The Economic Case for the Spatial Error Model with an Application to State Vehicle Usage in the U.S.

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Abstract

LeSage and Pace (2009) make an econometric case for the spatial Durbin model over, among others, the spatial error model. We make an economic case for the spatial error model because it captures spatial dependence more fully (i.e. beyond that which can be attributed to the dependent variables in neighboring units). Also, when faced with the choice between aggregate or disaggregated data the spatial error model or a related model (e.g. the seemingly unrelated spatial error model) should be fitted. This is to ensure that Wald tests of whole sets of coefficients against one another to establish if disaggregation is necessary are not invalidated. To illustrate the economic case which we make we extend the literature on the determinants of vehicle usage by modelling the spatial dependence of state travel for the U.S. over the period $1980-2008$. On the basis of Wald tests, aggregate data on state vehicle usage is progressively disaggregated and spatial error models for travel on all twelve types of highway are fitted. In all cases the spatial dependence in the spatial error models is greater than or approximately equal to that in the spatial lag models, confirming that the former does capture any additional sources of spatial dependence.

Keywords: Spatial Error Model; Spatial Lag Model; Spatial Durbin Model; Panel Data; Vehicle Miles; Rural Highways; Urban Highways

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1 Introduction

Elhorst (2010) believes that LeSage and Pace (2009) (LSP from hereon) initiated a 'sea change' in applied spatial econometrics because, among other things, they set out an econometric case for the spatial Durbin model over, for example, the spatial lag model and the spatial error model. In the spatial lag model, the spatially lagged dependent variable captures the spatial dependence between the cross sectional units. The spatial Durbin model is an extension of the spatial lag model to include spatially lagged independent variables. In the spatial error model, the spatial autocorrelation term captures the spatial dependence.

There are two strands to the econometric case which LSP make in support of the spatial Durbin model. The first is based on the belief that analyzing the spillovers should be the principal focus in spatial modelling (Anselin, 1988 and LSP). If this is the overriding aim, the spatial Durbin model is appealing because a distinction can be made between the direct impact and the indirect impact of a change in an explanatory variable. The direct impact estimates the effect of changing an explanatory variable in a particular cross sectional unit on that unit's dependent variable, which incorporates feedback effects which pass through the neighboring units and back to the unit which initiated the adjustment process. The indirect impact is an estimate of the effect of changing an explanatory variable in a particular unit on the dependent variables of all the other units.[1] The second strand of the econometric case for the spatial Durbin model concerns the unbiased parameters which the spatial Durbin model yields, even if the true Data Generating Process (DGP) is, among others, the spatial error model or the spatial lag model. We expand on both strands of the econometric case for the spatial Durbin model in due course.

Notwithstanding the strength of the econometric case which LSP make in favor of the spatial Durbin model, we posit two economic arguments in support of the spatial error model over the spatial Durbin and spatial lag models. Firstly, we argue that the spatial error model (and related models such as the seemingly unrelated spatial error model) constitutes a fuller representation of the spatial dependence than a spatial model without a spatial autocorrelation variable. This is because with the spatial error model the spatial dependence can be affected by other factors in addition to shocks to the spatially lagged dependent variable. Secondly, suppose total demand is disaggregated into two categories 1 and 2, a Wald test of the whole set of coefficients from the model for category 1 against the set of coefficients from the model for category 2 cannot be performed on a pair of spatial Durbin models or a pair of spatial lag models. This is because the spatially lagged dependent variables will differ between the two spatial Durbin models or the two spatial lag models. In contrast, the set of explanatory variables will be the same for a pair of spatial error models so such a test can be performed and is necessary to establish if there is more to be learnt from disaggregating the data. In light of the dramatic rise in interest in applied spatial econometrics in recent years, we feel it is important to bring these arguments to the attention of practitioners in the field. Both arguments are discussed in more detail further in the paper.

We illustrate the economic case which we make in favor of the spatial error model by extending the travel demand literature by modelling the spatial dependence of state vehicle usage for the U.S. over the period $1980-2008$. A complete set of significant Wald statistics for tests of whole sets of parameters against each other provides clear justification for fitting spatial error models for vehicle usage on all twelve types of highway, as classified by the Federal Highway Administration (FHWA, 1996; $1997-2009$).[2] As we would expect in light of the observed Wald statistics, in the spatial error models of disaggregated usage there are a number of cases where significant coefficients on a variable (e.g. real personal income per capita and family size) have different signs and are significantly different from one another. For example, we find that an increase in family size leads to an increase in travel on urban highways and a decrease in travel on rural highways. In all cases the spatial dependence in the spatial error models is greater than or approximately equal to that in the spatial lag models, confirming that the former does in fact capture any additional sources of spatial dependence.

Monocentric theories of urban travel behavior incorporate congestion by assuming that the marginal cost of travel time at a given distance from the central business district (CBD) is a positive function of the accumulated number of households residing beyond this point (or in other words accumulated travel demand) and a negative function of the amount of land that is devoted to roads at that point (Wheaton, 1998; and Bento *et al.*, 2003). Implicit in these models is the idea of spatial dependence because a rise in congestion further from the CBD, other things being equal, will lead to more congestion closer to the CBD. In practice, however, congestion spillovers do not occur simultaneously during a peak period which is not a feature of the above theories. Dynamic travel time spillovers between neighboring points in a city in the peak occur over a short period of time and are therefore unlikey to be accurately captured by variables such as residential density and road capacity. This is because residential density and road capacity will change very little from one day to the next. For this reason variation in daily travel time would be better explained by travel time at neighboring points in the city.

Several key empirical studies of the determinants of travel demand (Duranton and Turner, 2011; Cervero and Hansen, 2002; Small and Van Dender, 2007; Hymel *et al.*, 2010; Noland, 2001; Bento *et al.*, 2005; and Voith, 1997) have chosen not to explicitly focus on spatial dependence and have instead made seminal contributions on other issues such as induced vehicle usage from an increase in highway length and the rebound effect (the rise in vehicle usage following an increase in the fuel efficiency of vehicles). In recent years a small number of discrete choice studies of travel behavior have explicitly modelled spatial dependence (Dugundi and Walker, 2005; Páez and Scott, 2007; and Goetzke, 2008), although only the latter captures this dependence using a spatial weights matrix, albeit without taking account of the endogeneity of the spatial autoregressive variable. A logical extension of the empirical travel demand literature at the intensive margin is to appropriately model spatial dependence using a spatial weights matrix. The application in this paper also suggests that spatial econometric studies of travel demand would benefit from the development of theoretical models of travel behavior which do not rely on variables such as residential density and roadway capacity to model the spillover dynamics. Development of such theories would aid the construction of the spatial weights matrix which must be pre-specified. For a detailed discussion of the role of economic theory in the specification of the spatial weights matrix see Corrado and Fingleton (2011).

The remainder of this paper is organized as follows. In section 2, we use a brief overview of the spatial lag, spatial Durbin and spatial error models for panel data to present the econometric case which LSP make in favor of the spatial Durbin model and also to set out the economic case which we make for the spatial error model.[3] The specification of the spatial weights matrix and issues which arise in the estimation of the spatial error and spatial lag models are discussed in section 3. The salient features of the data set are discussed in section 4 and in section 5 the fitted aggregate and disaggregated spatial error models are presented and analyzed. We also present and analyze the spatial autoregressive parameters from the corresponding spatial lag models. In section 6 we conclude by arguing that there is merit in estimating a spatial error model even if analysts favor the spatial Durbin model because they are primarily interested in the spatial spillover effects. We also use the fitted spatial error models to make some policy recommendations in the concluding section.

