On statistical interference in time series analysis of the evolution of road safety

Jacques J.F. Commandeur[a,b,*], Frits D. Bijleveld[b], Ruth Bergel-Hayat[c], Constantinos Antoniou[d], George Yannis[d], Eleonora Papadimitriou[d]

[a]VU University Amsterdam, The Netherlands [b]SWOV Institute for Road Safety Research, P.O. Box 1090, 2260 BB Leidschendam, The Netherlands [c]IFSTTAR French Institute of Science and Technology for Transport, Development and Networks, France [d]NTUA National Technical University of Athens, Greece

Abstract

Data collected for building a road safety observatory include observations made sequentially through time. Examples of such data, called time series data, include annual (or monthly) number of road traffic accidents, traffic fatalities or vehicle kilometers driven in a country, as well as the corresponding values of safety performance indicators (e.g., data on speeding, seat belt use, alcohol use, etc). Some commonly used statistical techniques imply assumptions that are often violated by the special properties of time series data, namely serial dependency among disturbances associated with the observations. The objective of this paper is to demonstrate the impact of such violations to the applicability of standard methods of statistical inference, which leads to an under or overestimation of the standard error and consequently may produce erroneous inferences. Moreover, having established the adverse consequences of ignoring serial dependency issues, the paper aims to describe rigorous statistical techniques used to overcome them. In particular, appropriate time series analysis techniques of varying complexity are employed to describe the development over time, relating the accident-occurrences to explanatory factors such as exposure measures or safety performance indicators, and forecasting the development into the near future. Traditional regression models (linear, generalized linear and non-linear) are presented, discussing possible violations of their assumptions when dealing with time series data and the possibility to address these issues by adding suitable mod

*Corresponding author: Jacques J.F. Commandeur

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ifications. Dedicated time series analysis techniques, such as the ARMA-type and DRAG approaches are discussed next, followed by structural time series methods, which are a sub-class of state space methods. The paper concludes with general recommendations and practice guidelines for the use of time series analysis in road safety research.

Keywords: Road safety, time series analysis, regression, ARIMA models, DRAG model, state space methods, structural time series methods, statistical theory

1. Introduction

Time series analysis is used in road transport and road safety research for describing, explaining and forecasting trends at an aggregate level. The technique is applied to road safety indicators aggregated over an area (a country, road type or accident type, or combination thereof) and regular time intervals. Road safety indicators such as the number of injury accidents and victims – among which the number of road fatalities in particular – are chosen for measuring road safety at for instance a national level.

Since the 1980's, a systematic approach to modeling the road risk process has emerged: it consists of relating risk indicators to all of their determinants and to account for road safety measures simultaneously (Hakim et al., 1991). To this end, risk indicators and risk factors have been defined at different levels of the road risk process: in the DRAG approach (Gaudry, 1984, Lassarre, 1994, Gaudry and Lassarre, 2000) these are road demand, accident risk, and accident severity.[1] The three-level approach refers to the two dimensions of road risk (the risk that an accident occurs and the risk that a person is injured in that accident), on the one hand, and to the fact that exposure to risk is the inevitable primary risk factor on the other hand.

A review of time series analysis of road safety trends as performed at the national level in Europe since the 1980's highlights a progress in the time series analysis techniques: from descriptive towards explanatory models (see Bergel, 2008 and Bergel-Hayat, 2008), and from deterministic towards stochastic models under the form of structural models, see Harvey (1989),

[1]The name DRAG is formed by the acronym of the French words “Demande Routi`ere, Accidents, et leur Gravit´e”, which translates into “Demand for Road use, Accidents and their Severity”.

Durbin and Koopman (2001), Commandeur and Koopman (2007), and Bijleveld et al. (2008).

Research streams stemming from the former COST 329 project (COST329, 2004) and the International Cooperation on Time series Analysis (ICTSA, 2000-2006) network converged in a coherent common approach for modeling and comparing the development in road safety trends among different countries. This common approach was formalized within Work Package 7 of the SafetyNet project dealing with “Data Analysis and Synthesis”.

Not all types of models are appropriate for analyzing changes in sequential measurements of casualty data sets in the road safety field. The present paper contains a review of the different types of time series analysis techniques studied and applied within the SafetyNet project, with a focus on how to overcome the problem of dependencies between model residuals (measured by serial correlation). The importance of this issue for proper statistical inferences is outlined in Section 2.

For all considered techniques, whether they handle time dependencies explicitly or not, a standardized approach was followed in describing the successive steps (objective of the technique, model definition and assumption, data set and research problem, model fit, estimation, diagnostic and interpretation of application results) in conducting the modeling. Detailed information for understanding each of these steps can be found in the Methodology report (Dupont and Martensen, 2007b) and in the Manual (Dupont and Martensen, 2007a) produced by the members of Work Package 7 of the SafetyNet project. In this paper, the main features of each technique are presented, illustrating their use, outcomes, and interest through some applications.

The paper is structured as follows. The impact of ignoring serial correlation in time series residuals is first highlighted in Section 2. Classical statistical techniques are then discussed in Section 3 while dedicated techniques that handle time dependency explicitly are presented in Section 4. The paper concludes with a summary, along with recommendations for analyzing road safety developments at an aggregate level.

2. The impact of time dependencies

Many road traffic data consist of time series: sets of observations that are sequentially ordered over time. Examples are the annual or monthly number of road traffic accidents in a country, its annual or monthly number of road traffic fatalities, its annual or monthly number of vehicle kilometers driven, its annual or monthly values on safety performance indicators, etc.

Whenever one is interested in studying and analyzing such sequentially ordered observations, special issues arise. In this section we illustrate with a simple example what these special issues are, and how they can be dealt with by using a special family of analysis techniques collectively known as time series models.

The example consists of the logarithm of the total annual number of road traffic fatalities observed in Norway for the period 1970 − 2009, as displayed with circles in Figure 1. Since the period spans 40 years, there are n = 40 observations. In order to try and capture the dynamics of this time series, we first naively perform a classical linear regression of these 40 sequentially ordered observations on time.

Typically, in simple classical linear regression a linear relationship is assumed between a criterion or dependent or endogenous variable y, and a predictor or independent or exogenous variable x such that

$$y_i = \alpha + \beta x_i + \varepsilon_i, \varepsilon_i \sim NID(0, \sigma_\varepsilon^2) \quad (1)$$

where i =1,...,n and n is the number of observations. The expression

$$\varepsilon_i \sim NID(0, \sigma_\varepsilon^2) \quad (2)$$

in (1) is shorthand notation for: the residuals ε_i are assumed to be normally and independently distributed with mean equal to zero and variance equal to σ_ε^2.

Now suppose that the dependent variable y in (1) is the just mentioned series of the logarithm of the number of Norwegian road traffic fatalities. Also, suppose that the independent variable x in (1) consists of the numbered consecutive time points in the series (thus, x =1, 2,..., 40). The usual scatter plot of these two variables – including the best fitting line according to classical linear regression model (1) and its 95% confidence limits – is shown in Figure 1. The equation of the regression line in Figure 1 is

$$\hat{y}_i = \hat{\alpha} + \hat{\beta} x_i = 6.2958 - 0.02114\, x_i,$$

with error variance $\hat{\sigma}_\varepsilon^2 = 0.00936$. The standard t-test for establishing whether the regression coefficient

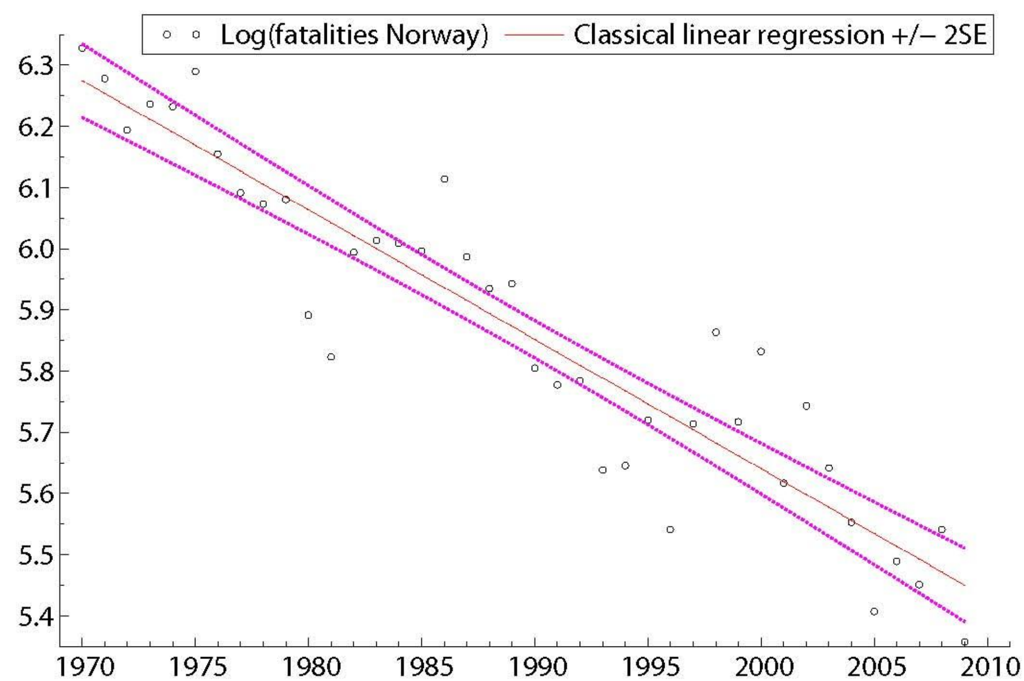

Figure 1: Classical linear regression results for logarithm of annual number of Norwegian fatalities, including 95% confidence limits.

