Deliverable D7.2: "Multilevel modelling and time series analysis in traffic safety research – An introduction"

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Introduction

In subsection 1.1 this introductory chapter first highlights one of the main objectives of work package 7 (WP7) of SafetyNet, i.e. to develop a best practice for the analysis of linked databases, consisting of a combination of accident data with risk exposure data and/or safety performance indicators. By touching upon this main objective this section reveals the rationale behind the structure of the deliverable. It is shown that this deliverable comprises a theoretical part and a manual.

Then, in subsection 1.2 special attention is given to the added value of two families of sophisticated analysis techniques in the field of traffic safety. Based on several empirical traffic safety examples it is illustrated that both techniques – multilevel modeling and time series analysis – are very valuable to traffic safety research. The use of those techniques in the field of traffic safety is advocated.

Throughout this text, the reader is only expected to master ordinary regression analysis as a basis for time series analysis and ordinary regression analysis and the corresponding level 1 models (e.g. binomial model, Poisson model, etc.) as a basis for multilevel modeling. Foreknowledge regarding multilevel modeling or time series analysis is not a prerequisite when reading this deliverable.

1.1 Best practice for the analysis of linked data

One of the main objectives of WP7 of SafetyNet is “to develop a best practice for analysis of linked data”, more precisely for the analysis of the combination of accident data (cf. WP1 and WP5 of SafetyNet) with exposure data (cf. WP2 of SafetyNet) and/or safety performance indicators (cf. WP3 of SafetyNet). Analysis of such complex datasets is not always as straightforward as one might think it is. Several issues related to complex data structures in time and space come into play.

To develop such a best practice and to pass it on to the reader as clearly as possible it was decided that the structure of this deliverable will comprise two main chapters: a theoretical part and a manual. Both chapters contain subparagraphs about multilevel modeling and time series analysis and are closely related to one another.

The theoretical chapter is model driven. Several models, relevant to traffic safety, are discussed. A standardized discussion format was adhered to when scrutinizing each model to maintain a certain consistency throughout this deliverable. Furthermore, theory is always explained by applying theoretical considerations to a real dataset. Therefore, in the theoretical part special attention is given to each of the following aspects of a particular model:

- Research problem
- Dataset

- Model definition
- Objectives of the technique
- Model assumptions
- Model fit and diagnostics
- Model interpretation

This standardized format should enable the reader to comprehend all the aspects relevant to statistical modelling, ranging from the intuitive understanding of a research problem at the outset to drawing socially relevant conclusions based on the model interpretation at the end.

The manual is developed in parallel with the theoretical part. It contains instructions to fit each model described in the theoretical part using a dedicated software package. Each model is gradually built, starting from the most basic form (1 level model for multilevel analysis and a deterministic level model for time series analysis) to more advanced forms of the model.

1.2 The added value of Multilevel and Time Series Analysis

1.2.1 Multilevel models[1] *(W. Vanlaar, IBSR)*

1.2.1.1. Definition and conceptual issues

Multilevel models have come of age, especially in educational research. In their introduction to multilevel modeling Kreft and de Leeuw (2002) give a brief history of this family of techniques, emphasising that developments similar to those going on in educational statistics are going on elsewhere, or have been going on. More precisely, the authors show that multilevel models are a conglomerate of known models, commonly used in different disciplines including bio-medical sciences where the terms mixed-effects models and random-effects models are used (e.g. growth curve analysis in Lindsey, 1993), economics (e.g. panel data research in Swamy, 1971) and econometrics (e.g. Longford, 1993) where the models are referred to as random-coefficient regression models, criminology (e.g. drug prevention research in high schools in Kreft, 1994) and geography (e.g. spatial analysis to study farms in counties in McMillan and Berliner, 1994). Nevertheless, multilevel modeling is relatively new to the field of traffic safety. In this paragraph the advantages of multilevel modeling compared to statistical techniques that ignore hierarchies are illustrated, based on two empirical traffic safety examples.

Today several introductory books are available on the market (e.g., Goldstein, 2003; Heck and Thomas, 2000; Hox, 2002; Kreft and de Leeuw, 2002; Snijders and Bosker, 1999) and each of those defines multilevel models in a specific way. However, these definitions share one concept in particular, namely the

[1] This paragraph on multilevel modeling is a summary of a commentary published in Traffic Injury Prevention (Vanlaar, 2005).

concept of hierarchies or nested data structures: “We have variables describing individuals, but the individuals also are grouped into larger units, each unit consisting of a number of individuals. We also have variables describing these higher order units.” (Raudenbush and Bryk, 2002: p. xix). The individuals are also referred to as micro-units, while the larger units are called macro-units (Tacq, 1986).

