HYBRID ELECTRIC VEHICLE OWNERSHIP AND FUEL ECONOMY ACROSS TEXAS: AN APPLICATION OF SPATIAL MODELS

Prateek Bansal
Graduate Research Assistant
Department of Civil, Architectural and Environmental Engineering
The University of Texas at Austin
prateekbansal@utexas.edu

Kara M. Kockelman
(Corresponding author)
E.P. Schoch Professor in Engineering
Department of Civil, Architectural and Environmental Engineering
The University of Texas at Austin
kkockelm@mail.utexas.edu
Phone: 512-471-0210

Yiyi Wang
Assistant Professor
Montana State University
Civil Engineering Department
yiyi.wang@ce.montana.edu

The following paper is a pre-print, the fnal publication can be found in the *Transportation Research Record* No. 2495: 53-64, 2015.

ABSTRACT

Policymakers, transport planners, automobile manufacturers, and others are interested in the factors that affect adoption rates of electric vehicles and more fuel efficient vehicles. Using Census-tract-level data and registered vehicle counts across Texas counties in 2010, this study investigated the impact of various built environment and demographic attributes, including land use balance, employment density, population densities, median age, gender, race, education, household size, and income. To allow for spatial autocorrelation (across census tracts) in unobserved components of vehicle counts by tract, as well as cross-response correlation (both spatial and local/aspatial in nature), models of ownership levels (vehicle counts, by vehicle type and fuel economy level) were estimated using bivariate and trivariate Poisson-lognormal conditional autoregressive models. The presence of high spatial autocorrelations and local cross-response correlations is consistent in all models, across all counties studied. Fuel-efficient-vehicle ownership rates were found to rise with household incomes, resident education levels, and the share of male residents, and fall in the presence of larger household sizes and higher jobs densities.

The average fuel economy of each tract's light-duty vehicles were also analyzed, using a spatial error model, across all Texas tracts; and this variable was found to depend most on educational attainment levels, median age, income, and household size variables, though all covariates used were statistically significant. If households registering more fuel-efficient vehicles, including hybrid EVs, are also more inclined to purchase plug-in EVs, these findings can assist in spatial planning of charging infrastructure as well as other calculations (such as gas-tax revenue implications).

Key Words: electric vehicles, fuel economy, vehicle ownership, spatial econometric models

INTRODUCTION

Many worry about the world's continuing reliance on petroleum as a transportation fuel, with various air quality impacts and energy security issues. Fuel economy is a salient feature of automobiles, and fuel-efficient hybrid electric vehicles (HEVs) are achieving some marketplace success (Keith 2012, Chen et al. 2014, Paul et al. 2011, Dijk et al. 2013). For example, 495,000 HEVs were sold in the United States in 2013, with over 1.5 million sold worldwide (EVs Roll 2014). Only 96,000 plug-in EVs (PEVs) were sold in the US in 2013, which includes 47,700 battery-only EVs (EVs Roll 2014), so the PEV future is less certain. Since market success depends on consumer response, understanding the factors that affect purchase and use of more fuel efficient and electric vehicles becomes crucial for sales and use forecasts, as well as energy and environmental policies (Koo et al. 2012).

While EV sales (including both HEVs and PEVs) have risen considerably in the United States over the past decade, high adoption rates tend to concentrate in a relatively few cities and neighborhoods. In the case of Texas, Figure 1 shows how HEV ownership rates (per 1,000 registered light-duty vehicles [LDVs]) concentrate in the state's biggest cities/regions: San Antonio, Austin, Dallas-Ft. Worth, and Houston. (Since almost no PEVs were registered in Texas in year 2010 [according to the vehicle decoder used on the DMV database], only HEV counts were non-negligible in the 2010 Texas data sets, and thus analyzed separately from conventional vehicles here.) Within these regions, spatial variation is striking (Figure 1). Understanding of the factors behind such variations provides direction for policymaking, planning, production, and marketing.

One reason for the clustering in HEV ownership rates is presumably spatial correlation in local government incentives and marketing, demographics, and land use patterns (Kodjak 2012, Chen et al. 2014). Another reason for the clustering relates to the theory of social contagion, with consumers more likely to buy EVs if they see them regularly, on nearby roads, in neighbor's driveways, and being driven by their friends and colleagues (Axsen and Kurani 2011). Positive contagion feedbacks can intensify to create adoption inhomogeneity at different scales.

This study's first two models employ a multivariate conditional autoregressive (MCAR) specification (as developed by Wang and Kockelman [2013] and applied in Chen et al. [2014]) to understand many of the factors responsible for adoption rates of HEVs and other classes (based on fuel economy) of LDVs across Texas' major cities, while recognizing correlations that emerge over space across vehicle ownership types. The paper's bivariate model (Model 1) estimates counts of HEVs vs. non-HEV passenger vehicles in each of the four largest counties of Texas' top 4 regions. The trivariate model (Model 2) examines tract-level registration numbers in each of 3 fuel-economy-based vehicle classes (fuel efficient [>25 mi/gal], regular [15 to 25 mi/gal], and fuel inefficient [≤15 mi/gal]). A third model (Model 3) is of average fuel economy, across all census tracts of Texas, and so relies on a continuous-response spatial error model for spatial autocorrelation (Wall 2004, Kissling et al. 2008, and Anselin 1988).

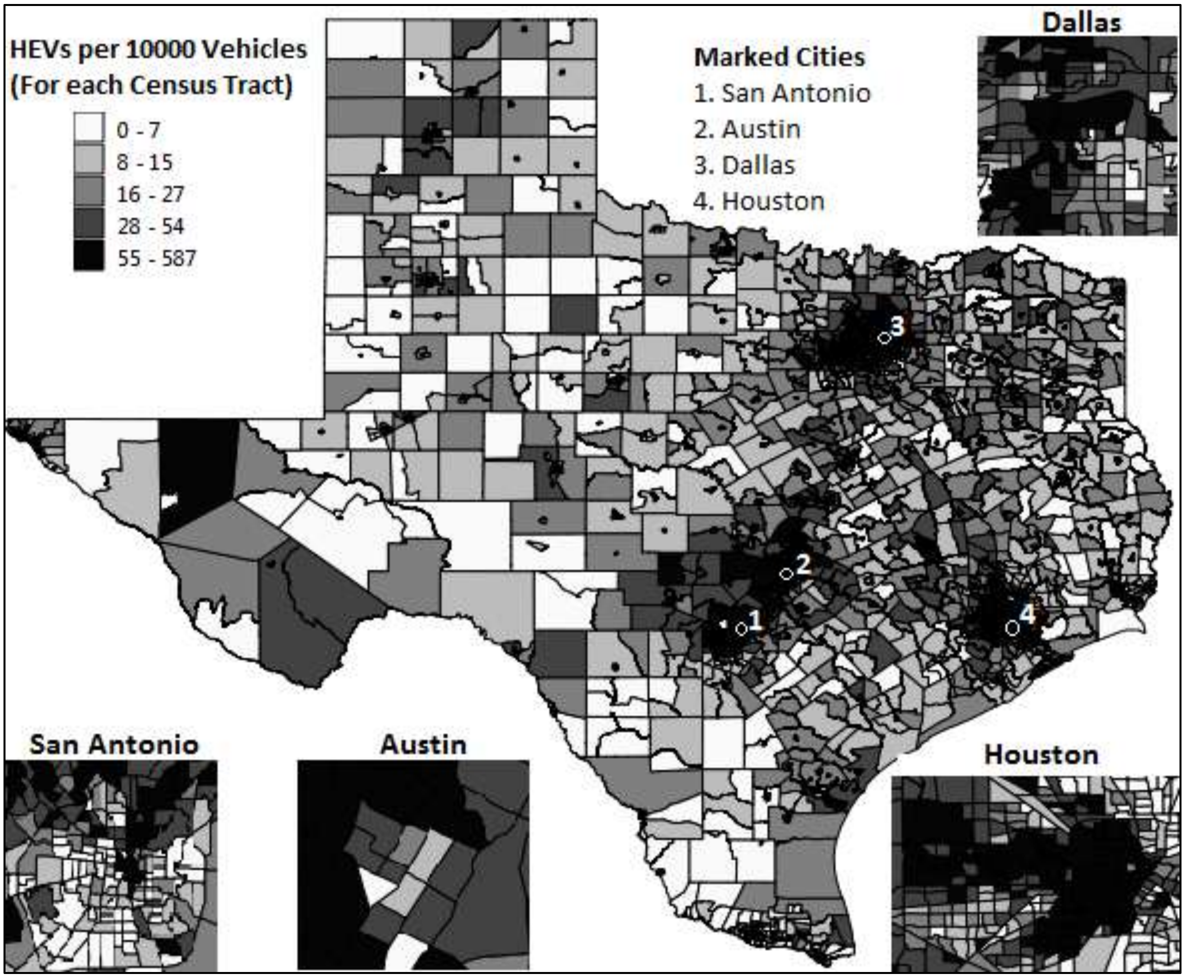

FIGURE 1. HEV Adoption Rates in Year 2010 HEV counts per 10,000 light-duty vehicles across Texas Census Tracts (using Texas Department of Motor Vehicles registration data, 2010)

