Improvements in Medical Care and Technology and Reductions in Traffic-related Fatalities in Great Britain

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Abstract

Great Britain has one of the lowest levels of traffic-related fatalities in the industrialized world with a current total of about 3500 fatalities per year. Large reductions have occurred over the last 20-30 years and the government has targets of achieving another 40% reduction by 2010. This paper analyzes some of the factors that have been statistically significant in helping to achieve those reductions with a focus on improvements in medical care and technology. Using a cross-sectional time-series of regional data a fixed effects negative binomial model is estimated which includes three proxies of medical care and technology changes. These are the average length of inpatient stay in the hospital, the per-capita level of National Health Service staff, and number of people per-capita waiting for hospital treatment. All are statistically significant with the expected sign showing that improvements in medical technology have reduced total fatalities with less of an impact from changes in medical care. Other variables are also found to be significant, including the percent of elderly people in the population, per-capita expenditure on alcohol, motorway capacity, and average vehicle age. The latter shows a surprisingly unexpected effect, with more older vehicles in a region leading to fewer fatalities. Models evaluating effects on serious and slight injuries are also estimated and serve to confirm the expected effects of medical care and technology.

Key words: transport safety, health policy, medical technology, negative binomial model

Introduction

Traffic-related fatalities in Great Britain have decreased by about 45% over the last 20 years dropping to a current level of about 3500 fatalities per year. Great Britain now has one of the lowest traffic-related fatality rates per capita and per kilometer traveled of any industrialized nation. Serious injuries currently total about 40,000 per year and have experienced a similar reduction in the last 20 years. Total casualties, which include slight injuries, still total about 300,000 per year. Overall, this represents large costs to society and the UK National Health Service (NHS). The UK government has recently proposed a further 40% reduction in fatalities and serious injuries between 2000 and 2010 (DETR, 2000).

The transport and safety community has traditionally attacked the problem of traffic fatalities from three different angles. Motor-vehicle safety regulations have dramatically improved the crash-worthiness of vehicles, traffic engineers have designed safer and more efficient roads, and educational efforts have attempted to improve driver awareness especially of the risks of driving while intoxicated. Downward trends in fatality rates suggest that these approaches are at least correlated with reductions in traffic fatalities implying that they have been effective. Broughton et al. (2000) estimate that only 13% of the UK fatality reductions can be attributed to these types of measures. Other factors must be playing a major role in reducing overall fatalities. The objective of this paper is to examine the impact of improvements in medical care and technology while controlling for many of the other factors associated with reducing fatalities.

The role of medical technology has been examined using US data (Noland, 2001a) and international data for industrialized countries (Noland, 2001b). Results from these prior studies have found that various proxy measures of improvements in medical technology are statistically significant and associated with reduced fatalities. A similar result is found for the British data which is analyzed here.

In addition we find surprising results for some of the other variables that we analyze, in particular the average vintage of vehicles on the road. Our analyses suggests that as the average age of registered vehicles increases, fatalities are reduced. This result suggests that changes in the type of vehicles or their relative safety may be increasing overall fatalities.

Various factors have been determined to be associated with reductions in traffic-related fatalities. Previous research has determined that decreases in alcohol consumption, the proportion of younger drivers, the amount of seat-belt usage, road design characteristics, traffic speed and speed variance, and vehicle safety improvements have all been associated with the level of traffic-related fatalities.

Much of this work has utilized macro-modelling techniques that exploit time-series cross-sectional data sources. Recent examples of this work include Voas et al. (2000) and Whetten-Goldstein et al. (2000) on the effect of alchohol consumption laws, McCarthy (1999) on policies including seat belt laws and speed limits, Noland (2001a) on highway infrastructure, and Dee (1998) on seat-belt laws. Hakim and Shefer (1991) summarize many of the results of macro-modelling studies.

One characteristic of the majority of this work is that it generally uses US data, primarily at the state-level. This is due partly to the easy availability of state-level data in the US and the lengthy time-series that are becoming increasingly available. Fridstrom & Ingebrigsten (1991) analyzed data from Norwegian counties and Karlaftis & Tarko (1998) analyzed county data from the US state of Indiana. Some studies have also analyzed international data using cross-sectional time-series analyses, including Noland (2001b) and Page (2001).

We are unaware of these techniques being applied using data from Great Britain. This study analyzes regional data based on the standard statistical regions of the UK (see

Figure 1). Data between 1979 and 1998 was collected from a variety of sources and is discussed further below.

The following section briefly reviews the medical literature which documents some of the improvements in care and technology that have occurred over the last few decades with a focus on identifying adequate proxies for measuring this change. The statistical methods used are then discussed and the data which we have used for this analyses is described. Results are then presented followed by conclusions.

