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

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Abstract

In this paper, macroscopic road safety trends in Greece are analysed using state-space models and data for 49 years (1960-2008). 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. Key related events during this time-period have been entered into the model formulation as interventions. 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, 1996 new road fatality definition) and found statistically significant. Furthermore, the forecasting results were compared with final actual data (2009-2010) indicating that the models perform properly, even in unusual situations, like the current strong financial crisis in Greece.

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. Lassare, 2001; Page, 2001; Abbas, 2004; Kopits and Cropper, 2005; Eksler et al., 2008; Yannis et al., 2011; Antoniou et al., 2011). 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 and state space modeling is recommended.

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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.

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 49 years (1960-2008). 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. 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. Sections 3 and 4 present the SUTSE and LRT model results respectively. Section 5 provides validation and prediction results for the LRT model. Concluding remarks 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. A detailed coverage of this model, 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. 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, 2011) and the ggplot2 package for graphical output (Wickham, 2009).

2.2. Considered data

The data that are considered in this research comprises fatalities and vehicles in circulation. The data have been collected for 49 years (1960-2008) 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 kilometer are an appropriate exposure measure. However, there are no vehicle kilometer data available for Greece and therefore the vehicle fleet is used as a proxy. 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 13 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.

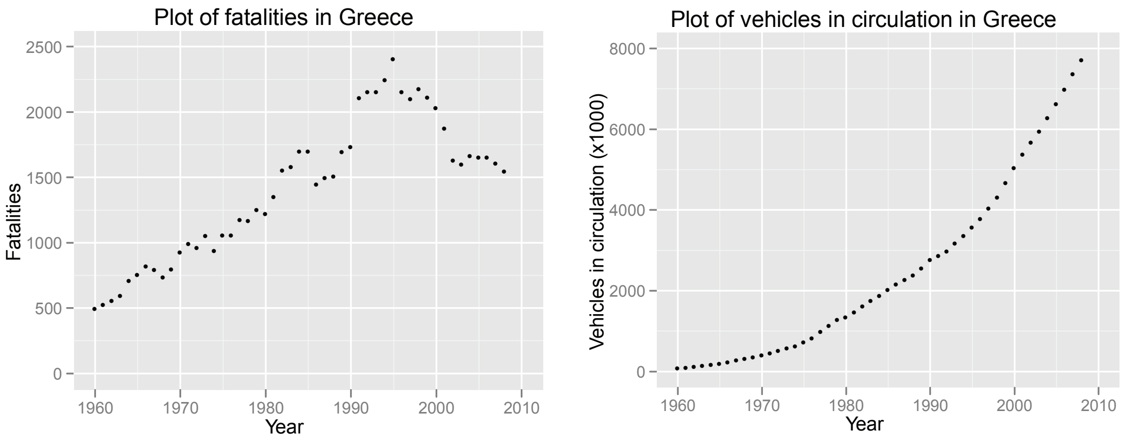

Fig. 1. (a) Fatalities and (b) Exposure (Number of Vehicles in circulation) for Greece from 1960 to 2008

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 (one could argue that replacing older cars with newer might increase exposure), the introduction of newer, safer cars had a positive net effect in road safety (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.

3. Model estimation results

This section presents the main estimation results of the SUTSE and latent risk models. As a simpler model this 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.

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	226.905	226.905	208.679
AIC	-453.442	-453.442	-416.991
Model Quality			
Box-Ljung test 1 Vehicles (x1000) Greece	4.22435*	4.2251*	5.4259*
Box-Ljung test 2 Vehicles (x1000) Greece	4.65272	4.65364	5.55397
Box-Ljung test 3 Vehicles (x1000) Greece	4.79784	4.79874	5.58741
Box-Ljung test 1 Fatalities Greece	2.68052	2.68041	4.65753*
Box-Ljung test 2 Fatalities Greece	3.34437	3.34381	6.24136*
Box-Ljung test 3 Fatalities Greece	5.11052	5.10953	6.3426
Heteroscedasticity Test Vehicles (x1000) Greece	0.303673*	0.303831*	0.327829*
Heteroscedasticity Test Fatalities Greece	0.829393	0.829395	0.704918
Normality Test standard Residuals Vehicles (x1000) Greece	55.1788***	55.1255***	45.7231***
Normality Test standard Residuals Fatalities Greece	0.987133	0.986293	2.26681
Normality Test output Aux Res Vehicles (x1000) Greece	14.1222***	14.1161***	10.0806**
Normality Test output Aux Res Fatalities Greece	0.77611	0.776338	0.348276
Normality Test State Aux Res Level exposure	32.0668***	39.7522***	37.1952***
Normality Test State Aux Res Slope exposure	26.547***	3.40707	2.01169
Normality Test State Aux Res Level risk	2.17191	2.1725	1.5996
Normality Test State Aux Res Slope risk	0.136326	0.136281	0.0888442
Model Q-matrix tests			
Level exposure	1.25E-04 ns	1.25E-04 ns	8.89E-05 ns
Level risk	4.15E-03 *	3.73E-03 *	2.02E-03 *
Slope exposure	2.31E-04 *	2.31E-04 *	2.66E-04 *
Slope risk	7.84E-05 *	2.49E-04 ns	1.61E-04 *
Transition Correlations			
Level exposure with Level risk	0.38	0.22	0.44
Slope exposure with Slope risk	0.22	-0.84	-1
Model H-matrix tests			
Vehicles (x1000) Greece	1.02E-09 ns	1.25E-09 ns	5.10E-06 ns
Vehicles (x1000) Greece	1.01E-09 ns	8.30E-09 ns	9.05E-05 ns
Intervention and explanatory variables tests			
(slope fatalities 1996)			-0.0607133 *
(level fatalities 1986)			-0.197501 *
(level fatalities 1991)			0.186924 *

