A Spatial and Temporal Analysis of Seat-belt Usage and Seat-belt Laws

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Abstract

Seat-belt usage has increased significantly in the US since the introduction of mandatory seat-belt usage laws in the 1980's. This paper analyzes the impact of these laws on increasing seat-belt usage while controlling for other state-specific variables. A fixed effects cross-sectional time-series analyses shows the relative significance of various state-level attributes in explaining seat-belt usage, including whether or not primary or secondary seat-belt laws have been passed. To further explore these relationships we employ spatial analyses techniques and find spatial autocorrelation in the data. Spatial correlation also exhibits a clear east-west direction. When the analyses is further corrected for temporal auto-correlation we find that the spatial autocorrelation is greatly diminished and that many variables lose their statistical significance, though seat-belt laws are still statistically significant.Results suggest that for this data, it is critical to control for temporal auto-correlation while spatial auto-correlation is less important. We also find that our spatial analyses does provide interesting information on similarities between various regions on the effectiveness of seat-belt laws.

1. Introduction

In the last 15 years nearly every state in the US has enacted mandatory seat belt legislation that requires the wearing of seat belts. Most states have passed laws where the driver only receives a citation if stopped for some other traffic offense. A handful of states have passed laws where the driver may be stopped and cited when a seat-belt is not being worn. The former are known as secondary enforcement laws while the latter are referred to as primary enforcement laws.

In the case of both types of enforcement, there has been strong evidence for the effectiveness of these laws with nationwide seat-belt usage increasing from about 15% in the early 1980's to about 65% in the late 1990's (US DOT, 1999). Clearly there is still room for improvement and the National Highway Traffic Safety Administration (NHTSA) is advocating that all states adopt primary enforcement statutes.

Several studies have analyzed the effectiveness of these laws. These have generally found an association between passage and enforcement of these laws and increases in seat-belt use (Campbell, 1988; Escobedo et al., 1992). One common trend is that immediately after passage of seat-belt laws, usage increases dramatically with a small drop-off after the initial publicity has subsided (Eby et al., 2000). There is also evidence that when a state changes from secondary to primary enforcement there is an increase in seat-belt usage (Ulmer et al., 1995). Loeb (2001) analyzed seat belt laws in Maryland and concluded that there was some reduction in fatalities and severe injuries, though varying with the type of accident. McCarthy (1999) found seat belt laws to be ineffective at reducing fatalities, which is surprising given their effectiveness at increasing seat belt usage. Noland (2001) found a similar effect for secondary laws, but not for primary laws. A recent review of the literature by Rivara et al. (1999) supports the conclusion that primary laws are more effective than secondary laws and that both have helped increase seat-belt usage.

While the usage of seat-belts has clearly been established as reducing the likelihood that traffic fatalities will occur (US DOT, 1996), there has been some suggestion that drivers may off-set the risk reduction through compensating behavior (Evans et al., 1982; Singh & Thayer, 1992). Evans & Graham (1991) developed a fixed-effects model across states to analyze whether seat-belt use decreases fatalities and found a positive significant effect, including some weak evidence of compensating behavior due to increased mortality amongst some non-occupants. Asch et al. (1991) analyzed the risk compensating effect of seat-belt laws in New Jersey and concluded that the effectiveness of the laws was reduced by some compensating behavior.

The purpose of this paper is to analyze the effectiveness of both primary and secondary enforcement statutes at increasing seat-belt usage and also to explore both spatial and temporal analyses methods. This is done while controlling for various other factors that have been found to influence seat-belt use (Fockler & Cooper, 1990; Lund, 1986; Chliaoutakis et al., 2000). These include various demographic characteristics and road infrastructure characteristics that have been hypothesized to influence the likelihood of using seat-belts. For example, increased income would normally be expected to increase seat-belt use and increased driving on interstate highways would likewise be expected to increase usage.

Many studies have identified an underlying trend towards increased seat-belt use while controlling for other factors (Dee, 1998). We attempt to analyze various spatial and temporal effects that help to explain this underlying trend. This includes accounting for the enactment of seat-belt legislation in neighboring states and applying spatial analysis to the time-series residual of our estimates.

