 | 0.194 | 0.000 | 0.119 | 0.000 |
| Land Area (sq. miles) | 0.066 | 0.000 | 0.194 | 0.000 | 0.120 | 0.000 |
| Water Area (sq. miles) | 0.160 | 0.000 | 0.412 | 0.001 | 0.203 | 0.000 |
| Median Year Houseunit Built | 0.301 | 0.001 | 0.375 | 0.706 | 0.375 | 0.004 |
| Population (thousands) | 0.372 | 0.000 | 0.404 | 0.473 | 0.329 | 0.000 |
| Male (%) | 0.238 | 0.000 | 0.481 | 0.001 | 0.247 | 0.000 |
| Female (%) | 0.239 | 0.000 | 0.474 | 0.000 | 0.247 | 0.006 |
| Male: 15-24 (%) | 0.261 | 0.000 | 0.219 | 0.000 | 0.260 | 0.091 |
| Male: 25-34 (%) | 0.418 | 0.001 | 0.387 | 0.001 | 0.238 | 0.000 |
| Male: 35-44 (%) | 0.158 | 0.000 | 0.305 | 0.000 | 0.431 | 0.000 |
| Male: 45-54 (%) | 0.232 | 0.000 | 0.223 | 0.000 | 0.291 | 0.000 |
| Male: 55-64 (%) | 0.313 | 0.000 | 0.277 | 0.000 | 0.074 | 0.000 |
| Male: 65-74 (%) | 0.213 | 0.000 | 0.400 | 0.788 | 0.172 | 0.000 |
| Male: 75-84 (%) | 0.314 | 0.000 | 0.350 | 0.435 | 0.323 | 0.000 |
| Male: >=85 (%) | 0.496 | 0.000 | 0.397 | 0.710 | 0.334 | 0.000 |
| Female: 15-24 (%) | 0.305 | 0.024 | 0.274 | 0.000 | 0.265 | 0.000 |
| Female: 25-34 (%) | 0.287 | 0.000 | 0.323 | 0.980 | 0.299 | 0.000 |
| Female: 35-44 (%) | 0.112 | 0.000 | 0.151 | 0.000 | 0.151 | 0.000 |
| Female: 45-54 (%) | 0.216 | 0.000 | 0.261 | 0.000 | 0.335 | 0.020 |
| Female: 55-64 (%) | 0.485 | 0.001 | 0.345 | 0.000 | 0.128 | 0.000 |
| Female: 65-74 (%) | 0.402 | 0.000 | 0.415 | 0.318 | 0.258 | 0.000 |

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**Table A.3 – continued from previous page**

