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Where are the electric vehicles? A spatial model for vehicle-choice count data

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Abstract

Electric vehicles (EVs) are predicted to increase in market share as auto manufacturers introduce more fuel efficient vehicles to meet stricter fuel economy mandates and fossil fuel costs remain unpredictable. Reflecting spatial autocorrelation while controlling for a variety of demographic and locational (e.g., built environment) attributes, the zone-level spatial count model in this paper offers valuable information for power providers and charging station location decisions. By anticipating over 745,000 personal-vehicle registrations across a sample of 1000 census block groups in the Philadelphia region, a trivariate Poisson-lognormal conditional autoregressive (CAR) model anticipates Prius hybrid EV, other EV, and conventional vehicle ownership levels. Initial results signal higher EV ownership rates in more central zones with higher household incomes, along with significant residual spatial autocorrelation, suggesting that spatially-correlated latent variables and/or peer (neighbor) effects on purchase decisions are present. Such data sets will become more comprehensive and informative as EV market shares rise. This work's multivariate Poisson-lognormal CAR modeling approach offers a rigorous, behaviorally-defensible framework for spatial patterns in choice behavior.

1. Motivation

As auto manufacturers introduce a variety of new vehicles to meet stricter fuel economy standards in the U.S. and abroad, and driver concerns regarding long-term energy prices remain high, hybrid electric vehicle (HEV), plug-in hybrid electric vehicle (PHEV), and battery electric vehicle (BEV) sales are on the rise (Schweinberg, 2013). However, according to *Consumer Reports*' Car Brand Perception Survey (Bartlett, 2012), range anxiety remains consumers' top concern consumer regarding a possible EV purchase. Spatial patterns in growing EV ownership may illuminate zone-level characteristics that increase or alleviate owner/consumer "range anxiety" (i.e., a user's concern for being stranded with a fully discharged battery and no reasonable recharge option (Tate et al., 2008)). As illustrated by Khan and Kockelman (2012), a 75-mile all-electric range (AER) BEV (like the 2013 Nissan LEAF) may be a very reasonable vehicle for 27% of single-vehicle households and nearly 70% of multiple-vehicle households in Seattle to own. Khan and Kockelman worked with existing travel patterns and assumed that households will charge the vehicle each night and are willing to charge more than once a day or find another travel option (e.g., a relative's car or rental vehicle) on the 3 days a year that those households are likely to exceed the BEV's range. Recent evidence from the U.S. Department of Energy's and ECOtality's EV Project (Smart et al., 2013) suggests that 73% of miles driven by Americans in a Chevy Volt stay within its 35-mile (EPA-rated) AER (thereby avoiding much gasoline use in this PHEV). Studies suggest that range anxiety may fall as drivers become more familiar with EV technology and EV use (see, for example, Wellings et al., 2011; Taylor, 2009). As with open-road tolling, adaptive cruise control, and other relatively new transport policies and technologies, it seems very possible that potential owners will worry less about EV range limitations as they are exposed to EVs on local roads, in neighbors' driveways, and nearby parking garages (Mau et al., 2008). Related to this, Axsen et al. (2009) surveyed over 1000 vehicle owners in Canada and California and found that willingness-to-pay (WTP) for HEVs rose with higher (existing) HEV market penetration rates. Our study econometrically models ownership rates of EVs and conventional vehicles across Philadelphia neighborhoods, while allowing for such neighbor (spatial autocorrelation) effects; it applies a new multivariate count model, with both spatially-lagged and (aspatial) cross-response correlation opportunities.

2. Previous studies

Most EV forecasts are simply an aggregate market share across a nation or region, with estimates widely varying. For example, Navigant Research (2013) projects the worldwide sales of light duty PEVs (including both PHEVs and BEVs) will reach 3 million units by 2020, or approximately 3% of the total LDV sales. The U.S. National Research Council (NRC, 2010) predicted 13 million EVs on U.S. roads by 2030 (4% of total fleet) in the most probable scenario and 40 million EVs (13.3% of total fleet) in the maximum practical case, while the U.S. Energy Information Administration (EIA, 2013) recently forecasted just 3% of all U.S. light duty vehicle (LDV) *sales* will be EVs by 2040. Simulating consumer behavior under a business-as-usual (BAU) model, Clement-Nyns et al. (2010) projected EVs to reach 30% of the Belgian passenger-vehicle fleet by 2030. McKinsey's (2011) survey suggested that in three of the world's "megacities" (New York City, Shanghai, and Paris), EVs may hit 16% of vehicle sales by 2015. Within the U.S. northeast corridor, Pike Research (2011) projects that Washington, DC and Delaware will have the highest annualized penetration rates of EVs by 2017, at 4.6% and 4.5%, respectively. Paul et al.'s (2011) microsimulation of U.S. household holdings forecasted 7.6% of the fleet to be HEVs and PHEVs by 2035 under BAU, and 13.1% under a feebate plus doubled-gas-price scenario, ceteris paribus. Examining both demand (for vehicles, batteries, and gasoline) and supply constraints (on production), Neubauer et al. (2012) projected California's PHEV plus BEV population to hit 500,000 sometime between 2018 and 2020. After tracking the EV market for 13 years, IDTechEX predicts that 35% of all vehicles in the world will be electric by 2025, with a likely mix of 25% hybrids and 10% BEVs (Harrop and Das, 2012). With such meaningful market share changes on the horizon, an ability to predict which households or neighborhoods are most likely to own such vehicles can provide important insights and opportunities for power-grid planning (e.g., updating transformers in certain locations), transportation investments (e.g., identifying where public charging stations should be installed for maximum utilization), and air quality policy-making (e.g., forecasting ozone level changes when more vehicle-miles are electrified).