2 Choice of Model Specification: The Econometric and Economic Arguments

Suppose total demand for a cross sectional spatial unit i in period t is denoted D_{it}, where the cross sectional units are indexed $i = 1,...,N$ and time is indexed $t = 1,...,T$. Assume D_{it} can be disaggregated into M demand categories indexed $m = 1,...,M$ and denoted $D_{m,it}$

$$D_{it} = D_{1,it} + D_{2,it} + ... + D_{M,it}. \tag{1}$$

The general forms of the spatial lag, spatial Durbin and spatial error models for the $m-$th category of demand are given in (2), (3) and (4), respectively.

$$D_{m,it} = \delta_m \sum_{j=1}^{N} w_{ij} D_{m,jt} + \alpha_m + \boldsymbol{x}_{it}\boldsymbol{\beta}_m + \mu_{m,i} + \varepsilon_{m,it} \tag{2}$$

$$D_{m,it} = \delta_m \sum_{j=1}^{N} w_{ij} D_{m,jt} + \alpha_m + \boldsymbol{x}_{it}\boldsymbol{\beta}_m + \sum_{j=1}^{N} w_{ij} x_{ijt}\theta_m + \mu_{m,i} + \varepsilon_{m,it} \tag{3}$$

$$D_{m,it} = \alpha_m + \boldsymbol{x}_{it}\boldsymbol{\beta}_m + \mu_{m,i} + \phi_{m,it} \tag{4}$$

$$\phi_{m,it} = \rho_m \sum_{j=1}^{N} w_{ij} \phi_{m,jt} + \varepsilon_{m,it},$$

where $\boldsymbol{x}_{it}$ is a $(1 \times K)$ vector of observations for the independent variables for all M categories of demand; $\boldsymbol{\beta}_m$ is a $(K \times 1)$ vector of fixed parameters to be estimated for the $m-$th category of demand; δ_m is the spatial autoregressive coefficient; $\varepsilon_{m,it}$ is an i.i.d disturbance for i and t with zero mean and variance σ_m^2; $\mu_{m,i}$ is an unobserved time-invariant effect which is included to capture spatial heterogeneity (i.e. spatial fixed effects, SFEs, or spatial random effects, SREs).

$\sum_{j=1}^{N} w_{ij} D_{m,jt}$ denotes the effect of the dependent variable for the $j-$th neighboring unit on the dependent variable for the $i-$th unit where w_{ij} is the $ij-$th element of the pre-specified spatial weights matrix $\mathbf{W}$. $\mathbf{W}$ is a non-negative $(N \times N)$ matrix of constants which describes the spatial arrangement of the cross sectional units and also the strength of the spatial interaction between the units. All the elements on the main diagonal of $\mathbf{W}$ will be zero and as is usual in the literature $\mathbf{W}$ is row normalized in the empirical analysis. In the spatial Durbin model, $\boldsymbol{x}_{ijt}$ is a $(1 \times K)$ vector of observations for the independent variables for the $j-$th neighboring unit and θ_m is a $(K \times 1)$ vector of fixed parameters to be estimated. Finally, in the spatial error model ρ_m is the spatial autocorrelation coefficient and $\phi_{m,it}$ is the spatial autocorrelated disturbance.

$\mathbf{I} - \delta_m \mathbf{W}$ and $\mathbf{I} - \rho_m \mathbf{W}$, where $\mathbf{I}$ denotes the $(N \times N)$ identity matrix, should be non-singular. This will be the case if δ_m or ρ_m lie in the interval $(1/\tau_{\min}, 1)$ where $\tau_{\min}$ is the most negative real characteristic root of $\mathbf{W}$ and 1 is its largest real characteristic root because $\mathbf{W}$ is row normalized. When the spatial weights matrix prior to row normalization, $\mathbf{W_0}$, is a binary matrix as is the case here, which is something we discuss in the next section, the row and column sums of $\mathbf{W_0}$, $(\mathbf{I}- \delta_m \mathbf{W_0})^{-1}$ and $(\mathbf{I}- \rho_m \mathbf{W_0})^{-1}$ are uniformly bounded in absolute value as N tends to infinity (Elhorst, 2010; Kapoor *et al.*, 2007; Kelejian and Prucha, 1998; 1999). This is necessary to ensure that the spatial correlation in the cross section is constrained such that the correlation between the units converges to zero as the distance between the units increases to infinity.

As we noted above there are two strands to the econometric case which LSP make in support of the spatial Durbin model over, among others, the spatial lag and the spatial error models. The first is because the spatial Durbin model yields unbiased parameters irrespective of the whether the true DGP is the spatial error model or the spatial lag model. This is because including spatially lagged independent variables when the coefficients on these variables are zero will not affect the estimates of the other parameters. The second strand, which is what we now consider formally, is because the spatial Durbin model can estimate direct and indirect elasticities without imposing an *a priori* restriction on their values.

Overlooking for the moment SFEs or SREs and rewriting the spatial Durbin model in vector form:

$$D_{m,t} = (\mathbf{I} - \delta_m \mathbf{W})^{-1} \alpha_m \iota_N + (\mathbf{I} - \delta_m \mathbf{W})^{-1} (\mathbf{X}_t \beta_m + \mathbf{W} \mathbf{X}_t \theta_m) + (\mathbf{I} - \delta_m \mathbf{W})^{-1} \varepsilon_{m,t}, \quad (5)$$

where $D_{m,t}$ is an $(N \times 1)$ vector, ι_N is an $(N \times 1)$ vector of ones, $\mathbf{X}_t$ is an $(N \times K)$ matrix of observations and $\varepsilon_{m,t}$ is an $(N \times 1)$ vector. Differentiating (5) with respect to the $k-$th explanatory variable $x_{k,it}$ yields the following vector of partial derivatives:

$$\begin{bmatrix} \frac{\partial D_m}{\partial x_{k,1}} & . & \frac{\partial D_m}{\partial x_{k,N}} \end{bmatrix}_t = \begin{bmatrix} \frac{\partial d_{m,1}}{\partial x_{k,1}} & . & \frac{\partial d_{m,1}}{\partial x_{k,N}} \\ . & . & . \\ \frac{\partial d_{m,N}}{\partial x_{k,1}} & . & \frac{\partial d_{m,N}}{\partial x_{k,N}} \end{bmatrix}_t \tag{6a}$$

$$= (\mathbf{I} - \delta_m \mathbf{W})^{-1} \begin{bmatrix} \beta_k & w_{12}\theta_k & . & w_{1N}\theta_k \\ w_{21}\theta_k & \beta_k & . & w_{2N}\theta_k \\ . & . & . & . \\ w_{N1}\theta_k & w_{N2}\theta_k & . & \beta_k \end{bmatrix}, \tag{6b}$$

where the right-hand side of $(6b)$ is independent of the time index. By setting θ_k in $(6b)$ equal to zero, which follows from the construction of the spatial lag model, we obtain a vector of partial derivatives where the ratio of the indirect and direct effects are the same for all explanatory variables, which is unrealistic. In the spatial Durbin model no such restrictions are imposed on the value of θ_k and as a result the ratio of the indirect and direct effects will not be the same for all the explanatory variables, which is much more plausible. See Elhorst (2010) for a simple illustrative example to verify this is the case because unfortunately general expressions for the direct and indirect effects cannot be derived as each empirical application will have unique N and $\mathbf{W}$. Moreover, the spatial Durbin model yields different direct and indirect effects on a unit so to facilitate interpretation LSP suggest reporting a mean direct effect (average of the diagonal elements on the right-hand side of $(6a)$) and a mean indirect effect (average row or column sum of the non-diagonal elements on the right-hand side of $(6a)$). It is sufficient for our purposes to show that it is possible to estimate unrestricted direct and indirect effects from a spatial Durbin model but for details on the estimation of the associated $t-$statistics and confidence intervals see LSP and Elhorst (2010; 2011).

Once again overlooking for the moment SFEs and SREs and rewriting the spatial error model in vector form:

$$D_{m,t} = \alpha_m \iota_N + \mathbf{X}_t \beta_m + (\mathbf{I} - \rho_m \mathbf{W})^{-1} \varepsilon_{m,t}. \tag{7}$$

In contrast to the spatial Durbin and spatial lag models the β parameters from a spatial error model are direct effects and can be interpreted in the usual way. This is because the partial derivative with respect to an explanatory variable in the same unit is not a function of the spatial autocorrelation variable, whereas for the spatial Durbin and spatial lag models it is a function of the spatial autoregressive variable(s). Moreover, since $\mathbf{W}$ is row normalized in the estimation of the spatial error models, the total and spillover effects of a change in $\varepsilon_{m,t}$ are simply $1/(1-\rho_m)$ and $[1/(1-\rho_m)]-1$, respectively, where in the application the spillover effect is taken to be the sum of the higher order direct effect and the indirect effect. The total and spillover effects are discussed in more detail in the analysis of the results.

