Road safety forecasts in five European countries using structural time-series models

Constantinos Antoniou[a*1], Eleonora Papadimitriou[b] and George Yannis[c]

[a] National Technical University of Athens, 9, Iroon Polytechniou St., Zografou Campus, 15780, Greece, Email: antoniou@central.ntua.gr

[b] National Technical University of Athens, Department of Transportation Planning and Engineering, 9, Iroon Polytechniou St., Zografou Campus, 15773, Greece, Email: nopapadi@central.ntua.gr

[c] National Technical University of Athens, Department of Transportation Planning and Engineering, 9, Iroon Polytechniou St., Zografou Campus, 15773, Greece, Email:geyannis@central.ntua.gr

ABSTRACT

Modeling road safety development is a complex task, which needs to consider both the quantifiable impact of specific parameters, as well as the underlying trends that cannot always be measured or observed.

Objective

The objective of this research is to apply structural time series models for obtaining reliable medium- to long-term forecasts of road traffic fatality risk, using data from five countries with different characteristics from all over Europe (Cyprus, Greece, Hungary, Norway and Switzerland).

Methods

Two structural time series models are considered: (i) the local linear trend model and the (ii) latent risk time-series model. Furthermore, a structured decision tree for the selection of the applicable model for each situation (developed within the 'DaCoTA' research project, co-funded by the European Commission) is outlined. First, the fatality and exposure data that are used for the development of the models are presented and explored. Then, the modeling process is presented, including the model selection process, the introduction of intervention variables and the development of mobility scenarios.

Results

The forecasts using the developed models appear to be realistic and within acceptable confidence intervals. The proposed methodology is proved to be very efficient for handling different cases of data availability and quality, providing an appropriate alternative from the family of structural time series models in each country.

Conclusions

A concluding section providing perspectives and directions for future research is finally presented.

Keywords: Road safety; State-space models; Structural time-series models; Latent risk time-series (LRT) models; Europe

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[1] corresponding author: Constantinos Antoniou, Tel: +302107722783

INTRODUCTION

Modeling road safety is a complex task, which needs to consider both the quantifiable impact of specific parameters, as well as the underlying trends that cannot always be measured or observed. The sensitivity of users to road safety campaigns, the improved quality of the vehicle fleet, the improvement of the driving skills of the general population, and the overall improvement of the condition of the road network are only some of the aspects that cannot be easily modeled directly. Therefore, modeling should consider both measurable parameters and the dimension of time, which embodies all remaining parameters.

The objective of this research is to apply structural time series models for obtaining reliable medium- to long-term forecasts of fatality risk. Considering the important decisions that depend on this kind of forecasting, such as road safety policy determination or decisions to select and implement infrastructure projects, it becomes apparent that reliable forecasting models may have significant impact. Besides developing reliable models, it is also important to educate decision makers on why such models are superior and how to assess the performance of different models.

The remainder of this paper is structured as follows. The next section presents the methodological background, highlighting the state-of-the-art in related methodologies and approaches and putting the proposed approach in context. The following section presents the methodology, both in terms of the structural form of the models as structural time-series models and in terms of the decision tree that has been developed within the 'DaCoTA' project for the selection of the appropriate models. (The "Road Safety Data, Collection, Transfer and Analysis" (DaCoTA) research project has been co-funded by the European Commission and further information can be found in the project website http://www.dacota-project.eu/). Application of the models in five countries are presented next; the collected data are presented first, followed by the results of the alternative models, while at the end a synthesis presents and compares the forecasts of the models. The paper continues with a section that discusses the methodology application in the various countries and presents a validation of the forecasting performance of the presented models, while a concluding section summarizes the main points and presents directions for future research.

BACKGROUND

A number of approaches for modelling road safety developments have been proposed, a critical review of which can be found in Hakim et al. (1991), Oppe (1989) and Al-Haji (2007). Page (2001) presented an exponential formula that yields fatalities as the product of all explanatory variables' influence and attempted to rank countries based on their road mortality level. Beenstock and Gafni (2000) show that there is a relationship between the downward trend in the rate of road accidents in Israel and other countries and suggest that this reflects the international propagation of road safety technology as it is embodied in motor vehicles and road design, rather than parochial road safety policy. Van Beeck et al. (2000) examine the association between prosperity and traffic accident mortality in industrialized countries in a long-term perspective (1962-1990) and find that in the long-term the relation between prosperity and traffic accident mortality appears to be non-linear. Kopits and Cropper (2005) use linear and log-linear forms to model region specific trends of traffic fatality risk and per income growth using panel data from 1963 to 1999 for 88 countries. Abbas (2004) compares the road safety of Egypt with that of other Arab nations and G-7 countries, and develops predictive models for road safety. Vehicle fleet may also affect the number of fatalities, given that an increase in the vehicle number leads to higher average traffic volumes, which in turn may translate to e.g. a reduction in average speeds, or an increase in the need for more and safer road environment, in which the drivers' behaviour tends to be also better (Koornstra, 1992; Harvey & Shephard, 1993).

During the last decade, the modeling approach of structural time-series models, such as those proposed by Harvey and Shephard (1993) and Harvey (1994), is applied by several researchers. In this approach, which belongs to the family of unobserved component models, latent variables are decomposed into components (hence the term "unobserved components"), which are incorporated into the structural models.

Lassarre (2001) presented an analysis of ten European countries' progress in road safety by means of a structural (local linear trend) model, yielding two adjusted trends, one deterministic and one stochastic. Stipdonk (2008) applied multivariate analysis of the "three levels of risk" (i.e. exposure, fatality risk and accident severity) with structural time series models to quarterly data for the years 1987-2000 in France and the Netherlands, both at the national level, and stratified by road type for France.