The next section discusses the data used in the analyses and the hypotheses that are tested. This is followed by a discussion of the basic statistical methodology used with a focus on the spatial analyses that are adopted from the literature on geostatistics. Results based upon this spatial analysis are discussed. In addition to spatial autocorrelation, temporal autocorrelation is also examined. Results are then presented followed by concluding comments.

2. Data and Hypotheses

Data on seat-belt use for each state (excluding Alaska and Hawaii) from 1990 to 1998 is used in the analysis. This data is based on data compiled by the US National Highway Traffic Safety Administration on state-wide seat-belt usage. Prior to 1990, data is not available for every state. To control for the seat-belt laws, dummy variables for both secondary and primary laws are included as the key independent variables of interest. The law is assumed to take effect in the year that it was passed, if passed before September. Otherwise it is assumed to take effect in the following year.

Our time series begins in 1990 which misses some of the early years of seat-belt laws, many of which were initially passed in the mid-1980's. Table 1 shows that while a large number of secondary laws were passed between 1985 and 1986, other laws have gradually been passed through to 1998 providing us with a good deal of variability within our time series. More recently there has been a trend towards changing from secondary laws to primary laws. Currently, only New Hampshire has not passed any seat-belt laws.

The basic hypotheses tested is that seat-belt laws have been effective at increasing seat-belt usage, but that other trends and the implementation of laws in neighboring states has had an additional effect beyond the direct effect. This could account for some of the background trend of increased seat-belt usage not accounted for directly by the passage of seat-belt laws.

Other variables have been found to be significant explanatory factors in studies of seat belt usage. These include per capita income, age levels in the population, per capita alcohol consumption, and variables characterizing the infrastructure of the state. This latter includes lane miles by functional road classification (interstate, arterial and collector roads) and the percent vehicle miles of travel within the state on each of these road classes. These variables are included in this analysis.

Lund (1986) found that higher income drivers were more likely to wear seat belts. Dee (1998) found that older drivers were more likely to wear seat-belts, up to about age 57, at which point they were less likely to wear seat-belts. Lund (1986) also found that young drivers were less likely to wear seat belts and that generally freeway drivers were more likely to wear seat belts. Fockler & Cooper (1988) reported a similar result from surveys and observation of drivers, that they were less likely to wear seat-belts for short trips. Alcohol consumption has also been hypothesized to reduce the likelihood of wearing seat belts (Dee, 1998). We include various demographic variables and alcohol consumption to control for and test for these effects.

3. Methodology

The data is analyzed using a fixed effects time-series cross-sectional model. The data is at the state-level and the inclusion of fixed effects allows for the control of other factors that might have influenced seat-belt usage for which data is unobservable (Johnston & Dinardo, 1997; Verbeek, 2001). For example, this could include public information campaigns that may have been implemented in some areas. These methods are simple to implement and consist of ordinary least squares regression with a dummy variable included for each cross-section, in this case the state. A time trend variable is also included to control for variation over time due to unobserved factors.

For the standard fixed effects model:

$$y_{it} = \alpha_i + x'_{it}\beta + \varepsilon_{it} \tag{1}$$

the error term ε_{it} is assumed to be independent and identically distributed over individuals i (i.e. the states) and time, with mean zero and variance σ_ε^2 (Verbeek 2001).

Two independent variables are specified to analyze spatial impacts of seat-belt laws. The first is a variable that tracks whether neighboring states also have passed a seat-belt law. The percent of neighboring states that have done so (for each law) is included as an independent variable.

After fitting a model, there is a need to examine the error estimates obtained in order to confirm that their distribution is in accord with our preconception. The presence of autocorrelated errors in the data leads to a deviation from the Gauss-Markov conditions for ordinary least squares (OLS) estimation. In this case for the error covariance matrix V, the off-diagonal cells of V contain non-zero values, which violates the conditions of the OLS procedure. Thus, though the OLS estimator is unbiased and linear, it does not have minimum variance, i.e. is not "best".

