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

T. Donna Chen [a], Yiyi Wang [b], Kara M. Kockelman [c,*]

[a] The University of Texas at Austin, 6.9E Cockrell Jr. Hall, Austin, TX 78712-1076, United States
[b] Montana State University, Civil Engineering Department, United States
[c] Department of Civil, Architectural and Environmental Engineering, The University of Texas at Austin, United States

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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

* Corresponding author. Tel.: +1 512 471 0210.
E-mail addresses: donna.chen@utexas.edu (T.D. Chen), yiyi.wang@ce.montana.edu (Y. Wang), kkockelm@mail.utexas (K.M. Kockelman).

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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).