At the other end of the data spectrum, many researchers have employed discrete choice models at a disaggregate (individual or household) level to explore various vehicle ownership decisions. For example, Brownstone et al. (1996) analyzed data from a stated preference survey on alternative-fuel vehicles and found that two-vehicle households with children express a greater WTP for cleaner (emissions-reducing) vehicles, as compared to childless households. Erdem et al. (2010) employed an ordered probit (OP) model to examine Turkish consumers' WTP for HEVs and found that higher-income females, with more education and concerns about global warming, are more likely to purchase HEVs. The relationship between income and vehicle preference tends to be complicated by household size: Paul et al. (2011) found that households with higher household income per member tend to prefer smaller vehicles, but larger households generally prefer larger vehicles (for seating-capacity reasons).

This research addresses a gap in our current understanding of EV ownership decisions by examining the effects of demographic and land use characteristics at the neighborhood or zonal level (here the Census block group), rather than at a regional level or individual/household level. In this way, the work is able to quantify spatial autocorrelation or "neighbor effects" that can emerge in the adoption of new technologies, and to predict adoption rates over space, without requiring details on individuals. There have been many previous studies on the influence of land use characteristics on vehicle ownership, but none specific to EV ownership with a spatial component, as employed in this study. For example, higher residential densities are associated with lower vehicle ownership and usage levels (e.g., Zhao and Kockelman, 2002; Fang, 2008). Holding other household attributes (control variables) constant, Brownstone and Golob (2009) predicted density reductions of 1000 housing units per square mile (or 1.56 units per acre) to be associated with another 1000 miles per year of vehicle-miles traveled and 65 more gallons of fuel consumed per household (with 20 gallons of this difference accounted by choice of more fuel-efficient vehicles in higher-density settings). The choice of higher fuel-economy vehicles may be largely attributable to lower light-duty truck[1] (LDT) ownership in such settings: Brownstone and Fang's (2009) Bayesian multivariate OP model associates a 50% residential density increase with a modest but statistically significant reduction on LDT ownership levels, and a 610-mile annual per-truck VMT decrease. In the same study, demand for passenger car ownership was estimated to be inelastic with respect to residential density (Brownstone and Fang, 2009), but fuel economy can change significantly within the car fleet, leading to EV purchases, rather than say, large luxury cars, and thereby offer substantial energy savings. Using a multiple discrete–continuous extreme value (MCDEV) specification, Bhat et al. (2009) also found that smaller vehicle sizes are more prevalent in neighborhoods high in both residential and commercial densities. Beyond simple density measures, Potoglou and Kanaroglou (2008) found vehicle ownership to depend somewhat on land use diversity and transit proximity. Khan et al. (2014) also investigated the linkage between vehicle ownership and a host of built environment factors, including network structure, bus stop density, land use mix and jobs density, using a standard negative binomial model.

Spatial autocorrelation across observational units is prevalent in transportation data sets, such as commodity flow prediction (LeSage and Polasek, 2005), land development decisions (Chakir and Parent, 2009; Wang et al., 2014), and crash prediction (e.g., Levine et al., 1995a, 1995b; Wang et al., 2009). In a continuous-response setting, overlooking spatial structure will not cause biased estimates of the coefficients, but loss of efficiency and precision, when the error term exhibits spatial autocorrelation. In a discrete-response setting, overlooking spatial structure, whether it occurs in the error terms or in the response variables, will likely cause biased estimates.

Spatial models can be designed to study discrete count data, such as vehicle ownership. A good example is found in Adjemian et al.'s (2010) investigation of vehicle ownership at the census tract level while controlling for spatial interdependence and various covariates – like income and population density. In a spatial logit model setting, they found that vehicle ownership exhibits spatial dependence, even after controlling for many zonal attributes, and those coefficient estimates tend to change between spatial and aspatial models, with spatial models surpassing aspatial models in model goodness-of-fit. These findings are echoed in Wang and Kockelman (2013), which compared a multivariate conditional autoregressive (CAR) model with an aspatial multivariate count model, and with a spatial count model that excludes cross-correlation between two crash severity levels.

This study combines data already collected on a regular basis by Pennsylvania's Department of Motor Vehicles and the U.S. Census to examine EV ownership patterns at a neighborhood level. It expands on the existing literature on vehicle ownership by

[1] In the U.S. the light-duty truck definition includes cargo vans, minivans, sport-utility vehicles, and pickup trucks weighing less than 8500 lbs loaded (i.e., the gross vehicle weight rating).

focusing on the contribution of household and land use factors specifically on EV ownership. In addition, the spatial count model employed here acknowledges interactions among nearby zones, the disregard of which can produce biased parameter estimates due to omitted and unobserved variables. Anticipating EV ownership at the zone level can provide important insights to utility providers and transportation planners for infrastructure investments, land use planning, and policymaking.

3. Data description

The analysis relies on April 2012 vehicle registration data collected for the southeastern region of Pennsylvania (near Philadelphia) by the Delaware Valley Regional Planning Commission (DVRPC). The data set covers 2980 census block groups containing 2,225,595 personal-vehicle registrations. 18,674 of these registered vehicles are considered EVs, among which most are HEVs, like the (original/non-plug-in) Toyota Prius and Honda Civic HEV. In fact, 13,421 (or 72%) of the EVs are Toyota Priuses.