Such serial autocorrelation, defined as the correlation between members of a series of observations, can occur in either time-series or spatial data. It is easier to deal with such autocorrelation in time series since such observations are ordered in chronological order and there are likely to be interrelations among successive observations, especially if the time between successive observations is short. A major problem in geographical regression is that no such chronological order exists, though some similar order may exist.

In this study, the units of observation are the states of the continental US. One could expect that the pattern of seat-belt usage in the different regions of the US, e.g. the north-eastern states or the states of the deep south, is likely to differ from one geographical region to another, although substantially similar within a given region. Therefore, the estimated residuals may exhibit a systematic pattern associated with the regional differences.

Should this spatial autocorrelation exist, one can state that the distribution of the e_{it} will have the same form as that of the estimated $\hat{e}_{it}$, but, whilst having the same zero mean, it will have a modified variance-covariance structure. Thus, if the model selected has the correct form, one can assess the probable distribution of e_{it} by studying the distribution of the $\hat{e}_{it}$. If $\hat{e}_{it}$ have independent observations from a normal distribution, then it is probable that this was true for the e_{it}. If they are spatially autocorrelated, then it is probable that the e_{it} were also spatially autocorrelated.

Of course, if the models chosen are inappropriate, then the estimated "errors" will include a mixture of experimental error and model error, in which it is difficult to make any useful deductions concerning the error distribution.

A potential problem arises in this study with regard to the spatial autocorrelation. The most common formal method for detecting the presence of spatial autocorrelation is Moran's I_k test for the residuals obtained from an OLS analysis, where:

$$I_k = \frac{\hat{e}W\hat{e}'}{\hat{e}\hat{e}'} \tag{2}$$

where $\hat{e}$ is the error residuals from OLS. This equation requires the specification of a weights matrix (**W**) for the data, such as binary weights for the proximity matrix (**W**) where,

w_{ij} = 1 if states i and j had a common boundary length,

w_{ij} = 0 if otherwise.

Under the assumption of normality, the mean and variance of I_k can be determined and the standardized I_k statistic is asymptotically normal, so a one-sided test procedure for large samples to test for the presence of spatial correlation is:

Test $H_0 : \boldsymbol{r} = 0$ versus $H_a : \boldsymbol{r} \neq 0$

Reject H_0 if:

$$z^* = \frac{I_k - E(I_k)}{\sqrt{Var(I_k)}} > z_{1-a} \tag{3}$$

where $\boldsymbol{r}$ is a constant and is a measure of the overall level of spatial autocorrelation amongst the elements of the error term ($\boldsymbol{e}_i$, $\boldsymbol{e}_k$) for which $W_{ik} > 0$.

The analysis in this particular case is complicated by the presence of both space and time elements. Moran's I_k is valid for the residuals in one time period, i.e. in any particular year. With time series data, it is not statistically valid to simply sum the I_k values over all the years and undertake the test procedures outlined above.

We hypothesize that there is a spatial pattern in the data that influences seat-belt usage, and the estimation of the error covariance structure will provide information on this effect. Geostatistics, a branch of applied statistics aimed at a mathematical description and analysis of geological observations and used in a variety of fields (Issacs and Srivastava, 1987), offers the possibility of analysing any such spatial structure by means of estimating what is known as the variogram function. Before considering variogram estimation, the following section outlines how to derive information about the error covariance structure.

3.1. Residual correlograms.

Information about the error covariance structure can be obtained from a display known as a *residual correlogram* that shows the variation in residual correlation with inter-locality distance. In the case for residuals, Upton and Fingleton (1985) state that a suitable distance measure is $(\hat{\varepsilon}_i - \hat{\varepsilon}_j)^2$. Pocock et al. (1982) and Cook & Pocock (1983), in their analysis of geographical mortality studies in the UK, use this distance definition to derive an estimate of the correlation between errors at *i* and *j* occurring at distance d_{ij}. Note that in both these studies, only one time period, i.e. a particular year, is considered. Therefore the residual terms can be thought of as $\hat{\varepsilon}_{it}, \hat{\varepsilon}_{jt}$, with $t = 1$ in both cases.