BACKGROUND AND LITERATURE REVIEW

Several researchers have developed choice models to identify key factors encouraging EV and other vehicle purchases. For example, Li et al. (2013) used a bivariate probit model to find that consumers with environmentally-relevant information (from the Internet or friends) were more likely to purchase HEVsthan flex-fuel vehicles, whereas males, those driving more miles, and those registered as Republicans were less inclined. He et al.'s (2012) hierarchical choice model analysis of the U.S. National Household Travel Survey (NHTS) 2009 and Vehicle Quality Survey data found that those primarily making local trips (versus highway-based trips) and those with higher education have a more positive attitude toward buying an HEV. Caulfield's (2010) survey of an Irish car company's new customers suggest that preferences depend significantly on vehicle price, reliability, safety, and fuel costs. Liu (2014) estimated that U.S. consumers are willing to pay, on average, from $960 to $1720 more (depending on their income category) for HEVs, which is lower than an HEV's typical price premium. Jenn et al. (2013) estimated that the Energy Policy Act of 2005 caused a 4.6% increase in U.S. HEV sales for every $1000 incentive provided (per HEV). Liu (2014) concluded that offering $1000 and $3000 tax savings would increase U.S. HEV sales by 4% and over 13% respectively. Using a 5% discount rate, Tuttle and Kockelman (2012) estimated that gas prices above approximately $5.90, $5.00, and $3.75 per gallon are estimated to make the Leaf, Volt, and Prius-PHEV (as offered in year 2011) more financially attractive, respectively, than their conventional counterparts - without any credits. In Musti and Kockelman's (2011) survey, 76% of Austinites (with sample weighted to reflect true local population) stated that fuel economy lies in their top three criteria for vehicle purchase, and 56% claimed they would consider purchasing a plug-in HEV if it were to cost $6,000 more than its internal combustion counterpart (vs. just 36% of all *U.S.* respondents in Paul et al.'s [2011] follow-up survey).

Very few studies have explored spatial variations and neighborhood effects in HEV adoption rates. Keith et al. (2012) developed a spatial diffusion model to understand the reasons behind high-adoption clusters of the Toyota Prius HEV across the United States. For greatest impact or sales increases, they concluded that HEV adoption should be incentivized in regions already exhibiting strong adoption. Chen et al. (2014) employed an MCAR model to anticipate LDV registration counts of the Prius HEV, other EVs, and conventional (internal combustion) vehicles across 1000 census block groups in the city of Philadelphia. They found that more central/core zones and those with more higher-income households have higher EV ownership rates, and that spatial correlations exist in unobserved terms (not controlled for by their set of eleven covariates).

Auto purchases by individuals are arguably not as rational as those by fleet managers, who have the time and expertise to do rigorous net present valuations. To understand Americans' willingness to pay for fuel savings, Greene et al. (2013) surveyed 1000 US households four times: in 2004, 2011, 2012 and 2013. Each time, they estimated that US car buyers expect fuel economy savings to payback up-front vehicle costs in just 3 years, suggesting consumer myopia, significant risk aversion (to car loss, rather than gas price increases), and/or a very high personal discount rate (on a vehicle's future benefits). They argue that accuracy of fuel economy information is extremely important, because its uncertainty leads loss-averse consumers to significantly undervalue fuel savings. In some contrast, Koo et al. (2012) calibrated mixed logit and mixed multiple discrete continuous extreme value (MDCEV) models for Koreans' recent vehicle purchases, and concluded that Koreans tend to care most about fuel economy. Axsen and Kurani (2013) found that new-vehicle buyers in California prefer HEVs and PEVs, not only because of their functional benefits (e.g., lowered gasoline use and emissions), but also due to their image association (with intelligence, responsibility, and support for the environment and national energy security).

As noted above, most studies on vehicle choice are disaggregated in nature. Few studies have explored spatial variations in adoption rates or have worked with complete samples. This study employs rigorous and behaviorally plausible spatial models to better illuminate overall factors that affect fuel economy choices and adoption rates of HEVs and other LDVs across much of the U.S.'s second largest state.

DATA DESCRIPTION

This study uses the Texas Department of Motor Vehicles' (DMV's) vehicle registration counts for year 2010. This database includes all registered vehicles in Texas, from cement trucks and combines harvesters to passenger cars and motorized scooters. The fuel type and fuel economy of vehicles were added to the DMV data using a vehicle identification number (VIN) decoder, as purchased by Texas A&M University's Dr. Steve Puller, and able to decode all vehicles with model years newer than 1980. To provide anonymity to households, the final data set shows only total vehicle counts by fuel type (hybrid, diesel, flex fuel, and gasoline) and fuel economy (miles per gallon, MI/GAL) across Texas census tracts.

Out of the state's 22.81 million registered-vehicle records, the LDV decoder was able to match 17.35M vehicles to fuel information, leaving 5.19 million unmatched due to an early model year (before 1981) or commercial-vehicle status (heavy- and medium-duty trucks and agricultural equipment that sometimes runs on roadways. The VIN decoder also placed all plug-in HEVs and battery EVs in the "unknown" category. For another 205,630 vehicle records (0.90% of the database), fuel type was identified but not census tract, and for another 63,296 vehicle records (0.28% of registered vehicles), neither tract nor fuel information was matched.

Puller's team coded the 2010 vehicles to the U.S. census tract system of year 2000 (in order to map to census income data). For consistency in covariate timing, the count data were transferred to the year 2010's system using a census tract relationship file (US Census Bureau 2010). Texas' tract counts in years 2000 and 2010 were 4388 and 5265, respectively; so 2010 tracts are somewhat smaller, reflecting a higher year 2010 state population (25.1M in 2010 versus 20.8M in 2000). 2200 of the year-2000 census tracts remained intact, while the rest split or merged. Vehicle counts in modified tracts come from a population-weighted average of year-2000 person counts.

This study relies on three models of vehicle type and fuel economy. The first two are multivariate models for vehicle counts by type: Model 1 is a bivariate model with HEV and non-HEV counts (in each census tract) as the response variables. Model 2 is a trivariate model with vehicle counts in three fuel economy bins as the response variables. Model 2's three fuel economy levels are determined by thresholds one standard deviation (4.81 mi/gal) away from the mean fuel economy (19.30 mi/gal) for the state's entire LDV fleet. After rounding those thresholds, the bins' cut points are 15 mi/gal and 25 mi/gal. The vehicles falling into these low, medium and high fuel economy categories are referred to here as "fuel inefficient", "regular" (fuel economy), and "fuel efficient" vehicles, respectively. Finally, Model 3 relies on a single, continuous response variable, average fuel economy per tract, along with a spatial error model (Cressie 1993 and Anselin 1988). Figure 2 shows a histogram of fuel economy across Texas's LDV fleet, as registered in the year 2010.

The model's covariates mainly capture census-tract-level demographic attributes, like average age, gender, race, household size, education, population density, number of commuting workers, and income. These tract-level covariates come from the U.S. Census of Population 2010 database (which offers a complete sample of many variables) and the 2010 American Community Survey (ACS) estimates (which samples a share of households every year, for a host of additional variables). 5,188 Census tracts (out of Texas's 5,265 tracts) offered complete data for the aforementioned covariates and response variables. Jobs density and land use balance[1] variables were also obtained for Travis County from the Capital Area Metropolitan Planning Organization. Table 1 provides summary statistics of all census tract level variables. Since vehicle counts should (in theory) scale with population counts (e.g., one may expect a doubling in vehicle registrations when tract population is doubled), tract population variable is used an exposure variable for the count models. Due to this scaling, many covariates are controlled for as fractions, rather than as counts.

---

[1] Land use balance was computed using the following entropy term (from Cervero and Kockelman [1997]): $-\left(\sum_{k=1}^{4} p_k \log p_k\right)/\ln(4)$, where p_k is the proportion of land use type k (including residential, commercial, office, and industry uses) in the tract. An equal or uniform balance (with 25% of land falling into each of the four categories) yields the maximum entropy value of 1.