Hierarchies are very common in the social and the behavioural sciences and often occur naturally: e.g., pupils in classes, classes in schools; employees in departments, departments in firms; suspects in courts; offspring within families. Less obvious examples of hierarchies are observations nested within subjects (repeated measurements) or observations nested in studies (meta-analysis). Leyland and Goldstein (2001) give a rather extensive overview of more advanced applications of multilevel models including repeated measurements, binomial regression, Poisson regression, multivariate models, non-hierarchical structures, spatial analysis, meta-analysis and survival data modeling.

In the field of traffic safety nested data structures can be seen in data on roadside surveys (drivers nested within police checks or locations, police checks or locations nested within regions; e.g., Vanlaar, 2005); on accidents (drivers and passengers in vehicles, vehicles in accidents, accidents in regions; e.g., Jones and Jørgensen, 2003); on repeated measurements (e.g., Burns et al., 1999); meta-analysis (e.g., Delhomme et al., 1999; van Driel et al., 2004); etc.

A straightforward definition of multilevel modeling is given by Heck and Thomas (2000). According to their definition multilevel modeling refers to a variety of statistical methods that may be used to handle these hierarchical, or nested data structures.

When analysing nested data structures some conceptual issues calling for a proper approach have to be borne in mind. In this paragraph of the introduction, using multilevel modeling techniques as opposed to less sophisticated techniques is justified by means of two empirical traffic safety examples. According to Rasbash et al. (2004: p. 6) “the point of multilevel modeling is that a statistical model explicitly should recognize a hierarchical structure where one is present: if this is not done then we need to be aware of the consequences of failing to do this.”

Broadly speaking there are two important consequences of ignoring a hierarchical structure: underestimation of standard errors leading to an increased level of committing type I errors (Rasbash et al., 2004) and problems related to an impoverished conceptualisation (Raudenbush and Bryk, 2002). The first problem is related to the dependence of nested observations while the second problem stems from the existence of variables on different levels of aggregation, describing the micro-units and macro-units and from possible interactions between those different kinds of units. Variables related to macro-units are also referred to as contextual information or context of the micro-units.

The issue of dependence of nested observations has also been recognized in sample survey research and is referred to as clustering effects. Complex sampling designs are developed to model the hierarchical population structure as truthfully as possible in terms of geography or administrative structures. Elaborate procedures are available to analyse data gathered within such sampling designs (Cochran, 1963; Kish, 1965; Levy and Lemeshow, 1999). According to Goldstein (2003: p. 5), however, such procedures usually have been regarded as necessary while they have not generally merited serious substantive interest. “In other words, the population structure, insofar as it is mirrored in the sampling design, is seen as a ‘nuisance factor’. By contrast, the multilevel modeling approach views the population structure as of potential interest in itself, so that a sample designed to reflect that structure is not merely a matter of saving costs as in traditional survey design, but can be used to collect and analyse data about the higher level units in the population.”

In the following paragraphs both conceptual issues will be briefly discussed and illustrated with an empirical traffic safety example. First consequences of ignoring dependence of nested observations are investigated and data from an observational study on seatbelt use are used as an illustration. Then consequences of impoverished conceptualisation of contextual information are discussed. This issue is illustrated with data from an observational study on drink driving. Finally conclusions regarding multilevel modeling in traffic safety are drawn.

1.2.1.2. Consequences of ignoring dependence of nested observations

Dependence of observations plays an important role in nested data structures. An assumption made by most statistical analysis techniques that ignore hierarchies is the independence of observations: one observation is supposed to be sampled independently of another. However, observations that are close in time or space are likely to be more similar than observations that are not close in time or space (Kreft and de Leeuw, 2002).

Nested data structures are close in time or space by definition, which makes it reasonable to assume that observations within a hierarchical data structure will not be sampled independently from one another. Pupils nested in the same class will be influenced by the same teacher and hence be more alike than pupils from another class. Drivers nested within a certain speed zone are more alike than drivers in another speed zone in that their speed behaviour will be influenced – within certain limits – by the speed limit in that zone. Although speed limits are frequently violated, they do lead to similar behaviour to a certain degree and hence, to dependent observations.

Ignoring the dependence of observations generally causes standard errors of regression coefficients to be underestimated (Rasbash et al., 2004). The mechanism leading to this underestimation is easily explained as follows (Snijders and Bosker, 1999). Imagine an extreme case of 10 groups of 100 identical observations each. Applying an ordinary regression analysis to the data leads to the calculation of standard errors based on 1000 observations.