The basis of the procedure in both Pocock et al. (1982) and Cook and Pocock (1983) is the algebraic identity:

$$E\{(\varepsilon_i - \varepsilon_j)^2\} = E(\varepsilon_i^{\,2}) + E(\varepsilon_j^{\,2}) - 2E(\varepsilon_i \varepsilon_j) \qquad (4)$$

where $E(\varepsilon_i^{\,2}) = E(\varepsilon_j^{\,2}) = \sigma^2$ and $E(\varepsilon_i \varepsilon_j) = \sigma^2 \rho(d_{ij})$, so that:

$$E\{(\varepsilon_i - \varepsilon_j)^2\} = 2\sigma^2\{1 - \rho(d_{ij})\} \qquad (5)$$

ρ is a constant and is a measure of the overall level of spatial autocorrelation amongst the elements of the error term. In order to estimate $\rho(d_{ij})$, one thus requires estimates of σ^2 and of $E\{(\varepsilon_i - \varepsilon_j)^2\}$. With the former independent of distance, attention turns on the estimate of the expectation:

$$E\{(\varepsilon_i - \varepsilon_j)^2\} \approx \frac{1}{n_d} \sum (\hat{\varepsilon}_i - \hat{\varepsilon}_j)^2 \qquad (6)$$

where the summation is taken over all those locality pairs occupying distance class *d*. For convenience denote the sample estimate given on the right hand side of equation (6) as *G*.

A correlogram is provided by plotting *G* against $\left(\sum d_{ij}\right)/n_d$, the mean inter-locality distance of the locality pairs belonging to distance class *d*. An autocorrelation near -1 will be represented by a large value of *G*, while a correlation near +1 will be represented by a 0 value of *G*. The variation in *G* with *d* will provide a clear idea of the extent to which the residuals display autocorrelation, although without an estimate of s^2, the precise nature of the autocorrelation will not be known.

If one does possess an accurate estimate of s^2, it is then possible to obtain $r(d_{ij})$ from Equation (5) and to show explicitly how $r(d_{ij})$ varies with d_{ij}. Pocock et al. (1982) and Cook & Pocock (1983) obtain their estimate of $\hat{s}^2$ by identifying from the *G* correlogram the distance *u* at which errors are evidently uncorrelated. This will correspond to the point where the correlogram flattens to approximately a zero slope.

The role of equation (6) is of great interest. In the geostatistics literature, this term is known as the *variogram function.* Geostatistical theory has a considerable body of literature detailing the intricacies of variogram estimation (Journel & Huijbregts, 1978; Issaks & Srivastava,. 1989). Various mathematical models have been developed to represent the distribution of values in mineral deposits. In all mineral deposits, one recognizes the presence of areas where the values are higher or lower than elsewhere. In addition, the values of two samples in a mineral deposit are more likely to be similar if these samples are taken close together than if they are far apart. This indicates a degree of *correlation* between sample values, and this correlation is a function of the distance between the samples. Models have been developed which account for this correlation, with the degree of correlation between sample values usually being measured by the variogram function. In these models the fact that two samples taken next to each other will most probably not have the same value, must also be considered; even for very short distances the correlations are usually not perfect and a purely random component is present in the value distribution. Thus the models assume the presence of two sources of variability in the values: a correlated component; and a random component.

In this study therefore, the variogram function is simply a model of the spatial dependence or continuity, of the residual terms obtained from the OLS analysis of the data. Basically, one is implying that the value of the residual $e(z)$, obtained from a model which has been fitted to explain seat belt usage in a state *z*, has properties of the function *z*, i.e. location. A certain spatial structure thus exists in the sample distribution and a model needs to be chosen to represent the spatial structure of the phenomenon. Since the variogram model is not known in advance, it must be estimated visually or by some estimation method. We analyze the variogram visually in the next section.

One additional consideration is the direction of the variogram. There is no reason to expect that the spatial correlation will exhibit the same behavior in every direction, i.e. be *isotropic*. It is important to calculate the variogram in different directions to see whether its properties change with direction. In particular for this study, *geometric anisotropy* should be considered. This occurs for a semivariogram whose degree of correlation is a function of direction, and a simple linear transformation of the coordinates is enough to restore isotropy. These results are also shown and discussed in the next section.

