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

Constantinos Antoniou* and George Yannis

National Technical University of Athens, 9 Heroon Politechniou st, Zografou 15780, Greece

Abstract

In this paper, macroscopic road safety trends in Greece are analysed 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.

Keywords: road safety, state-space models, seemingly unrelated time series equation (SUTSE) models, latent risk time-series (LRT) models, Greece

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, 2011b; Antoniou et al., 2011). 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

* Corresponding author. Tel.: +30-210-772-2783; fax: +30-210-772-2629.
E-mail address: antoniou@central.ntua.gr.

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. (2013).

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 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 analysed 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 analysed.

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). For instance, the local level with drift becomes, for an N-dimensional series $y_t = (y_{1t}, \dots, y_{Nt})'$,

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

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

where Σ_ε and Σ_η are nonnegative definite NxN 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 modelling framework is adopted to formulate a risk system for the observed variables exposure, outcome and loss. The latent risk model (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,…,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,…,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 x risk". When the logarithm of Equations (5) is taken (and the error term is explicitly written out) the –so called– measurement equations of the model can be rewritten as:

$$\begin{aligned} &Log\,Traffic\,volume = \log \exp osure + random\,error\,in\,traffic\,volume \\ &Log\,Number\,of\,\,fatalities = \log \exp osure + \log risk + random\,\,error\,of\,\,fatalities \end{aligned} \quad (6)$$

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…). Equations (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.

Equation (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.

Measurement equation:

$$\log Number\,of\,\,Fatalities_t = \log LatentFat._t + e_t \quad (7)$$

State equations:

$$\begin{aligned} &Level(\log LatentFat_t) = Level(\log LatentFat_{t\text{-}1}) + Slope(\log LatentFat_{t\text{-}1}) + x_t \\ &Slope(\log(LatentFat_t) = Slope(\log LatentFat_{t\text{-}1}) + z_t \end{aligned} \quad (8)$$

A more general formulation is presented in Equation (9), in which Y_t represents the observations and is defined by the measurement equation within which μ_t represents the state and ε_t the measurement error. The state μ_t is defined in the state equation, which essentially describes how the latent variable evolves from one time point to the other.

$$\begin{aligned} Y_t &= \mu_t + \varepsilon_t \\ \mu_t &= \mu_{t-1} + \nu_{t-1} + \xi_t \\ \nu_t &= \nu_{t-1} + \zeta_t \end{aligned} \quad (9)$$

The state μ_t thus corresponds to the fatality trend at year *t*. It is defined by an intercept, or level μ_{t-1} (thus the value of the trend for the year before, assuming an annual time-series) plus a slope ν_{t-1}, which is the value by which every new time point is incremented (or decremented depending on the slope sign, which is usually negative in the case of fatality trends). The slope ν_t thus represents the effect of time on the latent variable. It is defined in a separate equation, so that a random error term can be added to it (ζ_t). These random terms, or disturbances, allow the level and slope coefficients of the trend to vary over time.

The basic formulation presented in Equation (9) allows the definition of a rich family of trend models which covers an extensive range of series in a coherent way; when both the level and slope terms are allowed to vary over time the resulting model is referred to as to the local linear trend (LLT) model. The next model, Latent Risk Time-Series (LRT), simultaneously models exposure and fatalities. To accomplish this, the latent risk model contains two measurement equations: one for the exposure (e.g. traffic volume) and one for the fatalities; two state equations can be written for each measurement equation, modeling the level and slope of the corresponding latent variable.

For traffic volume:
Measurement equations:

$$\log TrafficVolume_t = \log Exposure_t + e_t^e \tag{10}$$

State equations:

$$\begin{aligned} Level(\log Exposure_t) &= Level(\log Exposure_{t-1}) + Slope(\log Exposure_{t-1}) + x_t^e \\ Slope(\log Exposure_t) &= Slope(\log Exposure_{t-1}) + z_t^e \end{aligned} \tag{11}$$

For the fatalities:
Measurement equation:

$$\log Number\,of\,Fatalities_t = \log Exposure_t + \log Risk_t + e_t^f \tag{12}$$

State equations:

$$\begin{aligned} Trend(\log Risk_t) &= Level(\log Risk_{t-1}) + Slope(\log Risk_{t-1}) + x_t^r \\ Slope(\log Risk_t) &= Slope(\log Risk_{t-1}) + z_t^r \end{aligned} \tag{13}$$