| Covariate | G1 Adjusted | G1 Unadjusted | G2 Adjusted | G2 Unadjusted | G3 Adjusted | G3 Unadjusted |
|---|---|---|---|---|---|---|
| Female: 75-84 (%) | 0.500 | 0.000 | 0.507 | 0.345 | 0.396 | 0.000 |
| Female: >=85 (%) | 0.329 | 0.004 | 0.463 | 0.287 | 0.415 | 0.000 |
| Age: 15-24 (%) | 0.294 | 0.000 | 0.244 | 0.000 | 0.207 | 0.000 |
| Age: 25-34 (%) | 0.284 | 0.000 | 0.321 | 0.037 | 0.213 | 0.000 |
| Age: 35-44 (%) | 0.112 | 0.000 | 0.182 | 0.000 | 0.224 | 0.000 |
| Age: 45-54 (%) | 0.170 | 0.000 | 0.185 | 0.000 | 0.297 | 0.000 |
| Age: 55-64 (%) | 0.370 | 0.000 | 0.285 | 0.000 | 0.100 | 0.000 |
| Age: 65-74 (%) | 0.282 | 0.000 | 0.395 | 0.672 | 0.174 | 0.000 |
| Age: 75-84 (%) | 0.489 | 0.000 | 0.381 | 0.823 | 0.473 | 0.000 |
| Age: >=85 (%) | 0.435 | 0.000 | 0.422 | 0.372 | 0.450 | 0.000 |
| Race: White (%) | 0.011 | 0.000 | 0.305 | 0.000 | 0.079 | 0.000 |
| Race: Black (%) | 0.082 | 0.000 | 0.324 | 0.000 | 0.447 | 0.000 |
| Race: Native American (%) | 0.131 | 0.000 | 0.209 | 0.000 | 0.194 | 0.000 |
| Race: Asian (%) | 0.078 | 0.000 | 0.100 | 0.000 | 0.235 | 0.000 |
| Race: Hawaiian (%) | 0.406 | 0.001 | 0.316 | 0.000 | 0.375 | 0.000 |
| Race: Other (%) | 0.294 | 0.000 | 0.145 | 0.000 | 0.007 | 0.000 |
| Race: Two or More (%) | 0.358 | 0.466 | 0.193 | 0.000 | 0.134 | 0.000 |
| Family Households (%) | 0.259 | 0.587 | 0.277 | 0.191 | 0.350 | 0.062 |
| Married, Family Households (%) | 0.311 | 0.011 | 0.259 | 0.000 | 0.266 | 0.000 |
| Non-family Households (%) | 0.257 | 0.860 | 0.278 | 0.008 | 0.350 | 0.012 |
| Education: Less than High School (%) | 0.228 | 0.068 | 0.158 | 0.000 | 0.096 | 0.000 |
| Education: High School (%) | 0.153 | 0.000 | 0.188 | 0.000 | 0.351 | 0.005 |
| Education: Some College (%) | 0.157 | 0.000 | 0.378 | 0.005 | 0.233 | 0.000 |
| Education: College (%) | 0.153 | 0.000 | 0.146 | 0.000 | 0.356 | 0.236 |
| Education: Masters Degree (%) | 0.165 | 0.000 | 0.194 | 0.000 | 0.359 | 0.000 |
| Education: Professional Degree (%) | 0.181 | 0.000 | 0.240 | 0.000 | 0.507 | 0.066 |
| Education: PhD (%) | 0.198 | 0.000 | 0.198 | 0.000 | 0.300 | 0.000 |
| Industry: Military (%) | 0.030 | 0.000 | 0.240 | 0.000 | 0.383 | 0.000 |
| Employment (%) | 0.096 | 0.000 | 0.080 | 0.000 | 0.289 | 0.000 |
| Unemployment (%) | 0.182 | 0.000 | 0.231 | 0.000 | 0.293 | 0.713 |
| Industry: Agriculture (%) | 0.012 | 0.000 | 0.015 | 0.000 | 0.002 | 0.000 |
| Industry: Construction (%) | 0.439 | 0.602 | 0.367 | 0.003 | 0.374 | 0.014 |
| Industry: Manufacturing (%) | 0.105 | 0.000 | 0.318 | 0.000 | 0.310 | 0.000 |
| Industry: Wholesale (%) | 0.157 | 0.000 | 0.248 | 0.000 | 0.069 | 0.000 |
| Industry: Retail (%) | 0.287 | 0.005 | 0.459 | 0.260 | 0.301 | 0.102 |
| Industry: Transport (%) | 0.172 | 0.000 | 0.391 | 0.004 | 0.091 | 0.000 |
| Industry: Information (%) | 0.120 | 0.000 | 0.266 | 0.000 | 0.187 | 0.000 |