METHODOLOGY

Following an introduction on multivariate state-space models, two structural time series models are considered in this paper: (i) the local linear trend model and (ii) the latent risk time-series model (Bijleveld, 2008). Furthermore, a structured decision tree for the selection of the applicable model for each situation (developed within the DaCoTA research project) is outlined. The models are briefly outlined in this section and presented in more detail in Appendix A.

Models' Outline

In a multivariate state space context, 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 (SUTSE) 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).

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). 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. 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”.

The basic formulation of the model 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 the local linear trend (LLT) model.

The next model is a Latent Risk Time-Series (LRT), which 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.

Model Selection Logic

The family of structural time-series models lends to a large number of assumptions that distinguish the resulting models into different categories. Within the framework of the DaCoTA research project, a decision process and model selection logic has been developed, in which the following steps are considered:

- Investigate exposure: the first step in every modeling effort is to assess the quality and characteristics of the underlying data. Do the available exposure data make sense? Can any sudden changes in the level or slope be explained from some real events?
- Establish whether the two series are statistically related: a SUTSE model is developed and based on the diagnostics, the modeler needs to decide whether the two time-series are correlated.

- Depending on the output of the SUTSE model determine whether an LLT or an LRT model should be pursued: If one or more of the null-hypotheses regarding the correlation of the disturbances is rejected, the time-series may be related and therefore an LRT can be estimated. If, on the other hand, none of the hypotheses can be rejected, then there is no evidence that the two time-series are correlated and therefore an LLT model would be more appropriate.

The presented models are based on a number of assumptions, in particular (in decreasing order of importance) those of independence, homoscedasticity and normality of the residuals (Commandeur and Koopman, 2007). In the model estimation results presented in the next section, a number of related model quality tests are presented, to test for violations in any of these assumptions.

MODEL APPLICATION

Data Collection and Analysis

Five European countries have been selected for the analysis in this research. These five countries have been chosen as they provide a good geographical coverage of Europe and also include countries with different characteristics (e.g. in terms of size, data availability, road safety maturity level). Based on these considerations, two Southern European countries have been selected (Greece and Cyprus), one Northern (Norway), one Central (Switzerland) and one Eastern (Hungary). Furthermore, Cyprus also represents new member states and also has a geographical peculiarity, as it is an island. This property considerably affects the road safety characteristics of Cyprus as e.g. international/through-traffic is essentially eliminated.

The fatalities and exposure series for the 5 examined countries are presented in Figures A1 and A2 in the Appendix. The fatalities series show quite distinct trends in different countries, and the available exposure measure is also different. Moreover, information on road safety or transport-related interventions, or other socio-economic events that may have influenced fatalities and exposure was collected, mainly from the members of the National Experts group on road safety of the European Commission. Interventions would ideally represent active road safety measures taken by a state, such as the adoption of 30-day fatality definitions, or the legislation of seat-belt laws. Within this work, we use the same framework to consider also exogenous events, such as national economic crises. Naturally, only major events are considered through this feature. The impact of smaller events would be captured through the uncertainty of the model and reflected in the range of the predictions (e.g. through the range of the 95% confidence intervals).

In the following sections, the proposed methodology is applied for modeling and forecasting road safety developments in the 5 European countries. Model selection is based on the decision tree presented in the previous section. Moreover, in each case, particular decisions are taken as regards data handling (e.g. outliers), introduction of intervention variables etc.

Models by Country

As a first step, the modeling process and results for Switzerland are presented in detail, that country being considered as a typical example of successful LRT modeling. Subsequently, the final models for the remaining 4 countries are presented and described more briefly. All models were fitted by means of the R software (R Development Core Team, 2013), on the basis of code developed by Bijleveld (2008). Table 1 summarizes the methods and results of modeling road safety developments in 5 European countries by means of structural time series models.

Table 1 to be inserted here

Modeling results for fatality risk in Switzerland: The SUTSE model was implemented for Switzerland, revealing a strong correlation between the fatality and the exposure series. More specifically, the correlation between the two levels is 0.84 and marginally significant at 90% (p=0.095). The correlation between the two slopes is equal to 1 and non significant (p=0.156) at 90% or 95%; it is however significant at approximately 85%. The relation between exposure and fatalities estimated by the beta coefficient in a restricted SUTSE/LRT model is 2.21 and is highly significant (p<0.001) at 99% suggesting that the two series are strongly related. Consequently, LRT models are examined for Switzerland.

Three versions of the LRT model are presented: a full model, a restricted model (fixed level exposure and fixed slope risk), and a restricted model with intervention variables (see Table A1 in the Appendix). The full LRT model (LRT 1) suggests that both the level and slope of both components are non significant. All components are also indicated to be common, suggesting that it might be wise to start fixing "half" of the related components (i.e. the slopes). Moreover, the covariances between components are significant in the full LRT model, and the correlation between them is close to one.

Initially, a restricted model with fixed slope of the risk was fitted (LRT2 – not presented here), in which the remaining three components were still non significant. Two alternatives were then examined: in the first one, both slopes (exposure and risk) were fixed; the output of this model (LRT3 – not presented here) was still problematic, as the covariance between the two levels was very significant and the smoothed output plots reflected a deterministic exposure level. The second option was a model with a fixed slope risk and a fixed level exposure (LRT4); this was proved to be a better option, as the remaining components were significant and the output was satisfactory overall.

Concerning the possible interventions, no information was available for specific road safety interventions or other socioeconomic events, it was therefore attempted to describe the most important changes reflected in the data series itself. A change in exposure level in 1993 was considered as intervention variable, in LRT5 model. This variable was significant at 99% (p-value lower than 0.001). This model presents significantly improved fit compared to the full model (the difference in log-likelihood is equal to 12) and the prediction errors for fatalities are improved compared to the full model. Consequently, this model (LRT5) is selected as the best performing model for Swiss fatality risk.