However, since each group contains 100 totally dependent observations, the useful information in the sample really is limited to only 10 observations. Obviously the standard errors will be much greater based on 10 observations, indicating less precision than in the case of 1000 observations. In reality observations are more likely to be similar to a certain degree instead of being identical. How similar they are exactly is measured by the intra-class correlation.

Multilevel modeling is capable of dealing with the issue of dependence of observations as opposed to statistical techniques that ignore hierarchies and thus the former calculates correct standard errors, taking account of the degree of dependence of the observations in the sample under study.

Table 1.1 contains the analysis results of observational data regarding seatbelt use in Belgium in 2004.[2] The data are analyzed according to a single-level model and according to a two-level model.

Parameter	Single-level logistic model		Two-level logistic model	
	Logit coefficients	s.e.	Logit coefficients	s.e.
Fixed parameters				
Intercept	0.883	0.169	0.776	0.184
Passenger	-0.260	0.130	-0.205	0.132
Male	-0.663	0.121	-0.670	0.114
Wallonia	-0.454	0.158	-0.510	0.182
Brussels	-0.583	0.137	-0.365	0.140
50km/h	0.648	0.137	0.649	0.171
70km/h	0.921	0.171	0.665	0.155
90km/h	0.461	0.159	0.433	0.191
120km/h	0.795	0.173	0.811	0.188
Weekday night	-0.092	0.214	0.037	0.156
Weekend day	-0.091	0.142	0.151	0.139
Weekend night	0.312	0.156	0.197	0.166
Random parameters				
Level 2 variance: Ω_u	not applicable	not applicable	0.197	0.039
Level 1 variance: Ω_e	1.000	0.000	1.000	0.000

Table 1.1: Comparison of logit coefficients and s.e. of a single-level and a two-level model regarding seatbelt use

Even though the significance levels of most variables in both the single-level and the two-level model remain unchanged, there are two variables in particular that are interesting when comparing the single-level model – which ignores the hierarchical structure in the data – with the two-level model – which

[2] A more detailed description and discussion of these data is available in Vanlaar (2005).

acknowledges this structure. Those two variables are Passenger (a dummy variable indicating whether the observed subject was a front seat passenger or a driver with the latter being the reference category) and Weekend night (a categorical variable consisting of 3 dummy variables indicating in what time span the observation took place: Weekday as reference category (week peak hours and week off-peak hours are merged into weekday), Weekday night, Weekend day or Weekend night). Both variables are significant at the 5%-level in the single-level model, which can be derived from the logit coefficients since they are a twofold of the standard error. However, these effects are no longer significant according to the two-level model. The p-value of the variable Passenger in Table 1.2 shifts from a significant p-value of 0.046 in the single-level model to a non-significant p-value of 0.121 in the two-level model, while the p-value of the variable Weekend night increases from the significant value of 0.045 to a non-significant value of 0.233. Note that since we are testing the significance of single parameters, a t-test would also suffice in our case. The Wald test and the t-test are equivalent, more precisely, the t-statistic is equal to the square root of the chi-square statistic.

Variable	Single-level logistic model Wald test		Two-level logistic model Wald test	
Passenger	Joint chi square test	3.989	Joint chi square test	2.402
	Degrees of freedom	1	Degrees of freedom	1
	p-value	0.046	p-value	0.121
Weekend night	Joint chi square test	4.015	Joint chi square test	1.424
	Degrees of freedom	1	Degrees of freedom	1
	p-value	0.045	p-value	0.233

Table 1.2: Results of the Wald test for the variables Passenger and Weekend night in the single-level and the two-level model

This example clearly illustrates the consequences of ignoring dependence of observations: the significance levels of both variables in the single-level model falsely lead us to believe that these two variables are significant while in reality they are not. The single-level model is therefore bound to lead to erroneous conclusions regarding variables that could have an impact on seatbelt use and ultimately, on increasing the level of traffic safety. Based on the significant negative coefficient of front-seat passengers compared to drivers in the single-level model (meaning that the odds of front-seat passengers of seatbelt use are lower than those of drivers) it could for example be decided to make front-seat passengers a special target group in a mass media campaign. However, in reality – as demonstrated in the two-level model – there is no significant difference in seatbelt use between those two groups.

1.2.1.3. Consequences of impoverished conceptualisation of contextual information

Contextual analysis is a development in the social sciences, which has focussed on the effects of the social context on individual behaviour (Snijders and Bosker, 1999). The second consequence of ignoring a multilevel structure, related to contextual information, is illustrated with the frog pond theory, (Hox, 2002: p. 6), “which refers to the idea that a specific individual frog may either be a small frog in a pond otherwise filled with large frogs, or a large frog in a pond otherwise filled with small frogs.” These interactions between variables measured at different levels in hierarchically structured data are called cross-level interactions (Kreft and de Leeuw, 2002). Applied to traffic safety, this metaphor points out that the effect of an explanatory variable like willingness to take risks on the dependent variable speed choice may depend on the average speed of other drivers at a certain location. A moderate risk taker in a speeding environment may thus become a dangerous speeder, while the same driver in a more abiding context may respect the speed limit rigorously.