4. Results and Discussion

Estimation results are shown in Table 2. Of most interest, both primary and secondary laws are highly significant at increasing seat-belt usage. The coefficient values suggest that secondary laws result in a 10% increase in state seat-belt use while primary laws account for about a 16% increase. This strongly suggests that seat-belt laws have been very effective at increasing seat-belt use with primary laws having a greater effect than secondary laws.

The percent of neighboring states with secondary seat-belt laws increases seat-belt usage with a 90% level of statistical significance, while the percent of neighboring states with primary laws has no significant effect. This is quite an interesting result as it supports the hypothesis that various spatial effects in seat-belt use are occurring. For example, publicity about a new law in a state may positively effect those in neighboring states. Additional spatial analyses is discussed further below.

The time trend is consistently significant in both models. This clearly shows that some other factor not controlled for is also influencing seat-belt usage in a positive way. This could be due to public-relations and media campaigns to increase seat-belt usage or may represent some serial correlation in the data which we explore further below.

Other factors are controlled for in the regressions. As can be seen, per-capita income is not statistically significant. This is surprising as higher seat-belt usage is usually associated with higher income levels (Lund, 1986). Higher per-capita ethanol consumption, however, is found to be strongly associated with lower seat-belt use. Dee (1998) determined that seat-belt laws had less effect on those who are more frequent drinkers. This result is consistent with his analysis.

The impact of different age cohorts within the population is less clear. Larger populations of people between the ages of 25 and 44 increases seat-belt usage. Surprisingly, larger populations in the 15-24 age group also increases state seat-belt usage. On the other hand, for ages between 45-64, results show no significance. For ages over 65, there is also a significant effect. While we can only speculate on the reasons for these results, it does suggest that younger people having grown up with the message that seat-belts should be worn are more likely to do so (despite typically engaging in riskier behaviors).

Fockler & Cooper (1990) used stated preference survey data to determine under which driving situations people are more likely to wear or not wear seat-belts. One of their conclusions was that seat-belt use was more likely for longer trips and for trips on interstate freeways. Two categories of variables are included to measure this effect. These are the percent lane miles of three road types and the percent vehicle-miles of travel (VMT) driven on the three road types (interstates, arterials, and collector roads). Coefficients on the VMT variables are inconclusive, with no significant effect shown, except when more VMT is on collector roads (at a 90% level of significance). The lane mile coefficients suggest that states with more lanes of interstates actually have less seat-belt usage, contradicting the results of Fockler & Cooper (1990). As will be shown, these effects generally disappear when serial correlation is accounted for.

4.1 Analyses of Variograms

The spatial analyses techniques discussed previously are now applied to the models estimated in Table 2. The variograms for the residuals obtained from OLS estimation of the panel data were calculated for two years: 1991 and 1998. In each case a variogram was derived for the residuals in that year. Values of residuals, $\hat{e}_i, \hat{e}_j$, for each state were obtained from the models. In order to estimate $\left(\sum d_{ij}\right)/n_d$ the mean inter-locality distance of the locality pairs belonging to distance class *d*, the distance between the centroids of each state must be calculated. Rather than choose the geographical centroid of each state, the major population center in each state was chosen as the centriod value. This is more appropriate for this type of analyses as we are analyzing behavioral responses. For variogram construction, it is not the exact location of the centroids that is of importance, rather it is the distance between the centroids that is of interest. Thus, using the major population center as the centroid for a state results in only minor differences from the use of a population-weighted centroid.

Two variograms for Model 1 are plotted in Figure 1, for 1991 and 1998. The variograms of the residuals indicate the presence of spatial autocorrelation. This is shown by the increase in value with lagged distance. A flat curve would indicate no spatial autocorrelation. This effect is also present in Model 2 (results not shown) which has a similar pattern. Despite our attempt to account for some spatial effects in Model 1 by including a variable that indicates whether a neighboring state had a seat-belt law there is some additional spatial residual that has not been accounted for. In practice, this would suggest that our t-statistics are biased downwards and we may be missing the effect of some coefficients that are statistically significant.