Note that Equation (12) now includes the Risk (and not the fatalities), which can be estimated as:

$$\log Risk_t = \log LatentFat_t - \log Exposure_t \tag{14}$$

The LRT models the observed development of traffic volume and fatalities (the measurement equations) but also of the latent, true values of exposure and fatality risk (state equations). Explanatory variables that are thought to affect either traffic volume or the number of fatalities can be added to the model in three different ways: 1) into the measurement equation, where they are assumed to explain the observation errors, 2) in the level equation, where they are assumed to explain the level disturbances and 3) in the slope equation, where they are assumed to explain the slope disturbances. An explanatory variable is inserted into the measurement equation if it is thought to have an effect on observation errors (if, for example, one has reasons to suspect that it affected the registration of fatalities or traffic volume). It will be included in the level equation if it is thought to have an effect on the level of fatalities or exposure, and in the slope equation if it is thought to affect the steepness or direction of change. Seemingly Unrelated Time-Series Equations (SUTSE) *(Petris et al., 2009)*, a third class of models, are also used in this approach as a preliminary step in establishing whether the two time-series may be correlated.

2.3. Considered data

The data that are considered in this research comprises fatalities and vehicles in circulation. The data have been collected for 52 years (1960-2011) and are presented visually in Figure 1. Before 1996 road accident fatalities in Greece were recorded based on the 24-hour definition (i.e. counting a person that has been injured in a traffic accident as a road-safety fatality, only if that person passed away within 24 hours of the occurrence of the accident), while since then the 30-day definition is used. The data presented in Figure 1 correspond to the 30-day definition for the entire period (converted via appropriate factors for the period prior to 1996). It is widely accepted that vehicle kilometers are an appropriate exposure measure. However, there are no vehicle kilometers data available for Greece and therefore the vehicle fleet is used as a proxy. A number of biases can be introduced by the use of vehicle fleet instead of vehicle-kilometers as the surrogate exposure measure. For example, the reduction in the use of the vehicles (kilometers per vehicle) is not directly reflected in the number of vehicles. Furthermore, the retirement of vehicles from circulation is a more long-term process that would be reflected in the exposure time-series with a lag.

A clear increasing trend is evident in the number of vehicles in circulation. The presented fatality data for Greece shows two distinct trends: an increasing one until approximately 1995, followed by a decreasing one thereafter. As there are only 16 data points describing the decreasing trend, it is expected that reserving a large number of observations for forecasting may affect the accuracy of the model.

While the exposure data seem rather smooth, the fatality data exhibit certain irregularities that could affect the model estimation results. In order to better account for these external shocks to the process, it was decided to seek possible events that could be identified and explicitly entered into the model. There are three main events that can be entered as interventions in the model for the period and data that are being analysed:

I1986: in 1986 Greece encountered a financial crisis, which affected mobility and therefore exposure (note that –due to lack of the data- the exposure variable in the Greek dataset is vehicles in circulation and not direct exposure). This intervention is entered into the model as a shock in the specific time point.

I1991: in 1991 Greece introduced an “old-car-exchange” scheme, under which old cars could be exchanged for a cash incentive to buy a new (safer and cleaner) car. While this did not affect the number of vehicles in circulation, the number of kilometres driven may have increased considerably, as newer cars replaced older cars that may have been driven only slightly. The introduction of the newer cars in circulation might have thus significantly increased exposure and related risk. On the other hand, the introduction of newer, safer cars could have had a positive effect in road safety. However, the overall net effect is apparently negative at the time of the intervention, while the positive effects themselves manifested themselves after a few years, i.e. around 1996 (it is noted that the system run from 1991 through the end of 1993) (Yannis, 2007). This intervention is also entered into the model as a shock in the specific time point.

I1996: in 1996 the fatality recording system in Greece switched from 24-hour to 30-day. This meant that the use of the adjustment factor (from 24-hour to 30-day fatality figures) stopped at that time and real data was used from that point on. This intervention has been entered in the slope of the fatalities, as its impact is assumed to be unlike a point shock, but rather a sustained shift.