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**Table A.3 – continued from previous page**

| Covariate | G1 Adjusted | G1 Unadjusted | G2 Adjusted | G2 Unadjusted | G3 Adjusted | G3 Unadjusted |
|---|---|---|---|---|---|---|
| Industry: Finance (%) | 0.079 | 0.000 | 0.055 | 0.000 | 0.399 | 0.050 |
| Industry: Professional (%) | 0.111 | 0.000 | 0.144 | 0.000 | 0.266 | 0.954 |
| Industry: Education (%) | 0.236 | 0.000 | 0.160 | 0.000 | 0.276 | 0.000 |
| Industry: Arts and Recreation (%) | 0.310 | 0.561 | 0.308 | 0.000 | 0.292 | 0.000 |
| Industry: Other (%) | 0.174 | 0.000 | 0.458 | 0.201 | 0.263 | 0.000 |
| Industry: Public (%) | 0.106 | 0.000 | 0.343 | 0.000 | 0.152 | 0.000 |
| Income: <$10k (%) | 0.154 | 0.000 | 0.151 | 0.000 | 0.219 | 0.000 |
| Income: $10-$15k (%) | 0.115 | 0.000 | 0.146 | 0.000 | 0.232 | 0.000 |
| Income: $15-$20k (%) | 0.129 | 0.000 | 0.105 | 0.000 | 0.396 | 0.000 |
| Income: $20-$25k (%) | 0.130 | 0.000 | 0.100 | 0.000 | 0.366 | 0.018 |
| Income: $25-$30k (%) | 0.168 | 0.000 | 0.099 | 0.000 | 0.257 | 0.000 |
| Income: $30-$35k (%) | 0.168 | 0.000 | 0.181 | 0.000 | 0.271 | 0.003 |
| Income: $35-$40k (%) | 0.189 | 0.000 | 0.125 | 0.000 | 0.329 | 0.000 |
| Income: $45-$50k (%) | 0.173 | 0.000 | 0.203 | 0.000 | 0.343 | 0.014 |
| Income: $50-$55k (%) | 0.199 | 0.000 | 0.197 | 0.000 | 0.344 | 0.018 |
| Income: $50-$60k (%) | 0.396 | 0.000 | 0.244 | 0.000 | 0.308 | 0.034 |
| Income: $60-$75k (%) | 0.577 | 0.002 | 0.425 | 0.000 | 0.304 | 0.208 |
| Income: $75-$100k (%) | 0.221 | 0.006 | 0.332 | 0.000 | 0.409 | 0.041 |
| Income: $100-$125k (%) | 0.162 | 0.000 | 0.152 | 0.000 | 0.357 | 0.000 |
| Income: $125-$150k (%) | 0.147 | 0.000 | 0.111 | 0.000 | 0.312 | 0.000 |
| Income: $150-$200k (%) | 0.120 | 0.000 | 0.113 | 0.000 | 0.211 | 0.000 |
| Income: >$200k (%) | 0.145 | 0.000 | 0.154 | 0.000 | 0.310 | 0.000 |
| Median Household Income, Occupied housing units ($1,000s) | 0.317 | 0.009 | 0.194 | 0.000 | 0.352 | 0.192 |
| Median Household Income: Owner occupied ($1,000s) | 0.276 | 0.000 | 0.184 | 0.000 | 0.378 | 0.462 |
| Median Household Income: Renter occupied ($1,000s) | 0.276 | 0.000 | 0.184 | 0.000 | 0.378 | 0.462 |
| With interest, dividends, or net rental income (%) | 0.171 | 0.000 | 0.147 | 0.000 | 0.085 | 0.000 |
| No interest, dividends, or net rental income (%) | 0.163 | 0.004 | 0.147 | 0.000 | 0.085 | 0.000 |
| Own Housing Unit (%) | 0.338 | 0.000 | 0.126 | 0.000 | 0.045 | 0.000 |
| Single House (%) | 0.112 | 0.000 | 0.347 | 0.494 | 0.042 | 0.000 |
| Single, Detached House (%) | 0.105 | 0.000 | 0.310 | 0.618 | 0.053 | 0.000 |
| Single, Attached House (%) | 0.178 | 0.000 | 0.196 | 0.000 | 0.305 | 0.019 |
| Houseunits: 2 (%) | 0.236 | 0.117 | 0.320 | 0.162 | 0.442 | 0.003 |

