Accident Analysis and Prevention 60 (2013) 268–276

Contents lists available at ScienceDirect

Accident Analysis and Prevention

journal homepage: www.elsevier.com/locate/aap

State-space based analysis and forecasting of macroscopic road safety trends in Greece

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ARTICLE INFO

Article history:
Received 15 October 2012
Received in revised form
13 December 2012
Accepted 28 February 2013

Keywords:
Road safety
State-space models
Seemingly unrelated time series equation (SUTSE) models
Latent risk time-series (LRT) models
Greece

ABSTRACT

In this paper, macroscopic road safety trends in Greece are analyzed using state-space models and data for 52 years (1960–2011). Seemingly unrelated time series equations (SUTSE) models are developed first, followed by richer latent risk time-series (LRT) models. As reliable estimates of vehicle-kilometers are not available for Greece, the number of vehicles in circulation is used as a proxy to the exposure. Alternative considered models are presented and discussed, including diagnostics for the assessment of their model quality and recommendations for further enrichment of this model. Important interventions were incorporated in the models developed (1986 financial crisis, 1991 old-car exchange scheme, 1996 new road fatality definition) and found statistically significant. Furthermore, the forecasting results using data up to 2008 were compared with final actual data (2009–2011) indicating that the models perform properly, even in unusual situations, like the current strong financial crisis in Greece. Forecasting results up to 2020 are also presented and compared with the forecasts of a model that explicitly considers the currently on-going recession. Modeling the recession, and assuming that it will end by 2013, results in more reasonable estimates of risk and vehicle-kilometers for the 2020 horizon. This research demonstrates the benefits of using advanced state-space modeling techniques for modeling macroscopic road safety trends, such as allowing the explicit modeling of interventions. The challenges associated with the application of such state-of-the-art models for macroscopic phenomena, such as traffic fatalities in a region or country, are also highlighted. Furthermore, it is demonstrated that it is possible to apply such complex models using the relatively short time-series that are available in macroscopic road safety analysis.

1. Introduction

The analysis of macroscopic road safety trends has received a lot of attention in the literature (e.g. Washington et al., 1999; Lassarre, 2001; Page, 2001; Abbas, 2004; Kopits and Cropper, 2005; Eksler et al., 2008; Yannis et al., 2011a,b; Antoniou et al., 2012). A critical review of a number of approaches for modeling road safety developments can be found in Hakim et al. (1991), Oppe (1989) and Al-Haji (2007). Beenstock and Gafni (2000) suggest that the downward trend in the rate of road accidents reflects the propagation of road safety technology and is embodied in motor vehicle and road design, rather than road safety policies. Many of the studies use simple statistical and econometric models, and one of the recommendations is often that more elaborate statistical approaches might yield better results. For the descriptive, explanatory, or forecasting analysis of time series from road safety research, using dedicated time series analysis techniques such as ARMA-type models for stationary data and ARIMA or state space models for non-stationary data is recommended. These two types of models are not exclusive of one another as each type of model may also be written under different forms, and equivalences between well-defined specifications have been empirically demonstrated. The introduction of exogenous variables in these models also responds to different objectives. In all cases, the performance of these explanatory models is significantly improved. A recent discussion of these models in the context of road safety time series data statistical inference is presented by Commandeur et al. (2012).

A number of other interesting approaches have been proposed in the literature, often targeted at specific challenges. To overcome the limited ability of safety models to properly reflect crash causality, an issue often associated with aggregated (and frequently of poor quality) data, Tarko (2012) proposes a modeling paradigm that integrates several types of safety models. Huang and Abdel-Aty (2010) propose a 5-level hierarchy that considers heterogeneity and spatiotemporal correlation to represent the general framework of multilevel data structures in traffic safety starting with the geographic region at the top level and considering the individual occupant at the lowest level. Huang and Abdel-Aty (2010) use Bayesian hierarchical models to show the improvements on model

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0001-4575/$ – see front matter
http://dx.doi.org/10.1016/j.aap.2013.02.039

fitting and predictive performance over traditional models. Abdel-Aty and Pande (2007) compare crash data analysis following two approaches (using aggregate data versus considering data at the individual crash level) and discuss the advantages and disadvantages of each.

In this research, the macroscopic road safety trends in Greece (as expressed through road safety fatalities) are analyzed using state-space models and data for 52 years (1960–2011). Simpler Seemingly unrelated time series equations (SUTSE) models are developed first, followed by richer latent risk time-series (LRT) models. Statistical tests on the results of the SUTSE model can indicate whether the time series are correlated. Restrictions of the stochastic model specifications (e.g. fixing the slope and/or the level components) are considered and evaluated versus the unrestricted model. Furthermore, both explanatory variables and intervention variables are entered into the model to improve its fit. As reliable estimates of vehicle-kilometers are not available for Greece, the number of vehicles in circulation is used as a proxy to the exposure. Naturally, the incorporation of surrogate measures of exposure has consequences as it introduces other effects into the equation. For example, the use of vehicle stock as the proxy measure may actually have different effects that those of the actual traffic, when e.g. the degree of motorization increases slowly (as is often the case even in times of recession), when the annual distance driven per vehicle may actually decrease sharply. In order to more accurately model exogenous factors, interventions that may have affected the road safety trends are identified, and – following statistical validation – three main events are considered and analyzed.