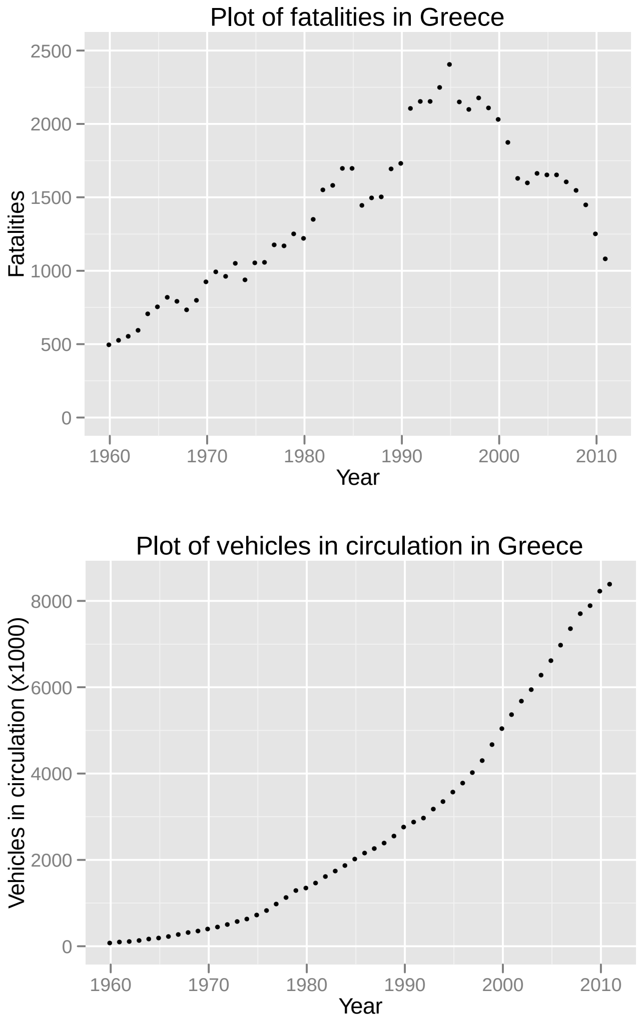

Fig. 1. Fatalities (top) and Exposure (Number of Vehicles in circulation, bottom) for Greece from 1960 to 2011

3. Model estimation results

This section presents the main estimation results of the SUTSE and latent risk models. As a simpler model, the SUTSE model was also used as a diagnostic in order to determine whether more elaborate models (such as the latent risk time-series model) would be beneficial for this application. The models have been implemented by the DACOTA EU project (www.dacota-project.eu/) participants in the R language for statistical computing (R Core Development Team, 2012) and the ggplot2 package for graphical output (Wickham, 2009).

Table 1 presents the main diagnostic tests for the three main specifications that were tested. The SUTSE model is first presented, followed by the two latent risk model specifications: one without and one with interventions. As can be seen from the bottom of Table 1, all three interventions are found to be statistically significant. In general the SUTSE results are very similar to the base LRT model. Since the three models are not nested, however, they cannot be compared based on their summary likelihood-based diagnostics (final log-likelihood and AIC, An Information criterion, Akaike, 1974). The considered models fit the model quality tests equally well. Essentially, the models test for autocorrelation (Box-Ljung test), heteroscedasticity, normality, as well as transition correlations. For a discussion of the various tests, the reader is referred to e.g. Bijleveld et al. (2008), where they are applied in the LRT case, or the general statistics literature.

As mentioned in the previous section, the interventions on the financial crisis (1986) and the vehicle exchange/renewal program (1991) are entered as shocks on the level of the fatalities, while the impact of the switch in the way that fatalities are recorded is entered as a change in the slope of fatalities.

Figure 2 presents the varying level and slope estimation results of the SUTSE model: in particular the smoothed state plots for the exposure (top) and risk (bottom) variables. The left subfigure in each row shows the level estimate for the corresponding variable and the right subfigure shows the slope estimate. Confidence intervals are also presented in these figures. The confidence intervals on the levels are rather tight and are closely following the trends. What is perhaps more interesting is the slope of the variables. The slope of the exposure (top right subfigure) is always positive, but its magnitude is declining. The slope of the risk (bottom right subfigure) is also decreasing.

Table 1. Main diagnostics for model specifications (ns: not significant; *, **, ***: significant at 90, 95, 99% level)

