ASSESSMENT OF EXPOSURE PROXIES FOR MACROSCOPIC ROAD SAFETY PREDICTION

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ABSTRACT

Road safety is a major global health problem and no effort should be spared in trying to limit its impacts. 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. Macroscopic data are often not available, or not in the form that they are desired. Therefore, it is often required to attempt to consider alternative sources of data, which may be correlated with the modeled phenomenon.

The objective of this research is to investigate the suitability of alternative proxy variables for macroscopic road safety modeling, using three suitable exposure proxies: (i) number of vehicles in circulation, (ii) GDP and (iii) fuel consumption. Several structural time-series models have been developed for each proxy for two Mediterranean countries with many similar socio-economic characteristics: Greece and Cyprus.

Based on the findings of this analysis, a number of observations can be drawn. Proxy variables can provide reasonable results, when exposure data are not available. Furthermore, even in two countries with many similarities the selected proxy measure differs. This suggests that the underlying conditions that make a variable a suitable proxy for exposure is complex and needs further investigation.

INTRODUCTION

Road safety is a major global health problem and no effort should be spared in trying to limit its impacts. 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. One of the key relationships in road safety links fatalities with risk and exposure (see also the discussion around Equation 2 later in the paper), where exposure reflects the amount of travel, which in turn translates to how much travelers are exposed to risk. It is reasonable to expect that –for the same level of risk– when there is a higher amount of travel, fatalities may increase, solely due to the increased exposure. Macroscopic data are often not available, or not in the form that they are desired. For example, the desired exposure measure for traffic is usually vehicle-kilometers; however, the estimation of such a variable is a complex task and such data are often not available. Therefore, it is often required to attempt to consider alternative sources of data, which may be correlated with the modeled phenomenon. Such data are often called proxy variables.

A macroscopic road-safety model commonly used in the late 60s was proposed by Smeed *(1)* linking the number of fatalities with the number of vehicles and the population. Jacobs *(2)* repeated this analysis for a number of developed and developing countries using data between 1968 and 1975 while Gharaybeh *(3)* applied the same formula to assess the development of road safety in Jordan, relative to that of other middle-eastern and developing countries. Many studies have criticised Smeed's model because it only concentrates on the motorisation level of country and ignores the impact of other variables [cf. *(4-5)*, while another useful review is provided by COST329 *(6)*, where a detailed analysis of the debate surrounding Smeed's formulas and analysis is available).

Kopits and Cropper *(7)* develop models to examine the relationship between traffic fatality risk and per capita income and use it to forecast traffic fatalities for multiple regions. Söderlund and Zwi *(8)*, after adjusting for motor vehicle numbers, find that the poorest countries show the highest road traffic-related mortality rates. Bishai et al. *(9)* observe that traffic fatalities increase with GDP per capita in lower income countries and decrease with GDP per capita in wealthy countries and explore this finding using fixed effects regression. This is an alarming finding, as it implies that as lower income countries become richer, traffic fatalities are expected to increase (and indeed the WHO predicts that the current number of 1.3 million global road fatalities per year, may rise to 1.9 million by 2020 *(10)*).

Road safety may also be linked with fuel consumption. The effects of fuel economy on automobile safety was examined by Ahman and Greene *(11)*. Haworth and Symmons *(12)* examine the possible safety benefits of eco-driving, i.e. driving in a way that lowers fuel consumption and emissions.

The objective of this research is to investigate the suitability of alternative proxy variables for macroscopic road safety modeling, using data from two European countries for which more appropriate exposure measures are not available. Gross Domestic Product (GDP), fuel consumption (in the transport sector) and number of vehicles in circulation are candidate variables that are considered in this research. Furthermore, unlike most previous research (much of which used simpler regression models), a state-of-the-art structural state-space modeling technique specifically suited to time-series data has been adopted in this research.

The remainder of this paper is structured as follows. The next section provides a review of the relevant literature, demonstrating how proxy variable are often used, when direct exposure data are not available. The considered data and an overview of the methodological modeling background are provided in the following section. The next two sections present a critical review of the developed models. The predictive accuracy of the selected models is demonstrated in the next section, while a concluding section provides directions for further research.

BACKGROUND

Obtaining direct exposure measures is not an easy task. One way to overcome this difficulty is the use of proxy measures, i.e. other measures that are correlated with the exposure measures, but are easier to collect. In an analysis of the effectiveness of changeable message signs on secondary crashes, Kopitch and Saphores *(13)* used proxies based on day of the week and time of day, as traffic characteristics were not readily available. Lin et al. *(14)* used proxies for traffic characteristics in their analysis of cultural differences of immigrants on their vulnerability in non-motorized crashes. In particular, the authors used total street length per area of census tract as a proxy for total traffic and percentage of the length of streets with four-or-more lanes as a proxy for vehicle volume and speed. In a model aimed at estimating pedestrian crash frequency, Ukkusuri et al. *(15)* use demographic data, land use and physical environment information as proxies for the level of pedestrian activity.

Yannis and Karlaftis *(16)* use independent variables capturing the day of the week as proxies for traffic conditions in a time-series analysis of weather effects on daily traffic accidents and fatalities. Buehler and Pucher *(17)* use state cyclist fatality rates as a proxy for city cyclist fatality rates in developing models for the assessment of bike paths and lanes on cycling in large American cities. The authors find a low correlation (below 0.3) between the supply of bike fatalities and fatality rates and attribute this to the unsuitability of the available/chosen proxy variables. Quddus et al. *(18)* use different proxies of congestion (including the more direct total delay, as well as traffic flow and traffic speed) to investigate the associate between the severity of individual crashes and the level of traffic congestion.

Of course, using proxies is not the same as using the exposure measures themselves, and this method receives critiques, e.g. *(19)*. Prior to their use, it is important to ensure that they capture the measure in hand correctly and –especially when used in a model- that they would provide reasonable estimates of the actual phenomenon. Similarly, attempts to replace the shipper-receiver commodity flow with proxies in a large-scale model have demonstrated these difficulties *(20)*. Wang et al. *(21)* discuss the limitations of using proxy measures for congestion in road safety models, using Noland and Quddus *(22)* and Kononov et al. *(23)* as examples.

In a slightly different context (optimal location of emergency response units), Kepaptsoglou et al. *(24)* use traffic safety metrics (frequency and severity) as proxies for the demand for emergency response units in a network. Kepaptsoglou et al. *(25)* discuss various proxies for the demand and supply in transport, including the income level (GDP), size and imports/exports.

DATA AND METHODOLOGY

Data

An overview of the available data is presented in Figure 1. The fatalities in Greece show two distinct trends: an increasing one until 1995, following by a decreasing one thereafter. The number of fatalities depends strongly on a measure reflecting the amount of traffic. In Greece and Cyprus there are no traffic volume data available, so to forecast the fatalities, indirect measures such as the number of vehicles in circulation, the GDP or the fuel consumption may be used.

The number of vehicles in circulation shows an increasing rate from 1991 to almost 2008. During the last couple of years, there appears to be a slower rate of increase, reflecting the effect of the recession. However, this effect is not as evident as it would be if a more appropriate measure of exposure, such as vehicle-kilometers, were available. If a measure such as the number of vehicle exposures were available, then the exposure measure would actually show a reduction, and not simply a reduced increase. The number of vehicles is a less volatile measure of the exposure, as (i) a reduction in the use of the vehicles does not necessarily correspond to a reduction on the number of vehicles and (ii) even when the vehicles are removed from circulation, it is not as easy to update the registry of vehicles.