A number of model quality tests are provided, testing for the main distributional assumptions of the presented models (i.e. independence, heteroscedasticity and normality). Following the notation and formulation from Commandeur and Koopman (2007) and Bijleveld (2008), a significant value for the model quality tests suggests that there is a violation of the assumption. Therefore, based on the results presented in Table A1, most tests are indeed satisfied, with the exception of a few tests that suggest a violation of the related assumption. Considering that we are dealing with short time-series of the variables representing a very complex phenomenon, it is not surprising that a small number of tests are indeed violated.

Many of these tests indicate that the assumptions are violated. Indeed, when working with short time-series from complex phenomena, like road safety, it is very difficult to expect that the desirable distributional assumptions will not be violated. Therefore, we often have to settle for milder indications, such as an improvement of the test statistics as the model structure is improved towards the finally selected model. This, for example, is evident in the models presented in Table A1, where the improvement of the model structure leads to the gradual satisfaction of more assumptions. If more data were available (both in terms of time-series length and additional covariates), then conceivably we could reach models where more assumptions would be satisfied.

Modeling results for fatality risk in Greece, Norway, Hungary and Cyprus: The final models for the remaining 4 countries, selected on the basis of a similar process, are presented in Table A2 in the Appendix.

From the SUTSE modeling results for Greece, it was concluded that the fatalities and vehicle fleet series are not related and therefore further modeling can be made using the LLT model (instead of the

LRT). Three versions of the LLT model were run. The full model (LLT1) was run first, and all residual tests did not indicate a violation of the underlying assumptions. Furthermore, the level and slope components were significant. Therefore, a new model (LLT2) with additional interventions was estimated, namely a level change in 1986 (economic crisis), a level change in 1991 ("old-car-exchange" scheme) and a slope change in 1996 (adoption of the 30-days definition of fatalities). While the fit of this model improved over the original model, the slope component became insignificant. Therefore, a third model (LLT3) was also run, with the interventions, but keeping the slope of the fatalities fixed, which was selected as the best fitting model for Greece.

As regards Hungary, a lot of effort was devoted to the selection of an appropriate modeling approach. It is reminded that, before 1990, although the exposure rised impressively, the fatalities presented a relatively flat trend, with several bigger or smaller peaks. Moreover, the change of political regime in the early nineties is associated with an impressive peak in fatalities, and - rather surprisingly - a drop in exposure. Preliminary modeling attempts suggested that the relationship between exposure and fatalities appears to differ significantly in different parts of the series, making it difficult to model the whole series. It was therefore decided to disregard the pre-1993 parts of both series and focus on the period 1993-2010 for forecasting.

The investigation of the SUTSE model clearly indicated a lack of a relation between exposure and fatalities in Hungary, therefore LLT models were tested. Initially, the level of the fatality series was fixed, as it was non significant in the full LLT model. Two intervention variables were tested, namely a level change in 2002 (increase of motorway length in the country by 19%), and a level change in 2008 (introduction of a large set of road safety measures). Both interventions were highly significant, but the slope of the fatalities became non significant and had to be fixed too. The final model is therefore a deterministic linear trend (LT) model with interventions (LT6).

As regards Norway, the investigation of the SUTSE model did not clearly indicate the presence of a relation between exposure and fatalities in Norway. However, there is also reasonable doubt that these two time series are unrelated. The coefficient (beta) that estimates the relation between the two series is not significant but with p=0.28 it is not small enough to confidently rule out a relation. It was therefore decided to base the forecasting procedure on the LRT model. A process for developing a concrete cutoff value for this selection could be very useful for policy makers and researchers alike and is considered an interesting future research direction.

The full LRT model indicated that the level of the exposure and the slope of the risk were non significant, and were therefore fixed. This restricted model showed slightly higher prediction errors, but this was considered a minor issue as the absolute value of these errors was still very low. No intervention variables were included in this model, as no specific information was available.

The SUTSE model for Cyprus did not clearly indicate the presence of a relation between exposure and fatalities in Cyprus. However, the coefficient (beta) that estimates the relation between the two series has p=0.16, which is not small enough to rule out a relation. The non significant relation between the two series, could be due to the small number of observations. It was therefore decided to base the forecasting procedure on the LRT model. The full LRT model suggests that only the slope of the exposure varies significantly. However, when fixing all the other components, there was no improvement in model's fit (AIC) and the quality of the prediction was also worse (when holding the last 10 points of the series for prediction). On the basis of the above, it was decided to keep the full LRT model as the final model for Cyprus.

SYNTHESIS AND FORECASTS

The forecasts obtained from the best fitting model in each country (shown in Figures 1 and 2) provide an indication of the fatality numbers to be expected between 2010 and 2020 provided that, throughout these years, the trends will keep on following the developments that they have shown in the past, and no principal changes occur in the meantime ("business as usual" assumption). More specifically, if the past development continues, the following forecasts can be made for the number of fatalities in 2020 (see Figure 2):

- In Greece, there were approximately 1300 fatalities in 2010, and the forecast for 2020 is 898 fatalities (95% confidence interval: 585-1379 fatalities).
- In Hungary, there were 740 fatalities in 2010, and the forecast for 2020 is 555 fatalities (95% confidence interval: 472-653 fatalities).
- In Switzerland, there were 329 fatalities in 2010, and the forecast for 2020 is 216 fatalities (95% confidence interval: 167-278 fatalities). The number of vehicle kilometres is expected to increase up to 70.8 billion in 2020, compared to 62.3 in 2010.
- In Norway, there were 212 fatalities in 2009, and the forecast for 2020 is 132 fatalities (95% confidence interval: 53-333 fatalities). The number of vehicle kilometres is expected to increase up to 42 billion in 2020, compared to approximately 40 in 2009.
- Finally, in Cyprus there were 60 fatalities in 2010, and the forecast for 2020 is 37 (95% confidence interval: 25-52 fatalities). The fuel consumption is expected to increase up to 894 million tn.eq. in 2020, compared to 860 million in 2010.