The metaphor clearly illustrates that relationships between variables are not always easily modelled in a simplified way. Failing to acknowledge the complexity of certain problems, for example because of statistical limitations, might induce impoverished conceptualisations of the research problem. A landmark in this regard according to Snijders and Bosker (1999) is the paper by Robinson (1950) about the ecological fallacy, meaning that a correlation between macro-level variables cannot be used to make assertions about micro-level relations. This means for example that one cannot draw conclusions about the relation between individual age and individual odds for having a traffic accident based on a statistical model relating the proportion of young drivers in a geographical region with proportion of accidents in a region.

Research problems in social and behavioural science often involve relationships between micro-level and macro-level variables and cross level interactions between those different variables. Those complex problems simply cannot be solved with aggregated or disaggregated analyses, which are bound to lead to erroneous conclusions. Multilevel analysis, however, overcomes these obstacles in an elegant and productive way. This technique allows researchers to translate a research problem into a design reproducing a lot of the nuances at stake and without giving in too drastically towards simplifying the nature of the issue under evaluation.

Table 1.3 contains an illustration of this asset of multilevel modeling using empirical data regarding drink driving. More information is available in Vanlaar (2005).

The outcome variable is a binary variable based on the blood alcohol concentration (BAC) of each driver. For the purpose of the multilevel analysis it has been recoded with 0 representing those drivers with a BAC below the legal limit and 1 representing those drivers with a BAC at or above the legal limit. Drivers at or above the legal limit are referred to as drink drivers.

The individual explanatory variables (level 1 explanatory variables) are Gender, Age (a categorical variable consisting of the following age groups: 16-25, 26-39, 40-54, 55+), Previously (a binary variable distinguishing between drivers who previously have been stopped and tested at a road site at least once and drivers who have never been stopped and tested at a road site before) and Probability (a categorical variable representing the driver's perception of the probability of being tested for drink driving; drivers could answer: very low, low, medium, high, very high).

Parameter	Binomial model	
	Logit coefficients (s.e.)	Exponential coefficients
Fixed parameters		
Intercept	-4.757 (0.285)	
Traffic count	-0.002 (0.000)	0.998
Intensity	0.896 (0.383)	2.450
Female	-1.375 (0.207)	0.253
Previously	0.409 (0.141)	1.505
Probability low	0.537 (0.167)	1.711
Probability medium	0.744 (0.169)	2.104
Probability high	0.312 (0.278)	1.366
Probability very high	1.432 (0.290)	4.187
Age26-39	0.710 (0.242)	2.034
Age40-54	1.314 (0.234)	3.721
Age55+	0.863 (0.272)	2.370
Random parameters		
Level 2 variance: Ω_u	0.991 (0.197)	
Level 1 variance: Ω_e	1.000 (0.000)	

<u>Table 1.3</u>: Logit and Exponential coefficients for the fixed and random effects of the binomial 2 level logistic model

The aggregated explanatory variables (level 2 explanatory variables) are Traffic count (a continuous variable indicating the total number of vehicles driving by the road site during the police check) and Intensity (a continuous variable calculated by dividing the number of policemen per road site by traffic count for that road site).

Data were analysed by means of the software package MLwiN (Rasbash et al., 2000). A two-level binomial model was fit with drivers at level 1 (n=11,186) and road sites (the PSU's) at level 2 (m=413). To model the relationship between the binary response and the set of explanatory variables, the logit function was used, meaning a multilevel logistic regression was performed (Rice, 2001). To interpret the relationship between the binary response and an explanatory variable, logit coefficients were transformed into odds ratios using the exponential transformation (see Rasbash et al. 2000 and Rasbash et al. 2004 for a detailed explanation). These odds ratios compare the odds for drink driving of a certain category of a variable to the reference category of that variable.

Of particular interest is the influence of the variables Gender and Traffic count on the outcome variable. The former relationship between Gender and the outcome variable is a nice illustration of the frog pond theory. A cross-level interaction would exist if the influence of Gender on Odds for drink driving would change according to different values of Traffic count. However, this cross-level interaction effect was found not to be significant according to a Wald test (joint chi square test=1.706, degrees of freedom=1, p-value=0.192).