Moving onto discuss the two economic arguments which we make in favor of the spatial error model. Firstly, it can capture more fully the sources of spatial dependence *vis-à-vis* a model with a spatially lagged dependent variable and no spatial autocorrelation term. This is because δ_m in a spatial lag or spatial Durbin model will only capture the spatial dependence pertaining to $D_{m,jt}$. In contrast, the spatial error model captures spatial dependence which relates to shocks to a wider range of unspecified variables. If the spatial error model does capture additional sources of spatial dependence ρ_m will be greater than δ_m. In general, we would expect this to be the case because if there is spatial dependence shocks to a range of variables in neighboring units are likely to be spatially correlated and not just shocks to the dependent variables. It is possible, however, that shocks to a wider range of variables in neighboring units may pick up some shocks which partially offset shocks to the spatially correlated dependent variables. In this case ρ_m will be less than δ_m. Irrespective of whether ρ_m is less than or greater than δ_m, by comparing ρ_m and δ_m we can see the effect of assuming that the spatial dependence is due to a wider range of shocks.

Secondly, the spatial error model permits Wald tests of whole sets of coefficients against one another. Suppose total demand D_{it} can be disaggregated into two demand categories $D_{1,it}$ and $D_{2,it}$. Wald tests can be used to test whole sets of coefficients from the models for $D_{1,it}$ and $D_{2,it}$ against the whole set of coefficients pertaining to D_{it}, providing the sets of explanatory variables are the same for any pairwise combination, which can be the case with spatial error models. If one or both test statistics are significant this suggests we can learn more by estimating at least one disaggregated model. Wald tests cannot be used to test a whole set of coefficients from a spatial lag or spatial Durbin model for $D_{1,it}$ or $D_{2,it}$ against the coefficients pertaining to D_{it} because the spatially lagged dependent variables will differ for any pairwise combination. If, for example, at least δ_1 or δ was significant we would have to reject the null in advance and conclude that the sets of coefficients pertaining to $D_{1,it}$ and D_{it} are different.

3 Specification of W and Estimation

The classification of highways by the FHWA into twelve types constitutes an ordering of the spatial dependence because the distance travelled and hence the degree of cross border mobility will rise with a move up the relevant FHWA hierarchy of highways (FHWA, 1989). This classification of highways will also influence the spatial dependence of aggregate travel because aggregate travel will be more spatially dependent if a relatively large proportion of travel is on highways which are at or towards the top of the FHWA hierarchy. We therefore posit that row normalizing the simple Rook contiguity matrix $\mathbf{W_0}$, where the $ij-$th element in $\mathbf{W_0}$ takes a value of 1 if i shares a border with j and 0 otherwise, is appropriate. This is because the classification of the highways will ensure that the degree of cross border mobility will be captured by ϕ_{jt} and $\phi_{m,jt}$ in the spatial error models and D_{jt} and $D_{m,jt}$ in the spatial lag models. The degree of 'neighborliness' will also affect the connectedness of neighboring highway networks and thus the spatial dependence of vehicle usage. Trying to further capture the connectedness of highway networks by weighting $\mathbf{W}$ by the average trade flow over the sample or by the length of borders were other possibilities. We did not explore these possibilities because using a row normalized contiguity matrix yielded models which fit the data very well. Moreover, the ranking of the spatial dependence of aggregate travel ($Total\ Usage$, $Total\ Urban\ Usage$ and $Total\ Rural\ Usage$) and disaggregated travel by type of highway is in line with our priors, which suggests that a row normalized contiguity matrix has accurately captured the spillover of traffic.

The spatial lag and spatial error models with SFEs and SREs are estimated using the maximum likelihood principle. Since the spatially lagged dependent variable and the spatially lagged disturbance are endogenous, the assumption of the standard regression model that $\mathrm{E}[\left(\sum_{j=1}^{N} w_{ij} D_{m,jt}\right) \varepsilon_{m,it}] = 0$ or $\mathrm{E}[\left(\sum_{j=1}^{N} w_{ij} \varepsilon_{m,jt}\right) \varepsilon_{m,it}] = 0$ is violated. We adjust for this endogeneity and also the fact that $\varepsilon_{m,t}$ is not observed by introducing a Jacobian term of the transformation of $\varepsilon_{m,t}$ to $D_{m,t}$ to the log-likelihood function (i.e.

$T \log |\mathbf{I} - \delta\mathbf{W}|$ and $T \log |\mathbf{I} - \rho\mathbf{W}|$ in the log-likelihood functions associated with the spatial lag and spatial error models, respectively). This is the same way in which these issues are dealt with when estimating a cross sectional spatial model using maximum likelihood (see Anselin, 1988). For a comprehensive discussion of the estimation procedures see Elhorst (2009). There are two points, however, worth noting about the estimation procedures which relate to the presentation of the spatial error models. The first relates to the SFEs, where $\mu_{m,i}$ denotes a dummy variable for the i-th unit. In the standard FEs model only the slope coefficients can be estimated consistently when T is small and fixed, and $N \to \infty$. Elhorst (2003) notes, however, if interest centres on estimating the slope coefficients and not the SFEs, which is usually the case, demeaning the dependent and independent variables for the i-th unit by subtracting the average of the relevant variable for the i-th unit over the sample will eliminate the intercept and the SFEs; thereby ensuring that the inconsistency of the SFEs parameters does not influence the estimates of the slope coefficients. The second point relates to the SREs models where $\mu_{m,i}$ denotes the i-th element of a random variable μ_m which is i.i.d with zero mean and variance $\sigma^2_{\mu_m}$. All the spatial error models with SREs which we report include the weight which is attached to the variation in the cross section, φ_m , where $\varphi_m = \sigma^2_{\mu_m}/\sigma^2_m$.

4 Data

All the models are estimated using data from $1980 - 2008$ and all the variables are logged prior to estimation, with the exception of *Urbanization*, *Urban Rail*, *Speed Limit*1 and *Speed Limit*2. In the analysis of aggregate vehicle usage the dependent variables in the estimations are: total vehicle miles per adult, *Total Usage*; total vehicle miles per adult on urban highways, *Total Urban Usage*; and total vehicle miles per adult on rural highways, *Total Rural Usage*. The cross sections of the panels for *Total Usage* and *Total Urban Usage* consist of the contiguous states plus the District of Columbia whereas the cross section for *Total Rural Usage* consists of the 48 contiguous states because there are no rural roads in the District of Columbia.[4] In the same vain as the aggregate analysis, *Total Urban Usage* is disaggregated into vehicle miles per adult on six categories of urban highway: *Urban Interstate Usage*; *Urban Merged Usage*;[5] *Urban Collector Usage*; *Urban Local Usage*; *Urban Minor Arterial Usage*; and *Urban Other Prinicpal Arterial Usage*.[6,7] *Total Rural Usage* is also disaggregated into vehicle miles per adult on six types of rural highway: *Rural Interstate Usage*; *Rural Local Usage*; *Rural Major Collector Usage*; *Rural Minor Collector Usage*; *Rural Minor Arterial Usage*; and *Rural Other Principal Arterial Usage*.[8,9]

The interrelationships between the six types of urban highway and the six types of rural highway are depicted in the FHWA highway hierarchies for urbanized areas, small urban areas and rural areas (FHWA, 1989). The three hierarchies have the same structure from top to bottom: (i) Principal arterials; (ii) Minor arterial roads/streets; (iii) Collector roads/streets; and (iv) Local roads/streets. The first and third nests of the rural highways is subclassified into interstates and other principal arterials, and major and minor collectors, respectively. Similarly, the first nest of the hierarchies for urbanized and small urban areas are subclassified into interstates, other freeways and expressways and other principal arterials. Most importantly, each hierarchy '...relates directly to the hierarchy of travel distances which they serve' (FHWA, 1989). The different characteristics, however, of urbanized, small urban and rural areas in terms of, for example, population density, land use, and travel patterns necessitates that corresponding nests of the hierarchies perform very different functions in serving the flow of trips. For more details on the different functions of highways in corresponding nests see FHWA (1989).

The specification of the models is largely based on the fitted equation for total vehicle miles per adult in Small and Van Dender (2007) with four modifications. (i) As was noted above the spatial dependence of vehicle miles per adult is modelled here. (ii) Three further explanatory variables are included, *Population Density*, and two variables to capture the effect of changes to the law on speed limits, *Speed Limit*1 and *Speed Limit*2 (see Table 1 for a detailed discussion of the dependent and independent variables and details of the data sources). (iii) Here adults per lane mile is an explanatory variable instead of adults per road mile. Small and Van Dender (2007) use adults per road mile as an explanatory variable because data on lane miles is not available for their entire study period. (iv) No lags of the dependent variable are included. This is because the application in this paper focuses on spatial dependence and disaggregation rather than drawing a distinction between short run and long run elasticities, which is frequently done in the travel demand literature. It is logical to extend our work by introducing at least one lag of the dependent variable to analyze inertia. This could be done using the dynamic maximum likelihood estimator for spatial panels in Elhorst (2005).