Figure 1 to be inserted here

Figure 2 to be inserted here

It can be seen in Figure 1 that there is strong uncertainty about the development of the exposure in the 3 countries for which LRT models were fitted (for the countries that an LLT was estimated, exposure is not modeled, so such a plot is not applicable). Given that the exposure influences the prediction of the fatalities, it is interesting to demonstrate how much of the possible variation indicated by the confidence interval around the fatalities is due to the variation in exposure.

Figure 3 presents three point-estimates for the number of fatalities that can be expected assuming three different scenarios for exposure. The three mobility scenarios presented here are actually the exposure as predicted from the selected LRT model plus/minus one standard deviation. Assuming that these predictions are correct, and thus ignoring the uncertainty surrounding the forecasts for the exposure, what would be the consequences for the number of fatalities to be expected in 2020?

- In Switzerland, a stronger growth in vehicle kilometres travelled would result in 75 billion in 2020, and 230 fatalities forecasted. On the contrary, a contraction in mobility resulting in 66 billion vehicle kilometres in 2020 would result in 202 fatalities forecasted.
- In Norway, a stronger growth in vehicle kilometres travelled would result in 61 billion in 2020, and 196 fatalities forecasted. On the contrary, a contraction in mobility resulting in 20 billion vehicle kilometres in 2020 would result in 89 fatalities forecasted.
- In Cyprus, a stronger growth in fuel consumption would result in 1132 million tn.eq. in 2020, and 49 fatalities forecasted. On the contrary, a contraction in fuel consumption resulting in 701 million tn.eq. in 2020 would result in 27 fatalities forecasted.

Figure 3 to be inserted here

DISCUSSION AND VALIDATION

The 5 examined countries are a quite representative sample of European countries, including Northern / Western, Central and Southern European countries, older and new EU Member States, good and poor performing countries in terms of road safety. In all these countries, fatality data are available from the early seventies up to 2010, except from Cyprus, for which data was available from 1990 onwards. For all the countries, the entire data series was used, except from Hungary. In that country, early modeling attempts indicated that there may be different relationships between exposure and fatalities in different parts of the series; especially the pre-1990 data seemed problematic, because a very strong growth in exposure appeared to have no effect on fatalities. It was therefore decided to discard that part of the series for modeling and forecasting.

Different exposure measures were available in different countries, ranging from the most appropriate ones, i.e. passenger and vehicle-kilometres, to the "second best", i.e. fuel consumption, to the less appropriate, i.e. vehicle fleet. The example of Greece seems to confirm the limited usefulness of vehicle fleet data as a proxy of exposure, as it was proved to be not at all related with road safety developments. However, there was the case of Hungary, where passenger kilometres were available but were not found to be (statistically) related to road safety developments. In the remaining countries, the fatalities and exposure developments were related: strongly in Switzerland, and weakly in Norway and Cyprus.

Consequently, a broad range of models from the family of structural time series models were developed, according to the particularities of each country, ranging from deterministic linear trend (LT) model for Hungary, to local linear trend (LLT) model in Greece, and to different forms of Latent Risk Models (LRT) in the other countries: full LRT in Cyprus, restricted LRT in Norway, and restricted LRT with interventions in Switzerland.

The decision to include intervention variables was based on the availability of information on specific interventions or events (road safety related or socio-economic). An exception was made for Switzerland, where a "data-driven" intervention variable significantly improved model's fit.

From the best fitting model in each country, road safety and mobility (where applicable) forecasts were made, and their 95% confidence intervals were calculated. The confidence intervals, and in particular their width, are a reflection of the uncertainty/variability of the time-series in a specific country. While it is true that some policy makers might get confused by the provision of a range of values [the quote "Ranges are for cattle; give me a number" is attributed to Lyndon Johnson, when presented with uncertainty in forecasts (Manski, 2013)], it is important to nurture a culture of understanding the inherent uncertainty in issues such as road safety, and hence providing and motivating the need for the confidence intervals.

In order to validate the forecasting performance of the models, we have used observed fatality data from the last few years (2010-2012). Table 2 presents these true fatality figures along with the corresponding model forecasts for these years (along with the 95% confidence intervals). In most cases, the true fatality figures fall within (or right on) the 95% confidence intervals, while in several cases the predictions are very close to the realized values. The only country for which the model performed poorly is Hungary. However, as discussed during the presentation of the modeling effort for Hungary, the data for that country was already problematic. If anything, this can be an empirical indication that when the modeling process seems overly problematic, there may be underlying issues that cannot be overcome even with the best modeling efforts.

Table 2 to be inserted here

Still, in order to better describe the uncertainty in these forecasts, mobility scenarios were calculated, assuming stronger or weaker than expected mobility developments. This may be particularly important when considering that in several countries a recession effect is visible at the end of the fatalities and / or the mobility series, which in turn affects the final forecast. The "optimistic" mobility scenario, in which the forecasted value for 2020 is increased by one standard deviation, may in some cases provide a more realistic picture of future developments, as it takes into account the fact that the recession will end sooner (while in the baseline "business-as-usual" scenario, the effect of the recession is assumed to continue in the future).

CONCLUSION

The present research applied a methodological framework for forecasting road safety and mobility developments with structural time series models on a representative sample of European countries. The proposed methodology was proved to be very efficient for handling different cases of data availability and quality, providing an appropriate alternative from the family of structural time series models in each case. The estimated forecasts in all 5 countries appear to be realistic and within acceptable confidence intervals. Although the forecasts are based on "business-as-usual" scenarios, stronger or weaker mobility development scenarios are provided where possible, providing insight on the effect of various mobility developments of the forecasts.

Different modeling approaches would have led to somewhat different results and it is worth investigating this. For example, instead of modeling fatality numbers, one could have modeled the fatality rate per population, thus allowing for more direct comparisons among the five countries. Another interesting research direction is that of co-integration, i.e. the concept of correlation between non-stationary time-series, in which case the concepts of classical linear regression cannot be used (Lassarre, 2012). Another interesting future research direction would be the determination of more concrete criteria for choosing one model over the other. As discussed above, for some countries an LRT model has been used, even though the formal criterion of correlation between the fatalities and the exposure of $p=0.05$ is not satisfied. A process for developing a cutoff value for this selection could be very useful for policy makers and researchers alike.

