Spatial Effects on Hybrid Electric Vehicle Adoption

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such dynamics in the adoption of HEVs can provide useful insights into the possible future trajectory of PEV adoption. Finally, Tuttle and Baldick (2015) explicitly state that because of the advanced nature of HEV technology and adoption dynamics, a number of studies use past HEV adoption rates as a baseline

3.1.2. Spatial Error Model

The SE model is used to capture a spatial influence in the error terms only. The model has the form:

$$y = X\beta + u, \tag{2}$$

where:

$$u = \lambda W u + \epsilon. \tag{3}$$

The terms y, X, β, W, and ϵ have the same interpretation as in the SAR model. The parameter λ is a coe□cient on the spatially autocorrelated error term, u. Anselin (1988) also provides a maximum-likelihood and:

$$W_b = \sum_{=1}^{N} \left(\sum_{=1}^{N} W \quad + \sum_{=1}^{N} W \quad \right)^2 . \tag{11}$$

Moran (1950) shows the derivations and interpretations of these terms. Using this mean and variance, Moran's I can be converted to Z-scores:

$$Z = \frac{I - \mathbb{E}[I]}{\sqrt{\mathrm{Var}(I)}}, \tag{12}$$

to test the hypothesis of no spatial autocorrelation.

3.2.2. Lagrange Multiplier Error: Testing for Autocorrelation Within Errors

The Lagrange multiplier error test is a common way to test for spatial autocorrelation in the residuals of a regression model. Spatially autocorrelated errors have the form:

$$u = \lambda W u + \epsilon, \tag{13}$$

where λ is a coefficient on the spatially autocorrelated error, W is the spatial-weighting matrix, and ϵ is a vector of mean-zero errors with variance-covariance matrix $\sigma^2 I_n$, where I_n is an $n \times n$ identity matrix. Under the null hypothesis that $\lambda = 0$, meaning that there is no spatial autocorrelation in the errors, a standard regression model of the form:

$$y = X\beta + \epsilon, \tag{14}$$

can be estimated. The Lagrange multiplier error test statistic is defined as:

$$LM = \frac{\left(\epsilon^\top W \epsilon / s^2\right)^2}{T}, \tag{15}$$

where:

$$s^2 = \frac{\epsilon^\top \epsilon}{N}, \tag{16}$$

and:

$$T = \mathrm{tr}\left[\left(W + W^\top\right) W\right]. \tag{17}$$

Under the null hypothesis of no spatial autocorrelation in the errors, LM has a χ^2 distribution with one degree of freedom.

3.3. Selecting a Spatial Model

Once it has been determined that spatial effects may be important within a dataset, the next question is what spatial model to use. It is important to note that estimating a model without spatial effects in such an instance can lead to biased and inconsistent parameter estimates. One possible method of selecting a spatial model, which LeSage and Pace (2009) mention, is to compare the log-likelihood value obtained after finding maximum-likelihood estimates for each model. This is because the log-lik

3.4. Time-Lagged Spatial Model

One potential use of a spatial econometric model is to understand the temporal dynamics of the spatial eﬀects captured in the model. As discussed in Section 4, our case study takes the y vector in these models to be the number of registered HEVs per 1000 passenger vehicles in each spatial unit. The X matrix contains a number of demographic and socioeconomic variables for each spatial unit. Thus, the models allow us to conduct a static analysis, insomuch as we can study the direct and spatial relationships between HEV adoption and the demographic and socioeconomic characteristics of the spatial units at a certain point in time.

An important and interesting question may be to examine the temporal dynamics of HEV adoption. For example, one may want to know what eﬀect time-lagged HEV adoption has on subsequent HEV adoption. A model with such a structure could allow one, for instance, to exam

Let $\hat{\rho}$, $\hat{\beta}$, and $\hat{\lambda}$ be maximum-likelihood coefficient estimates of the GWR model. Suppose that we are interested in examining what effect a change in the value of y for one spatial unit has on the values of y

Table 1: New HEV Registrations and HEV Adoption Penetration

There is an important limitation arising from our use of census tracts as the spatial units in our analysis. By definition, census tracts only capture the effects of geographic neighbors on HEV adoption. As such, our analysis neglects the effects of 'social neighbors.' For instance, technology experience by a friend or family member, who is not a geographic neighbor, could affect technology adoption. Axsen and Kurani

adoption penetrations in an adjacent census tract has a positive e�ect on HEV adoption penetration within a given census tract.

5.3. Time-Lagged Results

To further understand the dynamics of HEV adoption, we examine the e�ects of time-lagged HEV adoption on subsequent adoption. More specifically, we use the three time-lagged model structures introduced in Section 3.4. We define the HEV adoption penetration within each census tract between the years 2009 and 2012 as the dependent variable (i.e., as the y variable). We then let the HEV-adoption penetration

Table 6: Maximum Likelihood Estimators for Time-Lagged SAR, SE, and GWR Models. t**-statistics are in parentheses. Coe**cients with** * **and** ** **indicate significance at the 5% and 1% confidence levels, respectively.**

Table 7: Marginal E□ect of Increased HEV Adoption in Census T

the adoption of HEVs and PEVs by early adopters. Moreover, incentive programs can be tailored toward early adopters that have the greatest spatial ‘spillover’ effect on subsequent technology adoption. This spillover effect can be estimated or simulated using the marginal analysis discussed in Section 3.5.

The analysis conducted here focuses on HEV adoption in the state of Ohio. It is important to stress, however, that the case study conducted here can be generalized to other study regions, so long as the input data used are available. Many jurisdictions maintain socioeconomic, demographic, and vehicle-registration data, which can be used to repeat our analysis elsewhere. There are a number of important insights from this analysis that have implications for future transportation use. One is that our work demonstrates how spatial econometric models can be applied to discern spatial relationships in the adoption of new transportation technologies. Second, the patterns of HEV adoption can be used to proactively plan PEV-related infrastructure in anticipation of where PEVs may be adopted. As PEV adoption takes hold, the same types of models can be reestimated using the PEV-adoption data. The model results and coefficient estimates can be used to simulate and predict subsequent PEV adoption.

There are some important limitations to the work presented here, which raise areas of future research. One is that our analysis considers geographic neighbors only in constructing the spatial weighting matrix. This does not capture the effect of social networks and interactions, which could influence HEV adoption. Axsen and Kurani (2011) study the effects of social networks and demonstrate that they affect individuals’ perceptions of PEVs. Analogously, HEV adoption decisions by social neighbors, who are not geographic neighbors, may affect an individual’s HEV adoption decision. Such an analysis is limited by the difficulty of constructing social networks. Social networking data is increasingly available through social media outlets, however, which may make such an analysis possible. Another area of future research is to focus on a smaller study region (e.g., Central Ohio only), which would allow for including a more granular spatial weighting matrix. Our analysis uses census tracts, which typically have population sizes between 1200 and 8000 people, as the spatial unit. More interesting spatial autocorrelations may appear if this analysis is extended to consider individual households and their immediate geographic neighbors as spatial units. The only limitation of conducting such an analysis is that the size of the dataset increases considerably, which can raise memory and model-estimation difficulties.

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