	SUTSE	**Latent risk model**	**Latent risk model with interventions**
Model criteria			
Log-likelihood	242.432	242.433	223.856
AIC	-484.518	-484.519	-447.366
Model Quality			
Box-Ljung test 1 Vehicles (x1000) Greece	3.559	3.563	4.345*
Box-Ljung test 2 Vehicles (x1000) Greece	3.877	3.878	4.442
Box-Ljung test 3 Vehicles (x1000) Greece	4.033	4.032	4.531
Box-Ljung test 1 Fatalities Greece	3.296	3.291	4.456*
Box-Ljung test 2 Fatalities Greece	4.289	4.286	6.303*
Box-Ljung test 3 Fatalities Greece	6.846	6.851	6.332
Heteroscedasticity Test Vehicles (x1000) Greece	0.263*	0.263*	0.270*
Heteroscedasticity Test Fatalities Greece	0.885	0.884	0.776
Normality Test standard Residuals Vehicles (x1000) Greece	58.668***	58.719***	52.849***
Normality Test standard Residuals Fatalities Greece	0.317	0.320	1.438
Normality Test output Aux Res Vehicles (x1000) Greece	10.062**	10.059**	7.013*
Normality Test output Aux Res Fatalities Greece	0.957	0.956	0.644
Normality Test State Aux Res Level exposure	28.431***	36.716***	32.956***
Normality Test State Aux Res Slope exposure	27.537***	4.429	1.335
Normality Test State Aux Res Level risk	1.229	1.240	1.682
Normality Test State Aux Res Slope risk	0.214	0.215	0.175
Model Q-matrix tests			
Level exposure	1.38E-04 ns	1.38E-04 ns	1.28E-04 ns
Level risk	4.12E-03 *	3.77E-03 *	2.48E-03 *
Slope exposure	2.08E-04 *	2.08E-04 *	2.23E-04 *
Slope risk	1.59E-04 *	2.59E-04 ns	1.07E-04 *
Transition Correlations			
Level exposure with Level risk	0.32	0.14	0.34
Slope exposure with Slope risk	0.30	-0.66	-1
Model H-matrix tests			
Vehicles (x1000) Greece	2.08E-08 ns	1.09E-09 ns	1.28E-08 ns
Vehicles (x1000) Greece	3.66E-07 ns	2.43E-09 ns	1.83E-07 ns
Intervention and explanatory variables tests			
(slope fatalities 1996)			-0.0713 *
(level fatalities 1986)			-0.192 *
(level fatalities 1991)			0.191 *