$\hat{\beta} = -0.02114$ deviates from zero yields

$$t = \frac{\hat{\beta}}{\hat{\sigma}_{\hat{\beta}}} = \frac{\hat{\beta}}{\sqrt{\dfrac{\hat{\sigma}_{\varepsilon}^{2}}{\sum_{i=1}^{n}(x_i - \bar{x})^2}}} = \frac{-0.02114}{\sqrt{\dfrac{0.00936}{5330}}} = \frac{-0.02114}{0.00132} = -15.95.$$

Since the value of this t-test is associated with a p-value of 2E-18, the linear relationship between the criterion variable y and the predictor variable x is extremely significant. When the assumptions for classical linear regression are valid we may conclude that time is a highly significant predictor of the logarithm of the number of Norwegian road traffic fatalities, and that there is a negative relation between these two variables: as time proceeds the logarithm of the number of fatalities decreases.

However, one issue has completely been overlooked in this analysis. The validity of the just mentioned t-test is, amongst others, based on the fundamental assumption that the 40 observations in the time series, after their correction for the intercept α and the exogenous variable x, are independent of each other, as implied by (2). That the observations are not independent becomes more obvious by connecting them with lines, as has been done in the top graph of Figure 2. Inspection of the latter graph shows that the observations in a certain year tend to be more similar to the observation of the previous year than to other earlier observations.

The dependencies between the observations are also reflected in the residuals of model (1) shown at the bottom of Figure 2. Positive values of the residuals tend to be followed by further positive values, while negative values tend to be followed by further negative values, a clear sign that the residuals may not be independent as a result of their serial correlation. Diagnostic tests such as the Box-Ljung test for autocorrelation also confirm that the assumption of residual independence is not satisfied in the current analysis.

For the present analysis this means that all standard errors are too small, and the 95% confidence interval around the regression line (which is based on the standard error of regression) shown in Figure 1 clearly reflects this problem. Instead of the two out of 40 observations that are expected to exceed the 95% confidence limits, we find that almost half of them (i.e., 18) are located outside these limits. The value of −15.95 for the t-test of the regression coefficient is therefore also flawed, and certainly too large.

These issues can be solved by somehow absorbing the time dependencies

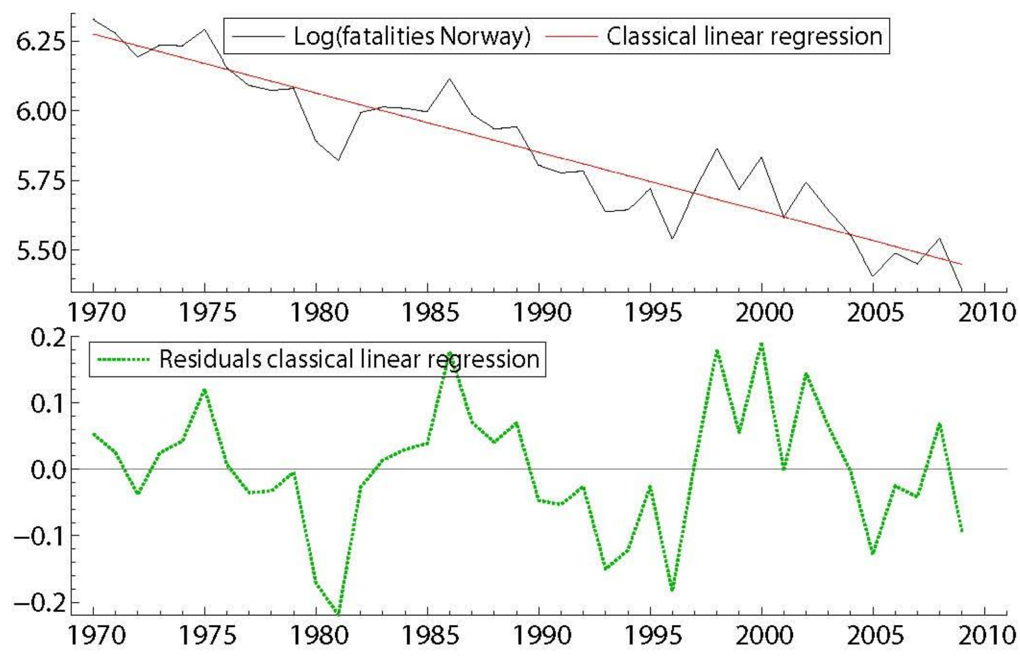

Figure 2: Classical linear regression results for logarithm of annual number of Norwegian fatalities (top), and residuals (bottom).

between the observations into the model predictions. One way to achieve this is by adding explanatory variables to the classical linear regression model in the hope that these explanatory variables – being time series also – will absorb at least part of the dependencies in the criterion variable. In fact, a misspecified model may suffer from many issues. In this paper it is however assumed that all relevant factors are included in a model. The second more general – and in the absence of suitable explanatory variables only possible – approach is to apply dedicated time series models such as ARMA-type and structural time series models (hereafter called state space models) for the analysis of time series data. ARMA-type and state space models handle the dependencies between the observations constituting a time series by absorbing them directly into the model. In state space models this is achieved by allowing the intercept and/or the regression coefficient – that are constants in classical linear regression – to vary over time.

As an example, consider the results of applying a what is called local level with fixed slope model (Harvey, 1989) to the logarithm of the number of Norwegian fatalities series. In this model the remaining time dependencies between the observations are handled by allowing the intercept α in model

(1) to vary over time, as follows:

$$\begin{aligned} y_t &= \alpha_t + \beta x_t + \varepsilon_t, \varepsilon_t \sim NID(0,\sigma_\varepsilon^2) \\ \alpha_{t+1} &= \alpha_t + \xi_t, \xi_t \sim NID(0,\sigma_\xi^2) \end{aligned} \quad , (3)$$

where $t = 1,...,n$, and n is again the number of observations. In the second equation in (3), which defines a random walk, dependencies in the observed time series are dealt with by letting the intercept at time $t + 1$ be a direct function of the intercept at time t. In this way it takes into account that the observed value of the series at time point $t + 1$ is usually more similar to the observed value of the time series at time point t than to other previous values in the series. Compared to model (1), model (3) requires the estimation of one extra parameter which is σ_ξ^2.

Applying model (3) to the logarithm of the number of Norwegian fatalities series, we find that $\hat{y}_t = \hat{\alpha}_t - 0.02334\, x_i$,

for $t = 1,...,n$, with variances $\sigma C_\varepsilon^2 = 0.00381$ and $\sigma C_\xi^2 = 0.00347$. The values of the latter $\hat{y}_t$ are plotted at the top of Figure 3, while the values of the residuals ε_t obtained with model (3) are graphed at the bottom of Figure 3.

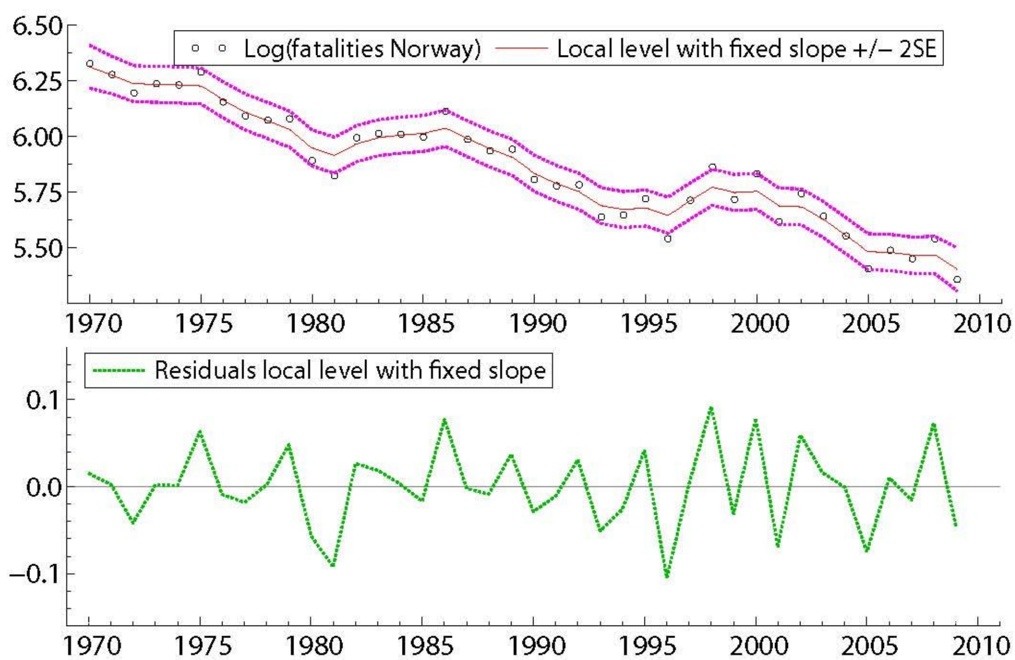

Figure 3: Time series analysis results for logarithm of annual number of Norwegian fatalities, including 95% confidence limits (top), and residuals (bottom).