The1998 variogram reaches its plateau at a lower value than for 1991. In geostatistics this plateau is known as the sill value (Issaks and Srivastava, 1989) and can be interpreted as implying that there is less spatial autocorrelation and less variance for the residuals in 1998, compared to 1991, although this difference appears minor.

None of the variograms have a zero value at the origin, i.e. the variogram represents a discontinuity at the origin. This so-called “nugget effect” (Journel and Huijbregts, 1978) is most likely due to the presence of local effects in each state which are not captured at the scale of measurement of the data.

The isotropic (i.e. direction invariant) variograms for both models, whilst indicating spatial interactions, do not have a shape that is easily recognisable from the common forms of variogram models developed in geostatistics (Journel and Huijbregts 1978). A better indication of the form of the variogram model that best represents this data is obtained by considering the anisotropic, i.e. direction-dependent variograms. These variograms, for the two directions North-South and East-West are shown in Figures 2 and 3 model 1.

The North-South variogram seems to indicate that there is little autocorrelation in this direction. However the variogram in the East-West direction indicates a variogram with two peaks: near the origin and near the plateau. This periodic behavior is commonly termed in geostatistics as the “hole effect”, and can be explained as a succession of states where the residuals exhibit similar characteristics followed by a succession of states that do not. Thus similar characteristics are exhibited by states on the coast of the east and west of the US.

5. Temporal Autocorrelation

One issue that also needs to be addressed is potential temporal autocorrelation (or serial correlation) in the data. When serial correlation follows a first-order autoregressive process the error term is assumed to depend upon its predecessor as,

$$e_{it} = r e_{i,t-1} + u_{it} \qquad (7)$$

where $|r|<1$, and u_{it} is i.i.d. $\left(0, s_v^2\right)$ across individuals and time. Typically the autocorrelation coefficient r and s_v^2 are unknown. Testing the null hypothesis of

$H_0 : r = 0$ against the one-sided alternative $r < 0$ or $r > 0$, in a first order autoregressive process has a long history of producing test statistics with extremely complicated distributions. This tradition has continued with extensions of these tests to cross-sectional time series data. Bhargava et al.(1982) proposed the extension of the Durbin-Watson statistic to the case of balanced equally spaced panel datasets. If $\hat{e}_{it}$ denote the residuals from the within regression then Bhargava et al. (1982) suggest the following generalization of the Durbin-Watson statistic:

$$dw_p = \frac{\sum_{i=1}^{N} \sum_{t=2}^{T} \left(\hat{e}_{it} - \hat{e}_{i,t-1}\right)^2}{\sum_{i=1}^{N} \sum_{t=1}^{T} \hat{e}_{it}^{\;2}} \qquad (8)$$

This allows for autocorrelation over time with the restriction that each individual has the same autocorrelation coefficient r. Using similar derivations as Durbin and Watson, Bhargava et al. (1982) are able to deliver lower and upper bounds on the true critical values that depend upon *N*, *T* and *K* only. Bhargava et al. (1982) suggest that for panels with very large *N*, simply to test if the computed statistic dw_p is less than two, when testing against positive autocorrelation.

If we take the residuals $\hat{e}_{it}$ from Models 1 and 2 in Table 2, and test for the Bhargava et al. (1982) modified Durbin-Watson statistic we find that it is 1.1604and 1.1563 respectively, clearly indicating serial correlation in the data.

Results for the estimation of a model fitted with an AR(1) model to the disturbance term are shown in Table 3. It is evident that there is a high degree of temporal autocorrelation in the data, with the r values for Models 3 and 4 being about 0.46. Comparing these results with those obtained without accounting for serial correlation lead to a different interpretation of the results. Many of the independent variables no longer are statistically significant.

The seatbelt law dummy variables remain statistically significant and show similar levels of effectiveness. Primary laws increase seat-belt usage by about 13-14% and secondary laws by nearly 9%, in both cases not much less than in the models estimated without correcting for serial correlation. The effect of whether neighboring states have a seat-belt law is now not significant, indicating that some of the spatial correlation effects may now be less important.