[Insert Table 1]

The adults per lane mile variable is worthy of further discussion. It is posited that adults per lane mile is a proxy for the level of urban congestion if the coefficient is negative. It turns out that the coefficient is sometimes positive, in which case it is argued that adults per lane mile is capturing the pool of potential drivers. The approach of Hymel *et al.* (2010) is slightly different from that of Small and Van Dender (2007) because rather than using adults per road mile to capture the effect of congestion they use an estimate of average delay time for a state. They calculate average delay time for a state using delay time data from the *2004 Urban Mobility Report* (Texas Transportation Institute, 2004) for the largest 85 urban areas in the U.S.. It is only possible, however, to estimate delay time for every state if at least one of the 85 urban areas is located in each state. The *2009 Urban Mobility Report* (Texas Transportation Institute, 2009) contains delay time data for the largest 90 urban areas in the U.S., none of which are located in eight states, so for this reason we attempt to capture the effect of congestion using adults per lane mile. The summary statistics for the continuous variables are presented in Table 2 and are for the raw data. The correlations between the dependent variables, which as we would expect can vary greatly across the pairs, are available from the corresponding author on request.

[Insert Table 2]

5 Results and Analysis

5.1 Results for Aggregate Usage

Throughout the preferred models are based on a Hausman test of the spatial error model with SREs against the corresponding model with SFEs. To test the significance of the SFEs or the SREs in the preferred model a likelihood ratio (LR) test is used. The null for the LR test of the joint significance of the SFEs in the preferred model for the m-th category of demand is $\mu_{1,m} = ... = \mu_{N,m} = \alpha_m$, where the test statistic has a chi-squared distribution with degrees of freedom equal to the number of restrictions which must be imposed on the unrestricted model to obtain the restricted model, which in this case is $N - 1$. For an LR test of the SREs in the preferred model the null is $\varphi_m = 0$ as this implies $\sigma^2_{\mu_m} = 0$, where the test statistic has a chi-squared distribution with 1 degree of freedom. Throughout each LR test statistic rejects the null which suggests that the SFEs or the SREs in the preferred model are significant, thereby justifying their inclusion.

As suggested by Elhorst (2009), throughout two measures of goodness-of-fit are reported for each model, R^2 and $Corr^2$. The R^2 reported here, which is widely used in the applied spatial econometrics literature, differs from the R^2 for an OLS regression with a disturbance variance-covariance matrix $\sigma^2\mathbf{I}$. This is because there is no direct counterpart of the R^2 for an OLS regression for a generalized regression with a disturbance variance-covariance matrix $\sigma^2\mathbf{\Omega}$, where $\mathbf{I} \neq \mathbf{\Omega}$. In contrast to the R^2, the $Corr^2$ ignores the contribution to the goodness-of-fit of the SFEs and SREs. For details on how R^2 and $Corr^2$ are calculated for spatial error models with SFEs and SREs see Elhorst (2009). Furthermore, Wald tests of each set of coefficients for aggregate usage or disaggregated usage against every other set suggest that each set is significantly different from one another at the 1% level. This provides unanimous support for the highest level of disaggregation of $Total\ Usage$ i.e. disaggregation of $Total\ Usage$ into usage on all twelve types of highway. The Wald statistics are available from the corresponding author on request. $t-$tests of the difference between corresponding coefficients from the models of aggregate and disaggregated usage are used to shed some light on the contribution which pairs of coefficients make to the significant Wald statistics. The full set of t-statistics are also available from the corresponding author on request.

The estimation results for the preferred aggregate models are presented in Table 3. The fit of the aggregate spatial error models is very good as indicated by the high R^2 values. The low $Corr^2$ for the $Total\ Rural\ Usage$ model *vis-à-vis* the R^2 suggests that the SFEs make a much larger contribution to the fit of the model than the SFEs and SREs in the models for $Total\ Usage$ and $Total\ Urban\ Usage$, respectively. In light of the complete set of significant Wald statistics it is not surprising that the $t-$tests suggest that there are numerous cases where corresponding coefficients are significantly different. To illustrate, t-tests of the difference between the ρ parameters from the models for $Total\ Usage$, $Total\ Urban\ Usage$ and $Total\ Rural\ Usage$ suggest that all three parameters are significantly different at the 1% level.

[Insert Table 3]

The ρ coefficients in the models for $Total\ Usage$, $Total\ Urban\ Usage$ and $Total$

$Rural\ Usage$ are all sizeable and significant at the 1% level. This is a key finding because it suggests that spatial dependence should not be overlooked in future theoretical and empirical travel demand models- doing so would be a big source of misspecified dynamics. Moreover, it is evident from the ρ coefficients that the spatial dependence of $Total\ Usage$ is primarily due to the spatial dependence of rural travel. Also reported in Table 3 are the spatial autoregressive coefficients from the corresponding spatial lag models. For $Total\ Usage$ $\rho > \delta$ which suggests that the ρ parameter is picking up spatial dependence beyond that which can be attributed to $Total\ Usage$ in neighboring units. $\rho > \delta$ is also the case for $Total\ Urban\ Usage$ and $Total\ Rural\ Usage$, albeit to a lesser degree than for $Total\ Usage$, which is to be expected because the models for $Total\ Urban\ Usage$ and $Total\ Rural\ Usage$ are only capturing the spatial dependence of travel on part of the $i-$th unit's network.

Since all the β coefficients from a spatial error model are direct effects, in Table 3 we report the total effect (TE) of a change in ε_{it} or $\varepsilon_{m,it}$ using the relevant estimate of ρ. From the results for $Total\ Usage$, for example, we can see that the total effect of a 1% increase in ε_{it} is a 3.07% increase in $\sum_{i=1}^{N} Total\ Usage_{it}$. If the total effect of a change in ε_{it} or $\varepsilon_{m,it}$ is 1 all the total effect is due to an own direct effect. In other words, there are no spillover effects i.e. no indirect or higher order direct effects. To illustrate, we expand $(\mathbf{I} - \rho_m \mathbf{W})^{-1}$ which yields:

$$\mathbf{I} + \rho_m \mathbf{W} + \rho_m^2 \mathbf{W}^2 + \ldots \quad . \tag{8}$$

The diagonal elements of $\mathbf{I}$ are the own direct effects of a change in $\varepsilon_{m,it}$. The diagonal elements of $\rho_m \mathbf{W}$ are zero and the non-diagonal elements are the first order indirect effects of a change in $\varepsilon_{m,it}$. The other terms on the right-hand side of (8) consist of higher order indirect and direct effects. Higher order direct effects come about because of feedback effects i.e. effects passing through units and back to the unit which initiated the adjustment process. We can therefore conclude for $Total\ Usage$ that following a 1% increase in ε_{it}, 2.07% of the 3.07% increase in $\sum_{i=1}^{N} Total\ Usage_{it}$ is due to spillovers. This spillover effect is greater than the corresponding effect for $Total\ Urban\ Usage$ or $Total\ Rural\ Usage$, which is again to be expected for the same reason that was given above to justify why $(\rho - \delta)$ for $Total\ Usage$ is greater than what we observe for $Total\ Rural\ Usage$ and $Total\ Urban\ Usage$.

The coefficients on the explanatory variables which typically feature in regression equations for vehicle miles ($No.\ of\ Vehicles$, $Real\ Fuel\ Cost$ and $Real\ Income/Head$) have the expected signs but only the $Real\ Fuel\ Cost$ parameters in all three models and the coefficient on $Real\ Income/Head$ in the model for $Total\ Usage$ are large and significant. The consensus in the literature is that the short run fuel price elasticity of vehicle miles is less than the income elasticity (Graham and Glaister, 2004). Interestingly, the results reported here are at odds with this widely held view. This is most probably because the real price of gasoline increased sharply in the last portion of the sample i.e. from 2002 onwards (for verification see Summary Figure 1 in the report by the Congressional Budget Office (CBO), 2008).