The latter relationship between Traffic count and the outcome variable is also relevant. According to the binomial two-level model there is a negative relationship between Traffic count and the odds of drink driving when controlling for intensity of stopping drivers and for the other independent variables. This relationship is significant according to a Wald test (Goldstein, 2003; joint chi square test=10.464, degrees of freedom=1, p-value=0.001). For each additional car at a road site the odds of drink driving are multiplied by a factor of 0.998. This means that the odds of drink driving decrease by 0.2%, or, per 100 extra cars on a site, the odds are multiplied by a factor of 0.819 (exp(-0.002x100)), meaning that the odds of drink driving decrease by 18.1%. In practice this means that police officers should not restrict their enforcement activities to sites where the frequency of vehicle traffic is high.

Strictly speaking the latter example is not an illustration of a cross-level interaction. Nevertheless, this relationship between an aggregated explanatory variable and an individual dependent variable does illustrate the relevance of statistical models enabling the examination of the relationships between variables on different levels of aggregation.

Without a technique capable of simultaneously modeling variables at micro-level and macro-level such a relevant research question about the influence of traffic count on drink driving behaviour would remain unanswered or it would be answered incorrectly, due to a wrong or impoverished conceptualisation of the problem.

1.2.1.4. Conclusion

Although multilevel models have come of age, they are relatively new to the field of traffic safety. The advantages of multilevel modeling compared to statistical techniques that ignore hierarchies were illustrated based on two empirical traffic safety examples.

Broadly speaking there are two important consequences of ignoring a hierarchical structure in the data. The first consequence, underestimation of standard errors, is related to the dependence of nested observations. Data from an observational study on seatbelt behaviour were analysed according to a single-level model and a two-level model to illustrate this. Two effects that were significant at the 5%-level in the former model were found not to be significant any longer in the latter. Obviously the single-level model is therefore bound to lead to erroneous conclusions regarding variables that could have an impact on seatbelt use and ultimately, on increasing the level of traffic safety.

The second consequence, related to the nature of contextual information and potentially leading to impoverished conceptualisation of the research problem, stems from the existence of variables on different levels of aggregation and from possible interactions between those different kinds of units. Data from a roadside survey on drink driving were analysed according to a two-level model. Of particular interest was the relationship between traffic count, an aggregated level 2 explanatory variable and odds of drink driving, an individual level 1 dependent variable. This relationship, while having relevance towards the drink driving enforcement policy, could not have been studied properly without a technique capable of dealing with variables at different levels and cross-level interactions between them.

Like every statistical technique, multilevel models should be used with caution and reservation. Kreft and de Leeuw (2002) point out that this technique is only of value if several conditions are fulfilled. Multilevel models might be more sophisticated than more conventional models, but they can only give answers if the data collection design and the data collected allow such answers. There are still several assumptions regarding distribution of the data for example that need to be found true. Parsimonious models are still preferred over complex models. However, given these limitations, multilevel modeling is very useful and valuable to traffic safety research.

1.2.2 Time series models *(J. Commandeur, SWOV)*

In the SafetyNet project, many road traffic data are collected that consist of *repeated measurements 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 kilometres driven, its annual or monthly values on safety performance indicators, etc., all repeatedly measured over a certain period of time.

Whenever one is interested in studying and analysing such developments of one and the same phenomenon over time, special issues arise not encountered in cross-sectional data analysis. In this section we will 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 log of the annual number of road traffic fatalities as observed in Norway for the period 1970-2003. It may be noted that the annual

number of road traffic fatalities are count data, which are non-negative. If count data were analysed as they are, one could obtain predicted counts that are negative. By analysing them in their logarithm, however, and then taking the exponent of the predicted values, it is guaranteed that non-negative predicted counts are obtained.
Since the period spans 34 years, there are n = 34 observations. Because the observations consist of repeated measurements in time of one and the same phenomenon (i.e., the number of fatalities), this variable is called a *time series*. We will first analyse this time series with classical linear regression.