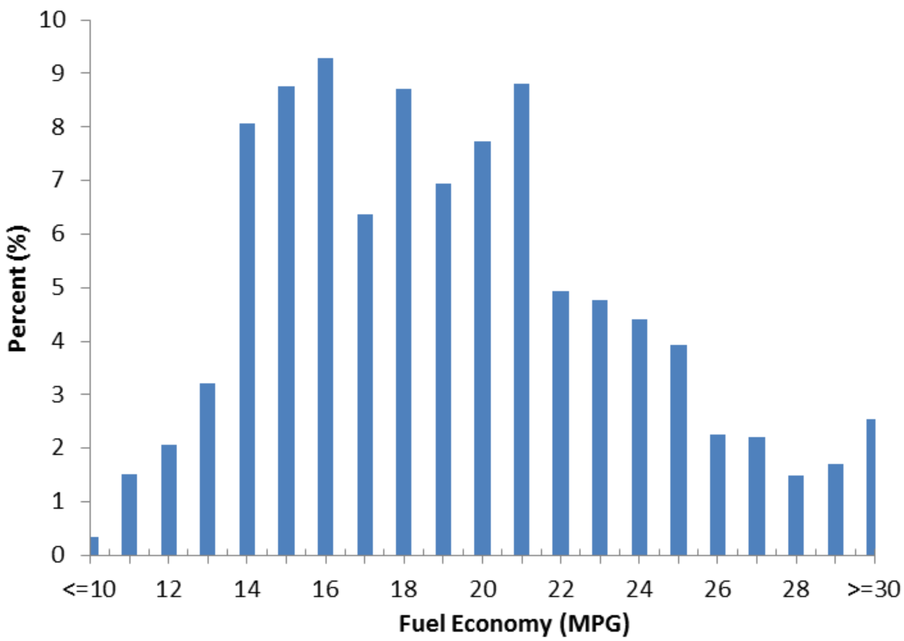

FIGURE 2. Histogram of Fuel Economy across All Registered Light-duty Vehicles in Texas (2010)

TABLE 1. Summary Statistics of Model Variables at Census Tract Level across Texas (2010)

Variable Name	**Mean**	**Median**	**Std. Dev.**	**Min**	**Max**
Dependent Variables					
Vehicle Count (# LDVs per tract)	3,336	2,968	2,134	74	51,399
Model 1					
# Hybrid EVs in tract	16.56	9.50	21.88	0	500
# Non-Hybrid LDVs in tract	3,320	2,956	2,122	74	50,993
Model 2					
# Fuel efficient LDVs (≥25 mi/gal)	470.3	403	523.2	0	22,715
# Regular LDVs (≥15 mi/gal & <25 mi/gal)	2,358	2,103	1,454	43	26,003
# Fuel inefficient vehicles (<15 mi/gal)	507.4	450	292.0	15	3,429
Model 3					
Average fuel economy of tract's LDVs (mi/gal)	19.23	19.19	0.825	16.70	23.07
Covariates (all Texas Census tracts)					
Total population of tract (exposure variable)	4,841	4,457	2,450	85	34,354
Fraction of population 16 years old or younger	0.236	0.238	0.059	0	0.515
Median age (years)	35.18	34.40	6.562	14.90	71.30
Male fraction	0.495	0.492	0.033	0.313	0.987
African American fraction	0.119	0.058	0.164	0	0.963
Average household size (# persons)	2.77	2.73	0.50	1.31	4.84
Fraction of pop. with Bachelor's degree or higher	0.248	0.188	0.191	0	0.893
Population density (per square mile)	3,103	2,451	3,288	0.1271	68,892
Fraction of workers commuting by driving	0.783	0.800	0.091	0.118	1
Mean household income (dollars per year, in 2010)	66,416	57,637	36,273	12,821	445,620
Fraction of households with income over $100,000	0.186	0.135	0.166	0	1
Fraction of families below poverty level	0.144	0.111	0.124	0	1
Additional Covariates (for Travis County tracts)					
Land use balance	0.645	0.712	0.229	0.036	0.988
Employment density (jobs per square mile)	1200.1	704.2	1379.2	1.5	7655.2

MODEL SPECIFICATION

Since Models 1 and 2 have bivariate and trivariate count values as response vectors, and the data are highly spatial in nature, Wang and Kockelman's (2013) Poisson-lognormal MCAR model specification was applied here. This model quantifies the contributions of tract-level heterogeneity, spatial dependence in error terms (unobserved attributes) for the same count type, and aspatial and spatially-lagged correlations across response types. The Model 1 specification is presented here, and Model 2's analogous specification can be found in Wang and Kockelman (2013). The first stage of these specifications can be expressed as a Poisson process:

$$y_{ik} \sim \text{Poisson}(\lambda_{ik}) \tag{1}$$

where y_{ik} is the observed vehicle count by vehicle type (*k* = 1 for HEVs and *k* = 2 for conventional passenger vehicles) for the i^{th} census tract of Texas, and the expected vehicle counts(λ_{ik}) for each vehicle type and tract are defined in the second step, as follows:

$$\ln(\lambda_{ik}) = \ln(E_{ik}) + \boldsymbol{x}_i{}'\boldsymbol{\beta_k} + \phi_{ik} + u_i \tag{2}$$

where E_{ik} is an exposure term (population of each census tract in this case), $\boldsymbol{x_i}$ is a column vector of covariates for the i^{th} census tract, $\boldsymbol{\beta}_k$ is a column vector of parameters specific to vehicle type *k*, ϕ_{ik} indicates the MCAR model's spatial random effects (shown in Equation 3), and u_i captures tract-specific heterogeneity or latent variations (not explained by spatial effects). The random error term, ϕ_{ik} captures spatial dependence, as measured by ρ_1 and ρ_2 in Equations 4 and 5, which are specific to each vehicle type. The model's overall covariance structure allows for aspatial and spatially-lagged correlations between error terms (unobserved effects) for the two vehicle types, as shown in Equations 3 to 5.

$$\begin{pmatrix}\boldsymbol{\phi_1}\\ \boldsymbol{\phi_2}\end{pmatrix} \sim N\left(\begin{pmatrix}\boldsymbol{0}\\ \boldsymbol{0}\end{pmatrix}, \begin{pmatrix}\boldsymbol{\Sigma}_{11} & \boldsymbol{\Sigma}_{12}\\ \boldsymbol{\Sigma}_{12}' & \boldsymbol{\Sigma}_{22}\end{pmatrix}\right) \tag{3}$$

where $\boldsymbol{\phi}_k$ is a *n* by 1 vector containing the spatial random effects across *n* census tracts for vehicle type *k*, and $\boldsymbol{\Sigma}_{kl}$ is the matrix of covariance terms across vehicle types *k* and *l*.

The spatial MCAR structure was constructed using a series of conditional distributions, expressed as follows:

$$\boldsymbol{\phi}_2 \sim N(\boldsymbol{0}, [(\boldsymbol{D} - \rho_2\boldsymbol{W})\tau_2]^{-1}) \tag{4}$$

$$\boldsymbol{\phi}_1 | \boldsymbol{\phi}_2 \sim N(\boldsymbol{A}\boldsymbol{\phi}_2, [(\boldsymbol{D} - \rho_1\boldsymbol{W})\tau_1]^{-1}) \tag{5}$$

where $\boldsymbol{D} = diag(m_i)$, with m_i denoting the number of neighbors for the i^{th} census tract, $\boldsymbol{W}$ is a second-order contiguity matrix (where all $W_{ii} = 0$, while $W_{ij} = 1$ if *i* and *j* share a common border and W_{ik} =1 if *j* and *k* share a common border, else $W_{ij} = 0$), τ_i is a scaling parameter for the covariance matrix of the i^{th} vehicle type, and ρ_i is a measure of spatial autocorrelation in error terms for counts of the i^{th} vehicle type (across tracts), Finally, $\boldsymbol{A}$ is a transformation matrix, which can be written as follows:

$$\boldsymbol{A} = \eta_0\boldsymbol{I} + \eta_1\boldsymbol{W} \tag{6}$$

Using Equations 5 and 6, $\boldsymbol{\phi}_1$'s conditional mean can be written as follows:

$$E(\boldsymbol{\phi}_1|\boldsymbol{\phi}_2) = (\eta_0\boldsymbol{I} + \eta_1\boldsymbol{W})\boldsymbol{\phi}_2 \tag{7}$$

where η_0 and η_1 are called the bridging parameters, since they associate ϕ_{i1} and ϕ_{i2} (for aspatial cross-response correlations within the same tract) and ϕ_{j2} (for spatially-lagged cross-response correlations). In other words, the conditional mean of $\boldsymbol{\phi}_{i1}$ is a weighted average of neighboring $\boldsymbol{\phi}_{j2}$ values, along with a scaled $\boldsymbol{\phi}_{i2}$ value at its own location.

Vehicle-count models 1 and 2 were implemented using a combination of R programming language and WinBUGS software. The model parameters were estimated using Bayesian Markov-chain Monte Carlo (MCMC) sampling techniques. Due to the complex nature of this multivariate sampling with spatial autocorrelation, it was not possible to estimate model parameters for all 5188 census tracts across Texas simultaneously. Moreover, spatial effects in vehicle ownership patterns are also expected to die out over miles of separation (after controlling for demographics and other local attributes). Therefore, the most populous counties in the state's 4 most populous regions were used to deliver a suite of separate models. These comprise the counties of Harris (with 780 tracts covering the central Houston region), Dallas (526 tracts), Bexar (361 tracts in central San Antonio), and Travis[2] (215 tracts in central Austin).