Indeed, the GDP and fuel consumption data in Greece reflect the effect of recession more clearly (i.e. not simply as a break in the increasing trend, but as a decreasing trend). The GDP in Greece was stagnant until about 1995, at which time a fairly stable increasing trend started, which continued until 2008, after which a decrease started. A similar trend is exhibited by the fuel consumption data.

The fatalities in Cyprus have dropped from almost 103 in 1991 to 60 in 2010. During the first years (1990s) there is some variability and no clear trend can be observed. There is a dip in the first half of the 2000s and a consistent drop after 2004. This could possibly be attributed to the accession of Cyprus to the EU (which took place that year) and to the implementation of the first Strategic Road Safety Plan 2005-2010.

The number of fatalities depends strongly on the amount of traffic. The number of vehicles in circulation in Cyprus is constantly increasing during this period; this increase is much steeper after 2004. Proxy measures that can be used to forecast the fatalities include GDP (in USD) and fuel consumption (measured in oil tn. equivalents). Both time-series show a similar trend for Cyprus during the study period. In particular, a fairly consistent increasing trend can be noticed until 2008, at which point –possibly due to the recession- GDP and fuel consumption started declining. The GDP increased from about 12.300USD in 1991 to about 17.850USD in 2008 and then dropped to about 17.150USD in 2010.

The fuel consumption increased from 460 million tn.eq. in 1991 to about 885 million in 2008 and then dropped to about 860 million in 2010. The increase did not take place at the same rate throughout this period. In the early nineties there was an increase of 8%, but since then the yearly increase became less and less and in the most recent years it has practically halted.

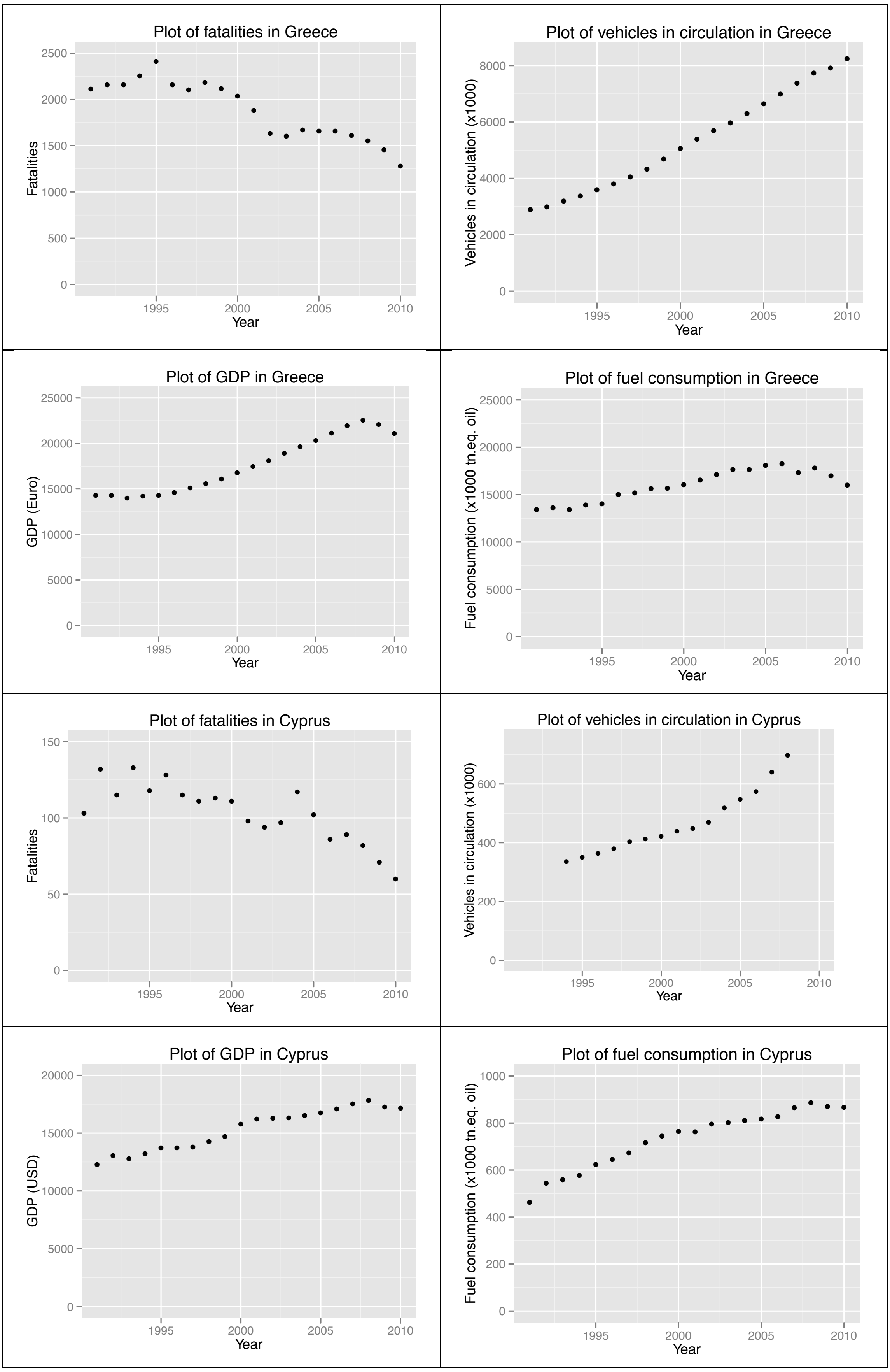


FIGURE 1. Overview of data (top: Greece, bottom: Cyprus)

Model types

Clearly, the topic of macroscopic road safety modeling and forecasting is an active research area, where active debate is taking place and interesting developments are still being made. One such attempt is through stratification involving specific vehicle types and population subsets (e.g. age groups or gender) *(26)*. It will then be much easier to distinguish cases and consider the presence of true impact due to GDP, vehicle fleet or other growth-related parameters; so, it is not advised to neglect the study of such elementary indicators, especially when difficulties are encountered in the reliability of more exposure-oriented analyses (e.g. using vehicle-kilometres travelled). 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 and can be used to construct appropriate indicators. Hollo et al. *(27)* use road safety performance indicators to analyze the trends in casualties in several Central European countries.

An alternative modeling approach would have been the use of structural time-series models, such as those proposed by Harvey and Shephard *(28)*, Harvey *(29)*, which belong to the family of unobserved component models. In this approach, latent variables are decomposed into components (hence the term "unobserved components"), which are incorporated into the structural models. Harvey and Sheppard *(28)* propose to decompose a univariate time-series y_t into the following components:

$$y_t = \mu_t + \psi_t + \gamma_t + \varepsilon_t \tag{1}$$

where μ_t is a trend, ψ_t is a cycle component, γ_t is a seasonal component and ε_t is an irregular component. All components are assumed stochastic (except for the mean, a zero mean is expected for the other components) with uncorrelated disturbances. This research builds upon the work presented in Commandeur and Koopman *(30)* and Bijleveld *(31)* on structural time-series models for road safety, which is introduced in the following section.

Two structural time series models are considered in this section: (i) the local linear trend model and the (ii) latent risk time-series model *(31)*. Furthermore, a structured decision tree for the selection of the applicable model for each situation (developed within the DACOTA project) is outlined.