The response variables used in this paper's trivariate model are the number of Prius EVs, non-Prius EVs, and conventional (internal combustion engine) vehicles (ICEVs) in each Census block group. These three categories encompass all vehicles in the dataset, as all non-Prius and non-EV vehicles are counted in the ICEV category. A bivariate model with EVs and conventional vehicles as response variables was also employed with similar parameter outcomes, but interesting results specific to Prius EVs (as discussed in Section 5) resulted in a preference for the trivariate specification, as presented here. Predictor variables (i.e., covariates) include block-group demographics, such as population, resident worker,[2] and job densities, plus household income shares (by income range), and built-environment attributes (including distance to the central business district or CBD [downtown Philadelphia] and centerline-mile densities of primary and secondary roads), as discussed below.

The demographic details were originally provided at the traffic analysis zone (TAZ) level, by the regional MPO, DVRPC. TransCAD's overlay function was used to impute such attributes at the block-group level, in order to spatially match them to the vehicle ownership data. Table 1 provides summary statistics of all variables at the Census block-group level.

After merging the demographic and employment count information from the DVRPC with the vehicle count layer (originally provided by the Delaware Valley Regional Planning Commission), there were 2909 Census block groups with both the response variables (vehicle counts by type) and explanatory variables available.

According to planners at the DVRPC, \$35,000 is an important household income threshold that is specially tracked, in part due to distinct travel patterns; thus, the density of these households was tested as a covariate. Densities for most variables were used here because the vehicle-ownership rate per zone is scaled by the number of households per zone. In other words, the Poisson log-normal process[3] – another common count model specification – modeled here (described in detail below) benefits from an exposure or size term, which here is the number of households (or population) per zone. (In theory, if the number of households or persons doubles, one expects the number of owned vehicles to double, ceteris paribus, in each of the three categories modeled. As is common in the practice of count-model estimation, this work allows for a non-unitary parameter on the natural logarithm of households per zone, in order to provide more flexibility than forcing the model to exactly scale.)

Network connectivity may also have a bearing on vehicle ownership. For example, abundance of roadway resources invites more vehicular travel, indirectly increasing household vehicle ownership. And poorly-connected networks can stymie direct travel while increasing congestion, possibly incentivizing the purchase of more fuel-efficient vehicles (including EVs). In this model, network features are proxied by the centerline-mile density of primary and secondary roads.[4] Centerline density (for primary and secondary roads) was computed as the ratio between miles of roadway and area of block groups (in square miles). The population and jobs data were used in map format to define the regional CBD. Both densities spike in the central Philadelphia area. For block groups within this rectangular (CBD) area, the distance-to-CBD values were set to zero; for block groups outside of this zone, Euclidean distances from each block group's centroid were computed, to the centroid of the CBD rectangle.

4. Methodology

Zone-level vehicle-ownership counts, by type of vehicle, can be modeled in a spatial count context with a multivariate response vector (of size 3×1 here), such as the model proposed and estimated by Wang and Kockelman (2013). Wang and Kockelman's (2013) new specification allows for multiple, simultaneous integer count responses, as well as spatial autocorrelation (due to missing variables that trend in space), zonal heterogeneity, and spatially-lagged[5] and aspatial cross-correlations (across counts). A three-level response model is specified here, with the first stage (for vehicle count values) expressed as a Poisson process:

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

where y_{ik} is the observed vehicle count by type (k = 1 denotes Prius EVs, 2 denotes non-Prius EVs, and 3 denotes ICEVs) for the i^{th} block-group polygon of the five-county Delaware Valley region. The (non-negative) average vehicle counts for each zone and vehicle type, λ_{ik}, are defined in the second stage, as follows:

$$\lambda_{ik} = E_i^{\alpha} \cdot \exp(\boldsymbol{x}_i' \boldsymbol{\beta}_k + \boldsymbol{\phi}_k + u_i) \tag{2}$$

where E_i^{α} is the exposure or scaling term, of household population (per zone), as discussed earlier. The vector of all spatial random terms $\boldsymbol{\phi} = (\boldsymbol{\phi}_1', \boldsymbol{\phi}_2', \boldsymbol{\phi}_3')'$ is multivariate normally distributed, where $\boldsymbol{\phi}_k$ is an n by 1 vector of spatial random effects or errors for ownership rates of the type k vehicle, such that:

$$\begin{pmatrix} \boldsymbol{\phi}_1 \\ \boldsymbol{\phi}_2 \\ \boldsymbol{\phi}_3 \end{pmatrix} \sim N\left(\begin{pmatrix} \boldsymbol{\mu}_1 \\ \boldsymbol{\mu}_2 \\ \boldsymbol{\mu}_3 \end{pmatrix}, \begin{bmatrix} \boldsymbol{\Sigma}_{11} & \boldsymbol{\Sigma}_{12} & \boldsymbol{\Sigma}_{13} \\ \boldsymbol{\Sigma}_{12}' & \boldsymbol{\Sigma}_{22} & \boldsymbol{\Sigma}_{23} \\ \boldsymbol{\Sigma}_{13}' & \boldsymbol{\Sigma}_{23}' & \boldsymbol{\Sigma}_{33} \end{bmatrix} \right) \tag{3}$$

where the n by 1 vector $\boldsymbol{\mu}_k$ indicates the average ownership rate for response/vehicle type k (k = 1, 2, 3), and $\boldsymbol{\Sigma}_{kl}$ are n by n matrices describing the covariance structure between response types k and l.

[2] The term "resident workers" refers to those who list themselves as employed (either full or part time) and reside in the zone. Such individuals typically work outside the zone in question.