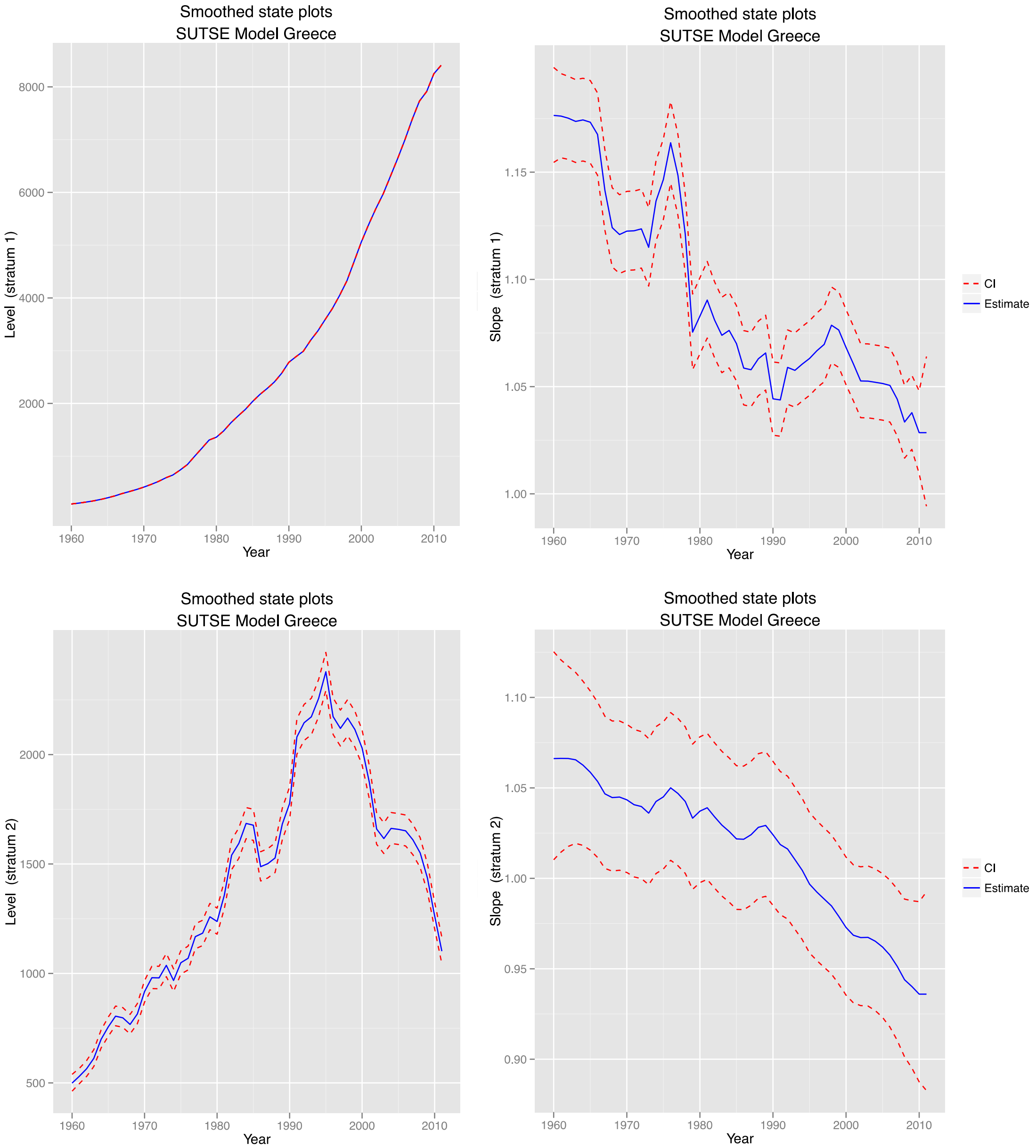

Fig. 2. SUTSE estimation results. Top row: (a) exposure level; (b) exposure slope, bottom row: (c) risk level; (d) risk slope

4. Validation and forecasting

Model estimation is a very complex task and there are a number of diagnostics that can be used to assess its quality. However, dangers, such as over-fitting, are always present. In order to overcome these and ensure that the estimated models provide a useful forecasting tool, several other steps can be taken. In this section, validation (prediction for a period for which data are available) is performed to assess the quality of the prediction. Furthermore, forecasting (prediction for a future period, for which data are not available) is also performed.

4.1. Validation results

In order to assess the model quality, the candidate models are run while holding a number of observations for validation. However, as can be seen from Figure 3, the nature of the data (i.e. the breakpoint in the mid 1990s) implies that the subsequent downward trend is only supported by few data points. Therefore, as the number of observations that are left aside for validation (and therefore not for model estimation) increases, then the model is less likely to capture the current (and forecasted) trend. Therefore, the LRT model has only been run keeping 4 observations (2008-2011) for validation, i.e. using the time-series from 1960 to 2007 for the model fitting. This allows for the downward trend that has started in the fatality data after the mid-1990s to manifest itself through the data. Still, one can notice that the model fails to predict the rapid decline of the fatalities, due to the sharp decline in the exposure (which is not manifested sufficiently by the small decrease in the rate of increase of the vehicles in circulation). It is clarified that while the model uses the real fatality and exposure time-series as inputs, it estimates the structural relationship between the two time-series (risk and exposure), and uses this information for the forecasts.