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 *(32,33)*. This implies that in order to model the evolution of fatalities it is required to model the evolution of two components: a road safety indicator and an exposure indicator. While fatalities is 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 *(31)* 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:

$$\begin{aligned} &Traffic\ volume = Exposure \\ &Number\ of\ \ fatalilties = Exposure \times Risk \end{aligned} \tag{2}$$

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

$$\begin{aligned} &Log\ Traffic\ volume = \log exposure + random\ error\ in\ traffic\ volume \\ &Log\ Number\ of\ \ fatalities = \log exposure + \log risk + random\ \ error\ of\ \ fatalities \end{aligned} \tag{3}$$

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…), as shown in Equation (1). Equations (4) and (5) 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 (4) 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:

$$\log Number\ of\ \ Fatalities_t = \log LatentFat._t + \varepsilon_t \tag{4}$$

State equations:

$$\begin{aligned} &Level(\log LatentFat_t) = Level(\log LatentFat_{t-1}) + Slope(\log LatentFat_{t-1}) + \xi_t \\ &Slope(\log(LatentFat_t) = Slope(\log LatentFat_{t-1}) + \zeta_t \end{aligned} \tag{5}$$

A more general formulation is presented in Equation (6), 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.

$$\begin{aligned} Y_t &= \mu_t + \varepsilon_t \\ \mu_t &= \mu_{t-1} + \nu_{t-1} + \xi_t \\ \nu_t &= \nu_{t-1} + \zeta_t \end{aligned} \tag{6}$$

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 (6) 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.

<u>For *traffic volume*:</u>
Measurement equations:

$$\log TrafficVolume_t = \log Exposure_t + \varepsilon_t^{\,e} \tag{7}$$

State equations:

$$\begin{aligned} Level(\log Exposure_t) &= Level(\log Exposure_{t-1}) + Slope(\log Exposure_{t-1}) + \xi_t^{\,e} \\ Slope(\log Exposure_t) &= Slope(\log Exposure_{t-1}) + \zeta_t^{\,e} \end{aligned} \tag{8}$$

<u>For *the fatalities*:</u>
Measurement equation:

$$\log Number\,of\;Fatalities_t = \log Exposure_t + \log Risk_t + \varepsilon_t^{\,f} \tag{9}$$

State equations:

$$\begin{aligned} Trend(\log Risk_t) &= Level(\log Risk_{t-1}) + Slope(\log Risk_{t-1}) + \xi_t^{\,r} \\ Slope(\log Risk_t) &= Slope(\log Risk_{t-1}) + \zeta_t^{\,r} \end{aligned} \tag{10}$$

Note that Equation (9) now includes the Risk (and not the fatalities), which can be estimated as:

$$\text{logRisk}_t = \text{log LatentFat}_t\text{-log Exposure}_t \tag{11}$$

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) *(34)*, 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.

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. Choosing the right model among this sea of models is not an easy task and –if left unstructured- can disorient the modeler and the reader. As a result, within the framework of the DACOTA project, partly funded by the European Union within the 7th Framework Programme (http://dacota-project.eu), a decision process and model selection logic has been developed, and followed in this research. 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?
- Develop a SUTSE (Seemingly Unrelated Time-Series Model) model: Before developing a bivariate model of exposure and fatalities, it is important to establish whether the two series are statistically related. To achieve this, a SUTSE model is developed and based on the diagnostics (i.e. whether the null hypothesis that the correlation between the disturbances of the time-series can be rejected), 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 (and develop it): If one or more of the null-hypotheses regarding the correlation of the disturbances (assuming the null hypotheses state that the correlations are equal to zero) is rejected, the time-series may be related and therefore an LRT can be estimated. In that case, of course, further analysis is needed, to investigate whether some of the level or slope components for the exposure and fatalities may be fixed. 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.

EXPLORATION USING SUTSE MODELS

Three SUTSE models are first estimated, one for each proxy for the exposure: (i) vehicles in circulation, (ii) GPD, and (iii) fuel consumption. The results are summarized in Table 1. The beta coefficient indicates that none of these models suggest that the fatalities data and the exposure proxies are correlated for the considered time period (1991-2010). However, when one considers the trend of the fatalities time-series, two different trends appear: an increasing one until 1995 and a decreasing one thereafter. As discussed in several research papers *(e.g. 35,36)* this is a phenomenon that occurs in all countries and is attributed to a number of reasons. From a statistical point of view, however, the fact that this trend is not reflected in the exposure data creates an issue that is resolved next.

Therefore, three more SUTSE models were estimated (also presented in Table 1), this time considering only the data from 1995 until 2010, i.e. the fatality data with the downward trend only. Comparing the significance of the beta parameter in the various models, the following observations can be made:

- Fatalities and vehicle fleet in circulation do not appear to be correlated. This is consistent with expectations and reflects the inertia of the vehicle fleet time-series to reflect changes in exposure. Restricting the considered data to the period 1995-2010 does not change the situation considerably.
- The correlation of both GDP and fuel consumption with the fatalities time-series increases considerably when only data from 1995 onwards (i.e. after the change in the fatalities trend) are considered (compared to when the entire time-series 1991-2010 is used).
- Fuel consumption for the period after 1995 shows a much stronger correlation with the fatalities time-series (p=0.14) than GDP for the same period (p=0.24). However, as both appear to be fairly correlated, both will be further assessed.

TABLE 1. Summary statistics of estimated SUTSE models (Greece)

	Veh 1991	GDP 1991	Fuel 1991	Veh 1995	GDP 1995	Fuel 1995
log likelihood	237.42	76.72	66.5714	60.9876	55.8204	39.2884
AIC	-474.53	-152.64	-132.343	-120.975	-110.641	-77.5767
Model Quality						
Box-Ljung test 1 Exposure	4.10*	0.599	0.808	0.366	3.224	0.593
Box-Ljung test 2 Exposure	4.44	0.614	1.090	0.852	3.230	1.372
Box-Ljung test 3 Exposure	4.62	0.619	1.128	0.957	3.260	1.401
Box-Ljung test 1 Fatalities	3.44	2.668	2.329	6.255*	4.671*	3.096
Box-Ljung test 2 Fatalities	4.55	3.233	2.646	11.835**	8.548*	6.410*
Box-Ljung test 3 Fatalities	6.67	3.281	2.689	13.737**	8.659*	6.501
Heteroscedasticity Test Exposure Proxy	0.238**	1.416	1.802	1.418	24.113**	1.138
Heteroscedasticity Test Fatalities	0.816	0.474	0.351	0.326	0.170	0.175
Normality Test standard Residuals Exposure Proxy	68.15***	2.174	0.239	0.115	10.126**	0.906
Normality Test standard Residuals Fatalities	0.319	0.316	1.070	0.468	1.761	1.886
Normality Test output Aux Res Exposure Proxy	12.71**	0.103	0.925	0.946	0.962	0.452
Normality Test output Aux Res Fatalities	1.18	2.300	0.110	1.452	0.321	0.278
Normality Test State Aux Res Level (stratum 1)	45.41***	0.565	0.610	2.621	0.056	0.918
Normality Test State Aux Res Slope (stratum 1)	20.49***	2.002	0.137	0.320	6.796*	0.310
Normality Test State Aux Res Level (stratum 2)	1.05	1.788	1.610	0.561	0.223	0.429
Normality Test State Aux Res Slope (stratum 2)	0.261	0.461	0.106	0.305	1.878	1.326
Model Q-matrix tests						
Level (stratum 1)	1.23E-04	4.38E-10	7.43E-18	5.27E-14	3.96E-12	7.68E-12
Level (stratum 2)	3.88E-03 *	1.60E-03	2.25E-03	2.28E-03	1.95E-06	1.05E-10
Slope (stratum 1)	2.09E-04 *	3.12E-04 *	1.71E-04 *	9.48E-05 *	2.51E-04 *	1.70E-04 *
Slope (stratum 2)	7.42E-05	4.89E-04	1.12E-04	8.03E-13	1.86E-03	1.75E-03
Model H-matrix tests						
GDP Greece	5.17E-06	1.13E-09	2.42E-04	3.62E-06	1.02E-09	1.75E-09
GDP Greece	9.00E-05	1.62E-09	6.50E-05	2.69E-05	2.57E-08	2.60E-09
Correlation between fatalities and exposure						
Beta test	0.448	0.635	0.455	0.902	0.982	2.042
Significance	0.338	0.324	0.609	0.391	0.239	0.139