The standard t-test for establishing whether the regression coefficient $\hat{\beta} = -0.01986$ deviates from zero now yields

$$t = \frac{\hat{\beta}}{s_{\hat{\beta}}} = \frac{-0.02334}{0.00960} = -2.43.$$

Since the value of the latter t-test is associated with a p-value of 0.020, the relation between the logarithm of the number Norwegian fatalities and time is still significant, but only at the 2.5% level. As the values of the regression coefficient obtained with classical linear regression and with time series analysis are very similar, the large difference between the values of the two t-tests can be almost completely attributed to the large differences in their standard errors: 0.00132 for classical linear regression versus 0.00960 for time series analysis. The former standard error is based on the residuals shown at the bottom of Figure 3. The assumption of independence of these residuals is not rejected with a Box-Ljung test. The appropriateness of model (3) is also reflected in the 95% confidence limits around its predictions as displayed at the top of Figure 3: In the present analysis only three of the forty observations exceed the 95% confidence limits. In conclusion, we have indicated adverse effects of neglecting serial correlation present in observations that are sequentially ordered over time. Statistical tests based on standard techniques like classical linear regression easily result in ‘overoptimistic’ (or the opposite, over conservative) or even plain erroneous conclusions. Dedicated time series analysis techniques like ARMA type and state space models, on the other hand, explicitly take the time dependencies between the observations into account, thus greatly improving the chances of obtaining residuals that do satisfy the model assumptions, and allowing to reliably test whether the estimated relationships between dependent and independent variables in the analysis are statistically meaningful or not.

3. Classical techniques

This section outlines the classical regression techniques and their extensions, as they apply to the field of serially correlated road safety time series data.

3.1. Classical linear regression models

The linear regression model is the most widely used model, as it is relatively straightforward and easy to apply and interpret. However, linear regression is based on a set of fairly stringent assumptions (see, for instance, Washington et al., 2003). If these assumptions are satisfied, it can be shown that the solution obtained by minimizing the sum of squared residuals is unbiased and has the lowest total variance among all unbiased linear estimators. These assumptions, however, are often violated in practice. For example, the linear regression model may not properly handle the time dependencies between consecutive observations. Therefore, the residuals obtained with this technique usually do not satisfy the important assumption of independence. As discussed and illustrated in Section 2, this limitation may result in inappropriate confidence intervals and in statistical tests that are overoptimistic or overpessimistic about the relation between variables, among others.

When the model assumptions are violated, other model forms need to be considered. The generalized linear model is considered in its time series aspects in Section 3.2 and the suitability of some distributions that can be applied to serially correlated road safety data is discussed. Nonlinear least squares models are considered in Section 3.3 as another family of models for which the treatment of time dependencies is additionally introduced.

3.2. GLM models

Generalized linear models (e.g., McCullagh and Nelder, 1989, Dobson, 1990, Gill, 2000) can be used to overcome some of the restrictions of classical linear regression. This technique is more flexible than classical linear regression in the sense that it allows for error distributions within the exponential family of distributions. Among others, this family includes the normal distribution, which is the one assumed in classical linear regression, the Poisson distribution and the negative binomial distribution.

Just like classical linear regression models, generalized linear models require uncorrelated error terms. As indicated in Section 2 time series data require special consideration in this respect, as neighboring errors are likely to be correlated. It is sometimes possible to include a large number of explanatory variables in a linear regression model, resulting in new serially uncorrelated residuals (and, therefore, the linear model theory would apply). There are, however, two difficulties with such a strategy. First, it may not be easy to identify the appropriate explanatory variables that would reflect the serial correlation. Second, and perhaps more importantly, the additional variables included in the model to reduce the serial correlation may dilute the effects of the main explanatory variables of interest, thus potentially affecting the interpretation of the model. Yannis et al. (2007) used variants of the generalized linear model framework for monthly casualty and police enforcement data from Greece for a period of six years. The developed models include sinusoidal terms to capture the serial correlation of observations. Several statistical goodness-of-fit diagnostic tests have been performed for the results of the estimated models, and the predictive capabilities of the models are investigated. The residuals of the quasi-Poisson and negative binomial models do not show any serial correlation. The signs of the estimated coefficients for all models are consistent and intuitive. In particular, a negative coefficient value for the number of breath alcohol controls indicates that the number of persons killed and seriously injured decreases as the intensity of breath alcohol controls increases.

3.3. Non-linear models

By using nonlinear models (e.g., Bates and Watts, 1988), even more restrictions of classical linear regression can be overcome. The biggest advantage of this technique over the previously mentioned is the broad range of functions that can be fitted. Many processes, as in road safety, are inherently nonlinear. This flexibility of nonlinear regression is also a caveat, since similarly good fits can be obtained with very different functional forms, whereas presumably only one of them represents the real underlying process in the best manner. These different models can be adequate for interpolation purposes, but may produce very different predictions when used to extrapolate,

i.e. to predict values outside the scope of the estimation data set (forecasting).

As an example of the application of the non-linear relationship between the annual number of fatalities, vehicles and population at a country's level (Smeed, 1949) was further investigated using annual data from 17 European countries between 1970 and 2002 in Yannis et al. (2011). The 25 first years of the data, i.e. 1970–1994, have been used for fitting the models while the seven last years have been used for validating the model. It was demonstrated that, with the strict Smeed's specification, the assumption of independent (in particular uncorrelated) disturbances was violated for most countries. Four extensions of Smeed's specification that tried to correct for correlation of the disturbances have also been tested to estimate the fatality rate for the 17 countries. Among them, an autoregressive nonlinear model was selected as it outperformed the other ones, while also overcoming the issue of serially correlated disturbances. The two estimated parameters for each country were interpreted, which led to separate the 17 countries into safer countries (among which the United Kingdom and the Netherlands at one extreme) and less safe countries (among which Greece and Portugal at the other extreme).

4. Dedicated techniques

For time series analysis the most important drawback of the classical linear, generalized linear and nonlinear regression models is that they do not naturally take into account the time dependencies between the consecutive observations of a time series. To adequately deal with these time dependencies, dedicated time series analysis techniques, such as ARMA (autoregressive moving average)-type models, its special case DRAG, and state space models can be employed.

It should be noted that ARMA-type and state space models are two types of model that have often been used for time series analysis of road safety indicators (Bergel, 2008; Bergel-Hayat, 2008). The first type of model typically consists in modeling an observed variable in reference to its past values, whereas the second one consists in the decomposition of an observed variable into its fundamental (and unobserved) parts assumed to be potentially stochastic: a local linear trend, a seasonal (if required), and residuals.

The remainder of this section focuses on these two types of time series models with the additional assumption of the disturbances having a Gaussian distribution.

4.1. ARMA-type models

ARMA models (in the case of stationary data – which roughly means that they result from observations of an underlying process that is constant in mean and variance over time) and ARIMA models (in the general case of non-stationary data, which is more common in road safety research) enable to describe the dynamics of a process over time and to extrapolate it into the future, without any call to additional variables and with the only assumption that the process dynamics will stay unchanged until the forecast horizon (Box et al., 1994), (Brockwell and Davies, 1987; Brockwell and Davis, 1998). Explanatory and intervention variables can also be included in ARMA and ARIMA models, and the additional corresponding regression coefficients can be estimated and interpreted.

For the analysis of road safety data, a disadvantage of ARIMA modeling may be its concept: the trend and the seasonal are removed before the modeling itself is performed on the stationary part of the process. The emphasis is on describing the dynamics of this latter process, by means of estimating a (small) number of relevant coefficients parameters. This is sufficient for many applications.