As noted earlier, a relatively standard spatial-error specification (Cressie 1993, Anselin 1988) was employed for Model 3, in order to predict the average fuel economy of LDVs in each tract. Thanks to the continuous nature of the response variable (average fuel economy), sample size is not an issue, and this model was estimable using all census tracts across Texas (n = 5,188). Model 3's parameters were estimated using classical maximum likelihood estimation techniques, via the R programming language.

MODEL 1 RESULTS, FOR HEV AND NON-HEV COUNTS

To evaluate the performance between spatial and aspatial models, goodness-of-fit statistics of three model specifications were compared using each of the four counties' data sets. The first model shown is the original Poisson lognormal MCAR specification, the most behaviorally flexible (and complicated) of the three. The second is a Poisson lognormal CAR (η_0 and η_1 =0), which allows for spatial dependence but removes cross-correlation among vehicle types. The last model tested uses a Poisson-lognormal multivariate specification ($\rho_1, \rho_2, and\ \eta_1 = 0$), which ignores spatial dependence but still permits cross-correlation. Table 2's comparison of average log-likelihood values (after convergence of the Bayesian MCMC sample chains) and deviance information criterion (DIC) values of these models suggest that the original model, with an MCAR specification, outperformed the simpler models (Table 2), as expected.

Table 2 also shows Model 1's parameter estimates for all four counties. The direction and magnitude of all covariates' effects, on vehicle ownership rates (per person), are consistent across counties, with a few exceptions (in cases of non-statistically and non-practically significant variables). Most variables are statistically significant (with pseudo t-statistic more than 1.64 or less than -1.64), and those that are most practically significant (as judged by highly elastic behaviors) have their estimates shown in bold. All elasticity estimates were generated by increasing each covariate's value by 1% in each census tract and obtaining the average of

[2] Models 1 and 2 were calibrated for Travis County using the additional covariates of employment density and land use balance.

proportional changes in the county's total/overall vehicle ownership rate predictions (for each of the two vehicle classes).

The presence of children (persons under 17 years of age) exhibits a positive[3] (and statistically significant) association with non-HEV ownership rates in Bexar and Travis counties. A plausible interpretation is that greater shares of children indicates the presence of more families, which tend to favor cars of larger size, and most larger vehicles are not available in hybrid design. Similarly, median age of tract residents positively affects both vehicle ownership rates (HEV and non-HEV) across all counties, with the exception of HEV ownership rates in San Antonio's Bexar County. This effect is very practically significant in Dallas County, where one-percent increase in the median age of population (in each tract) is predicted to come with an average 1.07 percent increase in HEV ownership rates (per person).

A high share of males leads to higher ownership rates (and counts), regardless of vehicle type and location. Evidently, males prefer to own more cars (and trucks), and have a preference for hybridization (perhaps because males drive more than females, on average [according to the 2009 NHTS], and so can harness more HEV fuel savings). Their effects are substantial: the average increase in HEV ownership rates following a one-percent increase in each tract's fraction of males are 3.62, 3.98, 2.43, and 1.99 percentage points - across Bexar, Dallas, Harris, and Travis counties, respectively. (The elasticities for non-HEV ownership rates are 1.25, 1.68, 0.78, and 3.37, respectively.).

Race and ethnicity were controlled for in these regressions, with the share of African Americans having a statistically significant effect. This race variable predicted lower vehicle ownership rates in all four counties, for both vehicle types (except in the case of Harris County's non-HEV ownership, where it was not statistically significant). In Dallas and Harris Counties, African Americans 21.5 and 19.5 percent of the population, respectively, and offer significant HEV ownership impacts in these counties.

Average household size is found to have significant (both statistically and practically[4]) negative effect on HEV ownership levels. As alluded to above, larger households may have seek to buy larger vehicles than is available in hybrid versions, to accommodate children, friends, pets, vacation baggage for recreational trips, and large shopping items (Turrentine and Kurani 2007). When hybrid versions are available, they are often much more expensive: e.g., the Chevrolet Tahoe hybrid is the most cost-effective SUV of its size, but $13,000 costlier than the conventional Tahoe (Wiesendelder 2013).

The share of population with higher education (i.e., at least a Bachelor's degree) has a consistently positive and statistically significant (but not very practically significant) impact on HEV ownership rates. Well-educated individuals know more about environmental issues, and new technologies; and owning a less environmentally damaging vehicle may allay some of their concerns (Egbue and Long 2012, Axsen and Kurani 2013). Moreover, HEV ownership can symbolize and communicate to others their personal values, as related to environmental awareness (Heffner et al. 2007).

While a host of other variables, like parking prices, transit provision, jobs access, and local land use balance would be valuable to have in these models, they are not available at the Census tract level across Texas. However, population density may proxy for several of these

[3] The presence of children is negatively associated with non-HEV ownership rates is Dallas and Harris counties, but it is not statistically significant.

[4] The effect of average household size on HEV ownership rates of Travis County is also negative, but neither statistically nor practically significant.

built environment and access attributes (Potoglou and Kanaroglou 2008), and is available at the tract level. As expected, population density has a negative and statistically significant impact on HEV and non-HEV ownership levels (Chu 2002). Elasticity magnitudes are relatively high for the population density variable, in several cases (e.g., -0.72 for Austin HEVs and -0.61 for Dallas HEVs), suggesting that this is a key variable (as confirmed by Chen et al.'s [2014]).

As expected, the share of workers commuting to work by driving has a positive (and statistically significant) impact on both vehicle ownership rates in Bexar and Harris counties[5], but was estimated to be practically significant only for HEV ownership rates in San Antonio's Bexar County. It is surprising that average household income shows no significant impacts (except for non-HEV ownership rates in Bexar County), perhaps due to the confounding effects of other income-related variables in the model. For example, the fraction of high-income households (those with annual income over $100,000) is positively associated with greater HEV ownership and lower non-HEV ownership rates. These results may reflect the tendency of high-income households to choose pricier vehicles over more (short-term) economical ones, rather than purchasing more vehicles (Prevedouros and Schofer 1992). Related to this, the tract-wide share of families living below the U.S. poverty level negatively[6] affects vehicle ownership rates of both types, but mostly significant for HEV ownership rates. Perhaps, financially disadvantaged people cannot afford HEVs' relatively higher prices (Gallagher and Muehlegger 2011), though fuel savings may offset such expenses over time (Tuttle and Kockelman 2012).

The positive and statistically significant coefficient on the land use balance (entropy) variables suggests higher vehicle ownership rates (per person) in Travis County's (Austin's) more mixed-use locations, per capita, perhaps due to smaller households sizes with fewer children and relatively high income per capita in such locations. Moreover, employment density is negatively associated with vehicle ownership rates in Travis County, as expected (due to a tendency for higher land values and relative scarcity of low-cost parking in more jobs-rich locations). However, Travis County's jobs-density variable is only statistically significant for HEV ownership rates.

The second-order autocorrelation coefficients, ρ_1 and ρ_2, seek to account for missing variables that affect vehicle ownership rates and vary over space, such as parking availability and congestion. The autocorrelation coefficients for both types are highly significant, but coefficients for HEV ownership rates (ρ_1 = {0.79, 0.81, 0.76, 0.74}, with t-stats. = {8.1, 9.2, 8.5, 7.1} for Bexar, Dallas, Harris, and Travis counties, respectively) are remarkably and consistently high across all counties, suggesting social contagion effects (Keith 2012, Lane and Potter 2007) and a high spatial clustering of HEVs (Chen et al. 2014).

The extremely high (and very statistically significant) aspatial correlations (within a census tract) between HEV and non-HEV adoption rates in each county are also of interest, and not unexpected (with η_0 = {0.58, 0.77, 0.66, 0.60}, and pseudo t-statistics = {4.1, 7.2, 3.8, 5.1}). In other words, high HEV and non-HEV adoption rates tend to co-exist in individual census tracts due to missing factors, which vary in the space. Interestingly, spatially-lagged cross-response correlation coefficient (η_1) estimates are quite low across all counties, suggesting that HEV adoption rates are not much affected by the non-HEV adoption rates in neighboring census tracts, which appears very reasonable.

[5] The share of workers commuting by car and has an unexpected negative impact on the HEV ownership rates of Dallas County, but it is not practically or statistically significant.

[6] The share of families below poverty level is exceptionally positively affecting the non-HEV ownership rates of Dallas, but it is not statistically significant.