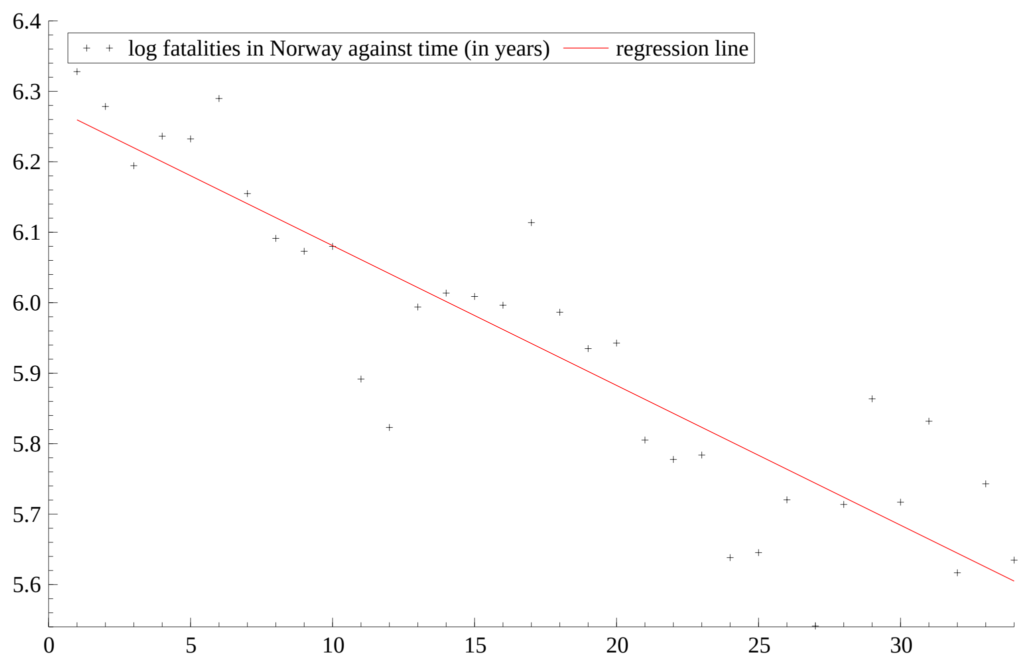


Figure 1.1: Scatter plot of log of fatalities in Norway against time (in years), including regression line.

Typically, in 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

$$y_i = a + bx_i + \varepsilon_i, \qquad \varepsilon_i \sim NID(0, \sigma_\varepsilon^2) \tag{1.1}$$

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

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

in (1.1) is a shorthand notation for: the residuals ε_i are assumed to be Normally and Independently Distributed (NID) with mean equal to zero and variance equal to σ_ε^2.

Now suppose that the dependent variable *y* in (1.1) is the just mentioned series of the log of Norwegian road traffic fatalities. Also, suppose that the independent variable *x* in (1.1) consists of the numbered consecutive time points in the series (thus, *x* = 1, 2, ..., 34). The usual scatter plot of these two variables -including the best fitting line according to classical linear regression- is shown in Figure 1.1.

The equation of the regression line in Figure 1.1 is

$$y_i = 6.2794 - 0.019837 x_i,$$

with residual variance $\sigma_\varepsilon^2 = 0.00985827$. Graphically, the intercept *a* = 6.2794 in model (1.1) is the point where the regression line intersects with the *y*-axis. Therefore, the intercept determines the 'height' or *level* of the regression line on the *y*-axis. The value of the regression coefficient or weight *b* = -0.019837 determines the *slope* of the regression line (i.e., the tangent of its angle with the *x*-axis).

The standard *t*-test for establishing whether the regression coefficient *b* = -0.019837 deviates from zero yields

$$t = \frac{b}{\sqrt{\frac{\sigma_\varepsilon^2}{\sum_{i=1}^{n}\left(x_i - \bar{x}\right)^2}}} = \frac{-0.019837}{\sqrt{\frac{0.00985827}{3272.5}}} = -11.43.$$

Since the value of this *t*-test is associated with a *p*-value of 1E^{-}12, 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, time is a highly significant predictor of the log of the number of Norwegian road traffic fatalities, and there is a negative relation between these two variables: as time proceeds the log of the number of fatalities decreases.

However, one crucial issue has completely been overlooked in this analysis. The just mentioned *t*-test was based on the fundamental assumption that the 34 observations in the time series are *independent* of one another. That the observations are not independent becomes more obvious by connecting the consecutive observations in Figure 1.1 with lines, as has been done in the top graph of Figure 1.2. 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 any other earlier observation.

The dependencies between the observations are also reflected in the fact that the residuals of classical linear regression model (1.1) shown at the bottom of Figure 1.2 are *not independent* of one another. Positive values of the residuals in Figure 1.2 tend to be followed by further positive values, while negative values tend to be followed by further negative values.