Besides developing reliable models, it is also important to educate decision makers on why such models are superior and how to assess the performance of different models. These results may be useful both to policy-makers and researchers in the field of road safety, for understanding past developments, as well as the dynamics and particularities of the relationship between exposure and fatality risk. The results could also provide insight on the effects of the most successful safety interventions or other socio-economic events on mobility and road safety. Thus, one could incorporate as interventions into the model possible future road safety policies and forecast their expected impact on forecasted future fatality figures. Since the estimated forecasts reflect the future situation if the existing policy efforts and the socio-economic context extent to the future, they could thus provide a reference future road safety condition, and thus may be motivating for devoting additional efforts in outperforming these forecasts.

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List of Figure captions

Table 1. Overview of data and models for the 5 countries

	Cyprus	**Greece**	**Hungary**	**Norway**	**Switzerland**
data available	1990-2010	1960-2010	1970-2010	1970-2009	1975-2010
Exposure	Fuel consumption	Vehicle fleet	Passenger kilometres	Vehicle kilometres	Vehicle kilometres
Recession effect	Yes	No	Yes	No	No
Information on inverventions	No	Yes	Yes	No	No
data used	1990-2010	1960-2010	1993-2010	1970-2009	1975-2010
Model type	LRT	LLT	LT	LRT	LRT
Equations	(A10)-(A13)	(A9)	(A9) with restrictions	(A10)-(A13)	(A10)-(A13)
Interventions	No	Yes	Yes	No	Yes
Intervention details	N/A	Fatality time-series: a level change in 1986 (economic crisis), a level change in 1991 ("old-car-exchange" scheme) and a slope change in 1996 (adoption of the 30-days definition of fatalities)	Fatality time-series: a level change in 2002 (increase of motorway length in the country by 19%), and a level change in 2008 (introduction of a large set of road safety measures)	N/A	Exposure time-series: a level change in 1993 was considered as intervention variable
Forecast 2020	Yes	Yes	Yes	Yes	Yes
Mobility scenario	Yes	No	No	Yes	Yes

Note: N/A denotes "Not Applicable"; Row label "Equations" refers to equation number in the manuscript

Table 2. Overview of short-term fatality forecasts and true values for the 5 countries

Year	Forecast fatalities	95% conf. interval (from – to)		Actual fatalities
Cyprus				
2011	55	44	69	71
2012	49	37	65	51
Greece				
2011	1257	1118	1414	1141
2012	1211	1029	1426	1027
Hungary				
2011	787	706	876	638
2012	757	677	846	606
Norway				
2010	210	177	251	208
2011	201	160	252	168
2012	192	144	255	145
Switzerland				
2011	317	288	350	320
2012	304	271	342	339