4.1.1. Background

ARMA models focus on describing the dynamics (the relationship between its values at different time points) of the stationary sample process $Y = (y_1, y_2, ..., y_n)$. This relevant property of stationarity allows separating Y_t in two parts: the one related to the past at time t, and the part that is new at time t – which is therefore called the “innovation”– in such a way that this latter component is a white noise, and is therefore called the innovation white noise.

Thus, the value Y_t taken by the process at time t, can be expressed as a function, and more precisely as a linear combination, of its passed values $Y_{t-1}, Y_{t-2}, ...$, and of the innovation white noise u_t. As different equivalent formulations can all be used for describing the process dynamics, for reasons of parsimony, a formulation that can be chosen such that Y_t is expressed as a linear combination of a small number (p) of its past values, and of a small number (q) of the past values of the disturbances.

This can be written the following way:

$$Y_t = \varphi_1 y_{t-1} + \cdots + \varphi_p Y_{t-p} + u_t + \theta_1 u_{t-1} + \cdots + \theta_q u_{t-q},$$

where $\varphi_1, \varphi_2, ..., \varphi_p, \theta_1, \theta_2, ..., \theta_q$ are $p + q$ unknown parameters, and u_t is the innovation disturbance.

In the general case where stationarity cannot be assumed, it is convenient to assume that another stationary process exists, which is derived from Y_t by removing its trend and its seasonal component. An easy way for doing this, as recommended by Box et al. (1994), is to apply a what is called filter of differences to the process Y_t, as many times as necessary until the result, the filtered process, can be considered as fulfilling the property of stationarity, and therefore be fitted with an ARMA model itself. In practice this comes to removing the trend and seasonality from a non stationary process, in other words to solving the first order non stationarity. The fact that the filtered or integrated process obtained by applying an appropriate filter of differences to Y_t is fitted with an ARMA is equivalent to say that Y_t is fitted with an ARIMA (or integrated ARMA). The second order stationarity can also be obtained by deriving another process from the initial one. The logarithmic transformation is therefore currently applied to the initial data in order to stabilizing their variance.

Exogenous – also called independent or explanatory – variables may also be considered. In that case, a single model can be constructed, comprising:

-the observations of the endogenous stochastic process, i.e. the sample of data $Y = (y_1, y_2, \ldots, y_n)$.

-the values taken by the k exogenous variables $Z_{it}, i = 1, \ldots, k$, is assumed to be known.

It is natural to distinguish several kinds of exogenous variables, depending on whether they affect the trend, the seasonal component, or the irregular component of the process Y_t. Moreover, effects of exogenous variables can be local – over time (the effect may be 'short-lived'), or permanent. It seems quite natural, again, to distinguish the dummy variables, which are created (outside the model) as witnesses of a local, isolated or repeated, effect usually having values zero or one, and the variables of measure of a phenomenon (of which the value is actually measured), assumed to be linked with the process Y_t, and which may have a permanent effect. As an example, climate and calendar variables can be used for modelling the seasonal component, or the residual; the variables used to model the trend are of a different nature, insofar as one can expect their effect to extend over time.

The ARMA and ARIMA models with explanatory variables can generally be written as

$$YC_t = \varphi_1 YC_{t-1} + \cdots + \varphi_p YC_{t-p} + u_1 + \theta_1 u_{t-1} + \cdots + \theta_q u_{t-q}$$

$$YC_t = Y_t - g(Z_t)$$

with YC_t the process corrected for the explanatory variables, and u_t the innovation disturbance of the process YC_t.

In that general specification, Y_t and $Z_t = (Z_{1t}, Z_{2t}, \ldots, Z_{kt})^{Y}$, $t = 1, \ldots, n$ may have been pre-transformed (e.g. by filter of differences or logarithmic transformation) in such a way that YC_t can be assumed to be stationary.

ARMA or ARIMA models with explanatory variables can also be seen as regression models with ARMA or ARIMA residuals, the two formulations being equivalent. It is relevant to determine whether the exogenous variables do have an effect on Y or on the variations of Y , after the trend and the seasonal components have been filtered out.

4.1.2. Applications

The use of ARIMA models is demonstrated in this section as applied to the following non stationary road safety time series data:

- Annual number of road fatalities in Norway from 1970 to 2003 (note that this is a shorter version of the data analyzed in Section 2 which contains six additional years);
- Monthly number of drivers killed and seriously injured (KSI) in the UK from January 1969 to December 1984; and
- Monthly number of injury accidents and fatalities in France from January 1975 to December 2001.

These datasets are illustrated in Figures 1 and 4 through 7. The estimated exogenous parameters, the dynamics parameters and the goodness of fit criteria of all ARIMA models presented in this section are provided in Tables 2 through 4.

An ARIMA(0, 1, 1) was fitted on the logarithm of the 1970–2003 number of Norwegian fatalities series and the model diagnostics were significant as all parameters were significant and the residuals could be considered as independent (i.e. tests did not reveal evidence against this assumption). At the same time, it was demonstrated on this example that this ARIMA (0,1,1) representation without constant term was equivalent to a local level representation of the class of the state space models discussed in Section 4.3.

A multiplicative ARIMA(2, 0, 0)(0, 1, $1)_{12}$ was then fitted on the logarithm of the monthly number of drivers KSI in the UK (Harvey and Durbin, 1986). The effect of the obligation in the UK from February 1983 onwards for motor vehicle drivers of wearing a seat belt was investigated using an intervention variable. The effects of the risk exposure and the petrol price variations, were also investigated by adding two other variables the model: the monthly car traffic index (more precisely the monthly number of vehicle-kilometers driven by cars in the UK), and the monthly prices of petrol in the UK.

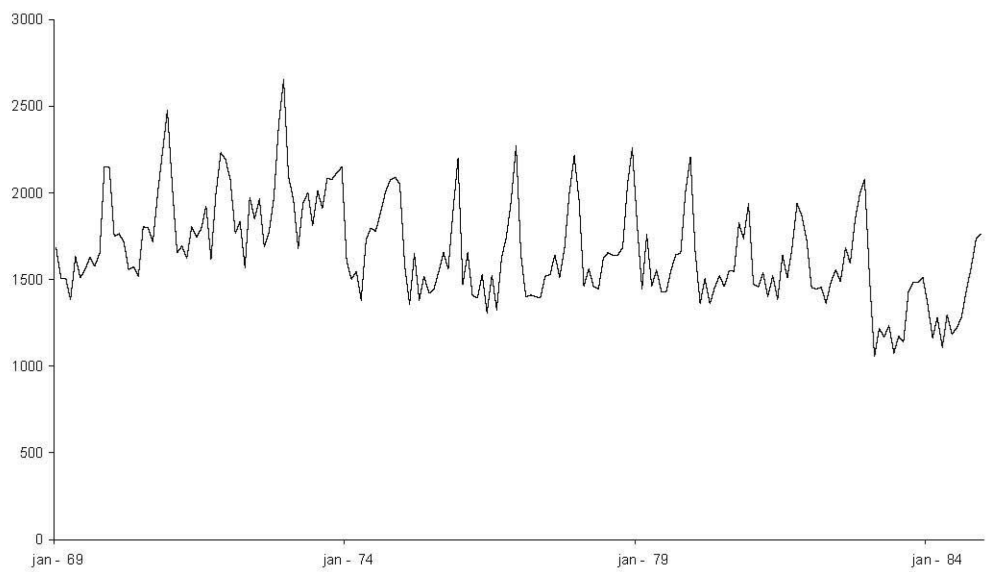

Figure 4: The monthly number of UK drivers killed or seriously injured, for January 1969 – December 1984.

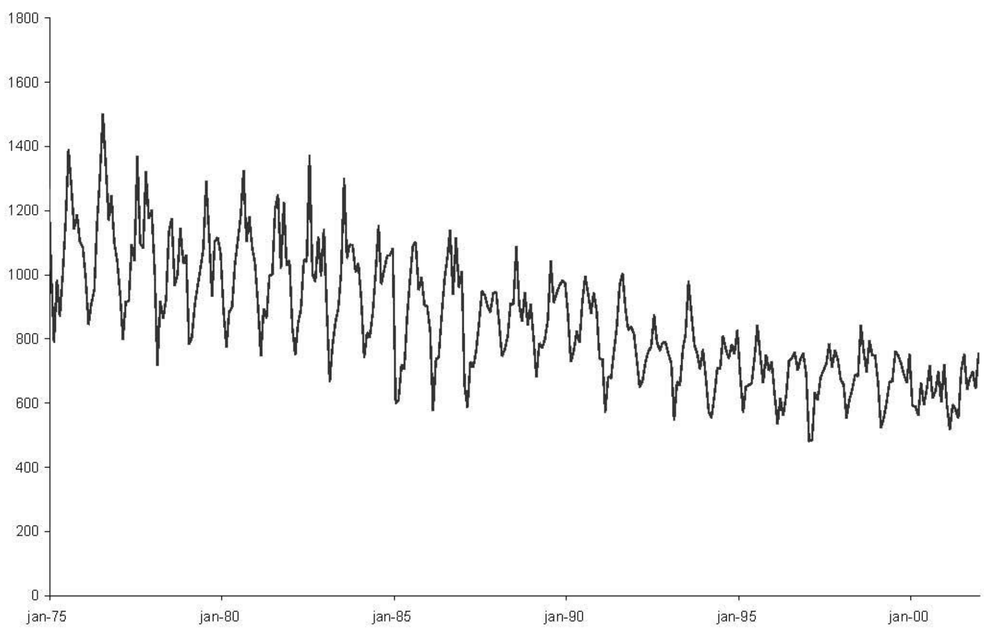

Figure 5: The monthly number of fatalities in France, for January 1975 – December2001.