Note: *, **, and *** denote significant at the 95%, 99% and 99.9% level respectively

Similarly, Table 2 summarizes the results from the SUTSE models for the Cyprus data. The model diagnostics do not reveal any systematic violations of the underlying assumptions. Therefore, based on the significance of the estimated beta parameters of the various models, it is observed that the number of vehicles in circulation and fuel consumption might be correlated with fatalities, and therefore will be further investigated using LRT models in the next section.

TABLE 2. Summary statistics of estimated SUTSE models (Cyprus)

	Vehicles	GDP	Fuel
log likelihood	42.38	56.10	52.81
AIC	-83.97	-111.41	-104.83
Model Quality			
Box-Ljung test 1 Exposure	4.15*	1.34	4.68*
Box-Ljung test 2 Exposure	4.15	1.50	5.17
Box-Ljung test 3 Exposure	6.69	1.51	5.43
Box-Ljung test 1 Fatalities	2.33	1.71	1.89
Box-Ljung test 2 Fatalities	3.83	3.15	2.02
Box-Ljung test 3 Fatalities	4.22	3.23	2.62
Heteroscedasticity Test Exposure Proxy	4.67	1.92	0.503
Heteroscedasticity Test Fatalities	0.37	2.13	2.63
Normality Test standard Residuals Exposure Proxy	2.15	0.126	1.23
Normality Test standard Residuals Fatalities	2.37	9.48**	5.06
Normality Test output Aux Res Exposure Proxy	0.329	1.57	0.359
Normality Test output Aux Res Fatalities	0.514	0.464	4.41
Normality Test State Aux Res Level (stratum 1)	0.784	0.0258	11.63**
Normality Test State Aux Res Slope (stratum 1)	0.0726	0.0210	0.108
Normality Test State Aux Res Level (stratum 2)	0.620	3.58	2.01
Normality Test State Aux Res Slope (stratum 2)	0.0129	0.00472	0.0669
Model Q-matrix tests			
Level (stratum 1)	1.42E-19	5.05E-04	7.13E-15
Level (stratum 2)	4.58E-17	9.06E-05	3.06E-04
Slope (stratum 1)	1.52E-04 *	1.95E-05	1.12E-04 *
Slope (stratum 2)	2.66E-19	2.43E-04	4.38E-17
Model H-matrix tests			
GDP Greece	1.68E-04	3.15E-05	4.12E-04
GDP Greece	1.82E-03	6.43E-04	7.76E-04
Correlation between fatalities and exposure			
Beta test	-1.257	0.615	1.213
Significance	0.102	0.691	0.161

Note: *, **, and *** denote significant at the 95%, 99% and 99.9% level respectively

DEVELOPMENT OF LRT MODELS

Based on the results of the SUTSE models analysis, three models are considered for Greece (for the period 1995-2010):

- An LLT model in which the fatalities are not assumed to be correlated with the available exposure measures
- LRT models in which the fatalities are considered to be correlated with the respective proxy to the exposure, i.e. GDP and fuel consumption.

Table 3 summarizes the main statistics of the estimated models for Greece. There are several criteria that can be considered in choosing a single model among these. The validation of the predictive ability of each model (using a subset of the observations for the model estimation and then using the remainder of the observations for validation) is one important aspect. In this case, three such validations have been performed for each model, each one holding out the last 4, 7 or 10 observations. Considering the small number of overall observations (16 or 20), it is noted that the number of observations available for the model estimation was limited in several cases. The violations in the various statistical tests are another criterion that can help identify possible issues with each model. Finally, the log-likelihood and AIC index can be used to compare among nested models; i.e. they cannot be used to compare e.g. the models using GDP versus the models using fuel consumption. A full model is estimated first, in which the level and slope of the exposure and risk are allowed to vary. Depending on the output of these models, restricted models (in which insignificant parameters were fixed) were also estimated. Therefore, the procedure of determining the "optimal" restrictions may be an iterative process in which the modeler incrementally fixes one or more variables and inspects the impact of these restrictions in the model performance. Similar models are presented in Table 4 for Cyprus.

Based on these criteria, a model has been singled out for each country and highlighted in Table 3 and 4. Regarding Greece, and considering that the various tests do not show significant differences between the models, the restricted LRT model when using GDP as a proxy for the exposure is selected, as it provides significant better (in sample) predictive performance. This may appear as a counter-intuitive finding, but it may be attributed to the noise incorporated in the (full) model by the (insignificant) terms that are (inappropriately) included as random. As shown in the table, the level of the exposure, as well as the level and slope of the risk variable have been considered as fixed (based on the results of the full LRT model). Similarly, for Cyprus the best model is a restricted LRT model with fuel consumption as the proxy variable. Again, while occasionally a test is violated, there are no significant differences in the diagnostics tests across models, so the optimal model is selected mostly based on in-sample predictions. One interesting observation is that both the proxy variables considered as potentially correlated with fatalities (resulting from the SUTSE model tests), and the finally selected (from the LRT model results) are not the same for the two considered countries. Considering that the two countries have several similarities, this is an interesting finding, suggesting that the selection of proxy variables may be a very volatile process, dependent on many variables.

TABLE 3. Model results and prediction validation for considered models (Greece)