TABLE 2. Comparison of Spatial and Aspatial Specification Results for Model 1 (HEV and Non-HEV Ownership Rates)

Model Specification		**San Antonio** (Bexar County, n=361 tracts**)**		**Dallas** (Dallas County, n=526 tracts**)**		**Houston** (Harris County, n=780 tracts)		**Austin** (Travis County, n=215 tracts)	
		DIC	Average log likelihood	DIC	Average log likelihood	DIC	Average log likelihood	DIC	Average log likelihood
Poisson Log-Normal MCAR		6331	-5720	9139	-8247	13549	-12284	4033	-3632
Poisson Log-Normal CAR (η_0 & $\eta_1 = 0$)		6952	-6199	9828	-8641	14790	-13183	4725	-4101
Poisson Log-Normal Multivariate (ρ_1, ρ_2& $\eta_1 = 0$)		7199	-6308	9967	-8835	14986	-13567	4802	-4285
Model 1's Parameter Estimates (using the Poisson-Lognormal MCAR specification)									
Variables	**Type**	**Mean estimate (t-stat.)**	**San Antonio elasticity**	**Mean estimate (t-stat.)**	**Dallas elasticity**	**Mean estimate (t-stat.)**	**Houston elasticity**	**Mean estimate (t-stat.)**	**Austin elasticity**
Constant	HEV (1)	-9.16 (-12.4)	-	-7.92 (-8.4)	-	-7.52 (-24.5)	-	-7.54 (-9.3)	
	Non-HEV (2)	-3.14 (-29.4)	-	-1.92 (-7.2)	-	-1.70 (-16.8)	-	-3.01 (-7.7)	
Fraction of population 16 years old or younger	1	2.77 (0.8)	0.652	1.75 (1.2)	0.216	2.34 (1.3)	0.564	1.05 (0.9)	0.126
	2	1.06 (2.5)	0.261	-1.34 (-1.4)	-0.124	-1.06 (-0.8)	-0.112	2.94 (3.04)	0.595
Median age of population (years)	1	-3.17E-03 (-0.6)	-0.121	2.88E-02 (3.8)	**1.075**	1.46E-02 (2.1)	0.374	2.48E-02 (2.2)	0.838
	2	1.41E-02 (4.2)	0.512	1.06E-02 (2.8)	0.363	8.14E-03 (2.4)	0.245	-7.95E-03 (-1.2)	-0.266
Male fraction	1	6.87 (7.2)	**3.621**	7.12 (6.5)	**3.982**	6.43 (7.3)	**2.435**	3.91 (2.6)	**1.994**
	2	2.45 (8.4)	**1.253**	3.21 (5.8)	**1.683**	1.56 (5.4)	0.789	6.56 (8.7)	**3.371**
African American fraction	1	-0.72 (-0.9)	-0.048	-1.28 (-5.2)	-0.224	-0.65 (-4.8)	-0.001	-2.64 (-3.5)	-0.219
	2	-0.62	-0.046	-4.23E-02	-0.008	4.12E-02	0.008	-1.39	-0.115

		(-2.0)		(-0.4)		(0.5)		(-1.8)	
Average household size	1	-0.85 (-4.4)	**-2.331**	-0.99 (-10.5)	**-2.456**	-0.75 (-10.6)	**-2.208**	-0.42 (-2.6)	-0.956
	2	-1.62E-02 (-0.4)	-0.045	7.36E-02 (1.5)	0.213	0.12 (6.1)	0.389	-0.47 (-3.1)	**-1.151**
Fraction of population with Bachelor's degree or higher	1	3.11 (2.3)	0.910	2.23 (3.2)	0.814	1.15 (4.1)	0.278	1.36 (3.1)	0.582
	2	0.12 (0.8)	0.036	0.22 (1.1)	0.062	2.22E-02 (0.5)	0.005	-1.06 (-3.6)	-0.451
Population density (per square mile)	1	-3.15E-05 (-3.1)	-0.455	-5.31E-05 (-5.2)	-0.612	-1.23E-05 (-2.3)	-0.027	-7.94E-05 (-4.5)	-0.724
	2	-2.11E-05 (-3.7)	-.091	-3.12E-05 (-4.5)	-0.112	-1.06E-05 (-2.7)	-0.079	-5.69E-05 (-5.1)	-0.232
Fraction of workers commuting by driving	1	1.88 (2.5)	**2.214**	-0.73 (-.7)	-0.626	0.81 (2.1)	0.105	0.36 (0.6)	0.466
	2	1.12 (6.1)	0.867	0.28 (1.2)	0.112	0.55 (3.3)	0.521	0.98 (2.5)	0.715
Mean household income (dollars)	1	2.11E-06 (0.6)	0.115	-1.02E-06 (-0.8)	-.0718	7.82E-07 (0.5)	0.062	-1.44E-06 (-0.5)	-0.111
	2	4.11E-06 (2.1)	0.256	-8.11E-07 (-0.5)	-0.044	-7.18E-07 (-0.3)	-0.037	-2.41E-06 (-1.2)	-0.186
Fraction of households with income over $100,000	1	0.45 (0.7)	0.091	1.11 (2.1)	0.132	1.38 (3.8)	0.292	0.97 (1.1)	0.226
	2	-1.12 (-2.2)	-0.121	-0.56 (-1.8)	-0.097	-9.23E-02 (-0.2)	-0.045	-9.15E-02 (-0.7)	-0.025
Fraction of families below poverty level	1	-1.01 (-3.1)	-0.126	-1.25 (-2.8)	-0.278	-1.68 (-3.8)	-0.319	-0.26 (-0.5)	-0.032
	2	-8.15E-02 (-0.3)	-0.011	4.12E-02 (0.1)	0.007	-0.22 (-1.3)	-0.061	-0.68 (-1.9)	-0.086
Land use balance	1	-	-	-	-	-	-	0.30 (1.8)	0.231
	2	-	-	-	-	-	-	0.44 (2.5)	0.303
Employment density	1	-	-	-	-	-	-	-6.88E-05 (-1.7)	-0.081

	2	-	-	-	-	-	-	-3.92E-05 (-0.8)	-0.043
η_0		0.58 (4.1)	-	0.77 (7.2)	-	0.66 (3.8)	-	0.60 (5.1)	-
η_1		0.21 (1.8)	-	.09 (1.6)	-	0.19 (1.2)	-	0.18 (2.2)	-
ρ_1		0.79 (8.1)	-	0.81 (9.2)	-	0.76 (8.5)	-	0.74 (7.1)	-
ρ_2		0.55 (6.2)	-	0.59 (4.2)	-	0.62 (5.1)	-	0.62 (5.9)	-

Notes: DIC is the deviance information criterion[7]. Highly elastic elasticities (|η| > 1.0) are shown in **bold**.

[7]The model with the smallest DIC is estimated to be the model that will best predict another sample data set with the same structure as that currently observed. $DIC = \overline{D} + P_D$, where P_D is effective number of parameters and $\overline{D}$ is posterior mean of deviance $D(\boldsymbol{\theta})$; $D(\boldsymbol{\theta}) = -2 \times loglikelihood + C$, where C is a constant that cancels across calculations and $\boldsymbol{\theta}$ is a vector of unknown parameters.

MODEL 2 RESULTS, FOR VEHICLE COUNTS BY FUEL ECONOMY CATEGORY

Table 3 shows Model 2's parameter estimates. Since most HEVs fall into the third ("fuel efficient") vehicle category, some Model 2 coefficients are quite consistent with those estimated for Model 1. The presence of children yields no significant effect on the adoption rates of fuel efficient and inefficient vehicles, but has a positive and statistically significant effect on adoption rates or counts of regular vehicles in two counties (for San Antonio and Austin locations). As in Model 1, higher (median) ages (of tract residents) and shares of males have significantly positive associations with all rates of vehicle ownership. Elasticity values of 1.10 to 2.17 (across the 4 counties) suggest that a higher share of males will have the greatest practical effect on the purchase of fuel-efficient vehicles. A higher tract share of African Americans and higher population density offer a negative association with vehicle ownership rates, regardless of fuel efficiency level, presumably for the same reasons discussed above, in the context of Model 1 results. Population density remains rather a key here, with elasticity magnitudes ranging from 0.099 to 0.332 (for the categories of fuel-inefficient vehicles in Houston and regular vehicles in Austin). Unlike many of the other covariates, density is a variable that almost has no bounds, and can vary by orders of magnitude in U.S. data sets; thus, its cumulative effects on ownership, vehicle choices, travel distances, and fuel use can be quite sizable.

Rising average household size is associated with lower ownership rates of fuel efficient vehicles and higher fuel-inefficient vehicle adoption rates across all counties. As suggested earlier, this may be attributed to larger households seeking more full-size vehicles (e.g., SUVs and minivans), which typically have fuel economy ratings below 25 mi/gal (U.S. Department of Energy 2014)[8]. As discussed earlier, for Model 1, higher education levels are positively associated with higher ownership of fuel efficient vehicles and lower rates of fuel-inefficient vehicles[9].