[3] The Poisson-lognormal process is more stable than the negative binomial process for low-sample mean and small sample size. Otherwise, the two processes are very similar (Lord and Mannering, 2011).

[4] Primary and secondary roadway networks were obtained from the 2011 Census Tiger/Line archive for the state of Pennsylvania, at http://catalog.data.gov/dataset/tiger-line-shapefile-2012-series-information-file-for-the-primary-and-secondary-roads-state-bas Primary roads essentially refer to freeways and expressways and other divided, limited-access highways that are state-maintained or part of the interstate highway system. Secondary roads are major arterial streets, with multiple lanes of traffic in each direction, at-grade intersections, and possibly undivided medians.

[5] "Spatially-lagged cross-correlation" captures the correlation across different vehicle types that occurs across space (mathematically expressed by the component $\eta_1 W$ in matrix A), while aspatial correlation describes the standard correlation (like that in an aspatial multivariate count model) across different response types, as formulated by the remaining component, $\eta_0 I$ in matrix A.

Table 1
Summary statistics of model variables at the zone level.

	Mean	Median	Std. Dev.	Min	Max
Number (#) of Households (#HHs)	513.2	455.7	277.5	0	2.494E+03
Resident Worker Density (# per acre)	8.899	5.561	10.90	0	208.1
Emp. Density (jobs per acre)	9.651	2.727	51.03	1.500E−05	1124.8
Pop. Density (persons per acre)	21.34	12.722	25.03	0	360.2
Income >$35K Density (# of households with incomes over $35,000 per year, per acre)	4.08	2.599	5.578	0	147.7
Centerline Density (centerline miles of roadway per square mile of zone area)	5.087E+04	1.521E+04	1.124E+05	0	1.920E+06
Euclidean Distance to CBD (mi.)	12.38	9.111	9.706	0	49.67
HH0wrk Density (# per acre)	2.874	1.269	4.276	0	92.52
HH1wrk Density (# per acre)	3.216	1.748	4.772	0	122.4
HH2wrk Density (# per acre)	1.868	1.214	2.257	0	38.96
HH3wrk Density (# per acre)	0.428	0.262	0.514	0	5.449
Response variables (Counts)					
ICEVs	736.9	598.0	558.0	1	14,697
Non-Prius EVs	1.749	1	2.333	0	19
Prius EVs	4.474	2	5.773	0	37

The three-level scheme developed here decomposes the massive covariance structure into a series of conditional distributions that allow for spatial autocorrelation (measured by parameters ρ_1, ρ_2, and ρ_3), aspatial cross-correlations (gauged by parameters $\eta_{0,23}$, $\eta_{0,13}$, and $\eta_{0,12}$), and spatially-lagged cross-correlations (expressed by parameters $\eta_{1,23}$, $\eta_{1,13}$, and $\eta_{1,12}$). Details about model specification are provided in Appendix A.

This three-level multivariate conditional autoregressive (MCAR) model structure was thus used to simultaneously predict counts of registered Toyota Prius EVs, non-Prius EVs (all EVs excluding the Prius), and ICEVs for the Philadelphia region. The parameters were estimated using Bayesian Markov-chain Monte Carlo sampling techniques, coded in R and WinBUGS, as described in Wang and Kockelman (2013). Due to computing limitations (in WinBUGS) with larger sample sizes (from non-standard posterior likelihoods [i.e., likelihood functions that do not follow a known distributional form] associated with discrete count process and complex covariance structures), Table 2's parameter estimates come from an $n = 1000$ block-group sub-sample for central Philadelphia, rather than the original 2909 block groups across the wider region (with complete data, as discussed earlier). Fig. 1 shows the spatial distribution of these vehicle counts (per household).

5. Results

As shown in Table 2, several control variables are associated with higher levels of vehicle ownership, per household (in the block group) – regardless of vehicle type. For example, increased resident worker density is associated with more vehicles of each type, as expected with household vehicle ownership typically rising with higher counts of household workers (see, e.g. Shimek, 1996; Zhao and Kockelman, 2002), and with more American workers driving alone to work (McKenzie et al., 2010). These effects are statistically significant – but not practically insignificant, if one considers their elasticities.[6] Zonal household counts (serving as the size measure in its logarithmic form) and employment density are also positively correlated with greater vehicle counts in a zone, with fairly strong statistical significance.

Population density is not statistically significant here, for Prius-EV and ICEV ownership levels, once household counts and resident-worker densities are accounted for, perhaps due to this variable being inflated by household members who do not drive (such as young children and the disabled or very elderly). However, population density can vary by orders of magnitude (from rural to suburban to downtown settings), so it is much easier for this variable to have a practical effect across the range of possible land use settings than many of the other covariates used here. Moreover, population density exhibits a stronger practical effect on ICEV ownership rates, in terms of its elasticity, suggesting a greater likelihood of higher ICEV ownership rates for households with non-driving persons. This finding is consistent with Brownstone and Golob's (2009) work, which showed a positive correlation between household fuel consumption (which reflects a combination of ownership and vehicle fuel economy) and the number of children in the household. Additionally, Brownstone and Fang (2009) estimated higher ownership rates of vans, SUVs, and pickup trucks in California households with young children (ages 15 and under). Indeed, as of model year (MY) 2012, the only EVs offering seating capacity above five were the Toyota Highlander HEV and the Chevrolet Tahoe/GMC Yukon/Cadillac Escalade HEVs (with the latter three vehicles all built on the same platform). In the current car market, larger families who require more passenger and cargo capacities simply have fewer choices when seeking an EV versus an ICEV.