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**Table A.3 – continued from previous page**

| Covariate | G1 Adjusted | G1 Unadjusted | G2 Adjusted | G2 Unadjusted | G3 Adjusted | G3 Unadjusted |
|---|---|---|---|---|---|---|
| Houseunits: 3-4 (%) | 0.348 | 0.001 | 0.233 | 0.001 | 0.216 | 0.000 |
| Houseunits: 5-9 (%) | 0.196 | 0.000 | 0.242 | 0.000 | 0.213 | 0.000 |
| Houseunits: 10-19 (%) | 0.133 | 0.000 | 0.332 | 0.000 | 0.029 | 0.000 |
| Houseunits: 20-49 (%) | 0.165 | 0.000 | 0.420 | 0.073 | 0.083 | 0.000 |
| Houseunits: >=50 (%) | 0.159 | 0.000 | 0.441 | 0.009 | 0.269 | 0.000 |
| Mobile House (%) | 0.113 | 0.000 | 0.227 | 0.000 | 0.228 | 0.000 |
| Houseboat or RV (%) | 0.226 | 0.000 | 0.440 | 0.002 | 0.230 | 0.000 |
| Primary heat source: Gas (%) | 0.091 | 0.000 | 0.149 | 0.000 | 0.362 | 0.831 |
| Primary heat source: Electric (%) | 0.443 | 0.000 | 0.398 | 0.193 | 0.405 | 0.000 |
| Primary heat source: Oil (%) | 0.079 | 0.000 | 0.199 | 0.000 | 0.102 | 0.000 |
| Primary heat source: Coal (%) | 0.036 | 0.000 | 0.107 | 0.000 | 0.008 | 0.000 |
| Primary heat source: Solar (%) | 0.442 | 0.000 | 0.417 | 0.152 | 0.302 | 0.000 |
| Primary heat source: Other (%) | 0.174 | 0.000 | 0.398 | 0.000 | 0.058 | 0.000 |
| Primary heat source: None (%) | 0.192 | 0.000 | 0.063 | 0.000 | 0.000 | 0.000 |
| House Value: Under $20k | 0.113 | 0.000 | 0.190 | 0.000 | 0.243 | 0.000 |
| House Value: $20-$50k (%) | 0.152 | 0.000 | 0.203 | 0.000 | 0.397 | 0.000 |
| House Value: $50-$100k (%) | 0.182 | 0.000 | 0.294 | 0.000 | 0.139 | 0.000 |
| House Value: $100-$150k (%) | 0.132 | 0.000 | 0.209 | 0.000 | 0.034 | 0.000 |
| House Value: $150-$300k (%) | 0.148 | 0.000 | 0.101 | 0.000 | 0.286 | 0.000 |
| House Value: $300-$500k (%) | 0.200 | 0.000 | 0.260 | 0.000 | 0.061 | 0.000 |
| House Value: $500-$750k (%) | 0.142 | 0.000 | 0.232 | 0.000 | 0.193 | 0.000 |
| House Value: $750-$1000k (%) | 0.198 | 0.000 | 0.201 | 0.000 | 0.309 | 0.570 |
| House Value: >$1000k (%) | 0.137 | 0.000 | 0.194 | 0.000 | 0.361 | 0.607 |
| Median House Value ($10,000s) | 0.157 | 0.000 | 0.161 | 0.000 | 0.220 | 0.000 |
| Median Rent ($1,000s) | 0.087 | 0.000 | 0.098 | 0.000 | 0.222 | 0.122 |
| Has Mortgage (%) | 0.070 | 0.000 | 0.166 | 0.000 | 0.239 | 0.000 |
| Has 2nd Mortgage (%) | 0.108 | 0.000 | 0.075 | 0.000 | 0.299 | 0.000 |
| Has Single Mortgage (%) | 0.196 | 0.000 | 0.381 | 0.325 | 0.134 | 0.000 |
| Below Poverty Line (%) | 0.120 | 0.000 | 0.119 | 0.000 | 0.339 | 0.006 |
| Commute: Auto (%) | 0.243 | 0.000 | 0.147 | 0.000 | 0.158 | 0.002 |
| Commute: Public Transport (%) | 0.020 | 0.000 | 0.103 | 0.000 | 0.253 | 0.000 |
| Commute: Motorcycle (%) | 0.438 | 0.000 | 0.496 | 0.085 | 0.381 | 0.000 |
| Commute: Bicycle (%) | 0.247 | 0.001 | 0.315 | 0.000 | 0.424 | 0.000 |
| Commute: Walk (%) | 0.337 | 0.702 | 0.272 | 0.784 | 0.318 | 0.509 |
| Commute: Other (%) | 0.226 | 0.000 | 0.449 | 0.004 | 0.347 | 0.000 |
| Work from home (%) | 0.312 | 0.000 | 0.262 | 0.000 | 0.197 | 0.000 |
| Work away from home (%) | 0.313 | 0.000 | 0.235 | 0.558 | 0.148 | 0.000 |