Proxy Variables for Medical Technology Improvements

A central hypothesis of our study is that advances in medical technology and medical care have played a significant role in reducing fatalities in road accidents. Substantial evidence suggests that medical technology has improved enormously over the last 20 years. Cales & Trunkey (1985) review many studies that suggest that many fatalities from traffic accidents could have been avoided if emergency medical procedures were improved, irrespective of changes in technology. However, measuring the outcomes of medical improvements has proven to be quite difficult. Cutler et al. (1998) examine this issue in the context of developing a medical cost index and conclude that there are large difficulties involved.

Advances in medical technology have been seen as a major factor behind the expansion of health care expenditure over several decades (Weisbrod, 1991; Newhouse, 1992). In recent decades extraordinary advances have occurred in many areas of the health sciences, including genetics, body imaging, microsurgery, transplantation, and in the technical ability to sustain life. The development of these new medical technologies continuously serves to increase both quality of life and longevity in the population (Newhouse, 1992). Technology also includes changes in procedures and management systems of treating accident victims. Sakr & Wardrope (2000) reviews the evolution of these changes in Britain while Cales & Trunkey (1985) discuss the ability of improved trauma care systems to reduce fatalities. Treatment of traumatic brain injury has also undergone significant advances over the last 30 years, including the introduction of clinical tools such as CT scanners, which were introduced in the 1970's (Gentleman, 1999).

New medical technologies tend to both increase and decrease health care expenditures (Weisbrod, 1991). Poorly understood diseases or conditions generally trigger minor health care expenditures since there are no technologies for treatment. Some technologies that can decrease mortality can be quite costly, such as organ transplantations. The most advanced technical solutions can actually be quite inexpensive as they tend to prevent diseases (for example, vaccinations) or in the case of traffic-related injuries, prevent fatalities (for example, seat-belts).[1] This naturally makes it difficult to clearly define health care expenditures as representing improvements in medical technology. Weisbrod (1991) elaborates upon the difficulties of defining medical technologies and how they ultimately effect quality of life, which in itself is a difficult output to measure. In any case, it would be misleading to use a health care expenditure variable as a proxy for medical technology improvements, as they may not be clearly linked.

With regard to changes that can specifically impact on the outcome of traffic accident victims, the development of accident and emergency medicine has played a role. It plays an important part in the care of acutely ill and injured patients especially from road accidents. One specific example of a change in medical technology associated with emergency medicine is computer based storage systems for clinical images, radiographs, photographs, and ECGs that can help in teaching and research within an accident and emergency department (Clegg et al., 2001). These technical improvements have clearly evolved over time enabling emergency medical facilities to reduce mortality rates amongst accident victims. In the UK,

[1] Some may not define seat-belts as a "medical technology" but clearly this illustrates the difficulty of defining an index for change over time.

telemedicine has also been applied to two major areas of accident and emergency practice (Benger, 2000). These are the transmission of computed tomography scans for urgent neurosurgery and the ongoing support of minor injury units.

Given that medical technology is likely to have improved over the course of our time series, it is necessary to find relevant measures that adequately track these changes over both space and time. The safety literature gives little guidance on this with few studies attempting to account for this sort of change. Lave (1985) used hospitals per square mile to attempt to account for access to medical services (in the event of an accident). This would serve to control for rural areas being less accessible to fast medical care for emergencies. He found this variable to be significant, though his analysis suffers from not controlling for either cross-sectional or time-series effects. Noland (2001a) also used this variable with cross-sectional time-series data but did not find this to be significantly associated with reduced fatalities. In fact this variable may be endogenous implying that those areas with more traffic-related fatalities may have comparatively more hospital facilities. The response of the health care profession in developing emergency medicine procedures would certainly suggest this possibility (Sakr & Wardrope, 2000).

Alberman (1985) has suggested that the downward trend in perinatal and infant mortality rates is a result of improved medical technology. While infant mortality is not explicitly linked to the type of injuries associated with traffic accidents, it is likely that underlying improvements in medical technology can explain trends in both. Therefore, infant mortality rates might be an adequate and readily available proxy variable for improvements in medical technology. Noland (2001a) used white infant mortality rates at the state level and found this to be significantly related to reductions in fatalities but not injuries. White infant mortality rates were used to minimize the correlation that total infant mortality rates typically have with per capita income. Noland (2001b) could not find as strong an association using international data, perhaps because of the relatively high correlation with per capita income. In our analyses we further examine infant mortality rates as a suitable proxy variable.

Increased numbers of physicians may also lead to better health care and shorter waiting times for service. Both the number of NHS staff per capita and the number of people per capita waiting for hospital treatment are readily available at the regional level and are used as proxies in our analyses. These will tend to represent the level of resources devoted to medical care, rather than explicitly to medical technology. Slade and Anderson (2001) suggest that more physicians may be endogenous representing a preference for better health care. While this may be true at the national level, we suspect it is less true within a country such as the UK where most policies are set at the national level.