The final model formulation is shown in (4):

$$\Phi(B)(I - B^{12})\log(y_t) - \sum_{i=1}^{2}\beta_i\log(x_{it}) - \lambda w_t = \mu + \Theta(B)a_t, \quad (4)$$

where y_t denotes the number of UK drivers KSI, x_{1t} and x_{2t} denote the car traffic index and the petrol price respectively, w_t denotes a dummy variable equal to 1 starting February 1983 and 0 before, $\Phi(B)$ and $\Theta(B)$ are two polynomials of the delay operator B, and a_t is white noise.

The models diagnostics were satisfactory, in the sense that all parameters were significant, and that the residuals could be considered as independent. One exception is to be made for one exogenous effect parameter related to the traffic index variable, which could only be considered as significant at the 70% confidence level. Thus, a 15% reduction in the number of UK drivers KSI from February 1983 onwards was observed, and an elasticity of -0.32 of

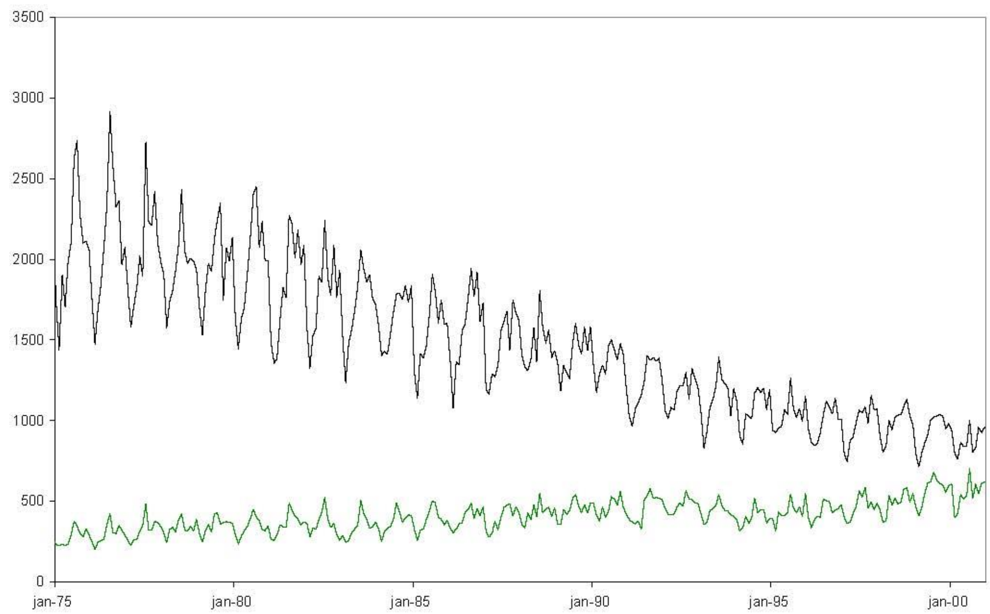

Figure 6: The monthly number of injury accidents in France, on A-level roads (top) and motorways (bottom), for January 1975 – December 2001.

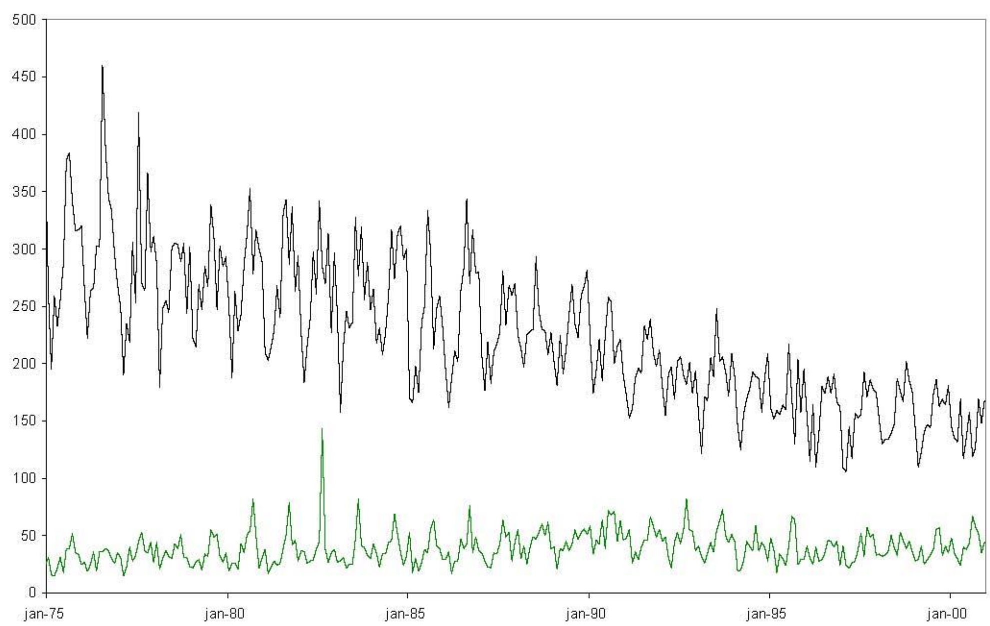

Figure 7: The monthly number of fatalities in France, on A-level roads (top) and motor-ways (bottom), for January 1975 – December 2001.

the number of UK drivers KSI with regard to the petrol price was obtained. The empirical performance of the model was evaluated by computation of different kinds of goodness of fit measures, and its performance, measured for instance with the mean average percentage error (MAPE, e.g. Makridakis et al., 1997, p. 41).

The third case study uses data from France (January 1975 to December 2001) to demonstrate that the ARIMA model with exogenous (explanatory and intervention) variables can become an efficient tool for analyzing the development of the aggregate number of injury accidents and fatalities, by taking account risk exposure (measured with oil sales as a proxy of monthly risk exposure for the whole of France), the car fuel price and factors of climatic nature (the highest temperature of the day, the rainfall height and the occurrence of frost, averaged or aggregated on the month, see Bergel-Hayat (2008) for more details with respect to the choice and measure of the climatic factor). The possible effects of two presidential amnesties on ‘driving faults’, in 1988 and in 1995, on the number of fatalities in France were also questioned through intervention analysis, as well as the effect of a fatal accident that received much attention in the media (a young woman was killed by a drunk driver) (Bergel et al., 2002).

The same approach was extended to other risk indicators such as the number of injury accidents and fatalities on A-level roads and on motor ways for the same period, and the preceding form was extended to the following form:

$$\Phi(B)(I - B^{12})\left(\log(y_t) - \sum_{i=1}^{I}\beta_i \log(x_{it}) - \sum_{j=1}^{J}\beta_j \log(x_{jt}) - \sum_{k=1}^{K}\lambda_k w_{kt}\right) = \mu + \Theta(B)a_t, \quad (5)$$

where y_t is the number of injury accidents or fatalities, the I variables x_{it} measure exposure and the economic factors, the J variables x_{jt} measuring the transitory factors, the w_{kt} ($k = 1,\ldots, 3$) are three dummy variables[2] modeling level interventions, $\Phi(B)$ and $\Theta(B)$ are two polynomials of the

[2] In all three cases, the intervention effect was first modeled by a more general form, which turned out to be a step (constant every month within the intervention period, and zero outside)

delay operator B, and a_t is white noise.

As can be seen in Tables 2 to 4 that summarize the estimation results of the models in this section, a general remark is that, in addition to the dynamics parameters, numerous exogenous parameters appear to be highly significant.

There is no surprise that the risk exposure indicator was the most significant when measured with the number of vehicle kilometers on disaggregated networks (the French motor ways and A-level roads). The petrol price was found to be significant on the only case of the number of UK drivers KSI. For France, the climatic variables were found to have distinct effects at the aggregate level and on the main roads or motorways, as the weather effect is expected to differ (in intensity and sign) according to the type of network. Finally, the intervention analysis enabled to answer the main question raised in the application, which was to determine whether there was a statistical relationship between the number of fatalities in France and the perspectives of an amnesty of driving faults some months before the presidential election, in 1988 and in 1995.