	LLT	LRT - GDP		LRT - Fuel	
Index		**Full**	**Restricted**	**Full**	**Restricted**
log likelihood	85.66	56.78	53.07	39.47	31.94
AIC	-171.20	-112.45	-105.65	-77.82	-63.39
Model Quality					
Box-Ljung test 1 GDP		3.32	3.15	1.75	0.648
Box-Ljung test 2 GDP		3.33	3.18	3.80	1.38
Box-Ljung test 3 GDP		3.35	3.20	3.97	3.19
Box-Ljung test 1 Fatalities	2.73	7.24**	7.44**	4.73*	10.17**
Box-Ljung test 2 Fatalities	3.63	14.66***	9.24**	9.91**	10.17**
Box-Ljung test 3 Fatalities	5.82	16.87***	15.83**	11.75**	11.68**
Heteroscedasticity Test GDP		22.34*	20.95*	1.36	1.28
Heteroscedasticity Test Fatalities	0.785	0.253	1.30	0.308	7.19
Normality Test standard Residuals GDP		10.77**	11.11**	0.707	0.777
Normality Test standard Residuals Fatalities	0.798	0.573	3.53	0.560	0.700
Normality Test output Aux Res GDP		1.02	0.374	0.360	0.448
Normality Test output Aux Res Fatalities	1.27	1.39	1.710	0.821	1.28
Normality Test State Aux Res Level exposure		0.13	0.169	1.18	0.802
Normality Test State Aux Res Slope exposure		8.06*	7.80*	0.233	0.420
Normality Test State Aux Res Level risk	1.61	0.929	0.699	0.795	0.621
Normality Test State Aux Res Slope risk	0.047	0.142	0.000	0.541	0.008
Model Q-matrix tests					
Level exposure		3.32E-06	-	3.59E-05	-
Level risk	3.91E-03 *	1.85E-03	-	1.91E-03	-
Slope exposure		2.4E-04*	2.4E-04*	1.1E-04*	1.5E-04*
Slope risk	1.25E-04 *	3.24E-06	-	1.34E-04	-
Transition Correlations					
Level exposure with Level risk		0.97		0.99	
Slope exposure with Slope risk		-1		-1	
Model H-matrix tests					
GDP Greece/Fuel consumption	1.00E-09	1.01E-09	2.14E-06	6.97E-09	9.62E-06
Fatalities Greece		4.75E-09	2.4E-03*	6.60E-08	4.7E-03*
Validation of predictive performance					
ME Fatalities 10	-900	-805	-263	-805	-210
MSE Fatalities 10	956930	757465	76753	757459	50784
ME Fatalities 7	-693	147	110	148	359
MSE Fatalities 7	551770	25790	15793	26023	137757
ME Fatalities 4	-131	-139	46	-139	208
MSE Fatalities 4	28162	31137	7061	30823	45604

Note: *, **, and *** denote significant at the 95%, 99% and 99.9% level respectively

TABLE 4. Model results and prediction validation for considered models (Cyprus)

	LLT		LRT -Vehicles		LRT - Fuel	
Index	**Full**	**Restricted**	**Full**	**Restricted**	**Full**	**Restricted**
log likelihood	13.68	13.68	42.39	42.39	52.96	52.72
AIC	-27.06	-27.16	-83.88	-84.18	-105.02	-105.05
Model Quality						
Box-Ljung test 1 GDP			4.15*	1.00	4.70*	4.25*
Box-Ljung test 2 GDP			4.16	4.16	5.30	4.76
Box-Ljung test 3 GDP			6.71	4.16	5.67	5.20
Box-Ljung test 1 Fatalities	1.25	1.19	2.33	2.16	1.61	2.16
Box-Ljung test 2 Fatalities	2.99	1.25	3.84	2.33	1.90	2.17
Box-Ljung test 3 Fatalities	3.06	2.99	4.23	3.84	2.27	2.32
Heteroscedasticity Test GDP			4.68	4.68	0.469	0.505
Heteroscedasticity Test Fatalities	2.13	2.13	0.37	0.37	2.44	2.39
Normality Test standard Residuals GDP			2.15	2.15	1.98	1.15
Normality Test standard Residuals Fatalities	6.83*	6.83*	2.38	2.38	5.88	4.61
Normality Test output Aux Res GDP			0.33	0.33	0.923	0.284
Normality Test output Aux Res Fatalities	0.375	0.375	0.51	0.51	3.737	4.36
Normality Test State Aux Res Level exposure			0.00546	1.63	1.63	10.01**
Normality Test State Aux Res Slope exposure			0.0789	0.10	0.10	0.0952
Normality Test State Aux Res Level risk	3.81	3.815	0.62	0.62	2.689	0.473
Normality Test State Aux Res Slope risk	0.00616	0.00616	0.01	0.01	0.0772	0.00454
Model Q-matrix tests						
Level exposure			6.2E-19	-	9.2E-05	-
Level risk	1.91E-16	-	3.2E-15	-	6.53E-04	-
Slope exposure			1.5E-04*	1.5E-04*	1.1E-04*	1.1E-04*
Slope risk	3.8E-04	3.8E-04*	7.7E-04*	7.7E-04*	8.1E-06	-
Transition Correlations						
Level exposure with Level risk			0.049		-1	
Slope exposure with Slope risk			-1	-1	1	
Model H-matrix tests						
Vehicles/Fuel consumption			1.6E-04	1.6E-04*	3.6E-04	4.1E-04*
Fatalities	1.0E-09	1.0E-09	1.8E-03	1.8E-03	1.1E-03	8.0E-04
Validation of predictive performance						
ME Fatalities 10	-11	-11	-19	-45	-19	-14
MSE Fatalities 10	256	256	525	2592	529	343
ME Fatalities 7	5	5	7	7	7	6
MSE Fatalities 7	156	156	170	178	170	159
ME Fatalities 4	-17	-17	-19	-26	-19	-6
MSE Fatalities 4	358	358	447	808	447	84

Note: * and ** denote significant at the 95% and 99% level respectively

ASSESSMENT OF PREDICTIONS

Figure 2 presents the forecast plots for the selected model for Greece, i.e. the restricted LRT model using GDP as a proxy to exposure. There are several observations that can be made about these figures. Starting from the top subfigure, the projection of the GDP for Greece appears to follow a downward trend all the way to 2020. While this is not impossible, it is highly unlikely. The reason for this trend is that the model detects the drop in the GDP in the last couple of years (due to the recession) but has no way to tell whether this trend will be reversed at some point. One way to overcome this would be to add an additional intervention variable to the model, which would indicate that the last few observations are part of a temporary recession phenomenon. This variable could then be used to indicate when the recession is expected to be over. Another way to indicate the same point (i.e. that these points are an intermediate disruption of an otherwise constant trend) would be to fix the slope of the exposure. However, the latter option would imply that the recovery would start from the first predicted point (i.e. 2011), which is clearly not the case. Therefore, the approach of an intervention recession variable has been selected, using 2013 as the last recession year. Figure 3 shows the results of this model, i.e. assuming that the recession is expected to last until 2013.

Figure 4 shows the predictions for Cyprus, which seem plausible and therefore no further investigations are made.

Table 5 summarizes the models' forecasts: for Greece there is the previously selected model (top), followed by the model that includes the intervention that captures the recovery from the recession (middle), assuming that the recovery will start after 2013, and the forecasts for the selected model for Cyprus.