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**Table A.3 – continued from previous page**

| Covariate | G1 Adjusted | G1 Unadjusted | G2 Adjusted | G2 Unadjusted | G3 Adjusted | G3 Unadjusted |
|---|---|---|---|---|---|---|
| Commute: <10 minutes (%) | 0.066 | 0.000 | 0.100 | 0.000 | 0.081 | 0.000 |
| Commute: 10-19 minutes (%) | 0.098 | 0.000 | 0.111 | 0.000 | 0.153 | 0.000 |
| Commute: 20-29 minutes (%) | 0.190 | 0.000 | 0.248 | 0.097 | 0.245 | 0.001 |
| Commute: 30-39 minutes (%) | 0.062 | 0.000 | 0.317 | 0.000 | 0.229 | 0.000 |
| Commute: 40-59 minutes (%) | 0.077 | 0.000 | 0.182 | 0.000 | 0.304 | 0.000 |
| Commute: 60-89 minutes (%) | 0.078 | 0.000 | 0.242 | 0.000 | 0.312 | 0.000 |
| Commute: >90 minutes (%) | 0.297 | 0.177 | 0.160 | 0.007 | 0.314 | 0.000 |
| Same house 1 year ago (%) | 0.295 | 0.374 | 0.240 | 0.188 | 0.188 | 0.657 |
| Moved within same county last year (%) | 0.246 | 0.437 | 0.256 | 0.056 | 0.236 | 0.247 |
| Moved from different county within same state last year (%) | 0.245 | 0.317 | 0.352 | 0.717 | 0.111 | 0.527 |
| Moved from different state last year (%) | 0.289 | 0.054 | 0.495 | 0.272 | 0.276 | 0.415 |
| Moved from abroad last year (%) | 0.358 | 0.577 | 0.346 | 0.832 | 0.425 | 0.441 |
| Native-born (%) | 0.080 | 0.000 | 0.543 | 0.347 | 0.040 | 0.000 |
| Foreign Born (%) | 0.080 | 0.000 | 0.548 | 0.471 | 0.040 | 0.000 |
| Foreign Born: Naturalized (%) | 0.069 | 0.000 | 0.149 | 0.000 | 0.130 | 0.000 |
| Foreign Born: Not a Citizen (%) | 0.176 | 0.000 | 0.318 | 0.000 | 0.065 | 0.000 |
| Year of Entry for the Foreign-Born Population: 2010 or Later (%) | 0.475 | 0.697 | 0.294 | 0.000 | 0.236 | 0.000 |
| Year of Entry for the Foreign-Born Population: 2000 to 2009 (%) | 0.327 | 0.052 | 0.372 | 0.000 | 0.314 | 0.000 |
| Year of Entry for the Foreign-Born Population: 1990 to 1999 (%) | 0.370 | 0.000 | 0.380 | 0.000 | 0.364 | 0.381 |
| Year of Entry for the Foreign-Born Population: Before 1990 (%) | 0.533 | 0.016 | 0.282 | 0.000 | 0.251 | 0.000 |
| Education: MA or PhD (%) | 0.173 | 0.000 | 0.205 | 0.000 | 0.357 | 0.000 |
| Education: Some College (%) | 0.267 | 0.410 | 0.187 | 0.000 | 0.151 | 0.000 |
| Income: $10-$30k (%) | 0.098 | 0.000 | 0.121 | 0.000 | 0.521 | 0.000 |
| Income: $30-$50k (%) | 0.188 | 0.000 | 0.133 | 0.000 | 0.244 | 0.000 |
| Income: $50-$100k (%) | 0.412 | 0.008 | 0.409 | 0.005 | 0.305 | 0.823 |
| Income: $100-$200k (%) | 0.125 | 0.000 | 0.098 | 0.000 | 0.309 | 0.000 |
| Moved in past year: Less than high school (%) | 0.188 | 0.000 | 0.138 | 0.000 | 0.288 | 0.000 |
| Moved in past year: College degree (%) | 0.228 | 0.628 | 0.170 | 0.000 | 0.256 | 0.000 |