The large and significant $Population\ Density$ parameter in the model for $Total\ Rural\ Usage$ is negative because a state with a high population density will be more urbanized and will most probably have a smaller rural highway network resulting in less rural travel. In the models for $Total\ Usage$ and $Total\ Urban\ Usage$ the $Adults/Lane\ Mile$ parameters are positive which suggests the variable is capturing the pool of potential drivers and not the effect of urban congestion. Furthermore, it is interesting to note that family size ($Population/Adult$) has a significant but very different effect on $Total\ Urban\ Usage$ and $Total\ Rural\ Usage$. This explains why the $Population/Adult$ parameter in the model for $Total\ Usage$ is not significant. Specifically, an increase in $Population/Adult$ leads to an increase in $Total\ Urban\ Usage$ and a substantial fall in $Total\ Rural\ Usage$. Why do the $Population/Adult$ parameters in the fitted equations for $Total\ Urban\ Usage$ and $Total\ Rural\ Usage$ have different signs? One possible reason is that urban households do not travel as far afield when family size increases because they need to remain closer to urban amenities. From the model for $Total\ Rural\ Usage$ it is evident that the higher speed limits which followed the rescinding of the federal controls resulted in an increase in vehicle miles per adult on rural highways. This is because the opportunity to cut journey time on rural highways as a result of the higher speed limits would not have been dampened by congestion.

5.2 Results for Disaggregated Urban Vehicle Usage

The preferred models for disaggregated urban usage are presented in Table 4. The fit of the models, as indicated by the R^2 values, ranges from quite good ($Urban\ Local\ Usage$)

to excellent ($Urban\ Merged\ Usage$). The ρ parameters are significant in five of the six models, the exception being the model for $Urban\ Local\ Usage$. It is perfectly plausible to find that $Urban\ Local\ Usage$ is not spatially dependent because it is characterized by very short distance travel and urban local roads/streets do not tend to be located near state borders. A comparison of the ρ parameters in the models for $Urban\ Interstate\ Usage$ and $Urban\ Merged\ Usage$ suggests that travel on urban other freeways and expressways is likely to be only mildly spatially dependent. We can therefore conclude from the ρ parameters for aggregate and disaggregated urban usage that the spatial dependence of $Total\ Urban\ Usage$ is primarily due to the spatial dependence of $Urban\ Interstate\ Usage$. As we would expect ρ is much larger in the model for $Total\ Urban\ Usage$ than in the model for $Urban\ Interstate\ Usage$. This is because the model for $Total\ Urban\ Usage$ captures the spatial dependence of travel on the whole of the $i-$th unit's urban network, whereas the model for $Urban\ Interstate\ Usage$ is capturing the spatial dependence of travel on just one type of highway in the $i-$th unit. This is also the reason why for $Urban\ Interstate\ Usage$ following a 1% increase in $\varepsilon_{m,it}$ there is only a 0.37% increase in $\sum_{i=1}^{N} Urban\ Interstate\ Usage_{it}$ from spillovers.

[Insert Table 4]

The models for $Urban\ Interstate\ Usage$ and $Urban\ Merged\ Usage$ are the only cases where ρ and δ are both significant and ρ is relatively large *vis-à-vis* δ. This suggests the ρ parameter in the model for $Urban\ Interstate\ Usage$ ($Urban\ Merged\ Usage$) is picking up spatial dependence beyond that which can be attributed to $Urban\ Interstate\ Usage$ ($Urban\ Merged\ Usage$) in neighboring units. This is entirely reasonable for two reasons. Firstly, travel on urban interstates and urban other freeways and expressways is at the top of the urban highway hierarchies and is therefore associated with longer journeys which are relatively income elastic and therefore more sensitive to economic conditions in neighboring units. Secondly, in the $j-$th neighboring unit travel on urban interstates and urban other freeways and expressways is likely to depend on changes in travel on highways further down the hierarchy. This is because traffic will tend to feed into highways further up the hierarchy as journey distance increases. This may explain why for other types of urban usage where ρ and δ are significant (i.e. $Urban\ Collector\ Usage$ and $Urban\ Minor\ Arterial\ Usage$) $\rho \approx \delta$. This suggests that the model for $Urban\ Collector\ Usage$ ($Urban\ Minor\ Arterial\ Usage$) is capturing very little spatial dependence beyond that which can be attributed to *Urban Collector Usage* (*Urban Minor Arterial Usage*) in neighboring units.

Whereas the *No. of Vehicles*, *Real Fuel Cost* and *Real Income/Head* parameters have the expected signs in the model for *Total Urban Usage* this is not the case for all the models of disaggregated urban usage. In particular, the *No. of Vehicles* and *Real Fuel Cost* parameters in the model for *Urban Collector Usage* and the *Real Income/Head* parameter in the model for *Urban Other Principal Arterial Usage* do not have the expected signs but only the latter is significant. The large negative *Real Income/Head* parameter in the model for *Urban Other Principal Arterial Usage* and the large positive and significant *Real Income/Head* parameters in the models for *Urban Interstate Usage* and *Urban Merged Usage* suggest that people make longer journeys when real personal income per head rises.

Interestingly, the large and significant *Population Density* parameters are very diverse. Such differences in the effect of *Population Density* is most probably because differences in the area of states gives rise to differences in the relative stock of particular categories of urban highway. The diversity of the *Population Density* parameters in the models of disaggregated urban usage means that some parameters are at odds with the *Population Density* parameter in the model for *Total Urban Usage*. Comparing the *Population Density* parameters in the models for *Urban Interstate Usage* and *Urban Merged Usage* suggests that the population density elasticity for travel on urban other freeways and expressways is likely to be large, positive and significant.

The *Population/Adult* parameters in the models for *Urban Collector Usage*, *Urban Local Usage* and *Urban Minor Arterial Usage* are very large, positive and significant. In the model for *Urban Other Principal Arterial Usage* the coefficient on *Population/Adult* is large, significant and negative. These findings are consistent with urban households cutting journey distance when family size increases and travelling shorter distances more frequently instead. Moreover, the large negative coefficient on *Adults/Lane Mile* in the model for *Urban Minor Arterial Usage* suggests that an increase in the pool of drivers leads to more urban congestion which dissuades drivers from travelling on urban minor arterials.

5.3 Results for Disaggregated Rural Vehicle Usage

The preferred models for disaggregated rural usage are presented in Table 5. The fit of all six models is very good, as indicated by the high values for the R^2. As was the case for the models of disaggregated urban usage, the ρ coefficients are significant in five models. It is not surprising that $Rural\ Local\ Usage$ is not spatially dependent because it tends to be relatively short distance travel and rural local roads do not tend to be located close to state borders. A comparison of the ρ parameters from the models of aggregate and disaggregated rural usage suggests that the spatial dependence of $Total\ Rural\ Usage$ is primarily due to the spatial dependence of $Rural\ Other\ Principal\ Arterial\ Usage$. For the most spatial dependent type of urban travel ($Urban\ Interstate\ Usage$), following a 1% increase in $\varepsilon_{m,it}$ we observe a smaller increase in $\sum_{i=1}^{N} Urban\ Interstate\ Usage_{it}$ from spillovers than for $Rural\ Other\ Principal\ Arterial\ Usage$. Specifically, for $Rural\ Other\ Principal\ Arterial\ Usage$ following a 1% increase in $\varepsilon_{m,it}$ there is a 0.75% increase in $\sum_{i=1}^{N} Rural\ Other\ Principal\ Arterial\ Usage_{it}$ from spillovers.

[Insert Table 5]

The only type of rural travel for which ρ and δ are both significant and ρ is relatively large compared to δ is $Rural\ Interstate\ Usage$. This suggests the ρ parameter in the model for $Rural\ Interstate\ Usage$ is capturing spatial dependence beyond that which can be attributed to $Rural\ Interstate\ Usage$ in neighboring units. This is perfectly feasible for the reasons given above to explain why the ρ parameters in the models for $Urban\ Interstate\ Usage$ and $Urban\ Merged\ Usage$ are capturing spatial dependence which is not confined to the corresponding type of vehicle usage in neighboring units. For other types of rural travel where ρ and δ are both significant $\rho \approx \delta$, which suggests that the only source of spatial dependence for, say, $Rural\ Other\ Principal\ Arterial\ Usage$ is the corresponding type of travel in the $j-$th neighboring unit. The large ρ in the model for $Rural\ Other\ Principal\ Arterial\ Usage$ is therefore likely to be because rural other principal arterials tend to straddle state borders.