Our year trend variable is now insignificant, as would be expected when serial correlation is corrected for. Per-capita alcohol consumption now appears to not have any relationship to seat-belt usage, contradicting the earlier result. Our age cohort variables also do not show any significant effect. The only variable that shows a small 90% level of significance is the percent VMT driven on arterial roads. Increased driving on arterials seems to reduce the level of seat-belt usage.

5.1.   Spatial effects when temporal correlation is accounted for

Having fitted an AR(1) disturbance term to account for the temporal autocorrelation in the cross-sectional time series analysis, it is appropriate to test the residuals obtained from the AR(1) models, $\hat{e}_{it}$, for spatial autocorrelation. More specifically in the equation:

$$\hat{e}_{it} = r\hat{e}_{i,t-1} + \hat{u}_{it} \tag{9}$$

$\hat{u}_{it}$ should be tested to ensure that there is no spatial autocorrelation. In order to estimate $\hat{u}_{it}$, the value of r, the temporal autocorrelation coefficient must be known. Therefore, based upon the theory outlined in Section 3 and 4.1, variograms for the residuals obtained from the estimation of the panel data with the AR(1) disturbance term were calculated for 1991 and 1998. In each case a variogram was derived for the residuals in that year and the previous year.

Examining the variograms for models with the AR(1) correction it is found that the values of the variogram are now an order of magnitude less than before as shown in Figure 4 for Model 3. For example, for Model 1, without any temporal autocorrelation correction the variograms reach a plateau (i.e. sill value) at 0.05. However, once the AR(1) correction is included (Model 3), this plateau value is only 0.004, an order of magnitude less. A similar result occurs for Model 2 and Model 4. Therefore, whilst for both models, the variograms of the residuals indicate the presence of spatial autocorrelation, its actual level is very small once the AR(1) correction has been applied.

In considering the anisotropic variograms of the AR(1) models, the North-South variograms still seem to indicate that there is little autocorrelation in this direction. However the variogram in the East-West direction still indicates a variogram with two peaks similar to the effects for the models without correcting for serial correlation. Thus similar characteristics are exhibited by states on the boundaries of the east and west of the US.

The use of an AR(1) correction for the temporal autocorrelation, followed by spatial correction, indicates that correcting for this temporal autocorrelation appears to be more important than correcting for spatial correlation. Therefore, whilst the variograms of the AR(1) models indicate that there is some additional spatial residual that has not been accounted for, the actual spatial effect may be quite small.

Finally, the order in which these corrections are applied to the models is of interest. The results obtained indicate that if the residuals are tested first for spatial autocorrelation, then this seems to be present and the effect is quite strong. However, if temporal autocorrelation is corrected for, any subsequent spatial autocorrelation, whilst present, seems to be quite small, at least for the data analyzed here. Therefore, there may well be an interaction of spatial and temporal correlations present in the data, though this has not been explored further.

6. Conclusions

This analyses has clearly shown that passage of seat-belt laws in the US has been associated with increases in seat-belt usage. Primary seat-belt laws appear to have a slightly larger effect on increasing seat-belt usage than secondary laws, though both are highly effective. Interestingly, when we correct for serial correlation, the seat-belt laws seem to be the only factor that has contributed to increased seat-belt usage as most demographic and infrastructure related factors have no statistical significance. This appears to refute other analyses that have found alcohol consumption, age, and infrastructure type to affect seat-belt usage. Our result differs primarily because of the correction for serial correlation.

Our other main result is to demonstrate the use of geostatistical methods for examining spatial autocorrelation. The spatial analyses of the variogram function shows that there is some residual spatial correlation in the data even after correcting for serial correlation. Extra information can be obtained by examining the anistropic variograms and we found similarities in residuals between the eastern and western US states though no similarities were apparent on a north-south axis. It is unclear why this effect would be apparent, but it may represent some unmeasured demographic variables that are still important in determining seat-belt usage.

While our results on the prior effectiveness of seat-belt laws is quite clear, further research using spatial analyses techniques could help to clarify some additional issues. The regional differences in spatial effects could be decomposed to analyze other directions. Understanding these spatial effects could be useful for devising policies to further increase seat-belt usage.