The results suggested that fatalities increased by 7% per month on average during the 10 months preceding the first presidential amnesty in 1988 – and by 4% respectively during the 7 months preceding the second one in 1995. In absolute numbers, more than 500 deaths could thus have been attributed to the presidential amnesty in 1988. To the contrary, the attention that the media devoted to the fatal drunk driver accident case seems to have saved lives, as fatalities were found to decrease by 6% per month on average during the 7 months following this tragic accident. On motorways in particular, the fatalities increased in the same proportion in 1988.

Second, the introduction of exogenous variables in the pure ARIMA models enabled the part of variance explained by the model to increase significantly (between 2,1% and 24% according to the indicator) and the absolute error made, measured in mean over the period and in percentage, to decrease significantly (between 4,4% and 11,9% respectively). Nevertheless, the normalized BIC decreased less significantly, and even happened to increase (varying between -0,5% and +1,3%), and this is due to the fact that this criteria is meant to take account of the parsimony of the model.

4.2. DRAG models

With the exception of a non-linear transformation of the variables, the DRAG model can be considered as an application of a special case of the

ARMA models, the AR (autoregressive) model with explanatory variables, specially designed for road safety analysis. The DRAG model has (at least) three levels: exposure, accident risk, and accident severity. The trend and the seasonal component are not removed by filtering but are modeled by the introduction of numerous explanatory variables, whether related to exposure, economic factors, transitory factors, behavioral factors or road safety measures. The use of a particular non-linear transformation – the Box-Cox transformation (Box and Cox, 1964) – allows a flexible form of the link between the dependent variable and each of the explanatory variables, but, for different reasons, that transformation is not systematically used.

Although the DRAG model has a powerful theoretical framework, its application requires voluminous databases (Gaudry and Lassarre, 2000) and therefore may currently not be easily applied to (EU) road safety data.

4.3. State space models

In the state space approach to time series analysis (see the classics by Harvey, 1989, and Durbin and Koopman, 2001, and the introductory treatment by Commandeur and Koopman, 2007) a time series is typically decomposed into a number of unobserved components. This is why the state space models discussed in this paper are commonly called structural time series models, or unobserved components models.

One such decomposition was already illustrated in Section 2 where it was shown that the logarithm of the annual number of Norwegian fatalities series for the years 1970–2009 can be appropriately described with the local level and fixed slope model defined by (3). In this example there are two unobserved components: a time-varying intercept α t, which is called the level component since it determines the “height” or level of the trend, and a fixed regression weight β, which is called the slope component because it determines the angle between the trend and the time axis. When a component (such as α t) is allowed to vary over time it is a stochastic component; when it is not allowed to change over time (such as β) it is a deterministic component. When β in model (3) is not only fixed over time but also fixed on zero, we obtain the most simple unobserved components model: the local level model. When β in model (3) is allowed to vary over time, on the other hand, we obtain the local linear trend model where both the level and the slope component are treated stochastically:

$$y_t = \alpha_t + \varepsilon_t, \varepsilon_t \sim NID(0,\sigma_\varepsilon^2) \quad \alpha_{t+1} = \alpha_t + \beta_t + \xi_t, \xi_t \sim NID(0,\sigma_\xi^2), \quad (6) \quad \beta_{t+1} = \beta_t + \zeta_t, \zeta_t \sim NID(0,\sigma_\zeta^2)$$

for t =1,...,n. In the state space literature the first equation in (6) – which links the observations with the unobserved components – is called the observation or measurement equation, while the second and third equation

– which determine how the unobserved components evolve over time – are collectively called the state or transition equations. It is interesting to note that (6) reduces to (1) when $\sigma_\xi^2 = \sigma_\zeta^2 = 0$, as is easily verified, which shows that classical linear regression model (1) is just a special case of local linear trend model (6).

If we are not dealing with annual but with quarterly, monthly, weekly, daily, etc., data, it is often required to also capture the periodicity present in such time series observations (see for example the monthly series displayed in Figure 4). This is achieved by adding a seasonal component to either the local level or the local linear trend model. If we let s denote the periodicity of the seasonal, then the modeling of a seasonal component requires s − 1 state equations. For quarterly data, for example, we could apply the following local level and what is called a dummy seasonal model:

$$y_t = a_t + \gamma_{1,t} + \varepsilon_t,$$

$$\alpha_{t+1} = \alpha_t + \xi_t, \quad \gamma_{1,t+1} = -\gamma_{1,t} - \gamma_{2,t} - \gamma_{3,t} + \omega_t, \quad (7) \quad \gamma_{2,t+1} = \gamma_{1,t},$$

$$\gamma_{3,t+1} = \gamma_{2,t},$$

for t =1,...,n, where the normally and independently distributed terms ω_t with mean zero and variance σ_ω^2 allow the seasonal component with s −1=3 state equations to slowly change over time. An important difference with the ARIMA models discussed in Section 4.1 is that when a time series exhibits a trend and a seasonal component (i.e., is non stationary) these components

– instead of being filtered out of the time series – are explicitly modeled in a state space context.

Just as in the ARMA-type approach, to all these descriptive unobserved component models explanatory and intervention variables can be added.

Here, we illustrate the unobserved component models approach by analyzing the logarithm of the monthly number of UK drivers KSI series already discussed in Section 4.1, and displayed in Figure 4. For this series, it is found that a local level and deterministic seasonal model yields an appropriate description of the data. The corresponding model residuals satisfy all the model assumptions of independence, homoscedasticity, and normality, although the diagnostic test for normality is somewhat close to the critical value. This is caused by the fact that the large level change that occurred in February 1983 as a result of the introduction of the seat belt law in the UK is neglected in the present analysis.

Therefore, two variables are added to the previous descriptive model (7): the logarithm of the continuous variable “petrol price” (denoted by x_t), and a dummy intervention variable (denoted by w_t) for the evaluation of the effect of the seat belt law. Algebraically, this model can be written as

$$\log(y_t) = \mu_t + \gamma_{1,t} + \beta_t \log(x_t) + \lambda_t w_t + \varepsilon_t,$$

$$\alpha_{t+1} = \alpha_t + \xi_t,\ \gamma_{1,t+1} = -\gamma_{1,t} - \gamma_{2,t} - \gamma_{3,t} + \omega_t,\ \gamma_{2,t+1} = \gamma_{1,t},\ (8)\ \gamma_{3,t+1} = \gamma_{2,t},$$

$\beta_{t+1} = \beta_t + \tau_t$, $\lambda_{t+1} = \lambda_t + \rho_t$, for $t = 1,...,n$, where $\varepsilon_t \sim NID(0,\sigma_\varepsilon^2)$, $\xi_t \sim NID(0,\sigma_\xi^2)$, $\omega_t \sim NID(0,\sigma_\omega^2)$, $\tau_t \sim NID(0,\sigma_\tau^2)$ and $\rho_t \sim NID(0,\sigma_\rho^2)$. The intervention variable w_t again contains zeroes at all time points before February 1983, and ones at time points at and after February 1983. To shorten the exposition, the local level and seasonal model plus intervention and explanatory variables is presented in (8) as if we are dealing with quarterly data. For the actual analysis of the monthly UK drivers KSI series where $s = 12$, however, not three but $s - 1 = 11$ state equations are required for the modeling of the seasonal component. It may be noted that in unobserved component models we may treat the regression component β_t in the one before last state equation of (8) stochastically, thus allowing this regression coefficient to vary over time. Here, however, only deterministic regression components are considered, meaning that σ_τ^2 and σ_ρ^2 are fixed on zero from which it follows that $\beta_t = \beta_1 = \beta$ and $\lambda_t = \lambda_1 = \lambda$ for $t = 1,...,n$.