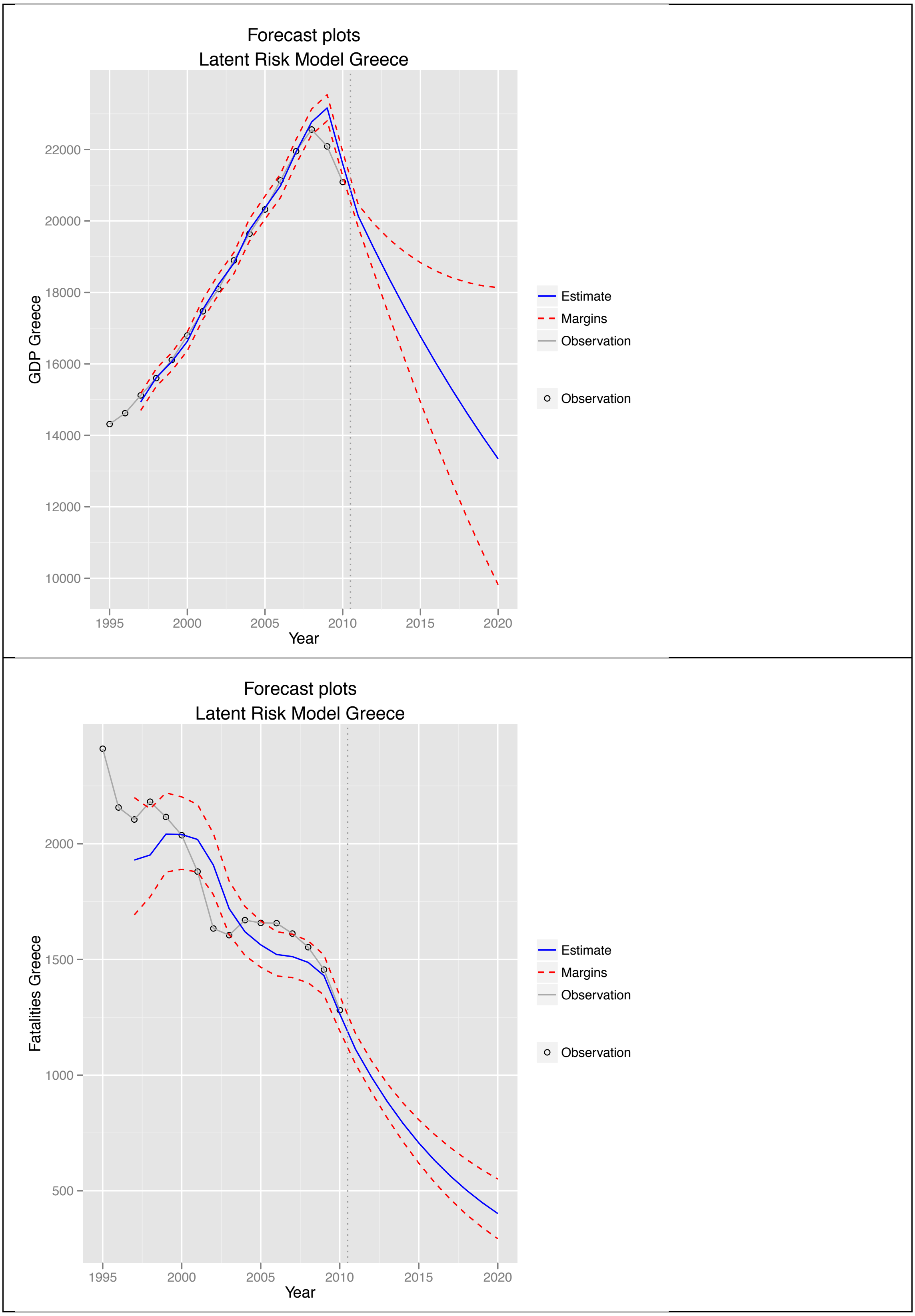
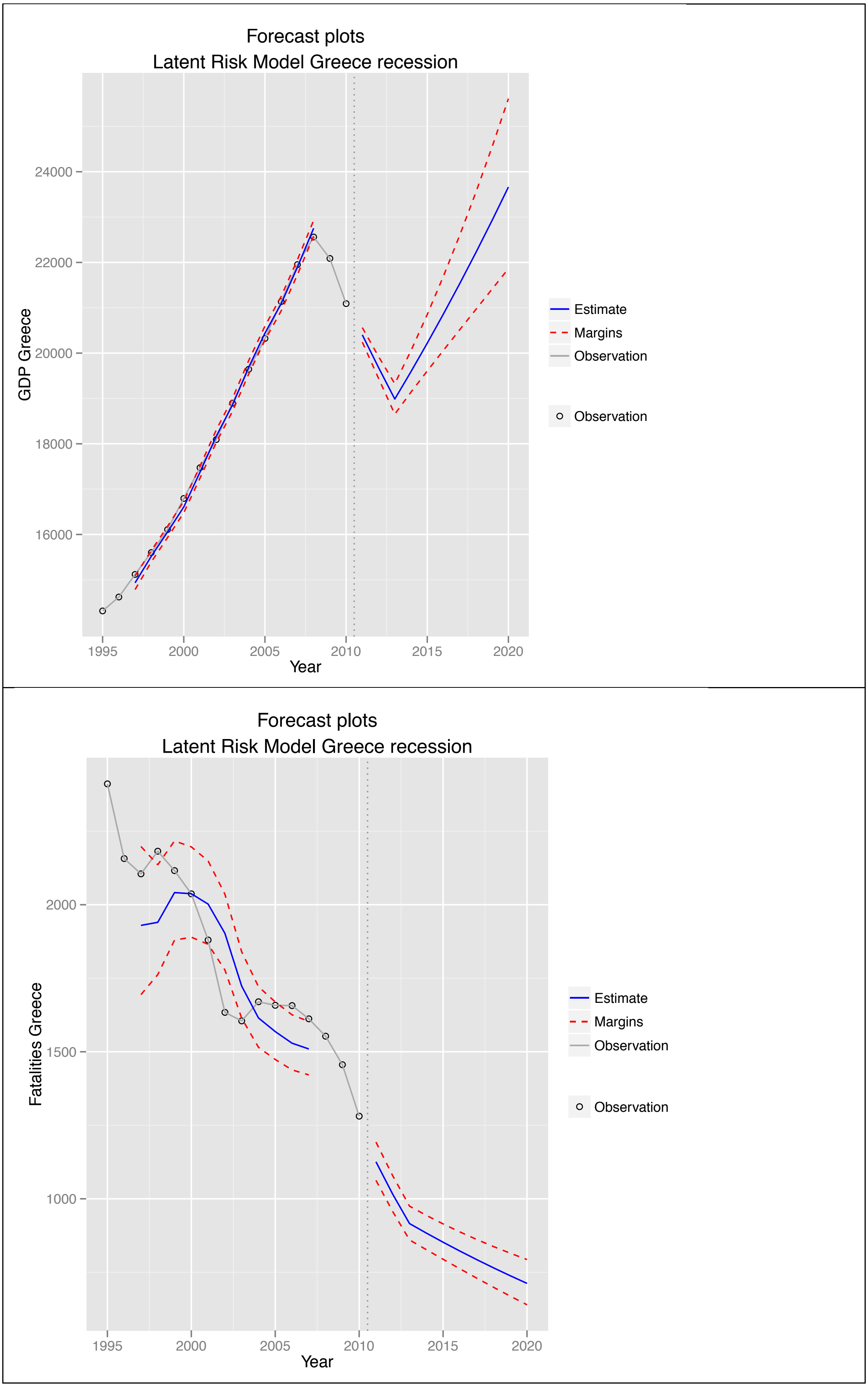
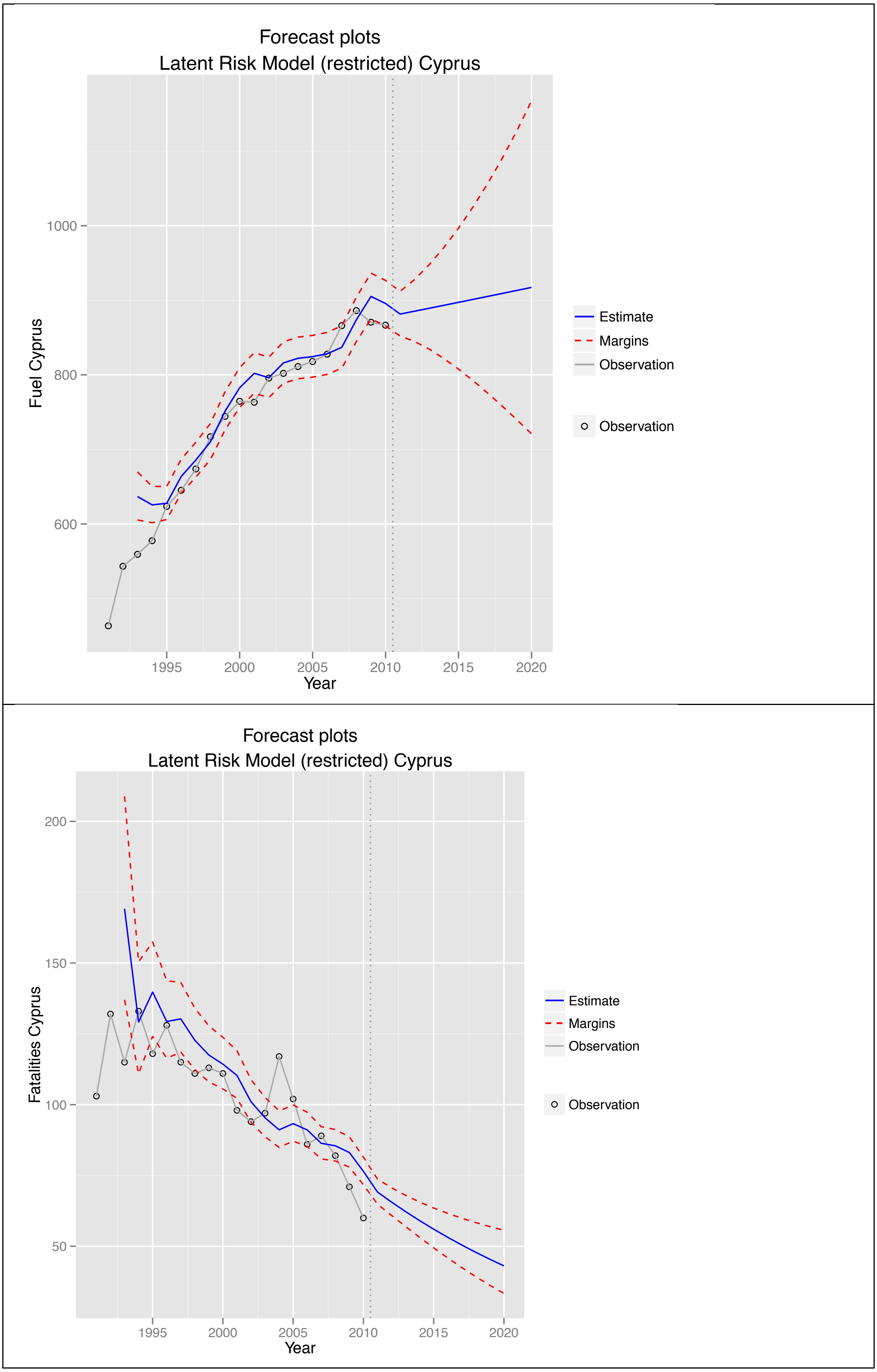