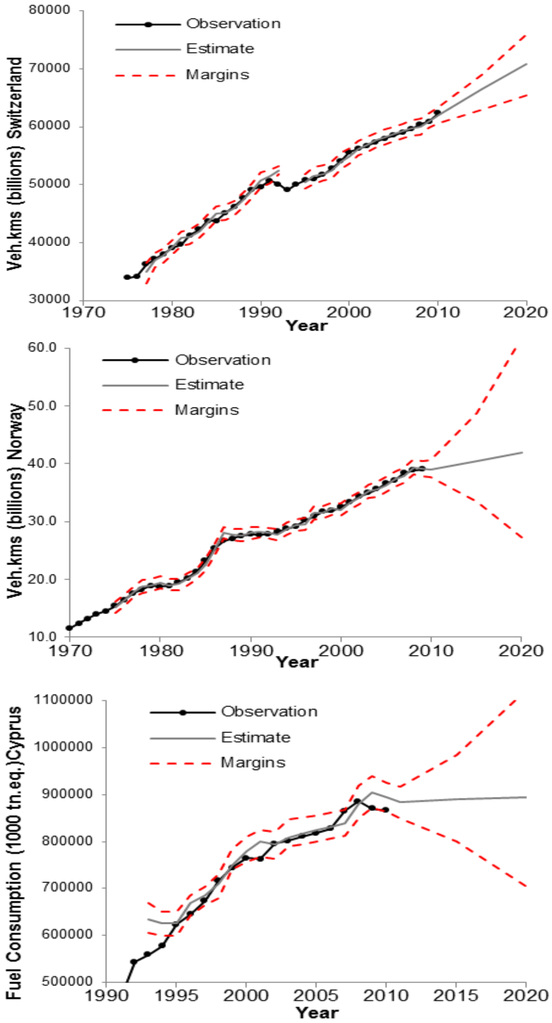

Figure 1. Forecasts of exposure for the examined countries for year 2020

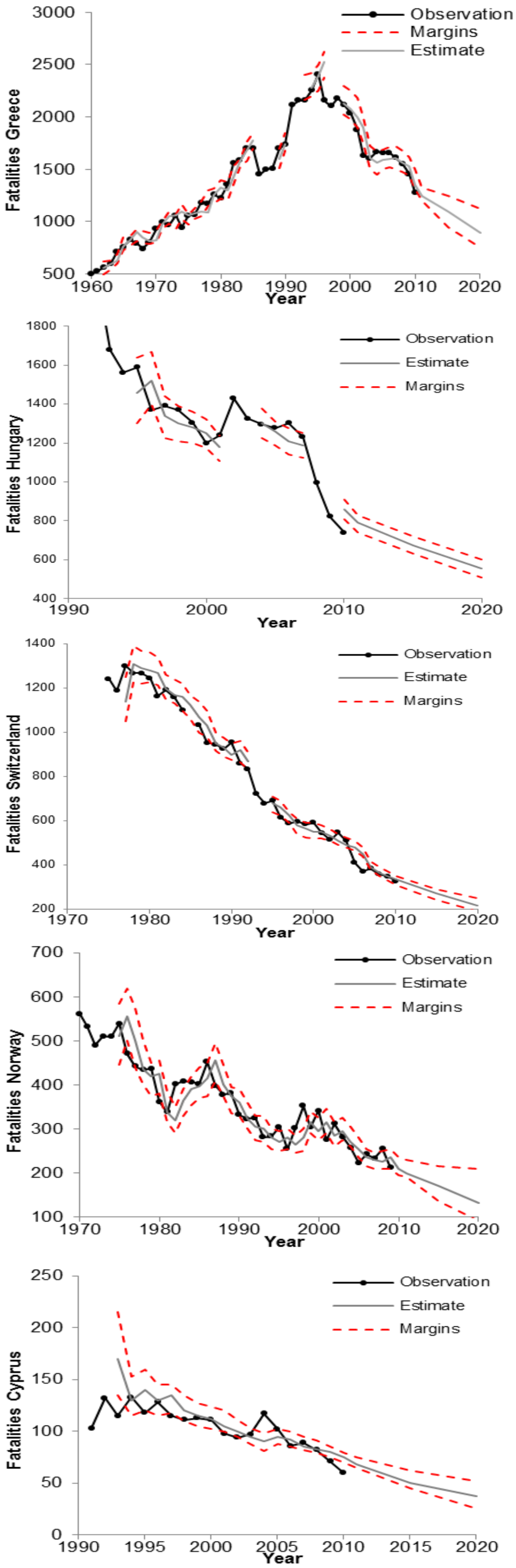

Figure 2. Forecasts of fatalities for the examined countries for year 2020

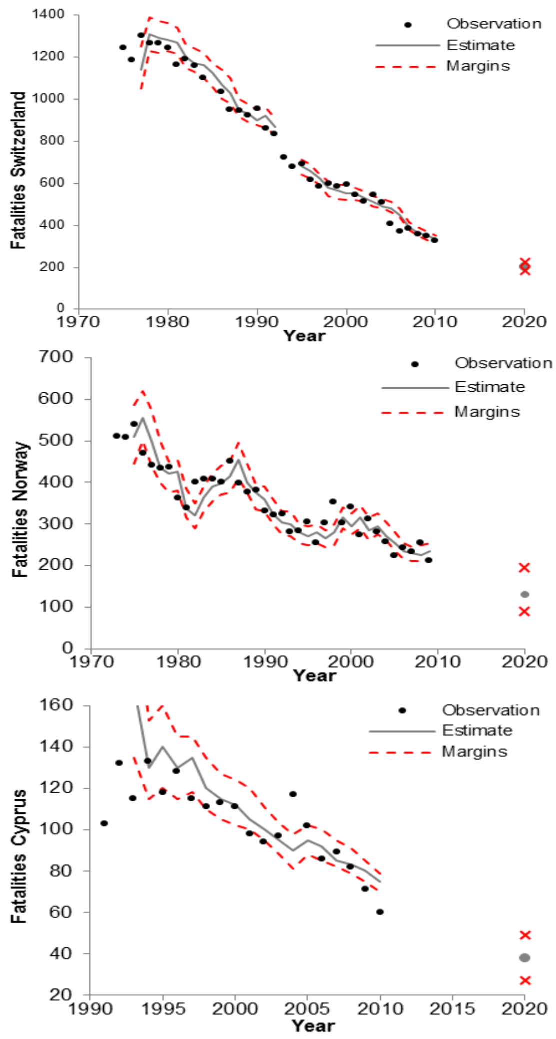

Figure 3. Forecasts for 2020 for different mobility scenarios • Continuation of development (as estimated by LRT model). ◦ Stronger growth (LRT estimate + 1 SD). ◦ No growth (LRT estimate - 1 SD)

APPENDIX A. Methodological components

Multivariate state-space models

In a multivariate state space context, 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 (SUTSE) 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 $y_t = (y_{1t}, \dots, y_{Nt})'$,

$$y_t = \mu_t + \varepsilon_t, \qquad \varepsilon_t \sim NID(0, \Sigma_\varepsilon) \tag{A1}$$

$$\mu_t = \mu_{t-1} + \beta + \eta_t, \qquad \eta_t \sim NID(0, \Sigma_\eta) \tag{A2}$$

where Σ_ε and Σ_η are nonnegative definite NxN matrices.

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 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:

$$X_t = E_t \times U_t^{(X)} \tag{A3}$$

$$Y_t = E_t \times R_t \times U_t^{(Y)} \tag{A4}$$

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.

Structural Time-Series Models: Local Linear Trend (LLT) and Latent Risk Time-Series (LRT) Models

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). 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:

$$\begin{aligned} &Traffic volume = Exposure \\ &Number of\ \ fatalilties = Exposure \times Risk \end{aligned} \tag{A5}$$

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 A5 is taken (and the error term is explicitly written out) the –so called– measurement equations of the model can be rewritten as:

$$\begin{aligned} &Log\, Traffic volume = \log exposure + random error\, in traffic volume \\ &Log\ Number\, of\ \ fatalities = \log exposure + \log risk + random\ error\, of\ \ fatalities \end{aligned} \tag{A6}$$

The latent variables [log (exposure) and log (risk)] need to be further specified by "state" equations, which, once inserted in the general model, describe the development of the latent variable. Equations (A7) and (A8) show how a variable can be modeled (to simplify the illustration only the number of fatalities is decomposed as an example):

Measurement equation:

$$\log Number of\ Fatalities_t = \log LatentFat._t + \varepsilon_t \qquad \text{(A7)}$$