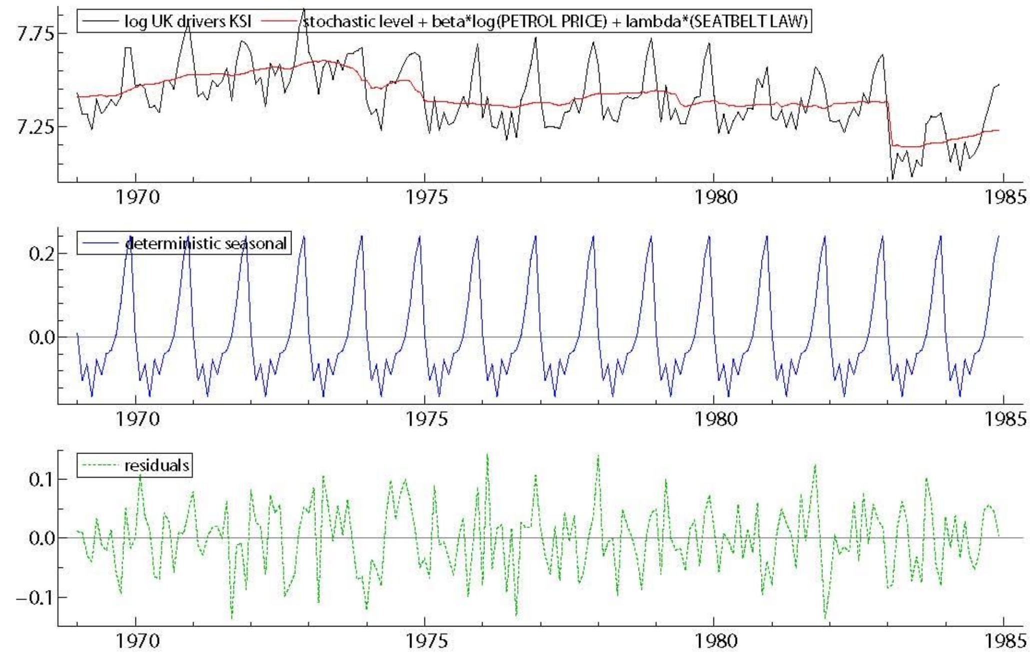

Figure 8: Local level plus intervention and explanatory variables (top), deterministic seasonal (middle), and residuals (bottom) for the logarithm of the number of UK drivers KSI series.

The assumptions of model (8) are that the observation, level, and seasonal disturbances ε_t, ξ_t, and ω_t are all mutually independent, and normally distributed with zero means, and variances equal to σ_ε^2, σ_ξ^2, and σ_ω^2, respectively.

For the UK drivers KSI series it is again found that treating the level component in (8) stochastically and the seasonal component deterministically yields the most appropriate model. For this model, maximum likelihood estimates of σ_ε^2=0.00403 and σ_ξ^2 =0.00027 for the disturbance variances are obtained, and maximum likelihood estimates of −0.2376, and −0.2767 for λ_1 and β_1, respectively. The latter parameter estimates both significantly deviate from zero, and indicate that the seat belt law of February 1983 was associated with a reduction of 21.1% (i.e., $100(\exp(\lambda_1) - 1)$)in the number of UK drivers KSI , while a 1% raise in the price of petrol was associated with a 0.28% reduction in the number of UK drivers KSI (i.e., equal to β_1).

Figure 8 displays all the components of this analysis. The sudden drop of −0.2376 units in February 1983 in the model predictions in the top graph is clearly visible. The (deterministic) seasonal component in the middle graph of Figure 8 indicates that in the years 1969–1984 the month of April was always the safest month while the months of November and especially December always resulted in the largest number of drivers KSI. We end the discussion of this illustration by noting that the residuals in the bottom graph of Figure 8 satisfy all of the model assumptions, while the value of the normality test that was almost significant in the previous analysis is much smaller in the present case due to the inclusion of the intervention variable for February 1983.

4.4. Equivalencies

The core methods used by the state space models and those used for the ARMA-type models have a lot in common if not are identical. As a matter of fact, each models may have an "identical twin" in the other approach, but with other parameterizations. This implies that in practice, the identification process may end up with formally different but statistically indistinguishable models.

Two examples of equivalencies between ARIMA models and state space models described in Sections 4.1 and 4.3 were discussed, and the relationships between the model parameters were checked on the basis of their estimations (provided by STAMP (Koopman et al., 2009) for the state space models and SPSS for the ARIMA models). Nevertheless, as these equivalencies only hold between well-defined specifications, other close specifications may in practice be obtained.

With the first example, it was demonstrated that the logarithm of the annual number of Norwegian road traffic fatalities in 1970–2003 could equally be modeled with a local level model or with an ARIMA(0,1,1) model without constant; nevertheless, in practice, an ARIMA(0,1,1) with constant was retained in Section 4.1. With the second example, it was demonstrated that the logarithm of the monthly number of UK drivers KSI could equally be modeled with a local level with seasonal model or with an ARIMA(0, 1, 1) $(0, 1, 1)_{12}$ model without constant; nevertheless, in practice an ARIMA(2, 0, 0) $(0, 1, 1)_{12}$ model was retained in Section 4.1.

5. Conclusions

Road safety data are voluminous and varied in the sense that several types of data and several dimensions are involved. The frequency of measurement of the road safety data varies: road safety data is mostly measured annually or monthly and sometimes weekly or even daily. Furthermore, the data comprises both national totals and disaggregated data for regions, for sections of the population (e.g. age classes, males, females, etc.), for vehicle types, or for road types among others. Between countries, but also between periods for the same country and between different types of data, there may exist large differences with respect to the availability, the periodicity, and reliability of (disaggregated) data.

The above-mentioned characteristics of the data and the different needs for analyzing the several time series and their interrelations – i.e. monitoring, explaining, and forecasting – make road safety analyzes complex and not straightforward. Furthermore, it appears that the time dependencies in road safety developments often do not allow for the application of cross-sectional statistical techniques. As such, the application of dedicated state-of-the-art time series analysis techniques is advocated.

5.1. Summary of methods for time series analysis

In this paper, several techniques used for the analysis of time series are presented. Classical linear regression is a standard technique, which is frequently used for the analysis of time series because of its straightforwardness and efficiency. However, this technique does not properly consider the time dependencies between consecutive observations, nor does it consider alternatives for some other assumptions. Therefore, the residuals obtained with this technique often do not satisfy the most important model assumptions, e.g., the assumption of independence. The latter problem may lead to statistical test results which are overoptimistic or too pessimistic about the relations between variables and also to poor forecasts, among others. Generalized linear models can be used to overcome part of the restrictions of classical linear regression. This technique is more flexible than classical linear regression in the sense that it allows for all error distributions within the exponential family of distributions. Among others, this family includes the normal distribution, which is the one assumed in classical linear regression, the Poisson distribution and the negative binomial distribution. Another extension in comparison with classical linear regression is that what is known as a link function can be defined to impose restrictions to the model output, which can be useful, for example, when the log-transformation is used to enforce positive forecasts.

By using nonlinear models even more restrictions of classical linear regression can be overcome. The biggest advantage of this technique over the previously mentioned is the broad range of functions that can be fitted. This flexibility of nonlinear regression is also a caveat, since similarly good fits can be obtained with very different functional forms, whereas presumably only one of them represents the real underlying process in the best manner. These different models can be adequate for interpolation purposes, but may produce very different predictions when used to extrapolate, i.e. to predict values outside the scope of the estimation data set (forecasting).

A common advantage of the parametric linear and nonlinear regression models is the efficient use of data. Good estimates of the unknown parameters in the model can be produced with relatively small data sets. Another shared advantage is a fairly well-developed theory for computing confidence, prediction and calibration intervals.

However, for time series analysis the most important drawback of the classical linear, generalized linear and nonlinear regression models is that they do not naturally take into account the dependencies between the consecutive observations of a time series. To adequately deal with these dependencies, dedicated time series analysis techniques, such as ARMA-type (autoregressive moving average) analysis, its special case DRAG, and state space analysis could be employed.

ARMA models (in the case of stationary data) and ARIMA models (in the most general case of non-stationarity data, which is the usual situation in road safety) enable to describe the dynamics of a time process and to extrapolate it in the future, without any call to additional variables and with the only assumption that the process dynamics will stay unchanged at the forecast horizon. Explanatory and intervention variables can also be included in ARMA and ARIMA models, and the additional corresponding regression coefficients can be estimated and interpreted.

For the analysis of road safety data, a disadvantage of ARIMA modeling may be its concept: the trend and the seasonal are removed before the modeling itself is performed on the stationary part of the process. The emphasis is on describing the dynamics of this latter process, once it has been corrected for the influence of explanatory and intervention variables, by means of estimating a small number of relevant coefficients.

The DRAG model is an application of a special case of the ARMA models, the AR (autoregressive) model with explanatory variables, specially designed for road safety analysis. The DRAG model has (at least) three levels: ex posure, accident risk, and accident severity. The trend and the seasonal component are not removed by filtering but are modeled by the introduction of numerous explanatory variables, whether related to exposure, economic factors, transitory factors, behavioral factors or road safety measures. The use of a particular non-linear transformation allows a flexible form of the link between the dependent variable and the explanatory variables. The DRAG model has a powerful theoretical framework, but needs voluminous databases and therefore currently cannot appropriately be applied to EU road safety data.

In state space models, also known as structural time series models or unobserved components models, an observed time series is typically decomposed into a number of components. The level, the slope and the seasonal are assumed to be random components – effectively meaning that they may gradually change over time, which may be an important advantage for longer time series – and are estimated for obtaining an adequate description of an observed time series. Explanatory and intervention variables can also be added in order to find explanations for the observed development in the series.

Contrary to ARIMA models, in state space modeling the trend and the seasonal are not removed but explicitly modeled. The focus here is on observing the development over time of the – usually unobserved – components, and mainly the development of the trend. Contrary to other decomposition techniques, the randomness of the trend is investigated, and described through its level and slope.