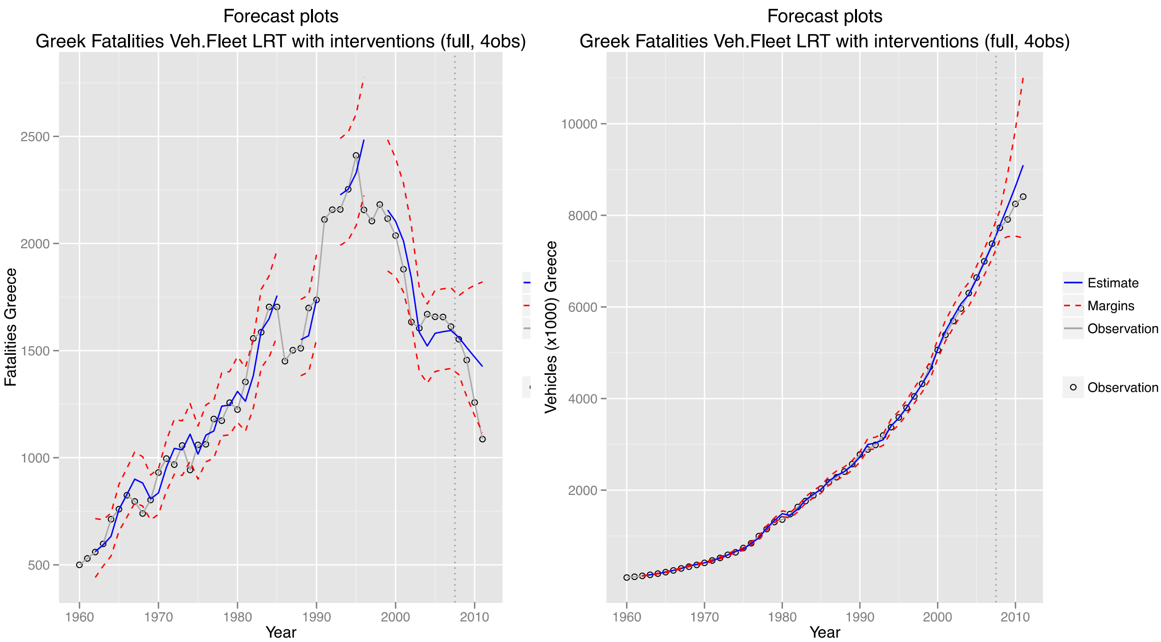

Fig. 3. Validation results for selected LRT model (a) risk; (b) exposure

The current global financial crisis, which has profound implications in vehicle traffic and road safety, is a prime example of the unforeseen different conditions that may throw off the predictive models. In this case, the most likely model forecasts provided by the model for 2009, 2010 and 2011 were 1514, 1469 and 1425 respectively. The actual fatality data for 2009, 2010 and 2011 in Greece were 1456, 1258 and 1087 fatalities respectively. Clearly, the model cannot be expected to foresee such dramatic exogenous forces, affecting the modeled level of road safety. However, even in this extreme situation, the lower bound estimates of the model were 1285, 1196 and 1116 fatalities for 2009, 2010 and 2011 respectively, indicating that indeed the calculated bounds, which might at first look seem very conservative, were appropriate for capturing such unusual events.

4.2. Forecasting results

Table 2 presents the forecasting results from the selected LRT model with the interventions until 2020, while Figure 4 presents the results in the context of the entire time-series with the observations and the confidence intervals super-imposed. Several observations can be made based on this information. First of all, as the prediction horizon increases, so does the width of the confidence interval. This is a natural and expected finding; however, when one encounters predictions such as “the expected forecast number of fatalities is 694 and we are 95% certain that it will be between 445 and 1081” decision makers might feel less than confident. Correspondingly, the actions that can be supported with such predictions may not be as bold as one might want. On the other hand, this is a true representation of the uncertainty, and more “tight” boundaries of the confidence intervals of the future predictions might result in unrealistic expectations (and thus possibly misguided policies and actions).

Table 2. Forecasting results for the LRT model with interventions

	Exposure (vehicles in circulation x1000)			Fatalities		
Year	Forecasted value	Lower limit (2.5%)	Upper limit (97.5%)	Forecasted number	Lower limit (2.5%)	Upper limit (97.5%)
2012	8674.0	8327.5	9035.0	1054	930	1193
2013	8948.5	8254.4	9701.0	1000	841	1189
2014	9231.6	8125.7	10488.0	949	765	1178
2015	9523.7	7949.1	11410.3	901	698	1163
2016	9825.1	7732.3	12484.3	855	638	1147
2017	10135.9	7482.4	13730.5	812	583	1130
2018	10456.6	7205.8	15174.1	770	533	1113
2019	10787.5	6908.2	16845.2	731	487	1097
2020	11128.8	6594.8	18780.0	694	445	1081

Note: The upper and the lower limit define the confidence interval in which the values lie with 95% chance *if* the present trend is continued.