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Table 1: Number of states (excluding AK and HI) that have passed seat-belt laws, by year.

	Primary law	Secondary law
1984	0	0
1985	1	3
1986	6	17
1987	6	18
1988	6	22
1989	6	25
1990	6	26
1991	7	29
1992	7	31
1993	8	31
1994	8	36
1995	8	37
1996	10	36
1997	10	36
1998	13	34

Table 2: Fixed Effects Models

Dependent variable = Percent Seat-belt Usage	Model 1		Model 2	
Years of data	1990-1998		1990-1998	
	Coefficient	t-statistic	Coefficient	t-statistic
Year	0.0165	2.712	0.0177	2.961
Primary Law	0.1666	6.729	0.1621	6.672
Secondary Law	0.1007	7.150	0.0989	7.110
Percent of Neighboring States with Primary Law	0.0291	0.580	-	-
Percent of Neighboring States with Secondary Law	0.0454	1.696	-	-
Per Capita Income	-0.0000035	-0.451	-0.0000046	-0.597
Per Capita Ethanol Consumption	-161.7743	-2.680	-176.1101	-2.941
Percent Population Aged 15-24	2.5287	2.423	2.4967	2.409
Percent Population Aged 25-44	2.3201	1.544	2.2735	1.511
Percent Population Aged 45-64	0.4884	0.366	0.5428	0.407
Percent Population Aged 65 and up	6.4169	2.661	6.6590	2.770
Percent VMT on Interstates	-0.1936	-0.401	-0.0603	-0.126
Percent VMT on Arterials	0.0704	0.246	0.0763	0.266
Percent VMT on Collectors	-0.5707	-1.835	-0.5404	-1.737
Percent Lane Miles of Interstate	-8.9563	-2.342	-8.9156	-2.333
Percent Lane Miles of Arterial	0.4618	0.616	0.4655	0.621
Percent Lane Miles of Collector	0.3776	1.094	0.3072	0.896
Constant	-33.7723	-2.844	-36.2229	-3.094
N	432		432	
R-Squared	0.559		0.555	

Table 3: Fixed Effects Models with AR(1) error term

Dependent variable = Percent Seat-belt Usage	Model 3		Model 4	
Years of data	**1990-1998**		**1990-1998**	
	Coefficient	**t-statistic**	**Coefficient**	**t-statistic**
Year	0.0042	0.41	0.0039	0.39
Primary Law	0.1373	5.09	0.139	5.24
Secondary Law	0.0862	4.96	0.089	5.15
Percent of Neighboring States with Primary Law	0.0017	0.03	-	-
Percent of Neighboring States with Secondary Law	0.0321	1.01	-	-
Per Capita Income	0.00000037	0.04	0.000000372	0.04
Per Capita Ethanol Consumption	18.14	0.25	5.860	0.08
Percent Population Aged 15-24	-1.135	-0.60	-1.001	-0.53
Percent Population Aged 25-44	0.904	0.43	1.052	0.51
Percent Population Aged 45-64	0.437	0.21	0.647	0.31
Percent Population Aged 65 and up	1.300	0.33	1.646	0.42
Percent VMT on Interstates	-0.419	-0.78	-0.36	-0.68
Percent VMT on Arterials	-0.666	-1.81	-0.673	-1.83
Percent VMT on Collectors	-0.047	-0.12	-0.050	-0.13
Percent Lane Miles of Interstate	-6.012	-1.37	-5.856	-1.33
Percent Lane Miles of Arterial	-1.12	1.44	1.06-	1.37
Percent Lane Miles of Collector	-0.506	-1.17	0.524	-1.22
Constant	-7.73	-0.71	-7.23	-0.67
N	384		384	
R-Squared	0.119		0.081	
Rho_ar	0.459		0.458	

Figure 1
Variograms for Model 1

Figure 2
East-West Anisotropic Variograms for Model 1

Figure 3
North-South Anisotropic Variograms for Model 1

Figure 4
Variograms for Model 3