The share of workers that commute by driving has positive and significant effects on all three vehicle ownership rates in Bexar and Harris counties, as expected. (Dallas County has negative coefficient estimates, but it is statistically and practically insignificant.) While average household income is not a significant predictor, the share of high-income households has positive (and significant except in Travis County) effects on ownership of more efficient vehicles in all counties, with strongest responses for San Antonio's and Dallas' central counties (thanks to elasticity estimates of 0.37 and 0.14, respectively). As noted earlier, this underscores the fact that fuel-efficient vehicles tend to cost more than other vehicles and are more affordable for higher-income households (Collins 2013, Prevedouros and Schofer 1992). Moreover, using the Travis County model results, greater land use balance is associated with higher vehicle ownership rates (in a statistically significant way), while greater employment density is correlated with lower vehicle ownership rates (but this latter relationship is statistically significant only for rates of fuel-efficient vehicles).

As before, spatial autocorrelation values (ρ's) suggest that sizable spatial clustering patterns exist in ownership rates, across all vehicle types (Keith 2012, Lane and Potter 2007). Within the same census tract, correlation between fuel-efficient and regular-vehicle ownership rates (η_{012}) is not significant, but correlations between rates of fuel-efficient and inefficient ownership (η_{013}), and between rates of-fuel inefficient and regular vehicle ownership (η_{023}) are

[8] Austin's Travis County yields the opposite sign on household size and education levels, but these estimates are not significant (and may come from the presence of many college-age students in Travis County, who reside in Travis County to attend U.T. Austin and other schools).

significant. Across census tracts, the spatially-lagged cross-correlations for all response pairs are statistically insignificant and very low in magnitude, suggesting that levels of fuel efficient vehicles in one census tract are not appreciably affected by adoption rates of other types of vehicles in neighboring (first- and second-order contiguity) tracts.

TABLE 3. Model 2's Parameter Estimates for Vehicle Ownership Counts at Different Fuel Economy Levels, using an MCAR Specification

Variables	**Type**	**San Antonio** (Bexar County, n=361 tracts)		**Dallas** (Dallas County, n=526 tracts)		**Houston** (Harris County, n=780 tracts)		**Austin** (Travis County, n=215 tracts)	
		Mean (t-stat.)	**Elasticity**	**Mean (t-stat.)**	**Elasticity**	**Mean (t-stat.)**	**Elasticity**	**Mean (t-stat.)**	**Elasticity**
Constant	Fuel Efficient (1)	-3.82 (-5.7)	-	-2.37 (-3.6)	-	-2.84 (-5.3)	-	-3.11 (-3.2)	-
	Regular (2)	-2.41 (-4.5)	-	-1.77 (-3.4)	-	-2.08 (-6.3)	-	-4.42 (-3.1)	-
	Fuel Inefficient (3)	-4.60 (-8.6)	-	-4.31 (-7.7)	-	-4.24 (-11.4)	-	-5.76 (-8.1)	-
Fraction of population 16 years old or younger	1	2.46 (0.3)	0.593	1.20 (0.6)	0.287	0.52 (0.9)	0.126	0.29 (0.3)	0.062
	2	1.72 (3.9)	0.415	-0.34 (-0.6)	-0.0816	-0.77 (-0.4)	-0.188	0.81 (2.1)	0.163
	3	0.97 (0.6)	0.233	-2.64 (-0.9)	-0.625	-0.79 (-0.9)	-0.192	0.29 (0.4)	0.056
Median age of population (years)	1	-7.11E-03 (-0.3)	-0.242	2.61E-03 (2.5)	0.088	1.11E-02 (2.7)	0.707	1.14E-02 (3.2)	0.678
	2	6.98E-03 (1.6)	0.238	1.69E-02 (3.8)	0.574	1.26E-02 (4.4)	0.424	3.11E-02 (3.1)	0.715
	3	1.79E-02 (4.1)	0.613	1.43E-02 (5.0)	0.425	1.69E-02 (5.3)	0.569	1.53E-02 (3.9)	0.502
Male fraction	1	2.24 (2.7)	**1.101**	3.78 (4.4)	**1.893**	2.62 (3.6)	**1.551**	3.11 (2.3)	**2.178**
	2	1.56 (2.4)	0.872	2.56 (3.7)	**1.085**	1.51 (3.6)	0.858	3.67 (2.8)	**1.871**
	3	2.07 (3.1)	0.821	2.60 (3.5)	0.933	2.44 (5.2)	0.852	6.31 (4.2)	**1.562**
African American	1	-1.06 (-4.4)	-0.098	-0.40 (-3.2)	-0.086	-8.44E-02 (-4.9)	-0.046	-1.62 (-3.3)	-0.134

fraction	2	-0.72 (-3.8)	-0.053	-0.84 (-1.4)	-0.062	8.89E-02 (0.7)	0.017	-1.12 (-2.4)	-0.091
	3	-1.05 (-5.5)	-0.078	-0.71 (-1.5)	-0.065	-0.28 (-1.8)	-0.056	-0.68 (-2.6)	-0.061
Average household size	1	-0.21 (-2.5)	-0.592	-0.25 (-3.3)	-0.702	-0.29 (-2.7)	-0.813	-4.56E-02 (-0.6)	-0.121
	2	-4.08E-02 (-0.6)	-0.115	3.43E-03 (0.05)	0.009	5.57E-02 (0.7)	0.160	0.14 (1.5)	0.398
	3	0.15 (2.2)	0.425	0.26 (3.9)	0.740	0.15 (4.2)	0.450	0.52 (3.8)	**1.267**
Fraction of population with Bachelor's degree or higher	1	0.41 (2.4)	0.101	0.25 (3.9)	0.076	0.63 (3.4)	0.171	-7.89E-02 (-0.6)	-0.034
	2	0.33 (1.4)	0.079	0.27 (1.2)	0.075	-5.97E-02 (-0.5)	-0.016	-0.23 (-0.2)	-0.098
	3	-0.26 (-1.2)	-0.065	-0.69 (-2.8)	-0.198	-1.16 (-9.0)	-0.313	-0.89 (-2.1)	-0.212
Population density (per square mile)	1	-3.92E-05 (-4.4)	-0.157	-4.91E-05 (-8.5)	-0.261	-5.56E-05 (-2.1)	-0.283	-6.19E-05 (-9.2)	-0.291
	2	-4.53E-05 (-6.4)	-0.181	-4.38E-05 (-9.4)	-0.151	-7.12E-06 (-3.1)	-0.036	-8.31E-05 (-6.1)	-0.332
	3	-6.11E-05 (-8.4)	-0.241	-3.95E-05 (-7.9)	-0.178	-1.94E-05 (-7.4)	-0.099	-7.19E-05 (-7.8)	-0.306
Fraction of workers commuting by driving	1	1.50 (5.8)	0.812	-0.19 (-0.3)	-0.151	0.64 (3.5)	0.494	1.11 (1.3)	0.747
	2	0.98 (4.8)	0.775	-0.18 (-0.3)	-0.141	0.49 (4.4)	0.382	0.48 (0.9)	0.435
	3	0.53 (2.6)	0.422	3.11E-02 (0.1)	0.024	0.33 (2.6)	0.253	0.51 (1.5)	0.342
Mean household income (dollars)	1	7.71E-06 (1.4)	0.485	-2.72E-06 (-0.6)	-0.192	3.12E-06 (0.2)	0.226	- 5.78E-06 (-1.4)	-0.413
	2	3.71E-06 (1.6)	0.233	-2.85E-07 (-0.3)	-0.020	-2.19E-07 (-0.5)	-0.016	-3.67E-06 (-1.1)	-0.247

	3	3.09E-06 (2.2)	0.194	-4.03E-06 (-0.4)	-0.284	-3.37E-06 (-0.3)	-0.245	-1.98E-06 (-1.3)	-0.156
Fraction of households with income over $100,000	1	2.22 (4.9)	0.370	0.74 (2.9)	0.142	0.25 (4.7)	0.053	3.13E-02 (0.8)	0.008
	2	-1.21 (-3.4)	-0.202	-0.72 (-2.3)	-0.137	2.19E-02 (0.2)	0.004	-8.12E-02 (-0.1)	-0.023
	3	-0.82 (-2.3)	-0.137	-0.71 (-2.1)	-0.126	-1.43E-02 (-0.08)	-0.003	-0.91 (-1.5)	-0.167
Fraction of families below poverty level	1	-0.54 (-2.1)	-0.078	-0.84 (-3.2)	-0.129	-0.81 (-4.4)	-0.123	-0.33 (-0.4)	-0.042
	2	-0.44 (-3.1)	-0.064	3.81E-02 (0.2)	0.006	-0.30 (-2.6)	-0.046	-0.25 (-2.9)	-0.034
	3	-0.10 (-0.5)	-0.015	0.91 (4.1)	0.139	-0.10 (-0.8)	-0.016	0.16 (0.2)	0.025
Land use balance	1	-	-	-	-	-	-	0.21 (2.1)	0.322
	2	-	-	-	-	-	-	0.11 (2.9)	0.412
	3	-	-	-	-	-	-	0.34 (1.9)	0.335
Employment density	1	-	-	-	-	-	-	-3.32E-04 (-2.1)	-0.112
	2	-	-	-	-	-	-	-8.27E-05 (-0.9)	-0.063
	3	-	-	-	-	-	-	-6.11E-05 (-0.3)	-0.045
η_{012}		0.32 (1.4)	-	0.39 (1.4)	-	0.36 (1.3)	-	0.45 (1.6)	-
η_{013}		0.40 (2.0)	-	0.49 (4.1)	-	0.52 (3.9)	-	0.56 (4.1)	-
η_{023}		0.59 (2.9)	-	0.58 (5.0)	-	0.67 (3.6)	-	0.61 (3.6)	-