Since median household income data is unavailable at the U.S. block group level, the variables used to account for household income here are densities of households with annual income above and below $35,000, measured per acre. Both variables have positive effects on ICEV counts. One explanation for such a result is that higher population densities are associated with more economic and non-economic activity, and thus more travel and higher vehicle ownership levels. Not surprisingly, higher shares of households with annual incomes above $35,000 are associated with higher vehicle ownership rates of all three types. In contrast, a higher density of lower-income households (those with less than $35,000 annual income) is negatively associated with EV ownership rates, though positively associated with ICEV ownership rates. The price premiums on new EVs as compared to their ICEV counterparts range from $2655 to $6160, for MY 2012 vehicles (Cunningham, 2012) and no doubt pose a barrier for lower income families when considering EVs (despite the value of EVs' longer term fuel-cost savings, as computed in Khan and Kockelman (2012) and Tuttle and Kockelman (2012)). Low EV ownership rates among lower income households may also be attributed to the limited selection of used EVs in the market, as compared to used ICEVs. Interestingly, more non-Prius EVs are expected (with a modest elasticity of +0.026 or +2.6%), when the density of households having over $35,000 annual income increases by 1%, versus ownership of Prius EVs (with an elasticity of just +0.008 or +0.8%). This finding

[6] Here, elasticities represent the average increase in the mean vehicle ownership rates (averaged across the 1000 zones in the sample) following a one-percent increase in each covariate (across all sampled zones), holding all other covariate values (in the sample) constant. For example, if the response variable increases by 0.2% for a 1% increase in one of the X's, the corresponding elasticity is 0.2%/1% = 0.2, or 20%, as reported in Table 2.

Table 2
Parameter estimates for the zone-level vehicle registration model.

		Mean	Std. Dev.	Pseudo *t*-stat	Elasticity
Constant	1 (Prius EV)	−2.138	0.425	−5.037	–
	2 (non-Prius EV)	−2.033	0.209	−9.709	–
	3 (ICEV)	2.628	0.235	11.188	–
ln(#HHs)	1	0.753	0.069	10.963	0.031
	2	0.801	0.038	21.214	0.019
	3	0.668	0.038	17.797	0.027
Resi. Worker Density (# per acre)	1	0.447	0.062	7.263	0.034
	2	0.303	0.058	5.236	0.037
	3	0.136	0.056	2.438	0.051
Emp. Density (# per acre)	1	0.020	0.007	3.080	0.025
	2	0.017	0.006	2.876	0.030
	3	0.003	0.003	1.049	0.069
Pop. Density (# per acre)	1	−0.027	0.043	−0.624	−0.004
	2	−0.058	0.018	−3.168	0.004
	3	0.010	0.015	0.666	0.027
HH > $35K Density (# per acre)	1	1.615	0.146	11.054	0.008
	2	1.446	0.148	9.770	0.026
	3	0.194	0.084	2.303	0.027
HH < $35K Density (# per acre)	1	−1.294	0.257	−5.035	−0.008
	2	−0.725	0.143	−5.065	−0.026
	3	1.239	0.063	19.61	0.027
Centerline Density (1/mi.)	1	−0.726	0.522	−1.390	−0.008
	2	−0.712	0.484	−1.472	−0.026
	3	−0.093	0.291	−0.319	**−0.321**
Dist. CBD (mi)	1	−0.029	0.008	−3.734	**−0.262**
	2	−0.029	0.007	−3.856	**−0.200**
	3	0.003	0.005	0.556	0.023
HH0wrk Density (# per acre)	1	−0.713	0.110	−6.507	−0.005
	2	−0.575	0.091	−6.294	−0.026
	3	−0.241	0.051	−4.752	−0.026
HH1wrk Density (# per acre)	1	1.473	0.087	16.883	0.008
	2	1.194	0.095	12.504	0.026
	3	0.306	0.096	3.178	0.023
HH2wrk Density (# per acre)	1	2.458	0.142	17.347	0.005
	2	1.809	0.156	11.633	0.027
	3	0.492	0.161	3.051	0.025
HH > 3wrk Density (# per acre)	1	3.241	0.369	8.776	0.006
	2	2.571	0.421	6.103	0.026
	3	0.323	0.353	0.916	0.030
η_{012}		0.813	0.056	14.524	–
η_{013}		0.334	0.198	1.689	–
η_{023}		0.269	0.191	1.407	–
η_{112}		0.074	0.025	2.932	–
η_{113}		0.073	0.025	2.919	–
η_{123}		0.058	0.072	0.810	–
ρ_1		0.655	0.108	6.078	–
ρ_2		0.491	0.102	4.831	–
ρ_3		0.913	0.147	6.217	–
τ_{v1}		4.982	0.753	6.616	–
τ_{v2}		5.628	0.784	7.178	–
τ_{v3}		2.179	3.701	0.589	–
τ_1		3.311	0.608	5.445	–
τ_2		1.056	0.228	4.632	–
τ_3		1.070	1.758	0.609	–

Note: Elasticity is a dimensionless value characterizing percentage change in the response variable (vehicle ownership level) due to a 1% change in the covariate. Bolded values indicate practical significance (i.e., elasticities >0.2 or <−0.2).

may reflect the Prius' relative modest price among all EVs, as well as its longer history on the market compared to other EVs (thus making more Priuses available in used-vehicle markets).