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**Table A.3 – continued from previous page**

| Covariate | G1 Adjusted | G1 Unadjusted | G2 Adjusted | G2 Unadjusted | G3 Adjusted | G3 Unadjusted |
|---|---|---|---|---|---|---|
| Moved in past year: Grad or Prof Degree (%) | 0.188 | 0.000 | 0.167 | 0.000 | 0.248 | 0.000 |
| Commute by Auto, Alone: Income $10-$35k (%) | 0.301 | 0.000 | 0.144 | 0.000 | 0.128 | 0.000 |
| Commute by Auto, Alone: Income $35-$75k (%) | 0.230 | 0.300 | 0.385 | 0.400 | 0.391 | 0.854 |
| Commute by Auto, Alone: Income >$75k (%) | 0.164 | 0.000 | 0.097 | 0.000 | 0.351 | 0.000 |
| Commute by Auto, Carpool: Income $10-$35k (%) | 0.296 | 0.000 | 0.286 | 0.000 | 0.309 | 0.132 |
| Commute by Auto, Carpool: Income $35-$75k (%) | 0.315 | 0.239 | 0.311 | 0.000 | 0.276 | 0.000 |
| Commute by Auto, Carpool: Income >$75k (%) | 0.169 | 0.000 | 0.101 | 0.000 | 0.099 | 0.000 |
| Commute by Auto: Under 15min (%) | 0.091 | 0.000 | 0.237 | 0.000 | 0.259 | 0.000 |
| Commute by Auto: 15-30min (%) | 0.258 | 0.000 | 0.229 | 0.210 | 0.297 | 0.010 |
| Commute by Auto: 30-60min (%) | 0.082 | 0.000 | 0.290 | 0.000 | 0.168 | 0.000 |
| Commute by Auto: Over 60min (%) | 0.139 | 0.000 | 0.223 | 0.000 | 0.220 | 0.377 |
| Leave Home 5-6am (%) | 0.222 | 0.000 | 0.209 | 0.000 | 0.360 | 0.096 |
| Leave Home 6-7am (%) | 0.411 | 0.000 | 0.286 | 0.000 | 0.301 | 0.019 |
| Leave Home 7-8am (%) | 0.265 | 0.177 | 0.296 | 0.000 | 0.378 | 0.000 |
| Leave Home 8-9am (%) | 0.147 | 0.000 | 0.142 | 0.000 | 0.423 | 0.010 |
| Leave Home 9-10am (%) | 0.204 | 0.000 | 0.207 | 0.000 | 0.371 | 0.000 |
| Leave Home 10am-noon (%) | 0.145 | 0.000 | 0.264 | 0.000 | 0.358 | 0.000 |
| Leave Home noon-4pm (%) | 0.377 | 0.965 | 0.501 | 0.493 | 0.327 | 0.461 |
| Leave Home 4pm-12am (%) | 0.350 | 0.009 | 0.412 | 0.000 | 0.355 | 0.143 |
| Number of Bottlenecks | 0.149 | 0.000 | 0.501 | 0.196 | 0.144 | 0.000 |
| Annual Average Daily Traffic Volume | 0.207 | 0.000 | 0.565 | 0.328 | 0.220 | 0.000 |