η_{112}	2.37E-02 (1.7)	-	8.94E-02 (1.9)	-	5.35E-02 (1.9)	-	5.25E-02 (2.8)	-
η_{113}	6.36E-02 (1.8)	-	0.15 (1.3)	-	0.10 (1.4)	-	0.31 (1.4)	-
η_{123}	0.13 (1.6)	-	0.16 (1.3)	-	0.11 (1.3)	-	0.18 (1.2)	-
ρ_1	0.75 (7.2)	-	0.89 (6.5)	-	0.88 (9.2)	-	0.71 (6.9)	-
ρ_2	0.55 (4.9)	-	0.73 (6.1)	-	0.61 (2.8)	-	0.61 (5.7)	-
ρ_3	0.67 (5.5)	-	0.82 (6.6)	-	0.63 (5.6)	-	0.59 (6.8)	-
Deviance information criterion (DIC)	11,238	-	16,322	-	24,453	-	6,655	-

Note: Highly elastic cases ($|\eta| > 1.0$) are shown in **bold**.

MODEL 3 RESULTS FOR AVERAGE FUEL ECONOMY

Table 4 shows Model 3's parameter estimates across Texas tracts. It is important to note that a tract having more fuel efficient vehicles (per resident) can also have a lower overall/average fuel economy value, due to an even higher count of inefficient vehicles. Thus, the results of Models 2 and 3 are not directly comparable here.

Table 4's robust LM test results suggest that one can use either a spatial error or spatial lag model specification here. A spatial error model is generally more behaviorally defensible, however, since it implies that unobserved factors are creating the spatial autocorrelation in model residuals, while a spatial lag model implies that response values in one location are simultaneously affecting responses values in nearby locations. Moreover, Kissling and Carl (2008) found that the spatial error model outperformed the spatial lag model across 1080 simulated data sets. For these reasons, a spatial error dependence specification was employed here, for Model 3.

All factors in Model 3 are found to be statistically significant predictors of average fuel economy. Census tracts with higher shares of children, males, and lower-income households are predicted to have lower average fuel economy, whereas a higher fraction of African Americans, Bachelor's degree holders, workers commuting by driving, and high-income households come with higher tract-level fuel economy. Higher median age, household size, and income variables, along with lower population density, are associated with lower fuel economy. A very high pratical magnitude (+0.943) and statistical significance (likelihood ratio test p-value of 0.000) for the autoregressive error coefficient implies the existence of high spatial correlation among missing variables that affect average fuel economy and vary over space (like jobs densities, land values, and distance to each region's CBD).

The small variation (σ = 0.825 mi/gal) in tract-level average fuel economy may be the primary reason behind very low elasticity values, so standardized coefficients were estimated, by multiplying each slope coefficient estimate by the standard deviation (SD) in the associated covariate (as shown in Table 1) and dividing by the SD on the response variable (tract-average fuel economy: SD = 0.825 mi/gal). This renders each "Std. Coef." dimensionless, as a metric of how many SDs in the response variable once can expect following a 1 SD change in the associated covariate. These standardized coefficient values are much more telling than the elasticities: they suggest that educational attainment, age, income, and then household size (in that order) are the most practically significant among the covariates. Only educational attainment is associated with a practically significant and positive improvement in fuel economy; tract-level increases in median age, average income, and average household size work against this desirable feature, of a more environmentally sustainable fleet.

TABLE 4. Lagrange Multiplier Test Results and Model 3's Parameter Estimates, for Average Fuel Economy, using a Spatial Error Specification (n = 5,188 tracts across Texas)

Robust LM Test	**LM Test Statistic**		**P-value**	
Error lag test	4480.6		0.000	
Dependent variable lag test	1050.1		0.000	
Model 3's Parameter Estimates				
Explanatory Variable	**Coef.**	**Std. Coef.**	**Z-value**	**Elasticity**
Intercept	21.74	-	137.8	-
Fraction of population 16 years old or younger	-1.232	-0.089	-6.7	-0.014
Median age (years)	-0.028	**-0.227**	-22.4	-0.052
Male fraction	-0.853	-0.035	-5.10	-0.022

African American fraction	0.681	0.136	14.0	0.004
Average household size (# persons)	-0.298	**-0.180**	-12.6	-0.042
Fraction of population with Bachelor's degree or higher	1.120	**0.259**	16.1	0.014
Population density (per square mile)	2.55E-05	0.102	12.6	0.004
Fraction of workers commuting by driving	0.199	0.022	3.2	0.008
Mean household income (dollars per year, in 2010)	-5.1E-06	**-0.225**	-13.8	-0.018
Fraction of households with income over $100,000	0.327	0.065	3.5	0.003
Fraction of families below poverty level	-0.443	-0.066	-7.3	-0.003
Simultaneous autoregressive error coefficient (λ)	0.943	-	140.2	-
Likelihood ratio test on λ	4673.2 (p-value = 0.000)			
Akaike information criterion (AIC)	3368.5 (vs. 8037.9 for OLS model)			

Note: Practically significant covariates have their standardized coefficients shown in **bold.**

CONCLUSIONS

This study employed a Poisson-lognormal CAR model to anticipate tract-level counts of HEVs and non-HEVs, fuel efficient and inefficient vehicles across Texas' most populous cities, along with a spatial error model for average fuel economy across all Texas tracts. Model results identify demographic (including population density) factors that most affect HEV ownership rates, vehicle ownership by fuel economy categories, and the average fuel economy of registered LDVs in each tract.

Results of the count models suggest that household size, resident gender, household income, jobs density, and education levels are key predictors for HEV adoption rates and fuel economy choices, though average fuel economy does not vary much across tracts (with $\mu = 19.2$, and $\sigma = 0.82$ mi/gal). It appears that larger households tend to not purchase HEVs or other fuel efficient vehicles, presumably due to a preference for larger vehicles (e.g., SUVs and minivans [Kockelman and Zhao 2000]), and possibly due to higher up-front pricing of fuel-saving technologies. Higher population densities are associated with statistically significantly lower vehicle ownership rates (regardless of vehicle type), presumably due to better access options to destinations without a private vehicle and due to more parking challenges or costs. All three model specifications exhibit high (and statistically significant) spatial autocorrelations and local (within a tract) cross-response correlations in unobserved attributes (like concern for the environment, parking challenges, manufacturers' marketing campaigns, locations of vehicle dealerships, and access to neighbors and friends who already own HEVs and/or vehicles that enjoy higher fuel economy). While the Bayesian sampling methods and the MCAR model specification are not familiar techniques for many data analysts, neglect of such correlations can result in biased parameter estimates. The spatial error model is more accessible to a variety of potential users (and exists in various software programs); it also can handle much larger data sets (though it effectively requires a continuous response variable).

Although modeling vehicle-choice behavior at the level of individuals or households, with disaggregate data, can also prove quite informative for understanding HEV ownership, such data are obtained for small samples of the population, and only sporadically. (For example, typically 1 percent or fewer households in a region provide data for a regional household travel survey, which is undertaken every 5 to 10 years. In contrast, DMV records contain all registered vehicles, continuously in time.) This study demonstrates how one can use rigorous spatial modeling methods at the census tract or other levels to understand vehicle ownership choices and fuel economy relationships across counties and a large state.

Opportunities for future research in this area are many. For example, while it is often challenging to obtain tract level data of various land use, transit provision, and other relevant variables across a state like Texas, inclusion of such covariates will provide even more insight for planners, policy-makers, automobile manufacturers, and other interested readers. Access to count data on PEVs (as these become non-negligible), average vehicle age information, and other features of DMV databases will also inform these analyses, while helping chart a course for charging infrastructure investments and other decisions. Vehicle age is relevant, for example, because lower-income households are less likely to buy new vehicles, and so may be holding less fuel efficient vehicles as rising Corporate Average Fuel Economy standards ensure the nation's new-sales fleet becomes more efficient. This study also was able to estimate rather complex MCAR count models for only subsets of Texas tracts, due to computing limitations; advances in Bayesian estimation and software programming may eventually permit estimation of such models for much larger data sets.