All the $Real\ Fuel\ Cost$ parameters in the six models have the expected sign and are significant. In contrast, only in the model for $Rural\ Local\ Usage$ is the $Real\ Income/Head$ parameter significant at the 5% level with the expected sign. The coefficients on $ReaI\ Income/Head$ in the models for $Rural\ Major\ Collector\ Usage$ and $Rural$

Minor Collector Usage are negative, large (particularly in the model for *Rural Minor Collector Usage*) and significant. It would seem therefore when *ReaI Income/Head* rises short distance rural journeys become more frequent but get shorter, hence the increase in travel on rural local roads/streets and the fall in travel on rural minor and major collectors.

Unlike the fitted models for disaggregated urban usage, in the models for disaggregated rural usage all the large and significant *Population Density* parameters have the same sign and, as expected, are negative. This is because states with a relatively high population density will be more urbanized and so there is likely to be less rural usage. Comparing the results for aggregate and disaggregated rural usage it is evident that the negative *Population Density* parameter in the model for *Total Rural Usage* is primarily due to the effect of population density on travel on rural interstates, rural major collectors and rural other principal arterials. Where *Population/Adult* has a large and significant effect on disaggregated urban usage the coefficient is always positive. In direct contrast, the models for disaggregated rural usage indicate that all the large and significant *Population/Adult* parameters are negative. In particular, the modelling of disaggregated rural usage suggests that an increase in *Population/Adult* will lead to a decrease in short distance rural travel (i.e. *Rural Local Usage* and *Rural Minor* and *Major Collector Usage*).

Further differences between the fitted models for disaggregated urban and rural usage relate to the speed limit parameters. These parameters tend to be larger in the models for disaggregated rural usage. There are two possible reasons for this. Firstly, *Speed Limit*1 relates specifically to rural interstate speed limits and secondly, when the speed limits were increased following the rescinding of the federal controls, congestion will not have limited the opportunity to cut rural journey time. Additionally, where *Adults/Lane Mile* has a large and significant effect on disaggregated urban and rural usage, in general, the coefficient is positive (*Urban Interstate Usage*, *Urban Merged Usage* and *Urban Local Usage*) and negative (*Rural Local Usage* and *Rural Minor Collector Usage*), respectively.

6 Concluding Remarks and Policy Recommendations

In summary, we make two simple economic arguments in support of the spatial error model over the spatial lag and spatial Durbin models. The basis of the first argument is that the spatial error model constitutes a fuller representation of spatial dependence than models which do not include a spatial autocorrelation term. The second argument which we make in favor of the spatial error model is that it is particularly appropriate when analysts are faced with the choice between using aggregate or disaggregated data. This is because the spatial error model permits Wald tests of whole sets of coefficients against one another to ascertain if models which are estimated using disaggregated data contain more information than the aggregate model. An application to state vehicle usage in the U.S. is used to provide support for the case which we make for the spatial error model.

On the basis of the Wald test results aggregate data on state vehicle usage is progressively disaggregated as far as possible and spatial error models for travel on all twelve types of highway, as classified by the FHWA (1996; $1997 - 2009$), are estimated. We report several spatial error and spatial lag models where ρ is substantially greater than δ ($Total\ Usage$; $Total\ Urban\ Usage$; $Total\ Rural\ Usage$; $Rural\ Interstate\ Usage$; $Urban\ Interstate\ Usage$; and $Urban\ Merged\ Usage$), which suggests that the spatial error models are picking up spatial dependence beyond that which can be attributed to the dependent variables in neighboring units. For all the other types of vehicle usage we find that $\rho \approx \delta$, the implication being that spatial dependence does not extend beyond the dependent variables in neighboring units.

Finding that ρ is greater than δ is not uncommon, although we are the first to crystallize an economic interpretation of this finding. For example, having developed a SUR model with a spatial autoregressive variable, a spatial autocorrelation term and an error component to capture heterogeneity, Baltagi and Bresson (2011) apply the model to estimate equations for the price of three types of flat in Paris. In all three equations for both specifications of the model, the spatial autocorrelation coefficient is large and significant and the coefficient on the spatial autoregressive variable is not significant. To investigate if there is yardstick property tax competition between Italian municipalities Bordignon *et al.* (2003) estimate spatial lag and spatial error models. The spatial autoregressive parameter is not significant, whereas the spatial autocorrelation coefficient is large and significant. Notwithstanding the strength of the econometric case which LSP make in favor of the spatial Durbin model we set out a clear economic case for the spatial error model, especially when using disaggregated data. When using aggregate data if analysts choose to fit a spatial Durbin model because they are primarily interested in the spillovers (i.e. they want to report indirect elasticities for the explanatory variables), we suggest that it is also useful to fit a spatial error model to analyze the effect of a broader interpretation of spatial dependence.

Since the Wald test results suggest that the disaggregated travel demand models are additional sources of information, they can be used to make more specific policy recommendations than is possible using a model of aggregate travel demand. We find that the $Real\ Income/Head$ parameters in the models for $Urban\ Interstate\ Usage$ and $Urban\ Merged\ Usage$ are positive and significant, whereas for $Urban\ Other\ Principal\ Arterial\ Usage$ the income elasticity is negative and significant. These results suggest that, other things being equal, the relative allocation of resources for the maintenance of different types of highway should reflect the business cycle. In an upturn relatively more resources should be dedicated to maintenance of urban interstates and urban other freeways and expressways, and relatively less to urban other principal arterials.

The income elasticities for disaggregated travel also have implications for policy on road safety. A number of road safety studies where the dependent variable is road fatalities or fatalities per head find that vehicle usage is a significant explanatory variable (e.g. McCarthy, 1994; Mast *et al.*, 1999; Merrell, *et al.*, 1999; Cohen and Dehejia, 2004; and Gayer, 2004, although it should be noted that it is much more common for the dependent variable to be road fatalities per vehicle mile). We suggest therefore that in an upturn in the business cycle more traffic police officers should be located on urban interstates and urban other freeways and expressways, and less on urban other principal arterials. Moreover, the income elasticities for $Urban\ Interstate\ Usage$, $Urban\ Merged\ Usage$ and $Urban\ Other\ Principal\ Arterial\ Usage$ can inform policy on road building. Given real personal income per capita will rise over time, if future road building is to reflect future changes in demand for road space less resources should be used to build urban other principal arterials and more resources should be used to build urban interstates and urban other freeways and expressways.

Notes

[1]The spatial lag model also distinguishes between the direct and indirect effects when an explanatory variable changes. That said, by construction the spatial lag model imposes an *a priori* restriction on the size of the direct and indirect effects. In particular, the ratio of the indirect and direct effects will be the same for all explanatory variables, which is unrealistic. This is not the case for the spatial Durbin model.

[2]It may appear that we should estimate seemingly unrelated spatial error and spatial lag models to allow for the correlation between shocks to vehicle usage on different types of highway. The data, however, on vehicle usage on different types of highway does not contain the same number of cross sectional units. To illustrate, there were only rural interstates in Delaware from $1980-1982$, so to ensure that the panel for rural interstate usage is balanced Delaware was omitted. Had the panels for usage on different types of highway contained the same number of cross sectional units we would have estimated seemingly unrelated spatial error and spatial lag models.

[3]For a more comprehensive discussion which covers a wider range of spatial panel data models see Anselin *et al.* (2008).

[4]On average over the study period *Total Urban Usage* makes up 52.76% of *Total Usage* with *Total Rural Usage* making up the remainder.

[5]The data on vehicle miles per adult on urban other freeways and expressways is an unbalanced panel. This is because for nine states no urban highways were classified as other freeways and expressways for all or part of the study period. It is, however, usual to fit a spatial model with a balanced panel. To create a balanced panel, vehicle miles per adult on urban interstates is merged with the unbalanced panel for vehicle miles per adult on urban other freeways and expressways. The new data is denoted *Urban Merged Usage*. By comparing the fitted models for *Urban Interstate Usage* and *Urban Merged Usage* some inferences can be made about the determinants of vehicle miles per adult on urban other freeways and expressways.

[6]The models for vehicle usage on different types of urban highway are all estimated using data for the contiguous states plus the District of Columbia.