The length of inpatient stay in the hospital could be affected by many factors such as better medical technology, reduced ambulatory care and efforts to reduce medical costs. Weisbrod (1991) considers another element to be cost constraints imposed by insurance companies that provide a financial incentive for earlier discharge of patients. Quicker healing is also possible with improvements in medical technology, such as use of laser surgery which necessitates smaller incisions. Noland (2001b) found that the average in-patient time across countries was a statistically significant factor in explaining fatalities. Regional data on average length of inpatient stay is used as a proxy in our study.

Data

Cross-sectional time-series data for the United Kingdom was used in our analyses. This data was collected for all 11 Standard Statistical Regions (SSRs) of the UK (except Northern Ireland) from 1979 to 1998. The SSRs are defined in Figure 1. The data used was obtained from several sources.

Regional data on road accidents over 20 years (from 1979 to 1998) was collected from the *Department of Environment, Transport and the Regions* (DETR). Over this time period, there were a total 6,423,709 casualties. The data is disaggregated based upon three levels of severity, which are fatalities, serious injuries, and slight injuries. Fatalities include only those cases where death occurs in less than 30 days as a result of the accident. Serious injuries include, for example, fractures, internal injuries, burns, concussion, and any accident resulting in hospitalization plus those deaths that occur 30 days or more after the accident. Slight injuries may require hospital treatment but not hospitalization and include whiplash, slight cuts, and minor shock. Over the 20 year time series 1.5% of the accidents are classified as fatal, 18.78% are classified as seriously injured and 79.72% are classified as slightly injured. Table 1 shows the trends between 1979 and 1998. Total casualties have decreased by 1.16% over this time period while total fatalities have shown a major decrease of 46.1% and serious injuries by 40.6%. On the other hand, slight injuries have increased by 13.5%.

Data on road infrastructure includes the total road length by functional road category (motorways, trunk roads, other roads) for each region. Motorways are controlled access highways built to the most scrupulous and consistent design standards. Trunk roads are generally multi-lane or intercity roads, perhaps with some controlled access but generally not. Other roads are smaller scale roads that generally provide local access rather than inter-city travel. This data was collected from *Basic Road Statistics* published by the *British Road Federation.* The data was available for all regions over 20 years. Table 1 provides an overview of the changes over time. Motorway length has increased by over 30% with other roads showing a smaller percent increase.

Data on regional vehicle ownership was also collected from the same source. Regional data on vehicles included number of cars currently licensed, vehicles per thousand population, average vehicle age, percentage of vehicles first registered in the current year, percent of households with no car, percent of households with one car and percent of households with two or more cars. In general, vehicle ownership has been increasing and the age of vehicles on the road has also been increasing.

Data on total population, household income, expenditure on alcohol, and population by age cohorts was also collected from *Regional Trends* published by the *Office of National Statistics.* These are used to control for other factors that are likely to affect casualties. GDP and alcohol expenditure were adjusted for inflation and set to real values for 1998 pound sterling. Age cohort data was not available for Scotland.

As discussed previously, several variables could be a good proxy for improvements in medical care and technology over time. These include the length of inpatient stay in the hospital, infant mortality rate, persons waiting for hospital treatment per capita, NHS staff per capita and General Practitioners (GP) per capita. This data was collected from *Regional Trends* and the *Compendium of Health Statistics* published by the *Office of Health Economics*. Health care data were not available for the London region.

Table 1 shows the average change in these variables over time. Further analyses (not shown) shows that in almost all regions the length of inpatient stay in the hospital has decreased by about 50% over 20 years. Infant mortality rates have decreased by 62% (highest) in the South East region and by 47% (lowest) in the Yorkshire region. The number of persons (per capita) waiting for hospital treatment has increased in some of the regions and decreased in some other regions. In Wales, it has increased by about 45% whereas in the West Midlands, it has decreased by about 27%. NHS staff per capita shows no clear trend between regions and almost no change in aggregate. It has increased in the East Midlands, North West, South East, South West, West Midlands and Yorkshire and decreased in the East Anglia, Northern region, Scotland and Wales.

Background on Statistical Models for Accident Analyses

In traffic accident studies, multiple linear regression models have been frequently used (Jovanis and Chang, 1986; Joshua and Garber, 1990; Miaou and Lum, 1993a). Accident data consists of counts and the use of regression models that assume a normal distribution can result in undesirable statistical properties, such as the possibility of negative accident counts as has been suggested by Zeeger et al. (1990), Miaou and Lum (1993a), and Jovanis and Chang (1986). Besides being unable to give appropriate statistical inferences about accident occurrence, linear regression models that assume normality can also result in inaccurate standard errors.