It should however be considered that the core methods used by the state space models and the ARMA-type models have a lot in common if not are identical. As described in Section 4.4, many models have an 'identical twin' in the other approach, but with other parameterizations. This means that in practice, the identification process may end up with formally different but statistically indistinguishable models.

5.2. Recommendations

For the descriptive, explanatory, or forecasting analysis of time series from road safety research, using dedicated time series analysis techniques such as ARMA-type or state space models is recommended. To obtain a 'quick and dirty' insight in the data and their possible interrelations, classical linear regression but also generalized linear models and nonlinear regression can be used. However, the user should always be aware of their limitations and therefore never forget to test the model assumptions. As such, linear and nonlinear regression models can be used as a first step in the analysis of road safety time series data. Should the residuals of such analyses display evidence of serial correlation, then dedicated time series techniques like ARMA-type or state space methods should be applied to obtain more reliable results. These two types of methods are not mutually exclusive as each type of model may also be written under different forms, and equivalencies between certain well-defined specifications have been empirically demonstrated. However, the emphasis should be put on the main objective addressed by the model, which fundamentally differs as regards the two types of dedicated techniques. The introduction of exogenous variables in these models also responds to different objectives, whether for descriptive purposes mainly as in the case of the weather variables, or for policy purposes. In all cases, the performance of these explanatory models is significantly improved when compared with the similar pure descriptive models.

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Table 1: The exogenous parameters -Summary. (*) t-value between 1 and 2, (**) t-value larger than 2

	Frequency fatalities	Frequency motorway no accident injury	Frequency road A-level no accident injury	Frequency motorway fatalities	Frequency road A-level fatalities
	0.21?0.297 -0.163 (**)	0.096 (*) -0.012 0.001 (*) 0.002 2.81 × 10⁻⁵ (*) -0.054 0.071 0.042	0.765 0.002 0.001 (*) 8.76 × 10⁻⁵ 0.007 -0.025 (*) 0.078 -0.039	0.526 0 −4.19 × 10⁻⁵ 10 6.07 × 10⁻⁵ 10 -0.001 (*) -0.036 0.057 0.007	1.788 (*) 0.001 0.002 (*) 1.73 × 10⁻⁵ 0.012 -0.044 (*) 0.145 -0.105

Other values printed in the rightmost column: 6 0.08 (*); 9 0.0 (*); 4 -0.05; 4 0.00 (*); −5 0 1 (**)

Row labels (partly legible): Intensity of ... ; Level ... ; -0.184 (**) ; Kilometers driven ; Ratio Norway

Traffic Price Summer volume temp Norwegian fatalities		Winter temp	Rainfall height (×10-5)	Occurrence of Frost	Interv. Var. 1	Interv. Var. 2	Interv. Var. 3
					-0.184 (**)		
UK drivers KSI 0.21 ?0.297 (*) (**)					-0.163 (**)		
French fatalities 0.096 -0.012 (*)	0.001 (**)	0.002 (**)	2.81 (**)	0	-0.054 (*)	0.071 (**)	0.042 (*)
French injury accidents on motorways 0.765 0.002 0.001 (**) (**) (*)			8.76 (**)	0.007 (**)	-0.025	0.078 (*)	-0.039
French injury accidents on A-level roads 0.526 0 -0.00004 (**)			6.07 (**)	-0.001	-0.036 (*)	0.057 (*)	0.007
French fatalities on motorways 1.788 0.001 (**)		0.002 (*)	1.73	0.012 (*)	-0.044	0.145 (*)	-0.105 (*)
French fatalities on A-level roads 0.598 0.001 0.001 (**) (*) (*)			8.38 (**)	0.004 (*)	-0.054	0.09 (*)	0.086 (*)

	φ_1	φ_2	φ_3	θ_1	θ_{12}	μ
Norwegian fatalities						
				-0.432 (**)		-0.02 (*)
UK drivers KSI						
	0.429 (**)	0.298 (**)			-0.898 (**)	-0.018 (**)
	0.378 (**)	0.279 (**)			-0.889 (**)	-0.01 (**)
	0.283 (**)	0.235 (**)			-857 (**)	-0.015 (**)
French fatalities						
	0.264 (**)	0.187 (**)	0.064 (*)		-0.907 (**)	-0.022 (**)
	0.149 (**)	0.191 (**)	0.231 (**)		-0.883 (**)	-0.026 (**)
French injury accidents on motorways						
	0.328 (**)	0.262 (**)			-0.841 (**)	0.023 (**)
	0.339 (**)	0.259 (**)			-0.845 (**)	-0.023 (**)
French injury accidents on A-level roads						

Table 2: The exogenous parameters -Summary. (*) t-value between 1 and 2, (**) t-value larger than 2

Traffic Price Summer volume temp Norwegian fatalities		Winter temp	Rainfall height ($\times 10^{-5}$)	Occurrence of Frost	Interv. Var. 1 -0.184 (**)	Interv. Var. 2	Interv. Var. 3
UK drivers KSI 0.21 ?0.297 (*) (**)					-0.163 (**)		
French fatalities 0.096 -0.012 (*)	0.001 (**)	0.002 (**)	2.81 (**)	0	-0.054 (*)	0.071 (**)	0.042 (*)
French injury accidents on motorways 0.765 0.002 0.001 (**) (**) (*)			8.76 (**)	0.007 (**)	-0.025	0.078 (*)	-0.039
French injury accidents on A-level roads 0.526 0 -0.00004 (**)			6.07 (**)	-0.001	-0.036 (*)	0.057 (*)	0.007
French fatalities on motorways 1.788 0.001 (**)		0.002 (*)	1.73	0.012 (*)	-0.044	0.145 (*)	-0.105 (*)
French fatalities on A-level roads 0.598 0.001 0.001 (**) (*) (*)			8.38 (**)	0.004 (*)	-0.054	0.09 (*)	0.086 (*)

	φ_1	φ_2	φ_3	θ_1	θ_{12}	μ
Norwegian fatalities						
				-0.432 (**)		-0.02 (*)
UK drivers KSI						
	0.429 (**)	0.298 (**)			-0.898 (**)	-0.018 (**)
	0.378 (**)	0.279 (**)			-0.889 (**)	-0.01 (**)
	0.283 (**)	0.235 (**)			-857 (**)	-0.015 (**)
French fatalities						
	0.264 (**)	0.187 (**)	0.064 (*)		-0.907 (**)	-0.022 (**)
	0.149 (**)	0.191 (**)	0.231 (**)		-0.883 (**)	-0.026 (**)
French injury accidents on motorways						
	0.328 (**)	0.262 (**)			-0.841 (**)	0.023 (**)
	0.339 (**)	0.259 (**)			-0.845 (**)	-0.023 (**)
French injury accidents on A-level roads						

Table 3: The dynamics parameters -Summary. (*) t-value between 1 and 2, (**) t-value larger than 2

Traffic Price Summer volume temp Norwegian fatalities	Winter temp	Rainfall height (×10-5)	Occurrence of Frost	Interv. Var. 1	Interv Var. 2
				-0.184 (**)	
UK drivers KSI 0.21 ?0.297 (*) (**)				-0.163 (**)	
French fatalities 0.096 -0.012 (*) 0.001 (**)	0.002 (**)	2.81 (**)	0	-0.054 (*)	0.071 (**)
French injury accidents on motorways 0.765 0.002 0.001 (**) (**) (*)		8.76 (**)	0.007 (**)	-0.025	0.078 (*)
French injury accidents on A-level roads 0.526 0 -0.00004 (**)		6.07 (**)	-0.001	-0.036 (*)	0.057 (*)
French fatalities on motorways 1.788 0.001 (**)	0.002 (*)	1.73	0.012 (*)	-0.044	0.145 (*)
French fatalities on A-level roads 0.598 0.001 0.001 (**) (*) (*)		8.38 (**)	0.004 (*)	-0.054	0.09 (

	φ_1	φ_2	φ_3	θ_1	θ
Norwegian fatalities					
				-0.432 (**)	
UK drivers KSI					
	0.429 (**)	0.298 (**)			-0.89 (*
	0.378 (**)	0.279 (**)			-0.88 (*
	0.283 (**)	0.235 (**)			-85 (*
French fatalities					
	0.264 (**)	0.187 (**)	0.064 (*)		-0.90 (*
	0.149 (**)	0.191 (**)	0.231 (**)		-0.88 (*
French injury accidents on motorways					
	0.328 (**)	0.262 (**)			-0.84 (*
	0.339 (**)	0.259 (**)			-0.84 (*
French injury accidents on A-level roads					
	0.337 (**)	0.192 (**)			-0.83 (*
	0.341	0.225			-0.83

Table 4: Goodness of fit criteria -Summary