[7]On average over the study period *Urban Interstate Usage* makes up 11.44% of *Total Usage*; *Urban Merged Usage* makes up 15.60%; *Urban Collector Usage* makes up 4.78%; *Urban Local Usage* makes up 7.61%; *Urban Minor Arterial Usage* makes up 10.77%; and *Urban Other Principal Artierial Usage* makes up 14.00%.

[8]The models for *Rural Local Usage*, *Rural Major Collector Usage*, *Rural Minor Arterial Usage*

and *Rural Other Principal Arterial Usage* are estimated using data for the contiguous states. In the same way that data for the contiguous states with the exception of Delaware is used to estimate the models for *Rural Interstate Usage*, the data set which is used to estimate the models for *Rural Minor Collector Usage* comprises observations for the contiguous states with the exception of North Dakota. This is because for North Dakota data on vehicle miles on rural minor collectors is only available for 1980 – 1994.

[9] On average over the study period *Rural Interstate Usage* makes up 11.64% of *Total Usage*; *Rural Local Usage* makes up 5.98%; *Rural Major Collector Usage* makes up 9.71%; *Rural Minor Collector Usage* makes up 2.44%; *Rural Minor Arterial Usage* makes up 8.13%; and *Rural Other Principal Arterial Usage* makes up 10.56%. These shares do not sum exactly to the share of *Total Rural Usage* for the reasons explained in the previous endnote.

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Tables in Main Text

(see following pages)

Table 1: Description of the Dependent and Independent Variables

Variable	Data Source and Further Details
Aggregate/Disaggregated vehicle miles per adult	Data on aggregate/disaggregated vehicle miles is from the Federal Highway Administration (FHWA). Specifically, Table VM-202 in the '*Highway Statistics Summary to 1995*' for 1980 – 1995 and Table VM−2 in the annual editions of '*Highway Statistics*' from 1996 – 2008. Data on the mid-year estimate of a state's adult population is from the Archives of the Population Estimates of the U.S. Census Bureau.
Population Density	Data on total population is from the Bureau of Economic Analysis- Regional Economic Accounts and data on total area in square miles is from the 2000 Census on Population and Housing. Specifically, the latter is from Table 17 in the '*United States Summary : 2000 – Population and Housing Unit Counts*'.
Number of vehicles per adult, *No. of Vehicles*	Data on number of vehicles is from Table MV−201 in the '*Highway Statistics Summary to 1995*' for 1980 – 1995 and Table MV−1 in the annual editions of '*Highway Statistics*' from 1996 – 2008.
Real fuel cost per vehicle mile (in cents at 1980 prices), *Real Fuel Cost*	Real fuel cost per mile at 1980 prices is obtained by deflating the nominal fuel cost per mile by the CPI. Fuel cost per mile is calculated by multiplying total gasoline consumption in gallons by the nominal price of a gallon of gasoline and dividing by total vehicle miles. Data on total gasoline consumption is from Table MF−226 in the '*Highway Statistics Summary to 1995*' for 1980 – 1995 and Table MF−21 in the annual editions of '*Highway Statistics*' from 1996 – 2008. The nominal price of gasoline was obtained from the U.S. Energy Information Administration.
Real personal income per capita (at 1980 prices), *Real Income/Head*	Nominal personal income per capita was obtained from the Bureau of Economic Analysis-Regional Economic Accounts and deflated by the CPI.
Population per adult, *Population/Head*	See Aggregate/Disaggregated vehicle miles per adult and *Population Density* above for details on the adult and total population data, respectively.
Adults per lane mile, *Adults/Lane Mile*	Data on total lane miles is from Table HM−260 of the '*Highway Statistics Summary to 1995*' for 1980 – 1995 and Table HM−60 in the annual editions of '*Highway Statistics*' from 1996 – 2008.
Urbanization	Is taken to be the percentage of a state's population living in Metropolitan Statistical Areas (MSAs). The data on the population of MSAs is from the Bureau of Economic Analysis- Regional Economic Accounts.
Urban Rail	Percentage of a state's population living in MSAs with a commuter rail, heavy rail and/or light rail system. Details of the opening of rail systems in urban areas was obtained from the American Public Transportation Association. Specifically, the details are from the *2010 Public Transportation Fact Book* (Table 16 in Appendix *A*).
*Speed Limit*1	A dummy which is 0 before 1987 and 1 thereafter (when states were permitted to raise the speed limit on rural interstate highways from 55 mph to 65 mph).
*Speed Limit*2	A dummy which is 0 before 1995 and 1 thereafter (when all federal speed limit controls were revoked, returning all authority on speed limit determination to the states).

Table 2: Summary Statistics

	Mean	**Std. Dev.**	**Min**	**Max**
Dependent Variables: Aggregate Usage				
Total Usage	12,598.93	2,631.55	6,031.08	24,228.70
Total Urban Usage	6,426.99	2,009.47	1,907.10	11,998.55
Total Rural Usage	6,300.52	2,951.90	814.84	17,823.65
Dependent Variables: Disaggregated Urban Usage				
Urban Interstate Usage	1,408.54	718.30	120.22	3,665.88
Urban Merged Usage (interstates plus other freeways and expressways)	1,890.55	1,023.62	161.20	5,103.47
Urban Collector Usage	582.26	210.52	168.75	1,469.63
Urban Local Usage	945.97	492.38	124.79	2,823.13
Urban Minor Arterial Usage	1,304.23	404.17	459.50	3,037.78
Urban Other Principal Arterial Usage	1,703.99	517.38	552.39	3,429.35
Dependent Variables: Disaggregated Rural Usage				
Rural Interstate Usage	1,548.78	928.71	163.69	6,693.81
Rural Local Usage	790.96	557.15	25.10	6,303.45
Rural Major Collector Usage	1,248.62	643.40	122.89	2,961.49
Rural Minor Collector Usage	313.78	248.23	30.76	1,857.27
Rural Minor Arterial Usage	1,040.62	513.70	105.20	2,800.03
Rural Other Principal Arterial Usage	1,392.01	760.46	54.37	4,863.63
Explanatory Variables				
Population Density	326.10	1,237.24	4.64	9,339.83
Number of Vehicles per Adult, *No. of Vehicles*	1.06	0.22	0.11	1.75
Real Fuel Cost per Vehicle Mile, *Real Fuel Cost*	5.63	1.80	3.05	12.39
Real Personal Income per Capita, *Real Income/Head*	14,442.70	3,057.58	8,203.67	29,805.15
Population per Adult, *Population/Adult*	1.36	0.05	1.23	1.60
Adults per Lane Mile, *Adults/Lane Mile*	27.85	26.31	2.64	190.32
Urbanization	72.57	19.15	28.95	100
Urban Rail	32.08	42.25	0	100

Table 3: Estimation Results for Aggregate Vehicle Usage

	Dependent Variable and Model Specification		
	Total Usage (SFEs)	*Total Urban Usage* (SREs)	*Total Rural Usage* (SFEs)
α	–	6.7779*** (13.08)	–
Time	0.0105*** (7.61)	0.0174*** (12.98)	−0.0093*** (−4.19)
Population Density	−0.2703*** (−9.88)	−0.0903*** (−4.03)	−0.5224*** (−8.23)
No. of Vehicles	0.0340*** (3.14)	0.0106 (0.75)	0.0637*** (2.93)
Real Fuel Cost	−0.2371*** (−19.04)	−0.1178*** (−9.02)	−0.2144*** (−10.48)
Real Income/Head	0.1235*** (3.33)	0.0794 (1.44)	0.1280 (1.55)
Population/Adult	−0.1375 (−1.34)	0.4050*** (2.90)	−1.56*** (−6.78)
Adults/Lane Mile	0.1377*** (7.74)	0.1696*** (6.88)	0.0359 (0.88)
Urbanization	0.0059*** (5.23)	0.0120*** (9.75)	0.0199*** (7.84)
Urban Rail	−0.0001* (−1.79)	−0.0003*** (−2.84)	0.0003** (1.97)
*Speed Limit*1	−0.0374** (−2.32)	0.0115 (0.78)	0.0598** (2.51)
*Speed Limit*2	0.0448*** (3.05)	−0.0187 (−1.50)	0.1750*** (8.59)
ρ	0.6740*** (32.74)	0.3025*** (9.20)	0.4560*** (15.99)
φ	–	5.048*** (6.05)	–
NOBS [N]	1421 [49]	1421 [49]	1392 [48]
Hausman Test Stat	23.99**	13.66	87.90***
Log-Likelihood	2446.95	1598.23	1331.45
R^2	0.93	0.96	0.97
$Corr^2$	0.83	0.75	0.46
LR Test Stat	2949.88***	1990.21***	2936.09***
TE	3.07	1.43	1.84
δ	0.3490*** (11.74)	0.1670*** (4.96)	0.3370*** (11.62)