State equations:

$$\begin{aligned} &Level(\log LatentFat_t) = Level(\log LatentFat_{t-1}) + Slope(\log LatentFat_{t-1}) + \xi_t \\ &Slope(\log(LatentFat_t) = Slope(\log LatentFat_{t-1}) + \zeta_t \end{aligned} \qquad \text{(A8)}$$

A more general formulation is presented in Equation (A9), 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.

$$\begin{aligned} Y_t &= \mu_t + \varepsilon_t \\ \mu_t &= \mu_{t-1} + \nu_{t-1} + \xi_t \\ \nu_t &= \nu_{t-1} + \zeta_t \end{aligned} \qquad \text{(A9)}$$

In the present case, 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 (A9) 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 the local linear trend (LLT) model. This model is shown in Equations (A7) and (A8). The next model is a Latent Risk Time-Series

(LRT), which 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:

$$\log TrafficVolume_t = \log Exposure_t + \varepsilon_t^{\,e} \tag{A10}$$

State equations:

$$\begin{aligned} Level(\log Exposure_t) &= Level(\log Exposure_{t-1}) + Slope(\log Exposure_{t-1}) + \xi_t^{\,e} \\ Slope(\log Exposure_t) &= Slope(\log Exposure_{t-1}) + \zeta_t^{\,e} \end{aligned} \tag{A11}$$

For *the fatalities*:

Measurement equation:

$$\log Numberof\ Fatalities_t = \log Exposure_t + \log Risk_t + \varepsilon_t^{\,f} \tag{A12}$$

State equations:

$$\begin{aligned} Trend(\log Risk_t) &= Level(\log Risk_{t-1}) + Slope(\log Risk_{t-1}) + \xi_t^{\,r} \\ Slope(\log Risk_t) &= Slope(\log Risk_{t-1}) + \zeta_t^{\,r} \end{aligned} \tag{A13}$$

Note that Equation (A12) now includes the Risk (and not the fatalities), which can be estimated as:

$$\text{logRisk}_t = \text{log LatentFat}_t\text{-log Exposure}_t \tag{A14}$$

Table A1. Model selection table for Switzerland

Model type	LRT full	LRT restricted	LRT restricted with interventions
Model Criteria			
ME10 Fatalities	-6037	-5374	-4918
MSE10 Fatalities	5.56827	4.79550	4.35124
log likelihood	18156	17675	17071
AIC	-36262	-35322	-34115
Variance of state components			
Level exposure	1.61E-04	-	-
Level risk	5.84E-04	7.66E-04 *	7.79E-04 *
Slope exposure	6.46E-06	4.15E-05 *	6.84E-06 *
Slope risk	9.41E-06	-	-
Correlations between state components			
level-level	0.64	-	-
slope-slope	1	-	-
Observation variance			
Observation variance exposure	2.95E-06	5.95E-05 *	7.32E-05 *
Observation variance risk	4.18E-06	2.99E-04	2.47E-04
Interventions			
(1993 exposure level)	-	-	-0.0501 *
Model Quality			
Box-Ljung test 1 Exposure	0.228	121.897	136.467
Box-Ljung test 2 Exposure	0.801	241.477	503.337
Box-Ljung test 3 Exposure	0.8525	329.751	583.505
Box-Ljung test 1 Fatalities	216.579	286.154	263.737
Box-Ljung test 2 Fatalities	255.335	316.426	265.737
Box-Ljung test 3 Fatalities	311.375	376.553	33.562
Heteroscedasticity Test Exposure	0.386	0.454	0.807
Heteroscedasticity Test Fatalities	269.171	302.679	280.834
Normality Test standard Residuals Exposure	5.99*	132.338	329.738
Normality Test standard Residuals Fatalities	0.0189	0.312	0.525
Normality Test output Aux Res Exposure	0.0439	0.458	353.243
Normality Test output Aux Res Fatalities	124.914	159.349	183.043
Normality Test State Aux Res Level exposure	338.426	307.695	0.0385
Normality Test State Aux Res Slope exposure	129.975	0.706	0.183
Normality Test State Aux Res Level risk	3.574	8.381*	7.704*
Normality Test State Aux Res Slope risk	0.068672	3.92E-05	3.37E-05

Note: * denotes significant at 95% level

Table A2. Summary table of selected models for Cyprus, Greece, Hungary and Norway

Country	Greece	Hungary	Norway	Cyprus
Model Type	LLT restricted with interventions	LT deterministic with interventions	LRT restricted	LRT full
Model Criteria				
ME10 Fatalities	-251.5	196297	24	-2.59
MSE10 Fatalities	70572.97	58253.62	967.3	118.25
log likelihood	65.82	167835	156.941	52.96
AIC	-131.55	-324559	-313.612	-105.02
Variance of state components				
Level exposure	-	-	-	9.22E-05
Level risk	2.67E-03*	-	3.84E-03 *	6.53E-04
Slope exposure	-	-	3.16E-04 *	1.08E-04 *
Slope risk	-	-	-	8.10E-06
Correlations between state components				
level-level	-	-	-	-1
slope-slope	-	-	-	1
Observation variance				
Observation variance exposure	-	-	1.45E-06	3.60E-04
Observation variance risk	1.00E-09	1.88E-03 *	5.40E-04	1.11E-03
Intervention and explanatory variables tests				
(slope fat 1996)	-0.080 *	-	-	-
(level fat 1986)	-0.211 *	-	-	-
(level fat 1991)	0.147 *	-	-	-
(level fat 2002)	-	0.220 *	-	-
(level fat 2008)	-	-0.259 *	-	-
Model Quality				
Box-Ljung test 1 Exposure	-	-	0.15	4.70*
Box-Ljung test 2 Exposure	-	-	1.34	5.3
Box-Ljung test 3 Exposure	-	-	2.35	5.67
Box-Ljung test 1 Fatalities	0.29	150.267	0.42	1.62
Box-Ljung test 2 Fatalities	2.78	188.584	0.42	1.91
Box-Ljung test 3 Fatalities	4.03	322.822	1.91	2.27
Heteroscedasticity Test Exposure	-	-	0.34	0.47
Heteroscedasticity Test Fatalities	0.76	263.094	1.1	2.45
Normality Test standard Residuals Exposure	-	-	1.63	1.98
Normality Test standard Residuals Fatalities	2.06	182.026	1.35	5.89
Normality Test output Aux Res Exposure	-	-	0.84	0.92
Normality Test output Aux Res Fatalities	1.17	118.117	0.55	3.74
Normality Test State Aux Res Level exposure	-	-	0.76	14.54***
Normality Test State Aux Res Slope exposure	-	-	1.71	0.16
Normality Test State Aux Res Level risk	1.1	0.943	1.76	2.69
Normality Test State Aux Res Slope risk	0	145.961	0.06	0.08