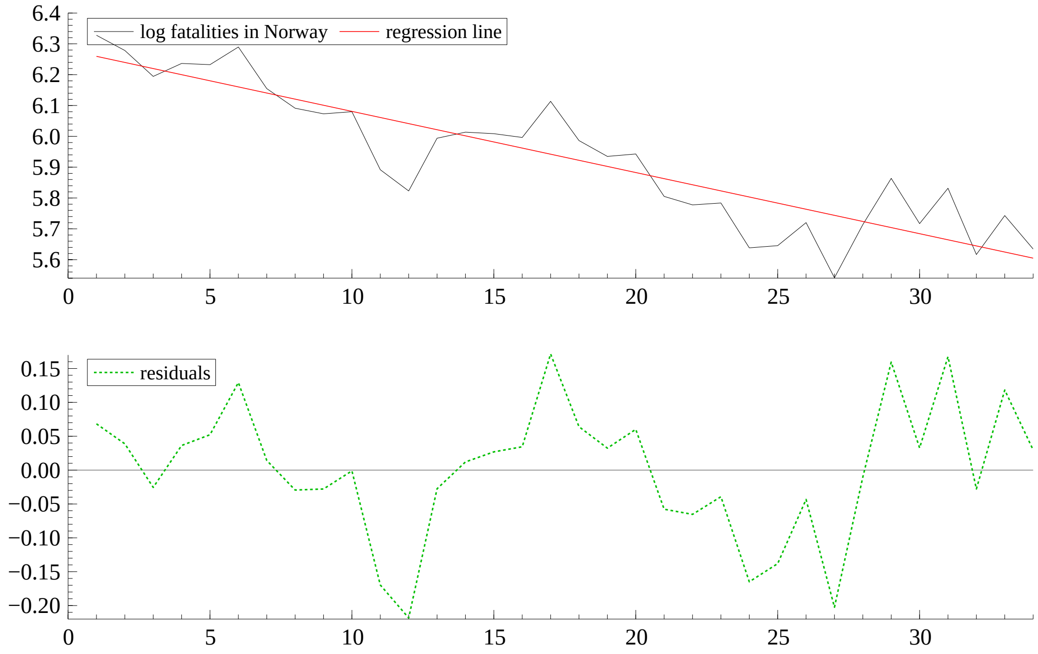
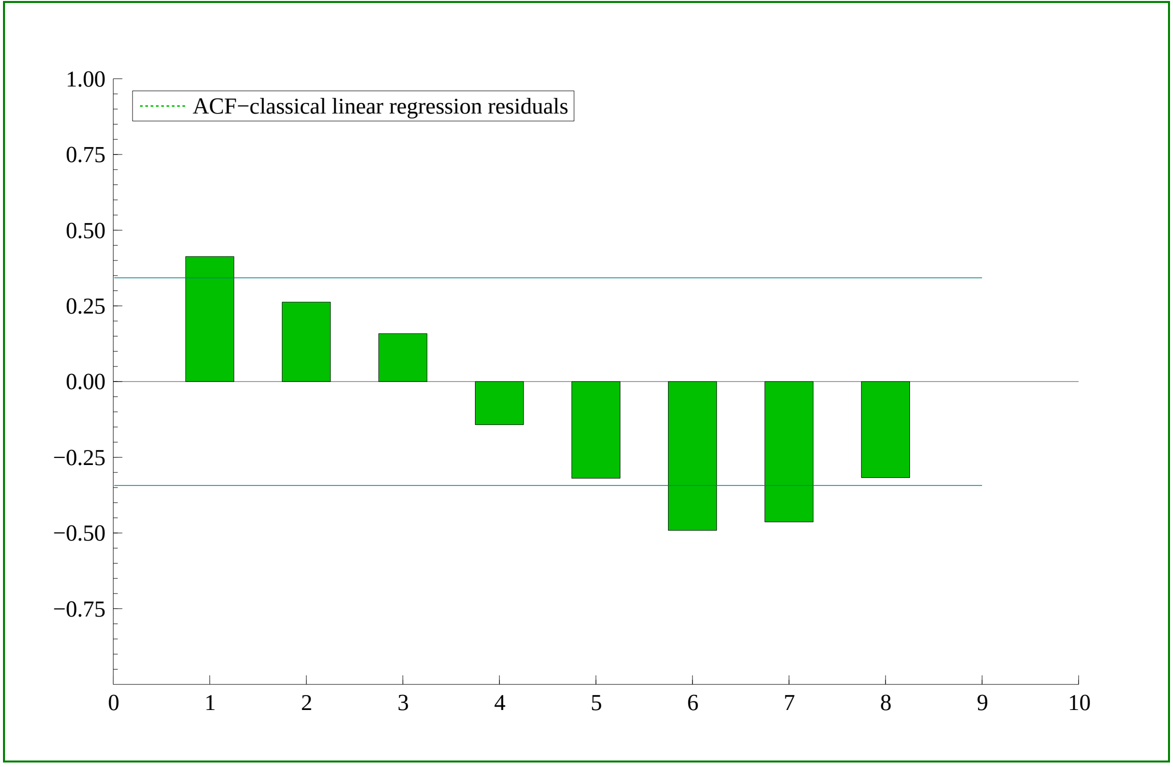


Figure 1.2: Log of fatalities in Norway plotted as a time series including regression line (top), and residuals of classical linear regression analysis (bottom).