Controlling for all other variables, greater distance to the regional CBD is associated with lower ownership of both EV types ($k = 1, 2$): A 1% increase in distance to CBD is accompanied by 0.26% and 0.20% reductions (practically significant elasticities of −0.26 and −0.20) in Prius EV and non-Prius EV ownership rates, respectively, at the block group level, while its effect on ICEV ownership appears negligible. The relatively significant effects of distance to CBD on EV ownerships suggest that the CBD distance variable is proxying for a variety of relevant attributes that change with distance but were not available as covariates here, such as parking prices and parking space availability (which track land values, mostly), transit access, and so forth. The fuel economy (Michalek et al., 2011) and vehicle size benefits of EVs (particularly for households closer to the CBD traveling more frequently in congested conditions), coupled with range anxiety for households living further from the regional center, may also be at play in this ownership versus distance relationship. The parameter coefficients of the ln(#HHs) variable (i.e., the natural logarithm of household counts per zone) across the three models were estimated to be 0.75, 0.8, and 0.67 for Prius EV, non-Prius EV, and ICEV counts, respectively, which suggests a slightly diminishing and non-linear (coefficient $\neq 1$) effect of household density on the number of vehicles per household. This may be due to more population-dense zones having more households, even though population density was also controlled for here (in a linear way).

Centerline-mile density appears to exert a negative influence on ownership rates, everything else constant, with a strong effect on ICEV ownership (elasticity = −0.321 or 32.1%). The density of zero-worker households (HH0wrk Density) is negatively associated with ownership rates of all vehicle types, presumably due to lower travel needs and lower incomes. A statistically significant, but practically insignificant, positive association is found between EV ownership rates and the densities of households with 2 workers and with 3+ workers. A positive correlation is evident between ICEV ownership rates and the density of households with 3+ workers. Higher jobs densities come with higher average vehicle counts across all types, although the effects appear practically negligible.

Seemingly random variations in all three vehicle ownership rates exhibit spatially clustering, as measured by the autocorrelation coefficients ρ_1, ρ_2 and ρ_3. By model construction, these spatial effects capture missing variables that trend in space, such as parking prices, congestion, and land use intensity, which affect vehicle ownership decisions. The remarkably high (aspatial) correlation between non-Prius EV and Prius EV error terms (described via the parameter $\eta_{012,}$ with mean estimate +0.813) reveals that higher Prius EV counts are likely to co-exist with higher non-Prius EV counts, as expected. However, their spatial correlation (gauged by the parameter η_{112}) is practically insignificant (i.e., neighboring zones' Prius-EV counts have no bearing on a zone's non-Prius EV counts). In other words, the cross-correlations among different vehicle types are local (within a zone), after controlling for spatial autocorrelation across zones (from missing variables).

ICEV ownership rates exhibit a modest *aspatial* correlation with Prius and non-Prius EV ownership rates, as reflected by the parameters $\eta_{013} = +0.334$ (pseudo *t*-stat. = 1.689) and $\eta_{023} = +0.269$ (pseudo *t*-stat. = 1.407), respectively. In other words, higher ICEV ownership rates tend to rise with EV ownership rates, which may come from underlying factors shared across all ownership rate decisions, and not captured by the model's covariates (e.g., other demographic factors and parking availability).

Interestingly, ICEVs show a rather weak spatially-lagged cross-correlation with the two EV categories ($\eta_{113} = +0.073$ and $\eta_{123} = +0.058$). Using measures of spatial correlation, the results in this paper support previous findings (using non-spatial models and arguments) that vehicle technology adoption is often influenced via a "neighbor effect," where new technologies become more desirable as market penetration increases nearby (see, e.g. Mau et al., 2008; Axsen et al., 2009).

To validate the spatial EV model, estimation and prediction performances were compared across a 3-level MCAR model (I), a Poisson-lognormal CAR model (II), a Poisson-lognormal multivariate model (III), and a Poisson-lognormal model (IV). Model I is the full-blown MCAR model, the base model that allows for spatial autocorrelation within each vehicle type (over space) and