Accident occurrences are necessarily discrete, often sporadic and more likely random events. Therefore, Poisson regression models are the appropriate statistical method to use. In a number of studies in recent years (Miaou and Lim, 1993a, 1993b; Miaou et al., 1992; Joshua and Garber, 1990; Jones et al., 1991; Kulmala, 1994; Maycock and Hall, 1984), Poisson regression models have been used to establish statistical relationships between traffic accidents and factors that contribute to accident occurrence.

The Poisson regression model also has limitations. One important constraint in Poisson regression models is that the mean must be equal to the variance. If this assumption is not valid, the standard errors, usually estimated by the maximum likelihood (ML) method, will be biased and the test statistics derived from the models will be incorrect. In a number of recent studies (Miaou, 1994; Shankar et al., 1995; Vogt and Bared, 1998), the accident data were found to be significantly overdispersed, i.e., the variance is much greater than the mean. This will result in incorrect estimation of the likelihood of accident occurrence.

In overcoming the problem of overdispersion, several researchers, like Miaou (1994), Kulmala (1995), Shankar et al. (1995), Poch and Mannering (1996) and Abdel-Aty and Radwan (2000) have employed the negative binomial (NB) distribution instead of the

Poisson. By relaxing the condition that the mean is equal to the variance, NB regression models are more suitable for describing discrete and nonnegative events.

An additional problem is unobserved heterogeneity which can occur with cross-sectional analyses. One way to overcome this limitation is to use panel data and to consider separate persistent individual effects in the NB models as suggested by Hausman, et al. (1984) in their study of patent applications. Hausman et al. (1984) considered both the fixed and random definitions of the individual effects; the former does not allow group-specific variations. In employing the model in what may be its first application in traffic accident studies, Shankar et al (1998) have indicated that the random effect negative binomial (RENB) model may be more appropriate because geometric and traffic variables are likely to have location-specific effects. With his study, it appears that the RENB models can significantly improve the explanatory power of accident models. Chin and Quddus (2002) applied the random effects version of Hausman et al.'s model to examine traffic accident occurrence at signalized intersections.

Noland (2001a, 2001b) used the fixed effects NB model to overcome the heterogeneity in cross-sectional time-series data. Olmstead (2001) also used the fixed effects version of Hausman et al.'s model to measure the impact of a freeway management system on the incidence of reported motor-vehicle crashes in Phoenix. These studies both suggested found the Hausman specification test (Hausman, 1978) rejected the random effects model in favor of fixed effects models in the vast majority of cases. The approach taken here is to use the fixed effects negative binomial model to examine the factors influencing vehicle casualties in the UK.

Methodology

The data in our analyses form a cross-sectional time-series consisting of repeated observations on the same UK regions. We utilize the method derived by Hausman et al.

(1984) for estimating NB models with panel data. This method has the advantage of factoring out the overdispersion parameters and accounting for heterogeneity in the data.

To account for the fixed individual effects in the NB model, we rewrite the Poisson parameter as,

$$\boldsymbol{l}_{it} = \boldsymbol{m}_{it}\boldsymbol{a}_i \qquad (1)$$

where,

$$\boldsymbol{m}_{it} = E(n_{it}) = \exp(\hat{\boldsymbol{a}}\ \boldsymbol{X}_{it}) \qquad i = 1, 2, \ldots. N \qquad t = 1, 2, \ldots\ldots. T \qquad (2)$$

in which $\boldsymbol{m}_{it}$ is the Poisson parameter indicating expected numbers of casualties in an observation unit *i* in a given time period *t*, n_{it} is the number of observed casualties in an observation unit *i* during a given time period *t*, $\boldsymbol{X}_{it}$ is a vector of covariates which describe the characteristics of an observation unit *i* during a given time period *t*, $\hat{\boldsymbol{a}}$ is a vector of estimable coefficients representing the effects of the covariates, and $\boldsymbol{a}_i$ is the individual-specific fixed effect. To derive the joint probability of the fixed effect NB model, it is necessary to find a convenient distribution for the sum of events for a given individual, $\sum_t n_{it}$. A detailed derivation can be found in Hausman et al. (1984). The resulting joint probability of the i^{th} individual conditional on total years is

$$\Pr(n_{i1}, \ldots\ldots, n_{iT} \mid \textstyle\sum_t n_{it}) = \left(\displaystyle\prod_t \frac{\Gamma(\boldsymbol{m}_{it} + n_{it})}{\Gamma(\boldsymbol{m}_{it})\Gamma(n_{it}) + 1}\right) \times \left[\frac{\Gamma(\sum_t \boldsymbol{m}_{it})\Gamma(\sum_t n_{it} + 1)}{\Gamma(\sum_t \boldsymbol{m}_{it} + \sum_t n_{it})}\right] \qquad (3)$$