Note: * denotes significant at 95% level, *** denotes significant at 99.9% level

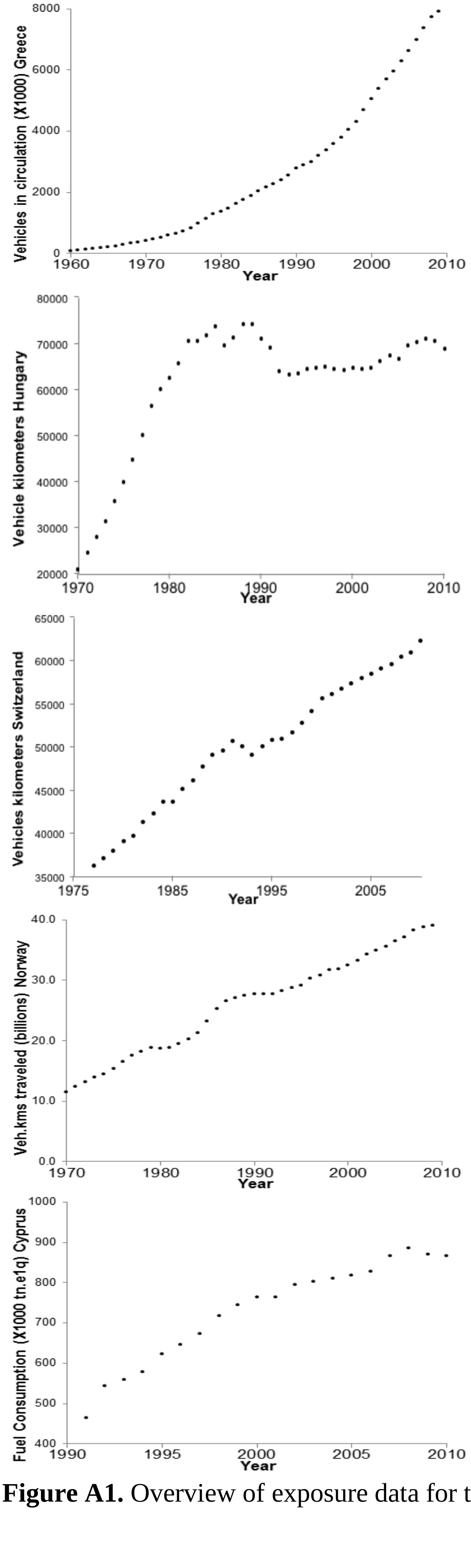

Figure A1. Overview of exposure data for the five countries

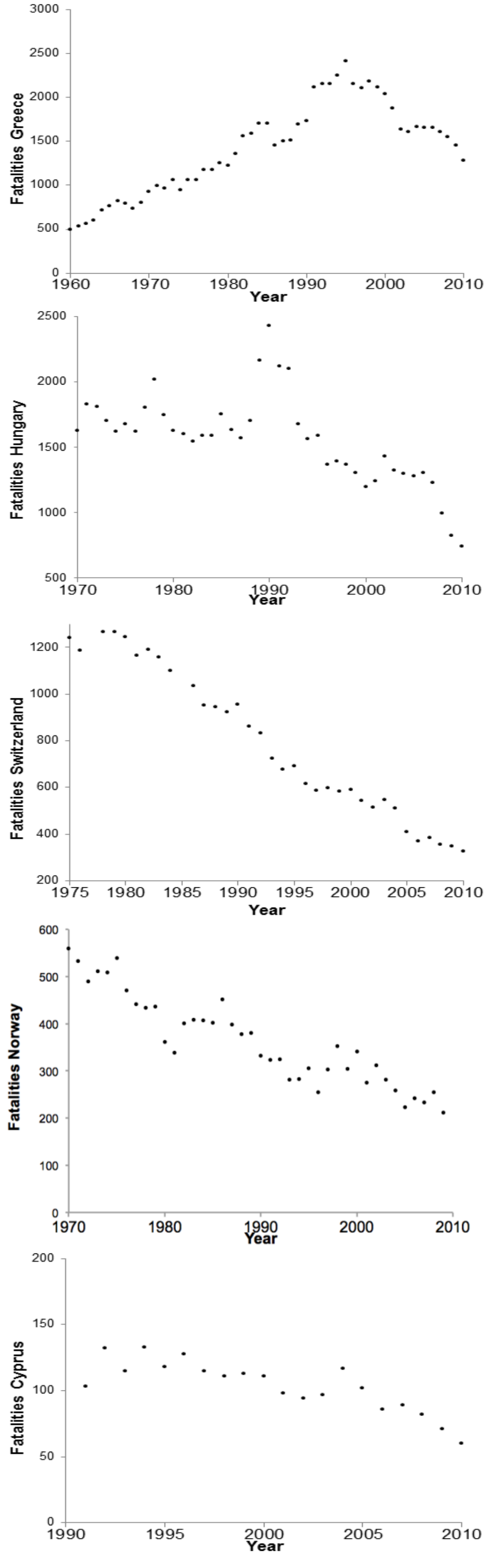

Figure A2. Overview of fatalities data for the five countries