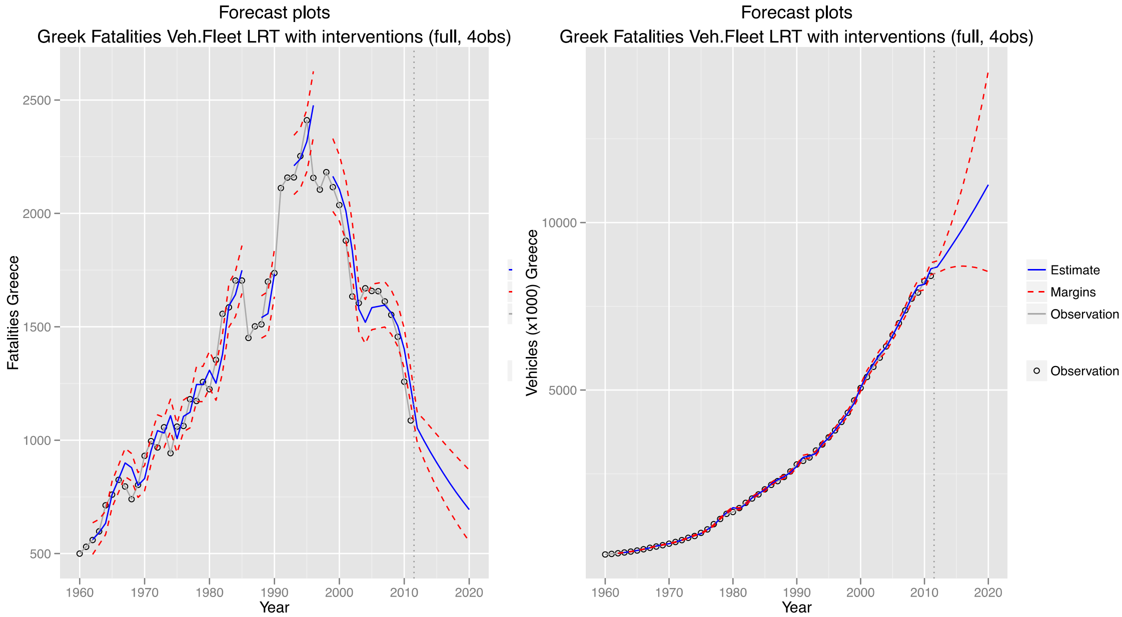

Fig. 4. Forecasting results for final LRT model (a) risk; (b) exposure

5. Considering recession

A critical assessment of the forecasting results presented in the previous section raises the following question. During the past few years, the precarious financial situation in Greece has resulted in a slow-down in the increase of vehicle fleet and –more evidently- to a significant reduction to the number of fatalities. It is well understood that this reduction is to a large degree due to the economy slowdown, leading to a reduction in exposure and possibly a traffic behavior change (less speeding for less fuel consumption, etc.). Basing the future forecasts on this situation introduces the risk of under-predicting fatalities, as the implicit assumption is that the current situation would continue. On the other hand, it is expected that the recession will end in the next few years and economic recovery will begin (bringing increased exposure and more fatalities as a side-effect).

In this section, an additional intervention has been incorporated into the model, representing recession. It is necessary to make assumptions about the start and end date of the recession. The beginning has been set as 2008, while it has been assumed that the recession will end after 2013. Table 3 presents the forecasting results for this scenario, while Figure 5 presents these results along with the entire time series.

Modeling the recession results in a higher forecast for vehicles in circulation for 2020 (approximately 13.8 million vehicles instead of approximately 11.1 million vehicles when the recession recovery is not modeled). This in turn results in a higher forecast of fatalities for 2020, i.e. 733 fatalities when the recession recovery is considered vs. 694 fatalities when it is not considered.

Table 3. Forecasting results for the LRT model with interventions and considering a recession ending in 2013

	Exposure (vehicles in circulation x1000)			Fatalities		
Year	Forecasted value	Lower limit (2.5%)	Upper limit (97.5%)	Forecasted number	Lower limit (2.5%)	Upper limit (97.5%)
2012	8655.9	8308.8	9017.4	1031	911	1166
2013	8908.5	8207.1	9669.7	959	806	1141
2014	9484.5	8295.0	10844.5	923	749	1137
2015	10097.8	8291.8	12297.0	888	697	1132
2016	10750.7	8232.7	14038.8	855	648	1127
2017	11445.9	8130.2	16113.7	822	603	1122
2018	12186.0	7991.0	18583.0	791	561	1117
2019	12973.9	7820.2	21524.0	762	522	1112
2020	13812.8	7621.9	25032.3	733	485	1108

Note: The upper and the lower limit define the confidence interval in which the values lie with 95% chance *if* the present trend is continued.

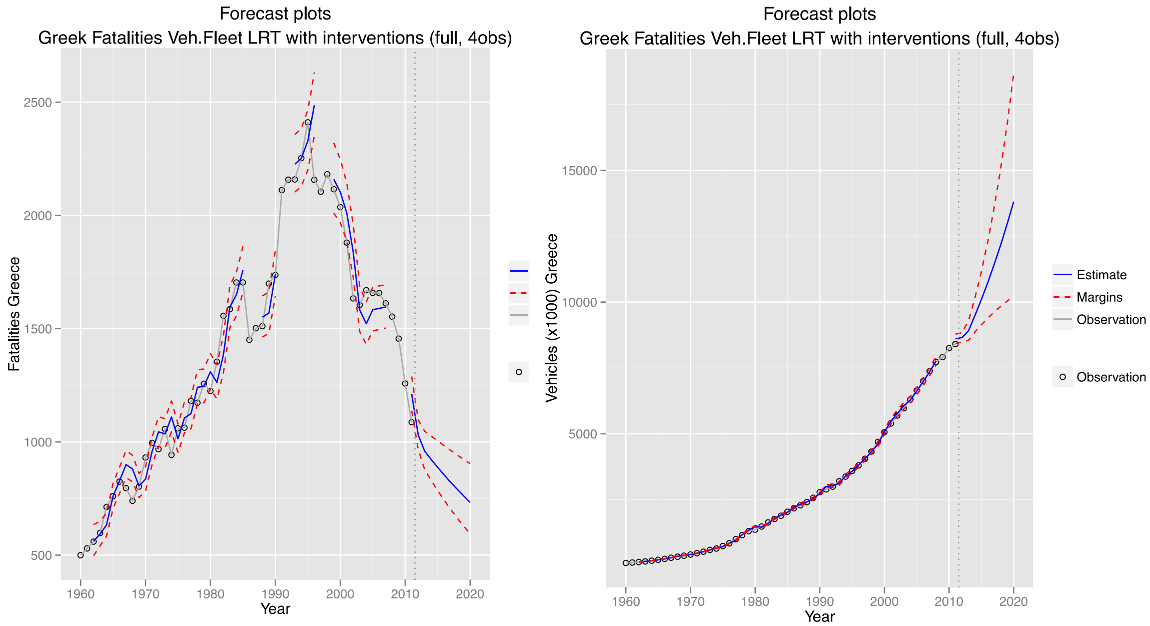

Fig. 5. Forecasting results for final LRT model considering the effects of a recession ending in 2013 (a) risk; (b) exposure