Table A.4: Second Stage Results by Vehicle Technology

| | (1)<br>PEV | (2)<br>BEV | (3)<br>PHEV |
|---|---|---|---|
| N | 0.365*** | 0.202*** | 0.164*** |
| | (0.036) | (0.022) | (0.016) |
| $N^2$ | -0.001*** | -0.0007*** | -0.0005*** |
| | (0.0001) | (7e-05) | (6e-05) |
| $N^3$ | 8e-07*** | 6e-07*** | 2e-07** |
| | (2e-07) | (1e-07) | (1e-07) |
| lnGPS | -0.137*** | -0.057 | -0.081*** |
| | (0.048) | (0.038) | (0.017) |
| $\text{lnGPS}^2$ | -0.036*** | -0.024*** | -0.012*** |
| | (0.009) | (0.006) | (0.004) |
| $\text{lnGPS}^3$ | -0.0006*** | -0.0004*** | -0.0002** |
| | (0.0002) | (0.0001) | (0.0001) |
| N*lnGPS | 0.032*** | 0.017*** | 0.014*** |
| | (0.007) | (0.004) | (0.003) |
| $N^2$*lnGPS | -6e-05*** | -3e-05*** | -3e-05*** |
| | (1e-05) | (7e-06) | (6e-06) |
| N*$\text{lnGPS}^2$ | 0.0008*** | 0.0005*** | 0.0003*** |
| | (0.0002) | (0.0001) | (9e-05) |
| Constant | 3.120*** | 1.569*** | 1.551*** |
| | (0.288) | (0.228) | (0.102) |
| Observations | 7,772 | 7,772 | 7,772 |
| $R^2$ | 0.105 | 0.074 | 0.113 |

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table A.5: OLS Results

| | Lasso-Selected | Intuition-Selected |
|---|---|---|
| HOV Lanes within 30-mile Radius | 0.001 | -0.011* |
| | (-0.004) | (-0.006) |
| Cumulative Hybrid Registrations | 0.129** | |
| | (-0.051) | |
| Level 2 Chargers (5-mile Radius) | -0.007 | 0.009 |
| | (-0.007) | (-0.008) |
| Level 1 Chargers (20-mile Radius) | -0.014 | |
| | (-0.010) | |
| Level 2 Chargers (20-mile Radius) | 0.006*** | |
| | (-0.002) | |
| DC Chargers (20-mile Radius) | 0.156* | |
| | (-0.079) | |
| Prop 23 Vote, % of District Voting "Yes" | -2.924 | -2.729 |
| | (-3.683) | (-4.501) |
| Avg Gas Price ($) | -1.721 | 0.345 |
| | (-2.412) | (-4.937) |
| Population Density (per sq. mile) | -9e-05*** | -0.0002*** |
| | (-0.00002) | (-0.00007) |
| Number of bottlenecks | 0.159* | 0.291 |
| | (-0.081) | (-0.272) |
| Race: White (%) | -1.354 | |
| | (-2.071) | |
| Race: Hawaiian (%) | -24.250*** | |
| | (-7.085) | |
| Race: Other (%) | -2.575 | |
| | (-1.847) | |
| Race: Two or More (%) | -0.048 | |
| | (-3.112) | |
| Industry: Agriculture (%) | -2.427 | -16.170** |
| | (-5.351) | (-7.962) |
| Industry: Construction (%) | -12.400** | |
| | (-5.241) | |
| Industry: Manufacturing (%) | 37.050** | |
| | (-15.570) | |
| Industry: Wholesale (%) | 3.294 | |
| | (-9.812) | |
| Industry: Transport (%) | -28.150** | |
| | (-10.620) | |
| Industry: Information (%) | -18.290 | |
| | (-12.670) | |