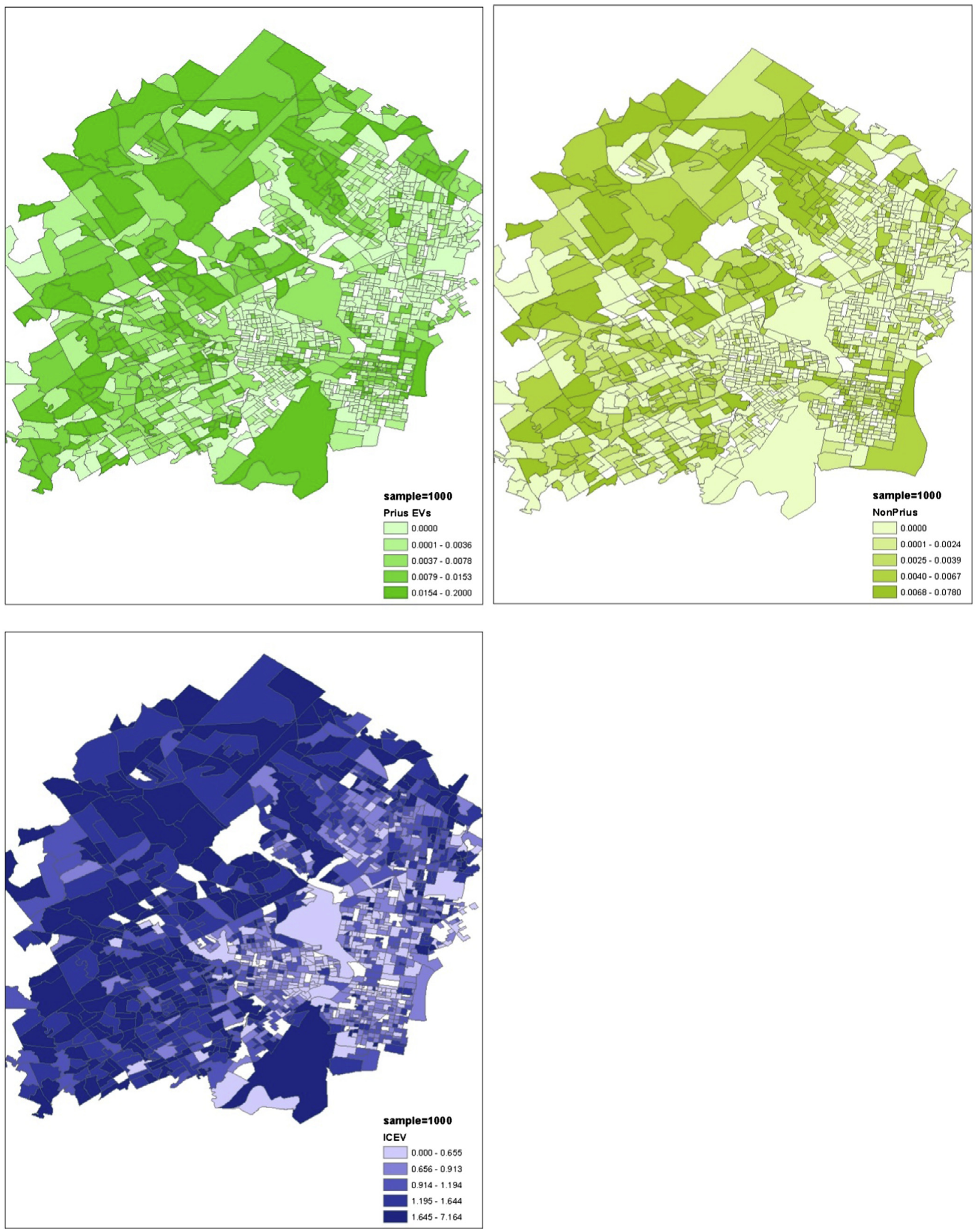

Fig. 1. Locations of vehicle counts (by type) per household across Philadelphia zones (clockwise: Prius EVs, non-Prius EVs, and ICEVs).

cross-correlations across vehicle types. The remaining three models are restricted versions of Model I, by imposing certain constraints on the unknown parameters, as shown in Table 3. Model II removes the multivariate component from Model I by assuming independence across types. Model III removes the spatial autocorrelation components but keeps the multivariate component. Model

Table 3
Model validation.

	Poisson log-normal MCAR	Poisson log-normal CAR	Poisson log-normal multivariate	Poisson log-normal
Model no.	I	II	III	IV
Parameter constraints	–	$\eta_{0,pq} = 0$, $\eta_{1,pq} = 0$	$\eta_{1,pq} = 0$, $\rho_1 = \rho_2 = \rho_3 = 0$	$\eta_{0,pq} = 0$, $\eta_{1,pq} = 0$, $\rho_1 = \rho_2 = \rho_3 = 0$
DIC	7429.12	7831.36	8293.37	8732.87
RMSE	142.01	194.06	298.15	364.8
Moran's I of residuals for total vehicle counts	0.145	0.238	0.431	0.485

IV is slightly more flexible than the standard Poisson model, thanks to permitting heterogeneity via the lognormal component; however, it neglects spatial autocorrelation and cross-correlation among vehicle types. The Deviance Information Criterion (DIC) is typically used to evaluate the goodness-of-fit of Bayesian models (Spiegelhalter et al., 2002). Root-mean-square errors (RMSEs) measure the variation in differences between predicted and observed values. Moran's I indicates spatial dependence in the residual terms for total vehicle counts: a value close to 1 or -1 indicates strong spatial cluster (i.e., positive autocorrelation) or spatial dispersion (i.e., negative autocorrelation), while a zero value indicates a random distribution. All metrics suggest that the full MCAR model outperforms the other models, thanks to having the lowest DIC value, the smallest RMSE, and a sizable reduction in spatial autocorrelation. However, there are still limitations with this analysis, such as the omission of other important variables (e.g., present of public charging stations in the block group, and better measures of household income), as discussed in the next section.

6. Policy implications and study limitations

Using a trivariate Poisson-lognormal CAR model, this study forecasts registered-vehicle counts across southeastern Pennsylvania to examine the effect of zone-level characteristics on vehicle ownership rates (per resident household) of Prius EVs, non-Prius EVs, and ICEVs while reflecting spatial autocorrelation. Results reveal that all three vehicle ownership rates rise with household counts (per zone) and resident-worker densities. In particular, EV ownership is predicted to rise as households get closer to the CBD, perhaps due to the relatively small size of most EVs, the diminished range anxiety issues (thanks to shorter trips), and desire for greater fuel economy (in congested central-city driving conditions). Actual (and perceived) range anxiety plays a significant role in households' decision to acquire electric vehicles (Aoki, 2010; Helveston et al., 2014). Provision of public EV charging infrastructure can alleviate potential range anxiety, and has been shown to be a more cost effective way to improve EV range than investing in bigger batteries (Morrow et al., 2008). Additionally, the spatial clustering effects identified in this study also point to the existence of missing variables that trend in space and possibly a "neighbor effect" (from nearby households owning such vehicles). Helveston et al. (2014) showed that range anxiety is a greater concern for American consumers than Chinese consumers, in part due to Chinese persons' familiarity with electric bikes (which also require vehicle-charging). As a technology becomes more prevalent, familiarity and perceived value of such technologies and products tends to rise. The spatial autocorrelation exhibited by the results here suggest that EV purchase rates will rise, via such familiarity, thanks to rising market penetration. These results also suggest that provision of public EV charging infrastructure (as a channel to increase exposure and consumer familiarity to EV technology, not just reduce range anxiety concerns) may also increase EV market shares in nearby areas.