6. Conclusion

Within this research, multivariate state-space models were developed for the analysis and forecasting of macroscopic road safety trends in Greece. The Latent Risk Timeseries (LRT) model developed includes several improvements over simpler models such as the SUTSE and the local linear trend (LLT) model. The main ones are the inclusion of an exposure measure (in this case the number of vehicles in circulation, as more direct exposure data was not available for this analysis) and the modelling of fatality risk instead of fatalities themselves. The model also allows the incorporation of interventions that can affect the modelled phenomenon. In the application presented in this paper, three interventions have been constructed based on real events that are expected to have affected the development of road safety in Greece. These interventions concerned the 1986 financial crisis, the 1991 old-car exchange and the 1996 new road fatality definition. Indeed, all three of them appear to be statistically significant. Therefore, the model that has been retained includes all the considered interventions.

Furthermore, validation and forecasting results of the models are presented, demonstrating the explicative power of the models. Comparisons with final actual data (2009-2011) indicate that the models perform properly, even in unusual situations, like the current strong financial crisis in Greece. Forecasting results until the 2020 horizon (set by the EU and national road safety plans) are also presented, along with similar forecasts obtained from a different model that explicitly accounts for the expected recession recovery after 2013. The results obtained from the recession model show somewhat higher (and more likely to be realized) fatality forecasts for 2020 and thus it is expected that this model is more credible.

This research provides both added value to the scientific literature in the field, as well as implications to practice. From a scientific point of view, state-of-the-art state-space models are developed, specified and estimated using long time-series of fatalities and vehicle fleet (as an exposure proxy). These models provide theoretical advantages over simpler time-series approaches used for road safety analyses (such as piece-wise linear regression, Yannis et al., 2011a, or non-linear regression, Yannis et al., 2011b). A natural question that arises from the discussion of more complex models relates to the degree of marginal contribution that the additional complexity offers. This concern becomes especially relevant when one considers that they are applied to macroscopic data of a very general phenomenon such as the number of traffic crash fatalities in a country or a region. Such phenomena depend on a large number of endogenous and exogenous factors that interact in unpredictable ways. The presented models rely on capturing the combined effects on the slope and the trend of the exposure and risk time-series, as well as their relation. By also capturing the structural relationship of the evolution of these measures over time, the structural time-series models used in this research capture the complex dynamics of road safety trends.

From a practical point of view, this study demonstrates how the presented models can be made approachable to practitioners, through the presentation of a series of statistical tests that are required to assess the validity of the models. Furthermore, practical ways to visualize and interpret the results are also presented. Decision makers and other practitioners may use these models not only to better support the road safety target setting process, but also to monitor safety performance progress, by comparing with the forecasted and expected outcome than simply comparing annual changes.

Further research directions include the enrichment of the model with additional macroscopic parameters, as well as the investigation of other functional forms and model specifications. A more direct measure of exposure (presumably vehicle-kilometers) is expected to considerably improve the performance of the model. In the absence of such data, additional parameters (such as the Gross Domestic Product, GDP, or fuel consumption) may assist separate exogenous effects and isolate road safety trends. GDP or fuel consumption are expected to more directly exhibit the reduction in exposure, while the vehicle fleet is less responsive, because while new vehicles may be added at a lower rate, older vehicles (whose use declines) are still not removed for the fleet. Other functional forms may also provide valuable insight into the road-safety problem. Comparing the models across multiple countries and regions may also provide valuable insights for the differences between the road safety patterns in these countries, thus helping policy makers focus on the parameters that are more pertinent for each country and region.

Acknowledgements

The authors are grateful to Dr. Sylvain Lassarre, Dr. Frits Bijleveld and Prof. Jacques Commandeur for their guidance and assistance throughout this research. This paper is based on work carried out within the

DaCoTA (Data Collection Transfer and Analysis) research project co-financed by the European Commission. Special thanks belong to all DaCoTa WP4 partners involved in the model development and particularly to Heike Martensen and Emmanuelle Dupont from IBSR, Belgium for the coordination of the model development and to Frits Bijleveld for being in charge of the overall model development process.

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