which includes $\hat{\boldsymbol{a}}$ via $\boldsymbol{m}_{it}$ but does not include $\boldsymbol{a}_i$ and the overdispersion parameter *k*. From this the likelihood function can be derived as,

$$L(\textstyle\sum_t n_{it} \mid n_{it}, \ldots\ldots, n_{iT}) = \displaystyle\prod_t \left[\left(\prod_t \frac{\Gamma(\boldsymbol{m}_{it} + n_{it})}{\Gamma(\boldsymbol{m}_{it})\Gamma(n_{it}) + 1}\right) \times \left(\frac{\Gamma(\sum_t \boldsymbol{m}_{it})\Gamma(\sum_t n_{it} + 1)}{\Gamma(\sum_t \boldsymbol{m}_{it} + \sum_t n_{it})}\right)\right] \qquad (4)$$

The BHHH estimator can be used to estimate $\hat{\boldsymbol{\beta}}$ (Greene, 2000).

We also use a simple ordinary least squares regression with fixed effects to analyze models with ratios as dependent variables. This model is defined simply as,

$$y_{it} = \boldsymbol{\alpha} + \boldsymbol{X}_{it}\hat{\boldsymbol{\beta}} + \boldsymbol{\nu}_i + \boldsymbol{\varepsilon}_{it} \qquad i = 1,\ldots\ldots, N;\ t = 1,\ldots\ldots, T_i \tag{5}$$

where y_{it} is the ratio of fatalities to injuries (explained further in the next section) in an observation unit *i* in a given time period *t*, $\boldsymbol{\nu}_i$ is the unit specific residual; it differs between units but, for any particular unit its value is constant, $\boldsymbol{\varepsilon}_{it}$ is the usual residual with the properties of mean 0, uncorrelated with itself, uncorrelated with $\boldsymbol{X}_{it}$, uncorrelated with $\boldsymbol{\nu}$ and homoskedastic. Other terms are as previously defined.

We also estimate a cross-sectional time series regression model when the disturbance term is first-order autoregressive to correct for serial correlation in the data. We choose the fixed-effects version of the linear model with an AR(1) disturbance that is defined simply as equation (5) where

$$\boldsymbol{\varepsilon}_{it} = \boldsymbol{\rho}\boldsymbol{\varepsilon}_{i,t-1} + \boldsymbol{\eta}_{it} \tag{6}$$

and where $|\boldsymbol{\rho}| < 1$ and $\boldsymbol{\eta}_{it}$ is independent and identically distributed with zero mean and variance $\boldsymbol{\sigma}_{\eta}^{2}$, $\boldsymbol{\nu}_i$ are assumed to be fixed parameters and may be correlated with the covarites $\boldsymbol{X}_{it}$.

Results

Several models were developed to test the hypothesis of whether various proxies for medical technology improvements are associated with reductions in traffic-related fatalities. Table 2 has results for estimates using a fixed effects negative binomial model. The dependent variables were total fatalities (model A and B), serious injuries (model C and D) , and slight injuries (model E and F). We include dummy variables for each year as opposed to a year time trend variable which was correlated with some of our independent variables, but omit the coefficients on these for brevity. The logarithm of the independent variables are used to eliminate heteroskedasticity in the data and also to allow easy interpretation of elasticity values which are equal to the coefficient estimates. Note that the models with medical technology proxies do not include data from the London region and hence have 180 observations rather than 200. Data from Scotland is not included as we did not have age cohort data for Scotland.

Model A in Table 2 contains no proxies for medical technology improvements. Most independent variables seem to be having no effect on total fatalities. Increased per capita expenditure on alcohol is statistically significant at increasing fatalities. This is not surprising as alcohol consumption has been shown to be related to increases in fatalities (Loeb, 1987). Whetten-Goldstein et al. (2000), however, did not find a price index of alcohol consumption to be significant, though they modeled fatality rates, rather than total counts. Increased population over 65 years is statistically significant and associated with increased fatalities and increased vehicle age is associated with reduced fatalities. This latter result is quite surprising as we would expect newer vehicles to reduce the level of fatalities since they are presumably safer (i.e., they may have newer safety features and also be better maintained). This variable was somewhat correlated (-0.72) with the percent of the population aged 15-24, but estimates with this variable omitted did not change the coefficient value which is fairly robust.

Model B in Table 1 introduces proxies for medical technology improvements. Three variables are tested. These are the average length of inpatient stay in the hospital which has been declining over time and could represent better medical technology as discussed previously. Per capita NHS staff is also included with increases in staff levels proxying for better medical care. The number of persons per capita on waiting lists for hospital treatment is also included and represents the amount of resources devoted to medical care (i.e., the more resources the fewer people on the waiting lists).