FIGURE 2. Forecasting results, without considering recession (Greece)



1 **FIGURE 3. Forecasting results, considering recession until 2013 (Greece)**



1 **FIGURE 4. Forecasting results (Cyprus)**

TABLE 5. Selected model forecasts (top: Greece, middle: Greece reflecting recession recovery, bottom: Cyprus)

Greece – (originally) selected model based on goodness-of-fit statistics

Year	Forecast GDP Greece (Euro)	Lower (2.50%) forecast (Euro)	Upper (97.50%) forecast (Euro)	Forecast Fatalities Greece	Lower (2.50%) forecast	Upper (97.50%) forecast
2011	20137.3	19520.3	20773.7	1111	988	1249
2012	19237.2	17952.4	20613.9	993	867	1136
2013	18377.3	16372.9	20627.1	886	751	1046
2014	17555.9	14826.9	20787.2	792	643	975
2015	16771.1	13342.9	21080.3	707	545	918
2016	16021.5	11939.5	21499.1	631	458	870
2017	15305.4	10628.1	22041.1	564	383	831
2018	14621.2	9414.8	22706.9	504	318	798
2019	13967.7	8302.0	23500.0	450	262	771
2020	13343.4	7289.1	24426.1	402	216	748

Greece – including recession intervention (to capture recovery from recession at the end of 2013)

Year	Forecast GDP Greece (Euro)	Lower (2.50%) forecast (Euro)	Upper (97.50%) forecast (Euro)	Forecast Fatalities Greece	Lower (2.50%) forecast	Upper (97.50%) forecast
2011	20401.7	20088.1	20720.3	1126	1005	1262
2012	19681.3	19213.1	20160.9	1015	902	1143
2013	18986.4	18336.4	19659.4	916	809	1036
2014	19593.1	18710.8	20517.1	883	776	1006
2015	20219.3	19029.3	21483.6	852	742	979
2016	20865.4	19313.8	22541.8	822	708	955
2017	21532.2	19574.0	23686.4	793	674	934
2018	22220.4	19814.7	24918.1	765	641	914
2019	22930.5	20038.3	26240.1	738	608	897
2020	23663.3	20246.1	27657.1	712	576	881

Cyprus – selected model based on goodness-of-fit statistics

Year	Fuel Cyprus (x1000 tn.eq. oil)	Lower (2.50%) forecast	Upper (97.50%) forecast	Fatalities Cyprus	Lower (2.50%) forecast	Upper (97.50%) forecast
2011	881.5	824.4	942.6	69	61	78
2012	885.4	807.0	971.4	66	57	76
2013	889.3	784.2	1008.5	62	52	74
2014	893.3	757.9	1052.8	59	48	73
2015	897.2	729.2	1103.9	56	44	72
2016	901.2	698.8	1162.2	53	40	71
2017	905.2	667.3	1227.8	50	36	71
2018	909.2	635.2	1301.3	48	32	71
2019	913.2	602.8	1383.5	45	29	71
2020	917.3	570.4	1475.0	43	26	71

DISCUSSION AND CONCLUSION

Developing credible road safety forecasting models is a key prerequisite to assessing and improving future road safety. One of the key requirements (and often the weakest link) in this process is reliable and up-to-date exposure data. While some countries may have the appropriate data, e.g. vehicle-kilometers as the suitable variable for exposure, many countries and regions face limitations. One practical way to overcome this issue is to identify and use appropriate proxy variables that could be used instead of the actual exposure variables. In this research, three alternative (and in general widely available) variables are considered as suitable exposure proxies: (i) number of vehicles in circulation, (ii) GDP and (iii) fuel consumption. A number of different structural time-series models have been developed for each proxy for two Mediterranean countries with many similar socio-economic characteristics: Greece and Cyprus.

Based on the findings of this analysis, a number of observations can be drawn:

- Proxy variables can provide reasonable results, when exposure data are not available;
- Even in two countries with many similarities, such as Greece and Cyprus examined in this research, the selected proxy measure differs. This suggests that the underlying conditions that make a variable a suitable proxy for exposure is complex and needs further investigation.

The findings of this research also suggest a number of directions for future research. Beyond the obvious need for investigation of more proxy variables, as well as application in more countries and regions, a useful test would use data from a country or region that does have exposure data to compare the predictive results of models using the proxy measures versus those obtained with models directly using exposure. As the available data sample is rather small for such complicated models, it is expected that longer time-series would lead to better models. The investigation of the impact of other parameters (such as the size of the region) is also an interesting endeavor, as e.g. in smaller regions (such as Cyprus and Greece) the annual number of accidents can fluctuate a lot, compared to larger regions such as Germany or the US.