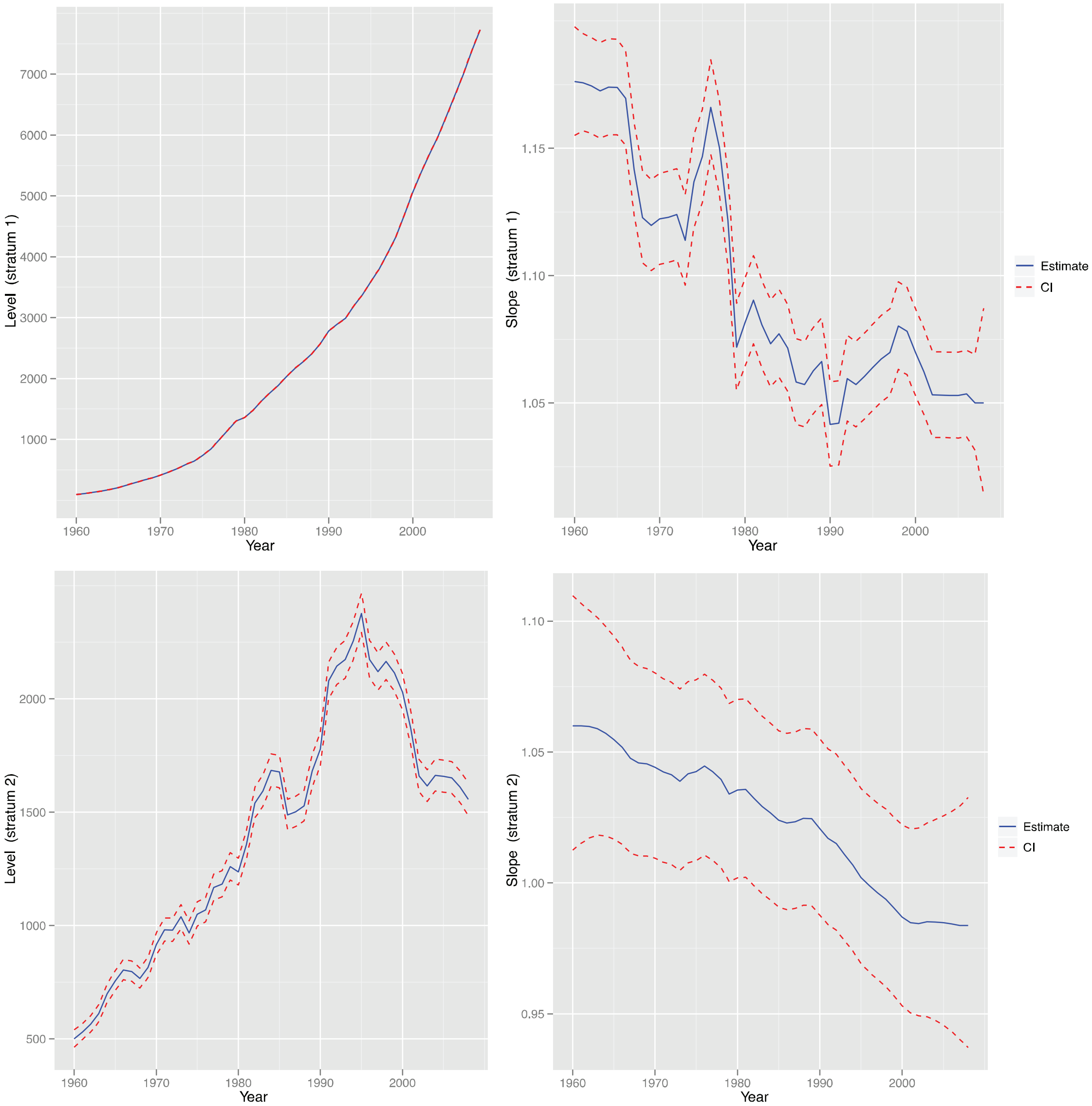

Fig. 2. SUTSE estimation results. Top row: (a) exposure level; (b) exposure slope, bottom row: (c) risk level; (d) risk slope

While the diagnostics presented in Table 1 provide the main information required to assess the model quality, visual diagnostics are often also useful. Figure 3 presents the residual Q-Q (theoretical quartiles vs. sample quartiles) plots for the exposure level and slope, from which one can infer that the residuals follow the normality assumption.