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**Table A.5 – continued from previous page**

| | Lasso-Selected | Intuition-Selected |
|---|---|---|
| Industry: Professional (%) | 13.880* | |
| | (-7.465) | |
| Industry: Public (%) | -25.540** | |
| | (-10.790) | |
| Households: With interest, dividends, or net rental income (%) | 16.910*** | |
| | (-5.054) | |
| Houseunits: 2 (%) | -4.626 | |
| | (-6.177) | |
| Houseunits: 3-4 (%) | -4.505** | |
| | (-2.249) | |
| Primary heat source: Electric (%) | -0.836 | |
| | (-1.356) | |
| Primary heat source: Coal (%) | -2.606 | |
| | (-3.317) | |
| Primary heat source: Solar (%) | -4.753 | |
| | (-25.000) | |
| Primary heat source: Other (%) | -18.100*** | |
| | (-6.542) | |
| Primary heat source: None (%) | -5.721*** | |
| | (-1.502) | |
| House Value: \$50-\$100k (%) | -15.480*** | |
| | (-2.640) | |
| House Value: \$100-\$150k (%) | -10.400*** | |
| | (-1.633) | |
| House Value: \$150-\$300k (%) | -15.500*** | |
| | (-2.394) | |
| House Value: \$300-\$500k (%) | -17.740*** | |
| | (-2.452) | |
| House Value: \$500-\$750k (%) | -18.630*** | |
| | (-3.028) | |
| Commute: Public Transport (%) | -7.863* | -11.250 |
| | (-4.322) | (-9.662) |
| Commute: 10-19 minutes (%) | -3.254 | |
| | (-2.684) | |
| Commute: 20-29 minutes (%) | -4.620 | |
| | (-3.390) | |
| Commute: 30-39 minutes (%) | 3.130 | |
| | (-4.454) | |
| Commute: 40-59 minutes (%) | 5.967* | |
| | (-3.396) | |
| Commute: 60-89 minutes (%) | 4.527 | |

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**Table A.5 – continued from previous page**

| | Lasso-Selected | Intuition-Selected |
|---|---|---|
| | (-4.109) | |
| Native-born (%) | -3.737 | |
| | (-3.781) | |
| Foreign Born: Naturalized Citizen (%) | -10.870** | |
| | (-5.296) | |
| Year Of Entry For The Foreign-Born Population: 2000 to 2009 (%) | -2.580 | |
| | (-1.819) | |
| Year Of Entry For The Foreign-Born Population: Before 1990 (%) | -2.810* | |
| | (-1.631) | |
| Commute by Auto, Carpool: Income $35-$75k (%) | -0.013*** | |
| | (-0.004) | |
| Commute by Auto, Carpool: Income >$75k (%) | 0.038*** | |
| | (-0.010) | |
| Commute by Auto: 15-30min (%) | 0.003 | 0.002** |
| | (-0.002) | (-0.001) |
| Leave Home 7-8am (%) | 0.002* | |
| | (-0.001) | |
| Median House Value ($10,000s) | | 0.348*** |
| | | (-0.049) |
| Median Rent ($1,000s) | | 3.942*** |
| | | (-0.644) |
| Income: $10-$30k (%) | | 5.041 |
| | | (-3.318) |
| Income: $100-$200k (%) | | -1.675 |
| | | (-2.861) |
| Education: College or Some College (%) | | -5.753 |
| | | (-4.319) |
| Commute by Auto: 30-60min (%) | | 0.009*** |
| | | (-0.002) |
| Single House (%) | | -1.431*** |
| | | (-0.407) |
| Constant | 24.840*** | -10.700 |
| | (-8.723) | (-19.620) |
| Observations | 7,836 | 7,902 |
| R-squared | 0.700 | 0.451 |

Standard errors in parentheses are clustered at the county level.
*** p<0.01, ** p<0.05, * p<0.1