While ownership of an HEV does not require special charging stations, larger power transformers, or very large batteries on board, their rising presence does affect future sales, of vehicles and gasoline, as well as state and federal gas tax receipts, air quality, and energy security. Since early adopters of HEVs are likely to be more sustainability-minded and technology savvy than others, on average; so their heavy presence in various neighborhoods may well be a strong signal for the early adoption and longer-term registration numbers of plug-in EVs in those same locations. Greater understanding of the factors causing spatial clustering in all EVs' adoption rates can help shape environmental policy, infrastructure planning, and vehicle marketing.

ACKNOWLEDGEMENTS

The authors are thankful to the NSF Industry-University Research Center titled "Efficient Vehicles and Sustainable Transportation Systems" for financially supporting this research, and to several anonymous reviewers for their suggestions. They are also obliged to Texas A&M University's Prof. Steve Puller for providing access to the coded and aggregate vehicle registration data, and to the Texas Department of Motor Vehicles for permitting this access.

REFERENCES

Anselin, L. (1988) *Spatial Econometrics: Methods and Models*. Dordrecht: Kluwer Academic Publishers.

Anselin, L. (2003) An introduction to spatial regression analysis in R. University of Illinois, Urbana-Champaign. Retrieved from: https://geodacenter.asu.edu/drupal_files/spdepintro.pdf (October 26, 2014).

Anselin, L., Bera, A. K., Florax, R., and Yoon, M. J. (1996) Simple diagnostic tests for spatial dependence. *Regional Science and Urban Economics*, 26(1):77-104.

Axsen, J., and Kurani, K. S. (2013) Hybrid, Plug-in Hybrid, or Electric-What do Car Buyers Want? *Energy Policy* 61: 532-543.

Axsen, J., and Kurani, K. S. (2011) Interpersonal influence in the early Plug-in Hybrid Market: Observing Social Interactions with an Exploratory Multi-Method Approach. *Transportation Research Part D: Transport and Environment* 16(2): 150-159.

Caulfield, B., Farrell, S., and McMahon, B. (2010) Examining Individuals Preferences for Hybrid Electric and Alternatively Fuelled Vehicles. *Transport Policy* 17(6): 381-387.

Cervero, R., and Kockelman, K. (1997) Travel demand and the 3Ds: density, diversity, and design. *Transportation Research Part D* 2(3): 199-219.

Chen, T. D., Wang, Y., and Kockelman, K. M. (2014) Where are the Electric Vehicles? A Spatial Model for Vehicle-Choice Count Data. Forthcoming in *Journal of Transport Geography*.

Chu, Y. L. (2002) Automobile Ownership Analysis using Ordered Probit Models. *Transportation Research Record: Journal of the Transportation Research Board* 1805(1): 60-67.

Collins A.P. (2013) New Fuel Standards: Costlier Cars, but Less Expensive to Run. Retrieved from: http://www.csmonitor.com/Business/In-Gear/2013/1005/New-fuel-standards-Costlier-cars-but-less-expensive-to-run (July 4, 2014)

Cressie, N.A.C. (1993) *Statistics for Spatial Data*. Wiley Series in Probability and Mathematical Statistics. Wiley, New York.

Dijk, M., Orsato, R. J., and Kemp, R. (2013) The Emergence of an Electric Mobility Trajectory. *Energy Policy* 52: 135-145.

Egbue, O., and Long, S (2012) Barriers to Widespread Adoption of Electric Vehicles: An Analysis of Consumer Attitudes and Perceptions. *Energy Policy* 48: 717-729.

EVs Roll (2014) Hybrid Car Statistics. Retrieved from: http://www.evsroll.com/Hybrid_Car_Statistics.html# (June 12, 2014)

Gallagher, K. S., and Muehlegger, E. (2011) Giving Green to Get Green? Incentives and Consumer Adoption of Hybrid Vehicle Technology. *Journal of Environmental Economics and Management* 61(1): 1-15

Greene, D. L., Evans, D. H., and Hiestand, J. (2013) Survey Evidence on the Willingness of US Consumers to Pay for Automotive Fuel Economy. *Energy Policy* 61: 1539-1550.

He, L., Chen, W., and Conzelmann, G. (2012) Impact of Vehicle Usage on Consumer Choice of Hybrid Electric Vehicles. *Transportation Research Part D: Transport and Environment* 17(3): 208-214.

Heffner, R. R., Kurani, K. S., and Turrentine, T. S. (2007) Symbolism in California's Early Market for Hybrid Electric Vehicles. *Transportation Research Part D: Transport and Environment* 12(6): 396-413.

Jenn, A., Azevedo, I. L., and Ferreira, P. (2013) The Impact of Federal Incentives on the Adoption of Hybrid Electric Vehicles in the United States. *Energy Economics* 40: 936-942.

Keith, D. R. (2012) Essays on the Dynamics of Alternative Fuel Vehicle Adoption: Insights from the Market for Hybrid-electric Vehicles in the United States. Doctoral dissertation in Engineering Systems Division. Massachusetts Institute of Technology.

Keith, D., Sterman, J., and Struben, J. (2012) Understanding Spatiotemporal Patterns of Hybrid-Electric Vehicle Adoption in the United States. In Transportation Research Board 91st Annual Meeting (No. 12-4164).

Kissling, W. D., and Carl, G. (2008) Spatial Autocorrelation and the Selection of Simultaneous Autoregressive Models. *Global Ecology and Biogeography* 17(1): 59-71.

Kodjak, D. (2012) Consumer Acceptance of Electric Vehicles in the United States. Retrieved from: http://www.epa.gov/oar/caaac/mstrs/dec2012/kodjak.pdf (June 16, 2014)

Koo, Y., Kim, C. S., Hong, J., Choi, I. J., and Lee, J. (2012) Consumer Preferences for Automobile Energy-Efficiency Grades. *Energy Economics* 34(2): 446-451.

Lane, B., and Potter, S. (2007) The Adoption of Cleaner Vehicles in the UK: Exploring the Consumer Attitude–action Gap. *Journal of Cleaner Production* 15(11): 1085–1092.

Li, X., Clark, C. D., Jensen, K. L., Yen, S. T., and English, B. C. (2013) Consumer Purchase Intentions for Flexible-Fuel and Hybrid-Electric Vehicles. *Transportation Research Part D: Transport and Environment* 18: 9-15.

Liu, Y. (2014), Household Demand and Willingness to Pay for Hybrid Vehicles. *Energy Economics* 44: 191-197.

Murakami, E., and Young, J. (1997) *Daily Travel by Persons with Low Income*, US Federal Highway Administration.

Musti, S., and Kockelman, K. (2011) Evolution of the Household Vehicle Fleet: Anticipating Fleet Composition and PHEV Adoption in Austin, Texas. *Transportation Research Part A* 45 (8): 707-720.

Paul, B., Kockelman, K., Musti, S. (2011) Evolution of the Light-Duty-Vehicle Fleet: Anticipating Adoption of Plug-In Hybrid Electric Vehicles and Greenhouse Gas Emissions Across the U.S. Fleet. *Transportation Research Record* No. 2252: 107-117.

Potoglou, D., and Kanaroglou, P. S. (2008) Modeling Car Ownership in Urban Areas: A Case Study of Hamilton, Canada. *Journal of Transport Geography* 16(1): 42-54.

Prevedouros, P.D., and Schofer, J.L. (1992) Factors Affecting Automobile Ownership and Use. *Transportation Research Record* 1364:152–16.

Tuttle, D., and Kockelman, K. (2012) Electrified Vehicle Technology Trends, Infrastructure Implications, and Cost Comparisons. *J of the Transportation Research Forum* 51 (1): 35-51.

Turrentine, T. S., and Kurani, K. S. (2007) Car Buyers and Fuel Economy? *Energy Policy* 35(2): 1213-1223.

United States Census Bureau (2010) Census Tract Relationship File. Retrieved from: https://www.census.gov/geo/maps-data/data/relationship.html (June 16, 2014)

U.S. Department of Energy (2014) Best and Worst MI/GAL Trucks, Vans and SUVs.

Wall, M. M. (2004) A Close Look at the Spatial Structure Implied by the CAR and SAR Models. *Journal of Statistical Planning and Inference* 121(2): 311-324.

Wang, Y., and Kockelman, K. M. (2013) A Poisson-lognormal Conditional-Autoregressive Model for Multivariate Spatial Analysis of Pedestrian Crash Counts across Neighborhoods. *Accident Analysis & Prevention* 60: 71-84.

Wiesendelder J. (2013) Best Hybrids for the Money 2013.Retrieved from: http://blogs.cars.com/kickingtires/2013/04/best-hybrids-for-the-money-2013.html (June 2, 2014).

Zhao, Y., and Kockelman, K. (2000) Behavioral Distinctions: The Use of Light-Duty Trucks and Passenger Cars. *Journal of Transportation and Statistics* 3 (3): 47-60.