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REFERENCES

1. Smeed, R J., 1968. Variations in the pattern of accident rates in different countries and their causes. Traffic Engineering Control, 10(7), 364-371.
2. Jacobs, G. D., 1986. Road accident fatality rates in developing countries-a reappraisal. In: PTRC. Summer Annual Meeting, University of Sussex, 14-17 July 1986., Proc of Seminar H. London: PTRC Education and Research Services, pp. 107-119.
3. Gharaybeh, F. A., 1994. Application of Smeed's formula to assess development of traffic safety in Jordan, Accident Analysis and Prevention, Volume 26, Issue 1, pp. 113-120.
4. Broughton, J., 1991. Forecasting road accident casualties in Great Britain. Accident Analysis and Prevention, 23(5), October, pp 353-362.

5. Andreassen, D., 1991. Population and registered vehicle data vs. road deaths. Accident Analysis and Prevention, 23(5), October, pp 343-351.
6. COST329, 2004, Models for traffic and safety development and interventions. Final Report of the Action. European Commission, Luxembourg.
7. Kopits, E. and M. Cropper (2005). Traffic fatalities and economic growth. Accident Analysis and Prevention, Vol. 37, Iss. 1, pp. 169-178.
8. N. Söderlund and A. B. Zwi (1995). Traffic-related mortality in industrialized and less developed countries. Bulletin of the World Health Organization, Vol. 73, Iss. 2, pp. 175-182.
9. Bishai, D., A. Quresh, P. James and A. Ghaffar (2006). National road casualties and economic development. Health economics, Vol. 15, Iss. 1, pp. 65-81.
10. WHO (2011). UN Decade of Action for Road Safety 2011-2020. Available online: http://siteresources.worldbank.org/EXTTOPGLOROASAF/Resources/2582212-1265307800361/decade_of_action_2011.pdf (Accessed November 13, 2012)
11. Ahmad, S., and D.L. Greene (2005). Effect of fuel economy on automobile safety: A reexamination. Transportation Research Record: Journal of the Transportation Research Board, Vol. 1941, pp. 1-7.
12. Haworth, N. and M. Symmons (2001). Driving to reduce fuel consumption and improve road safety. Road Safety Research, Policing And Education Conference, Melbourne, Victoria, Australia
13. Kopitch, L. and J.-D. Saphores (2011). Assessing the Effectiveness of Changeable Message Signs on Secondary Crashes. Proceedings of the 90th Annual Meeting of the Transportation Research Board, January 2011, Washington, D.C.
14. Lin, H., C. Chen and C. McKnight (2011). Exploring impacts of safety culture on immigrants' vulnerability in non-motorized crash: a cross-sectional study. Proceedings of the 90th Annual Meeting of the Transportation Research Board, January 2011, Washington, D.C.
15. Ukkusuri, S., S. Hasan and H.M. Abdul Aziz (2011). A Random-parameter Model to Explain the Effects of Build Environment Characteristics on Pedestrian Crash Frequency. Proceedings of the 90th Annual Meeting of the Transportation Research Board, January 2011, Washington, D.C.
16. Yannis, G. and M. G. Karlaftis (2010). Weather Effects on Daily Traffic Accidents and Fatalities: A Time Series Count Data Approach. Proceedings of the 89th Annual Meeting of the Transportation Research Board, January 2010, Washington, D.C.
17. Buehler, R., and J. Pucher (2011). Impacts of Bike Paths and Lanes on Cycling in Large American Cities. Proceedings of the 90th Annual Meeting of the Transportation Research Board, January 2011, Washington, D.C.
18. Quddus, M. A., C. Wang and S. G. Ison (2009). The Impact of Road Traffic Congestion on Crash Severity Using Ordered Response Models. Proceedings of the 88th Annual Meeting of the Transportation Research Board, January 2009, Washington, D.C.
19. Holguín-Veras, J., M. Jaller, L. Destro, X. Ban, C. Lawson and H. S. Levinson (2011), Freight Generation, Freight Trip Generation, and the Perils of Using Constant Trip Rate, Proceedings of the 90th Annual Meeting of the Transportation Research Board. January 2011, Washington D.C.
20. de Jong, G., and M. Ben-Akiva (2007). A micro-simulation model of shipment size and transport chain choice. Transportation Research Part B, Vol. 41, pp. 950-965.
21. Wang, C., M. A. Quddus and S. G. Ison (2012). Factors affecting road safety: a review and future research direction. Proceedings of the 91st Annual Meeting of the Transportation Research Board, January 2012, Washington, D.C.
22. Noland, R. B., and M. A. Quddus. Congestion and Safety: A Spatial Analysis of London. Transportation Research Part A: Policy and Practice, Vol. 39, No. 7-9, 2005, pp. 737- 754.

23. Kononov, J., B. Bailey, and B. Allery. Relationships between Safety and both Congestion and Number of Lanes on Urban Freeways. Transportation Research Record: Journal of the Transportation Research Board, Vol. 2083, 2008, pp. 26-39.
24. Kepaptsoglou, K., M. G. Karlaftis and G. Mintsis (2011). A model for planning emergency response services in road safety. Proceedings of the 90th Annual Meeting of the Transportation Research Board, January 2011, Washington, D.C.
25. Kepaptsoglou, K., D. Tsamboulas, M. G. Karlaftis and V. Marzano (2009). Analyzing Free Trade Agreements Effects in the Mediterranean Region: A SURE Gravity Model Based Approach. Proceedings of the 88th Annual Meeting of the Transportation Research Board, January 2009, Washington, D.C.
26. Stipdonk, H., P. Wesemann and B. Ale (2010). The expected number of road traffic casualties using stratified data. Safety Science, 48, pp. 1123-1133.
27. Hollo, P., V. Eksler and J. Zukowska (2010). Road safety performance indicators and their explanatory value: A critical view based on the experience of Central European countries. Safety Science, 48, 1142-1150.
28. Harvey, A. C. and N. Shephard, 1993. Structural Time Series Models. In G. S. Maddala, C. R. Rao and H. D. Vinod, eds., Handbook of Statistics, Vol. 11, pp. 261-302, Elsevier Science Publishers, B. V.
29. Harvey A.C., 1994. Forecasting, Structural Time Series Models and the Kalman Filter, Cambridge University Press.
30. Commandeur, J.J.F., and S.J. Koopman (2007). An Introduction to State Space Time Series Analysis. Oxford University Press.
31. Bijleveld, F. (2008). Time series analysis in road safety research using state space methods, Doctoral Dissertation, Free University, Amsterdam, Netherlands.
32. Oppe, S., 1989. Macroscopic Models for Traffic and Traffic Safety. Accident Analysis and Prevention, 21 (3), pp. 225-232.
33. Oppe, S. (1991). "The development of traffic and traffic safety in six developed countries". Accident Analysis and Prevention 23 (5): 401–412.
34. Petris, G., S. Petrone and P. Campagnoli, 2009. Dynamic Linear Models with R. Springer Science + Business Media
35. Yannis, G., C. Antoniou, E. Papadimitriou and D. Katsochis (2011). When may road fatalities start to decrease? Journal of Safety Research, 42(1), pp. 17-25.
36. Borsos, A., C. Koren, J. Ivan and N. Ravishanker (2012). Long-Term Safety Trends Related to Vehicle Ownership in 26 Countries. Transportation Research Record: Journal of the Transportation Research Board (in press).