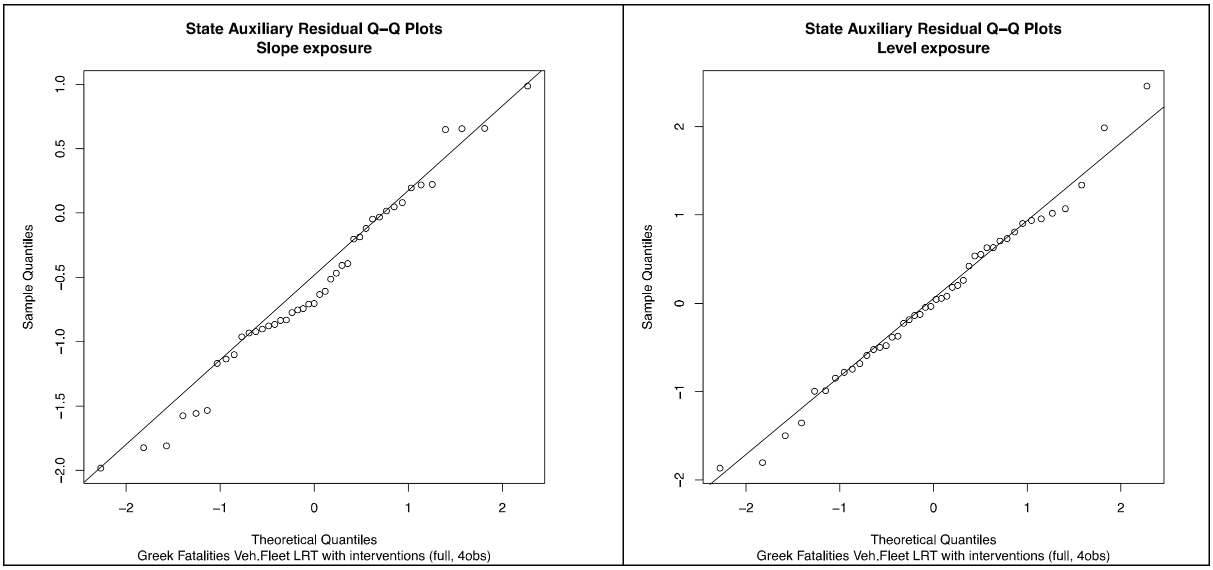

Fig. 3. Residual analysis for final LRT model (a) exposure level; (b) exposure slope

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 4, 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 for validation. This allows for the downward trend that has started in the fatality data after the mid-1990s to manifest itself through the data.