The medical technology proxies all have the expected sign with two of them being significant at the 95% level. We also examined in a separate model the effect of infant mortality rate as a proxy. This variable was highly correlated with other variables in the model. Our results did not indicate that this variable was statistically significant, though this may be due to the confounding effect of other variables. Average length of inpatient stay does have a relatively high correlation with the percent of the population aged 15-24 (0.84). Omission of the correlated variable does not change the robustness of the coefficient value of the variables of interest.

To further examine the impact of medical technology, models were estimated with both serious injuries and slight injuries as the dependent variable. If medical technology is reducing fatalities associated with traffic accidents, we would expect many of these fatalities to now be classified as injuries, especially serious injuries. If this is the case we would expect the medical technology proxy variables to either have no significant effect on the number of injuries or to have the opposite sign from the fatality model. We find the latter effect for our variables as shown in Table 2, models D and F. Reduced inpatient stays in the hospital are associated with increases in serious and slight injuries. Increased per-capita NHS staffing levels also are associated with increased serious and slight injuries. Reductions in hospital waiting lists are associated with increased serious injuries but there is no effect on slight injuries. These results suggest that these changes could be due to better treatment of what would have formerly been fatalities. More importantly, the difference in the sign of the coefficients suggests that there is an inherent difference between the association of these variables with fatalities as opposed to injuries.

We also see various other effects in the injury models that occur both with and without inclusion of the medical technology variables (models C and E). Increased vehicle age is statistically significant in the serious injury models but not in the on slight injury models. For serious injuries the effect is opposite that of average vehicle age on fatalities. Increases in the motorway and trunk road network are now significantly associated with increases in serious injuries, though the level drops when medical technology variables are included (especially the effect on slight injuries). Interestingly, as the fraction of the network which is “other roads” increases, serious injuries decrease with no effect on slight injuries. Increased motorway length per area decreases injuries but this effect again disappears when medical technology variables are included. There is no collinearity amongst these variables with the medical technology variables so the associations appear quite robust.

Other control variables in the injury models include alcohol expenditure which is positive and significant and population which is also positive and significant. Increased GDP per capita appears to be associated with reductions in injuries, though this effect is not robust across different specifications of the model. Age effects are also not clearly robust across the specifications, although increased population in the 45-64 age range does seem to have an association with reductions in both injury categories.

Additional evidence on the effect of the medical technology proxies can be found by examining the time trend variables. These were included in the models as dummy variables and results are not shown due to space limitations. In all cases the coefficient values of the year dummy variables are reduced in magnitude when the medical technology proxy variables are included. This would suggest that these variables are picking up some of the residual time trend associated with reduced fatalities. Models with a time trend variable rather than a year dummy variable were also estimated and similar results were found. These latter models suffered from multicollinearity between the time trend and some of the independent variables and thus the use of year dummy variables provided better estimates.

Table 3 presents two additional models. These are specified with the logarithm of the ratio of total fatalities to total slight injuries as the dependent variable. This ratio has declined over time and we would expect this sort of decline to be primarily due to medical technology improvements. When these variables are not specified, in Model A, most independent variables are not statistically significant. Two exceptions are the average age of the car which has a negative sign and percent of households with no car which is positive. More importantly we find that when the medical technology variables are included they are all statistically significant at (or near) the 95% level with the expected signs.

This result is reinforced in models C and D where we correct for serial correlation in the data. In this model the most significant variables appear to be the medical technology proxies, again all with the expected sign. The level of significance is above 90%. GDP per capita is also at a similar level of significance. The value of the autocorrelation parameter $|\boldsymbol{r}| < 1$ indicates that serial correlation is present and needs to be taken into account in the estimations.[2]

Given that the medical technology variables are quite significant, we can evaluate the relative magnitude of their effect. Table 4 calculates the estimated change in fatalities, using elasticities from the NB model in Table 2 and from the ratio model that corrects for serial correlation in Table 3. These are calculated by aggregating for the 9 regions for which we had data (i.e, excluding London and Scotland). The average length of inpatient stay clearly has had a large effect accounting for a reduction of 640 fatalities when estimated from model 2-B. The estimate using the ratio model produces a slightly larger value of 726. The other

[2] Currently there are no methods available for adjusting for serial correlation in negative binomial models which may suggest that the t-statistics in these models are biased upwards.

proxies used to measure medical care and technology improvements have had a smaller effect with the ratio model showing somewhat larger estimated changes.