The remainder of the paper is structured as follows. Section 2 presents the methodological tools that are used and outlines the used data. Section 3 presents the model estimation results and diagnostics, while Section 4 presents the validation and forecasting results until the 2020 horizon. Section 5 presents validation and prediction results for the LRT model that explicitly considers recession. Concluding remarks and a discussion of the main findings and the relevance of the presented research for researchers and practitioners are presented in Section 6.

2. Methodology and data

2.1. Multivariate state-space models

In a multivariate state space analysis, the observation and state equations have disturbances associated with a particular component or irregular. The multivariate time series model with unobserved component vectors that depend on correlated disturbances is referred to as a seemingly unrelated time series equations model. The name underlines the fact that although the disturbances of the components can be correlated, the equations remain 'seemingly unrelated' (Commandeur and Koopman, 2007).

The structural time series models can easily be generalized to the multivariate case (Harvey and Shephard, 1993; Harvey, 1994). For instance, the local level with drift becomes, for an N-dimensional series $y_t = (y_t, \ldots, y_{Nt})'$,

$$y_t = \mu_t + \varepsilon_t, \quad \varepsilon_t \sim NID(0, \Sigma_\varepsilon) \tag{1}$$

$$\mu_t = \mu_{t-1} + \beta + \eta_t, \quad \eta_t \sim NID(0, \Sigma_\eta) \tag{2}$$

where Σ_ε and Σ_η are nonnegative definite $N \times N$ matrices. Such models are called seemingly unrelated time series equations (SUTSE), reflecting the fact that the individual time series are connected only via the correlated disturbances in the measurement and transition equations.

The multivariate unobserved components time series modeling framework is adopted to formulate a risk system for the observed variables exposure, outcome and loss. The latent risk time-series (LRT) model relates these observed variables within a multivariate system of equations. This model is outlined in the context of road safety in the next section, while a detailed coverage, along with practical applications can be found in e.g. Bijleveld et al. (2008). The two-level form that is being used in this research and includes latent factors for exposure E_t and risk R_t, which are associated with the observed variables exposure X_t and outcome Y_t, for time index $t = 1, \ldots, n$, is outlined next. The basic form of the model links the observable and the latent factors via the multiplicative relationships:

$$X_t = E_t \times U_t^{(X)} \tag{3}$$

$$Y_t = E_t \times R_t \times U_t^{(Y)} \tag{4}$$

where $U_t^{(a)}$ are random error terms with unit mean for $t = 1, \ldots, n$ and $a = X,Y$. The non-linear formulation can be transformed to a linear formulation by taking the logarithm of each equation. In this research, this approach has been followed.

2.2. Structural time-series models for road safety: the latent risk time-series (LRT) model

A basic concept in road safety is that the number of fatalities is a function of the road risk and the level of exposure of road users to this risk (Oppe, 1989, 1991). This implies that in order to model the evolution of fatalities it is required to model the evolution of two parameters: a road safety indicator and an exposure indicator. While fatalities are a common and intuitive road safety indicator, exposure may include a number of direct or indirect (proxy) measures, depending on the data available for each modeled situation (e.g. country or region). Bijleveld (2008) formalizes the assumption that "the development of traffic safety is the product of the respective developments of exposure and risk" in the following, using traffic volume as the exposure measure:

$$\begin{aligned} &\textit{Traffic volume} = \textit{Exposure} \\ &\textit{Number of fatalilties} = \textit{Exposure} \times \textit{Risk} \end{aligned} \tag{5}$$

which represents a latent risk time-series (LRT) formulation. In this case, both traffic volume and number of fatalities are treated as dependent variables. Effectively, this implies that traffic volume and fatality numbers are considered to be the realized counterparts of the latent variables "exposure", and "exposure × risk". When the logarithm of Eq. (5) is taken (and the error term is explicitly written out) the – so-called – measurement equations of the model can be rewritten as:

$$\begin{aligned} &\textit{log Traffic volume} = \log \textit{exposure} + \textit{random error in traffic volume} \\ &\textit{log Number of fatalities} = \log \textit{exposure} + \log \textit{risk} + \textit{random error of fatalities} \end{aligned} \tag{6}$$

The latent variables [log (exposure) and log (risk)] need to be further specified by state equations, which, once inserted in the general model, describe (or explain) the development of the latent variable. It is under their unobserved, or "state" form that the variables investigated can be decomposed into the several components (trend, seasonal, cycles, etc.). Eqs. (7) and (8) show how the variables can be modeled (to simplify the illustration only the number of fatalities is decomposed as an example). Note that the variables of exposure and risk in this case are modeled independently, and not simultaneously as in the case of the LRT model presented next.

Eq. (7) reflects the fact that the recorded number of fatalities is only a (possibly erroneous) observation of the true number of fatalities. The true development of the fatalities time-series is therefore modeled through the state equations and then used as independent variable in the measurement equation, where – along with the error term – result in the total observed fatalities.