Notes:
NOBS and N denote the number of observations and the size of the cross section in the panel, respectively.
Asymptotic t-statistics are in (.)
***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Table 4: Estimation Results for Disaggregated Urban Vehicle Usage

	Dependent Variable and Model Specification					
	Urban Interstate Usage (SREs)	*Urban Merged Usage* (SFEs)	*Urban Collector Usage* (SREs)	*Urban Local Usage* (SFEs)	*Urban Minor Arterial Usage* (SFEs)	*Urban Other Principal Arterial Usage* (SREs)
α	2.3560***	–	4.8341***	–	–	9.5187***
	(2.72)		(4.46)			(12.03)
Time	0.0228***	0.0201***	0.0180***	0.0127***	0.0135***	0.0174***
	(10.49)	(9.80)	(6.95)	(2.73)	(6.15)	(9.46)
Population Density	−0.1890***	0.2236***	−0.0164	−0.8185***	0.1898**	−0.0531
	(−4.15)	(3.02)	(−0.44)	(−4.38)	(2.28)	(−1.59)
No. of Vehicles	0.0248	0.0106	−0.0390	0.0035	0.0356*	0.0055
	(1.10)	(0.53)	(−1.38)	(0.08)	(1.67)	(0.28)
Real Fuel Cost	−0.1366***	−0.1157***	0.0105	−0.0647*	−0.0828***	−0.1518***
	(−6.60)	(−6.61)	(0.42)	(−1.69)	(−4.48)	(−8.80)
Real Income/Head	0.2941***	0.3707***	0.0430	0.3171	0.0953	−0.2946***
	(3.23)	(4.42)	(0.37)	(1.59)	(1.04)	(−3.52)
Population/Adult	−0.3285	0.1848	0.8820***	1.3069**	0.7339***	−0.3808*
	(−1.40)	(0.80)	(3.00)	(2.36)	(2.88)	(−1.79)
Adults/Lane Mile	0.1620***	0.1037**	0.0363	0.8240***	−0.1419***	0.0435
	(3.79)	(2.18)	(0.74)	(6.94)	(−2.66)	(1.16)
Urbanization	0.0301***	0.0307***	0.0069***	−0.0065	0.0127***	0.0127***
	(12.69)	(10.37)	(3.25)	(−0.89)	(3.86)	(6.87)
Urban Rail	−0.0010***	−0.0009***	−0.0006**	0.0000	0.0004*	−0.0006***
	(−5.32)	(−5.09)	(−2.35)	(0.01)	(1.91)	(−2.97)
*Speed Limit*1	0.0744***	0.0579***	0.0234	0.0753*	0.0314	0.0065
	(3.20)	(2.97)	(0.85)	(1.78)	(1.53)	(0.34)
*Speed Limit*2	−0.0043	−0.0189	−0.0418*	0.0133	−0.0071	−0.0330**
	(−0.22)	(−1.14)	(−1.79)	(0.37)	(−0.41)	(−2.04)
ρ	0.2675***	0.1599***	0.0945**	−0.0140	0.0890**	0.0662*
	(7.95)	(4.56)	(2.57)	(−0.37)	(2.46)	(1.78)
φ	10.5091***	–	1.7762***	–	–	3.4833***
	(6.08)		(5.98)			(6.04)
NOBS [N]	1421 [49]	1421 [49]	1421 [49]	1421 [49]	1421 [49]	1421 [49]
Hausman Test Stat	6.57	20.40*	15.51	33.14***	21.68**	10.96
Log-Likelihood	872.81	1094.20	404.03	−251.25	918.65	869.80
R^2	0.96	0.97	0.78	0.73	0.85	0.86
$Corr^2$	0.59	0.87	0.36	0.26	0.59	0.40
LR Test Stat	2667.69***	3005.67***	1205.11***	1555.98***	1336.52***	1734.33***
TE	1.37	1.19	1.10	1.00	1.10	1.07
δ	0.2030***	0.1040***	0.0850**	−0.0220	0.0630*	0.0330
	(6.20)	(3.04)	(2.36)	(−0.60)	(1.74)	(0.91)

Notes:
NOBS and N denote the number of observations and the size of the cross section in the panel, respectively.
Asymptotic t-statistics are in (.).
***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Table 5: Estimation Results for Disaggregated Rural Vehicle Usage

	Dependent Variable and Model Specification					
	Rural Interstate Usage (SREs)	*Rural Local Usage* (SFEs)	*Rural Major Collector Usage* (SFEs)	*Rural Minor Collector Usage* (SFEs)	*Rural Minor Arterial Usage* (SFEs)	*Rural Other Principal Arterial Usage* (SFEs)
α	7.8362*** (8.74)	–	–	–	–	–
Time	0.0027 (1.34)	−0.0209*** (−4.29)	−0.0057** (−2.32)	−0.0126*** (−3.33)	−0.0296*** (−9.97)	−0.0001 (−0.03)
Population Density	−0.6342*** (−10.94)	0.2380 (1.26)	−0.9825*** (−10.54)	0.1235 (0.83)	−0.0874 (−0.78)	−0.7943*** (−6.26)
No. of Vehicles	0.0702*** (3.23)	0.0515 (1.06)	0.1097*** (4.43)	0.0491 (1.26)	0.0362 (1.21)	0.0259 (0.61)
Real Fuel Cost	−0.2065*** (−11.16)	−0.1064*** (−2.64)	−0.1792*** (−8.66)	−0.1842*** (−3.46)	−0.1436*** (−5.78)	−0.2204*** (−5.54)
Real Income/Head	0.1529 (1.64)	0.5516** (2.55)	−0.2208** (−2.04)	−0.5399*** (−3.12)	0.2321* (1.78)	0.2751* (1.67)
Population/Adult	−0.3696 (−1.51)	−1.4532** (−2.44)	−1.1374*** (−3.81)	−3.2141*** (−6.80)	−1.7662*** (−4.90)	0.0659 (0.14)
Adults/Lane Mile	−0.0452 (−0.99)	−0.2898** (−2.39)	−0.0006 (−0.01)	−0.3546*** (−3.75)	−0.1005 (−1.39)	0.1447* (1.77)
Urbanization	0.0136*** (5.26)	0.0375*** (5.05)	0.0220*** (5.98)	0.0287*** (4.58)	0.0409*** (9.21)	0.0167*** (3.29)
Urban Rail	−0.0003 (−1.60)	0.0004 (0.90)	0.0004* (1.83)	−0.0002 (−0.57)	0.0016*** (5.72)	−0.0002 (−0.59)
Speed Limit1	0.1372*** (6.62)	0.0596 (1.32)	0.0831*** (3.60)	0.1328*** (4.21)	0.0867*** (3.12)	0.0874* (1.90)
Speed Limit2	0.1644*** (9.35)	0.1811*** (4.73)	0.1464*** (7.46)	0.1762*** (5.53)	0.1587*** (6.73)	0.1874*** (4.77)
ρ	0.1454*** (3.98)	0.0460 (1.24)	0.0979*** (2.69)	0.0840** (2.28)	0.0870** (2.38)	0.4270*** (14.53)
φ	13.5778*** (5.19)	–	–	–	–	–
NOBS [N]	1363 [47]	1392 [48]	1392 [48]	1363 [47]	1392 [48]	1392 [48]
Hausman Test Stat	14.25	100.57***	44.24***	918.91***	244.70***	115.83***
Log-Likelihood	837.36	−235.65	760.63	128.00	494.55	366.05
R^2	0.96	0.85	0.95	0.91	0.92	0.91
$Corr^2$	0.54	0.10	0.39	0.11	0.26	0.37
LR Test Stat	2385.03***	1659.98***	2919.32***	2721.63***	1972.73***	2043.52***
TE	1.17	1.00	1.11	1.09	1.10	1.75
δ	0.0629* (1.85)	0.0260 (0.70)	0.0730** (2.20)	0.0749** (2.09)	0.1000*** (2.87)	0.4100*** (14.04)

Notes:
NOBS and N denote the number of observations and the size of the cross section in the panel, respectively.
Asymptotic t-statistics are in parentheses.
***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.