To put these results in context, the total reduction in fatalities was about 2100 over this time period (for the 9 regions). Therefore, medical technology improvements may be accounting for nearly one-third of this reduction. While these results strongly support the hypothesis that changes in medical care and technology have played an important role in reducing traffic-related fatalities, it is also possible that the technology improvements are merely delaying death. If technology manages to keep seriously injured victims alive beyond the 30 day threshold for being counted as a traffic-related fatality, then this effect would be picked up our analyses as a reduction in deaths (as well as in the national statistics). Broughton (2000), however, found that over 80% of deaths occur in the first 24 hours and only about 1% of deaths occur after the 30 day cut-off point. While beyond the scope of this analyses, increased ability to defer death from serious injuries would clearly imply that the definition of what is considered a traffic-related fatality should change.

Conclusions

The work presented here has used various proxy variables to represent changes in medical care and technology and has estimated models that demonstrate an effect on traffic-related fatalities. The three variables used were the average length of inpatient stays in the hospital, which has declined over time representing improvements in treatment; the per-capita NHS staff, which would represent the level of resources devoted to medical care; and, the per-capita number of people waiting for hospital treatment, which also proxies for the level of resources put into medical care. Of these three proxy variables, the first is representative of changes in medical technology while the latter two represent changes in medical care. Results suggest that the medical technology improvements seem to be more important than the changes in medical care.

These results support a stream of research that has analyzed similar effects in the US (Noland, 2001a) and with international data (Noland, 2001b). One element that has not been fully analyzed is to examine actual changes in survival rates for severe traffic-related injuries and determine how technology may be changing the probability of survival. This type of information will be needed by policy makers to better understand the relationships between health care policy and reductions in traffic-related fatalities.

Other results were that increased average vehicle ages seem to be reducing fatalities. This is a surprising result as newer vehicles would presumably be safer. Increased alcohol expenditure was also found to be associated with increased fatalities and injuries which is not a surprising result. Increased motorway length per area reduced fatalities and injuries, while increases in the percent of the population over aged 65 increased fatalities.

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Figure 1
The Standard Statistical Regions (SSRs) of the United Kingdom (except Northern Ireland)

East Anglia
East Midlands
Northern region
Northwestern
Scotland
Southeast
Southwest
Wales
West Midlands
Yorkshire
London

Table 1
Changes in Variables between 1979 and 1998

Values	1979	1998	% change
Total fatalities	6352	3421	-46.1%
Serious injury	68757	40834	-40.6%
Slight injury	247347	280957	13.5%
Total	321489	325212	1.16%
Motorway length (km)	2366	3187	34.7%
Trunk roads length (km)	12463	12620	1.3%
Other roads length (km)	323163	362367	12.1%
Road length /square km	1.5	1.6	6.67%
Length of in-patient stay in the H	9.36	5.1	-45.5%
Infant mortality rate	13.3	5.7	-57.13%
Persons awaiting treatment per 1000 population	13.47	15.67	-16.33
NHS staff per 1000 population	19.57	20.96	0.07%

Table 2
Fixed effect negative binomial regressions

Dependent Variable	Total Fatalities				Serious Injuries				Slight Injuries			
	A		B		C		D		E		F	
Variables	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
ln(average vehicle age)	-0.362	-2.64	-0.295	-1.66	0.471	2.20	0.466	2.36	-0.029	-0.27	0.046	0.42
ln(% network miles of motorway & trunk road)	-0.134	-0.55	-0.158	-0.56	0.565	2.66	0.499	1.72	0.457	2.78	0.166	0.99
ln(% network miles of other roads)	0.047	0.48	-0.007	-0.07	-0.458	-3.67	-0.516	-4.63	0.062	1.04	0.070	1.36
ln(Motorway length per square km of area)	0.008	0.10	-0.195	-1.80	-0.182	-3.78	-0.130	-1.28	-0.151	-2.38	-0.068	-1.17
ln(Trunk road length per square km of area	0.115	0.66	0.133	0.68	-0.144	-0.79	-0.195	-0.90	-0.418	-3.63	-0.114	-0.95
ln(Vehicles per thousand population)	0.047	1.31	0.053	1.04	0.027	0.61	0.063	1.28	0.023	0.64	0.003	0.09
ln(% of household having no car)	0.108	1.09	0.131	1.38	0.143	1.25	0.147	1.39	-0.131	-1.85	-0.016	-0.27
ln(GDP £ per capita 1998 £)	0.062	0.27	0.259	1.17	0.030	0.11	-0.605	-2.36	-0.367	-2.14	-0.203	-1.35
ln(Per capita expenditure on alcohol, 1998 £)	0.395	4.09	0.223	2.24	0.408	3.86	0.441	4.42	0.210	2.92	0.118	1.89
ln(Average length of inpatient stay in the hospital)			0.283	2.48			-0.449	-3.41			-0.157	-2.16
ln(NHS staff per thousand population)			-0.090	-1.57			0.194	2.98			0.160	3.69
ln(Persons waiting for hospital treatment)			0.138	2.18			-0.159	-2.32			0.000	0.00
ln(Total population)	0.079	1.16	-0.050	-0.52	0.305	3.60	0.607	6.08	0.101	1.89	0.231	3.44
ln(% population age 0-14)	-0.245	-0.92	-0.294	-1.07	0.156	0.46	0.004	0.01	0.210	1.01	0.297	1.66
ln(% population age 15-24)	0.063	0.67	0.064	0.64	0.212	1.73	0.074	0.64	0.149	2.00	0.166	2.60
ln(% population age 25-44)	-0.131	-0.61	0.158	0.70	-0.460	-1.82	-0.314	-1.34	-0.238	-1.41	-0.050	-0.33
ln(% population age 45-64)	0.164	0.68	-0.376	-1.48	-1.901	-6.78	-1.314	-4.76	-0.336	-1.54	-0.572	-3.43
ln(% population age 65 or over)	0.615	2.91	0.562	2.37	0.587	2.15	0.443	1.64	0.358	2.25	-0.141	-0.89
constant	2.271	0.64	5.974	1.50	-2.503	-0.59	-0.422	-0.09	3.179	1.16	3.368	1.43
Number of observations	200		180		200		180		200		180	
Log likelihood function at convergence	-858.930		-756.541		-1367.160		-1194.350		-1553.930		-1341.510	
Log likelihood function at zero	-1207.726		-1207.726		-1787.880		-1787.880		-1858.280		-1858.280	
Log likelihood ratio index	0.289		0.374		0.235		0.332		0.164		0.278	