The results of this study underscore the high continuing demand for ICEVs, thanks in part to the far larger choice set of vehicles in that class, versus the mostly smaller vehicles offered in the EV classes to date. (ICEVs presently offer greater passenger and cargo capacity.) Policies that encourage auto companies to electrify more vehicle body types, thereby expanding the vehicle choice set, would also likely increase EV ownership. In general, lower income households are less likely to purchase EVs; but, when they do, they are more likely to purchase Toyota Priuses (the EV model with the longest market history) than non-Prius EVs, suggesting that vehicle affordability and familiarity, along with used-vehicle availability, may also be influencing EV purchase decisions.

A household's decision to purchase an EV is also influenced by many relatively complex residential and transportation characteristics, not included in this study's set of covariates. These include such things such as availability of designated parking for a home charger to be installed, nearby public charging infrastructure, and commute distances (versus AER, in the case of BEVs). Furthermore, because the model uses aggregate data, these parameters cannot be generalized to apply at an individual household level. Nevertheless, the model presented here uses existing data sets to address important gaps in current research in terms of the scale of observational units (neighborhoods or zones, instead of individual households or entire regions), while reflecting spatial autocorrelation patterns, without which the estimated parameters may be biased. The zone-level EV ownership predictions should be of strong interest to decision makers in energy and transportation infrastructure planning, helping them identify "hot spots" where EV owning households tend to cluster.

Finally, this model structure offers a solid framework for spatially-based choice behavior, as EV market shares rise over time, and data sets on EV ownership and infrastructure become more detailed. Limitations of this empirical work relate to several theoretical notions incorporating a temporal component to account for time dependence and time–space interaction, goodness-of-fit measures for spatial models with count responses (see, e.g., Páez et al.'s (2013) measures for spatial discrete choice models), and identification issues for parameters in complex spatial models (see, e.g., Lee, 2004).

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Appendix A

The three-level scheme relies on a series of conditional distributions, starting from the marginal distribution of $\boldsymbol{\phi}_3$ which follows a multivariate normal distribution: $p(\boldsymbol{\phi}_3) \sim \boldsymbol{N}(\boldsymbol{\mu}_3, \boldsymbol{\Sigma}_{33})$, with $\boldsymbol{\mu}_3 = \mathbf{0}$ and $\boldsymbol{\Sigma}_{33} = [\tau_3(\mathbf{D} - \rho_3\mathbf{W})]^{-1}$. The diagonal matrix, $\mathbf{D}$, stores the number of neighbors for each geographic unit along its diagonal line; τ_3 is a scaling factor to fine-tune the covariance matrix, $\boldsymbol{\Sigma}_{33}$; ρ_3 measures the strength of spatial autocorrelation of the response type 3 (i.e., ICEVs); and the square weight matrix, $\mathbf{W}$, is defined by contiguity (i.e., $\mathbf{W}_{ij} = 1$ if i and j share a border and $\mathbf{W}_{ij} = 0$ if otherwise). For ease of exposition, one can assume the following sequence of conditional normal distributions: $p(\phi) = p(\phi_1|\phi_2,\phi_3)\cdot p(\phi_2|\phi_3)\cdot p(\phi_3)$. Moreover, the marginal distribution of (ϕ_2,ϕ_3) can be obtained by removing irrelevant elements (with respect to ϕ_2 and ϕ_3) from the full distribution, leading to the following distribution:

$$\begin{pmatrix}\phi_2\\ \phi_3\end{pmatrix} \sim N\left(\begin{pmatrix}\boldsymbol{\mu}_2\\ \boldsymbol{\mu}_3\end{pmatrix}, \begin{bmatrix}\boldsymbol{\Sigma}_{22} & \boldsymbol{\Sigma}_{23}\\ \boldsymbol{\Sigma}_{23}' & \boldsymbol{\Sigma}_{33}\end{bmatrix}\right)$$

Conditionally, $\phi_2|\phi_3 \sim N(\mathbf{A}_{23}\phi_3, [(\mathbf{D}-\rho_2\mathbf{W})\tau_2]^{-1})$ (see Wang and Kockelman, 2013) where $\mathbf{A}_{23}$ describes the aspatial correlation between response types 2 and 3, as well as the spatially-lagged correlation between the two response types, formally: $\mathbf{A}_{23} = \eta_{0,23}\boldsymbol{I} + \eta_{1,23}\mathbf{W}$.

Taking this conditioning one step further, $\phi_1|\phi_2,\phi_3 \sim N(\mathbf{A}_{13}\phi_3 + \mathbf{A}_{12}\phi_2, [(\mathbf{D}-\rho_1\mathbf{W})\tau_1]^{-1})$, where $\mathbf{A}_{13}$ and $\mathbf{A}_{12}$ capture the aspatial and spatially-lagged correlation across response types 1 and 3, and response types 1 and 2, formally: $\mathbf{A}_{13} = \eta_{0,13}\boldsymbol{I} + \eta_{1,13}\mathbf{W}$ and $\mathbf{A}_{12} = \eta_{0,12}\boldsymbol{I} + \eta_{1,12}\mathbf{W}$.

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