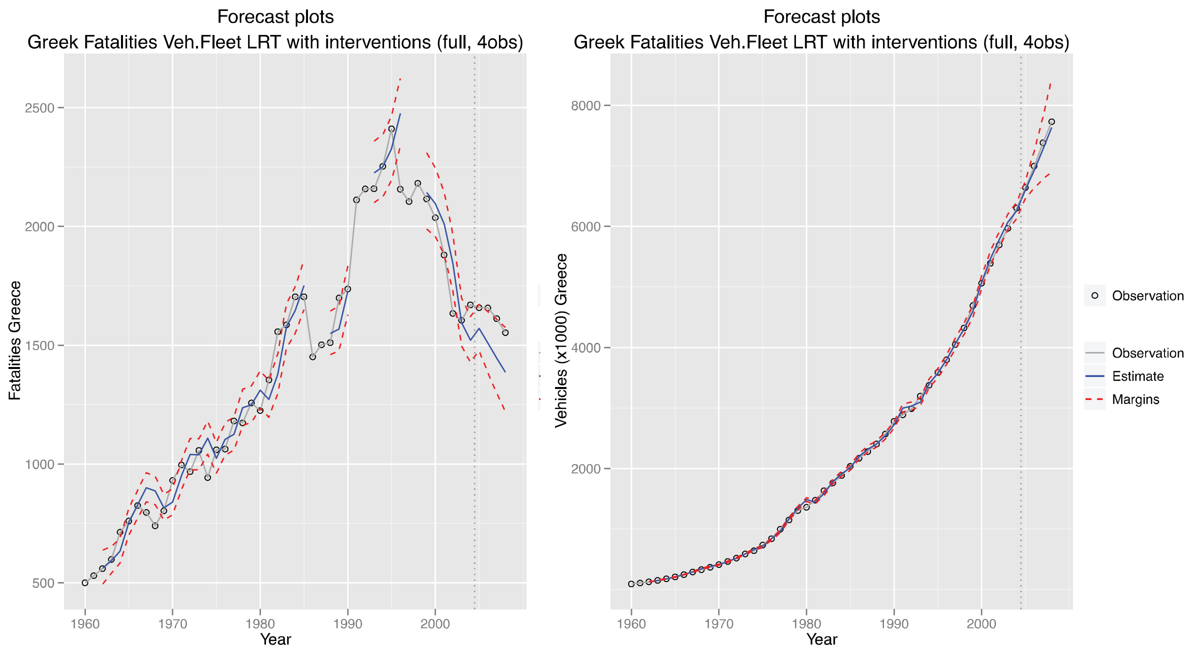

Fig. 4. Validation results for final LRT model (a) risk; (b) exposure

4.2. Forecasting results

Table 2 presents the forecasting results from the selected LRT model with the interventions until 2020. 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 1062 and we are 95% certain that it will be between 641 and 1762" 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).

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 provide by the model for 2009 and 2010 were 1505 and 1458 respectively. The actual fatality data for 2009 and 2010 in Greece were 1456 and 1258 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 1341 and 1241 fatalities for 2009 and 2010 respectively, indicating that indeed the calculated bounds, which might at first look seem very conservative, were appropriate for capturing such unusual events.

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%)
2009	8107.0	7783.1	8444.5	1505	1341	1690
2010	8503.0	7828.4	9235.7	1458	1241	1713
2011	8918.2	7810.4	10183.2	1413	1156	1727
2012	9353.8	7737.4	11307.9	1369	1079	1737
2013	9810.6	7616.6	12636.7	1326	1008	1745
2014	10289.7	7454.5	14203.4	1285	943	1752
2015	10792.3	7257.0	16049.8	1245	882	1758
2016	11319.4	7029.7	18226.7	1206	825	1764
2017	11872.2	6777.6	20796.1	1169	771	1770
2018	12452.0	6505.7	23833.3	1132	721	1777
2019	13060.1	6218.3	27429.8	1097	675	1784
2020	13698.0	5919.6	31696.9	1063	631	1791

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.

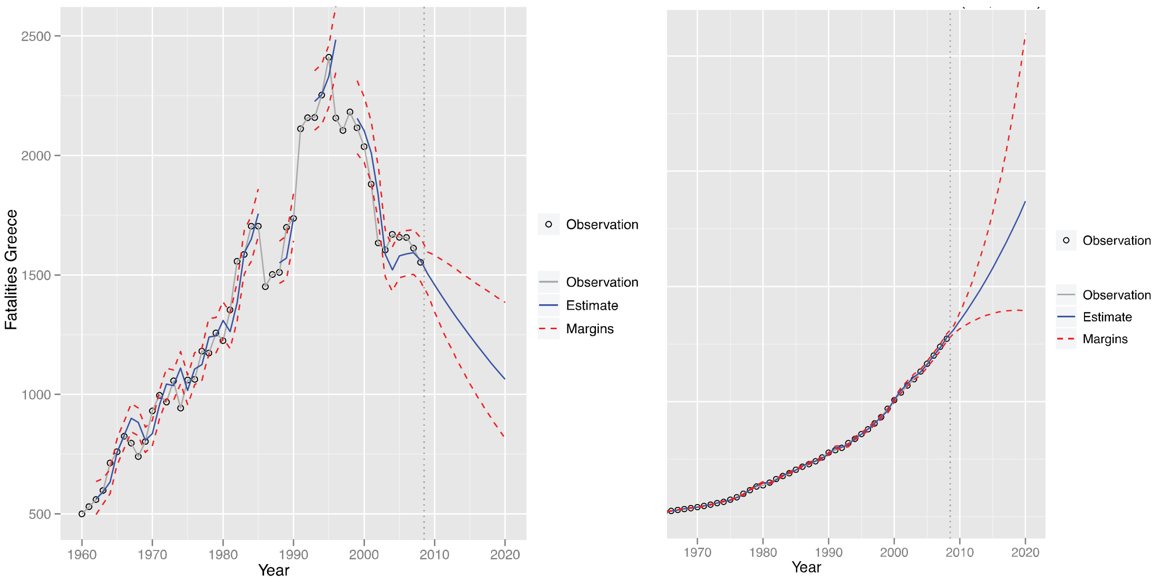

Fig. 5. Prediction results for final LRT model (a) risk; (b) exposure

5. 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 (2009-2010) indicate that the models perform properly, even in unusual situations, like the current strong financial crisis in Greece.

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. Additional parameters (such as the Gross Domestic Product, GDP) may help separate exogenous effects and isolate road safety trends. 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.

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