* year dummy variables are not shown for brevity

Table 3
Fixed effect OLS models: ratio of fatalities/slight injuries

Dependent variable	**Ratio of Fatalities / Slight Injuries**							
	OLS fixed effect model				**Model with AR(1) correction**			
	A		**B**		**C**		**D**	
Variables	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
ln(average vehicle age)	-0.351	-1.99	-0.272	-1.16	0.032	0.23	0.204	0.96
ln(% network miles of motorway & trunk road)	0.538	1.41	-0.294	-0.76	0.411	0.88	-0.046	-0.09
ln(% network miles of other roads)	-0.097	-0.81	-0.116	-1.08	0.119	0.85	0.063	0.47
ln(Motorway length per square km of area)	-0.183	-1.66	-0.131	-0.92	-0.125	-0.93	-0.283	-1.54
ln(Trunk road length per square km of area	-0.246	-0.89	0.222	0.83	-0.149	-0.44	0.098	0.29
ln(Vehicles per thousand population)	0.015	0.24	0.031	0.36	0.062	0.99	0.032	0.33
ln(% of household having no car)	0.290	2.26	0.171	1.42	0.193	1.55	0.204	1.60
ln(GDP £ per capita 1998 £)	0.381	1.24	0.445	1.52	0.273	0.72	0.696	1.80
ln(Per capita expenditure on alcohol, 1998 £)	0.173	1.35	0.065	0.51	0.266	1.71	0.155	0.96
ln(Average length of inpatient stay in the hospital)			0.501	3.39			0.321	1.94
ln(NHS staff per thousand population)			-0.255	-3.02			-0.140	-1.88
ln(Persons waiting for hospital treatment)			0.161	1.93			0.209	1.78
ln(Total population)	0.020	0.21	-0.292	-2.08	0.071	0.54	-0.096	-0.58
ln(% population age 0-14)	-0.436	-1.22	-0.637	-1.80	-0.031	-0.10	-0.395	-1.09
ln(% population age 15-24)	-0.001	-0.01	-0.166	-1.27	-0.152	-1.31	-0.193	-1.48
ln(% population age 25-44)	0.184	0.59	0.309	0.98	-0.177	-0.59	0.019	0.06
ln(% population age 45-64)	0.117	0.35	0.203	0.60	0.069	0.21	-0.214	-0.59
ln(% population age 65 or over)	0.434	1.49	0.566	1.82	0.393	1.37	0.160	0.49
constant	-14.065	-2.83	-1.782	-0.34	-15.635	-6.27	-10.049	-2.77
Number of observations	200		180		190		171	
R-Squared (within)	0.923		0.942		0.752		0.853	
Autocorrelation parameter, *ñ*					0.584		0.434	

* year dummy variables are not shown for brevity

Table 4
Estimated Change in Fatalities between 1979 and 1998

Estimated change in fatalities	From NB model 2-B	From OLS ratio model 3-D
Average vehicle age	-370	-
Motorway length per square km of the area	-308	-
Per capita expenditure on alcohol, 1998£	232	-
Average length of inpatient stay in the hospital	-640	-726
NHS staff per thousand population	-80	-124
Persons awaiting for hospital treatment	98	149
Percent population age 65 or over	314	-