A useful diagnostic tool for investigating whether the residuals are independent is called the *correlogram*. As will be explained in more detail in Section 2.2.3.1, the correlogram is a graph depicting the correlations between the residuals and the same residuals shifted k time points into the future. These correlations are therefore called autocorrelations.

The correlogram containing the first eight autocorrelations of the classical linear regression residuals in Figure 1.2 takes on the form shown in Figure 1.3. The two horizontal lines in the correlogram are the 95% confidence limits $\pm 2/\sqrt{n} = \pm 2/\sqrt{34} = \pm 0.343$. If residuals are independently distributed then all autocorrelations in the correlogram are close to zero, and do not exceed the confidence limits. The dependence in the classical linear regression residuals is therefore confirmed by the fact that three of the eight autocorrelations in the correlogram in Figure 1.3 significantly deviate from zero.

Generally, when the first order residual autocorrelation is positive and significantly deviates from zero, a positive residual tends to be followed by one or more further positive residuals, and a negative residual tends to be followed by one or more further negative residuals. As pointed out in the literature (e.g., Ostrom, 1990; van Belle, 2002), the error variance for standard statistical tests is seriously underestimated in this case. This in turn leads to a large overestimation of the *F*- or *t*-ratio, and therefore to overly optimistic conclusions about the linear relation between the dependent variable and time.



<u>Figure 1.3</u>: Correlogram of residuals of classical linear regression of the log of the Norwegian fatalities on time.

Note that this is exactly what is found to be the case in the classical linear regression analysis of the log of the Norwegian fatalities series discussed above: the first autocorrelation in the correlogram of the residuals is positive and significantly deviates from zero (see Figure 1.3), and positive residuals tend to be followed by one or more further positive residuals, while negative residuals tend to be followed by one or more further negative residuals (see Figure 1.2). All this implies that the value of -11.43 for the *t*-test is seriously flawed, and probably much too large.

The problem of dependencies between the residuals in the classical linear regression analysis of time series data can be solved in a number of different ways:

1. additional predictor variables can be added to the regression of the dependent variable on time such that the dependencies are removed from the residuals;
2. the relation between the dependent variable and time can be analysed with generalised linear models and/or non-linear models;
3. the dependent variable can be analysed with (dedicated) time series analysis techniques like ARIMA, DRAG and state space models.

In Chapter 2 containing the theoretical part of this deliverable, the first option is the topic of Section 2.2.3.1. In Sections 2.2.3.2 the analysis of time series data with generalised and non-linear models is presented. The ARIMA and DRAG approaches to time series analysis are discussed in Sections 2.2.4 and 2.2.5, while the state space methods are presented in Section 2.2.6.

In this introductory chapter, we illustrate how the time dependencies between the observations are dealt with in state space methods (Harvey, 1989; Durbin and Koopman, 2001). In state space methods it is assumed that the development over time of the system under study is determined by an unobserved number of components which are collectively called the state, and with which are associated a series of observations y_1, …, y_n. The relation between the state and the observations is specified by the state space model. The purpose of time series analysis by state space methods is to infer the relevant properties of the state given a series of observations y_1, …, y_n.
State space methods handle the dependencies between the observations constituting a time series by absorbing them directly into the model. This again is achieved by allowing the intercept and/or the regression coefficient -that are constants in classical linear regression- to *vary over time*.

The dependencies in the log of the Norwegian fatalities series, for example, can be handled by allowing the intercept in model (1.1) to vary over time, as follows:

$$y_t = a_t + bx_t + \varepsilon_t, \qquad \varepsilon_t \sim NID(0,\sigma_\varepsilon^2) \tag{1.2a}$$

$$a_{t+1} = a_t + \xi_t, \qquad \xi_t \sim NID(0,\sigma_\xi^2) \tag{1.2b}$$

where t = 1, …, n, and n is the number of observations. The second equation in (1.2b) allows the intercept (i.e., the level) to change from time point to time point. Moreover, in this equation 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. Therefore, 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.

Applying model (1.2) to the log of the Norwegian fatalities series, we find

$$\hat{y}_t = a_t - 0.019860x_t,$$

for t = 1, …, n, with variances $\sigma_{\varepsilon}^{2} = 0.00367357$ and $\sigma_{\xi}^{2} = 0.0035908$. The values of $\hat{y}_t$ are plotted at the top of Figure 1.4, while the values of the residuals ε_t obtained with model (1.2) are graphed at the bottom of Figure 1.4.

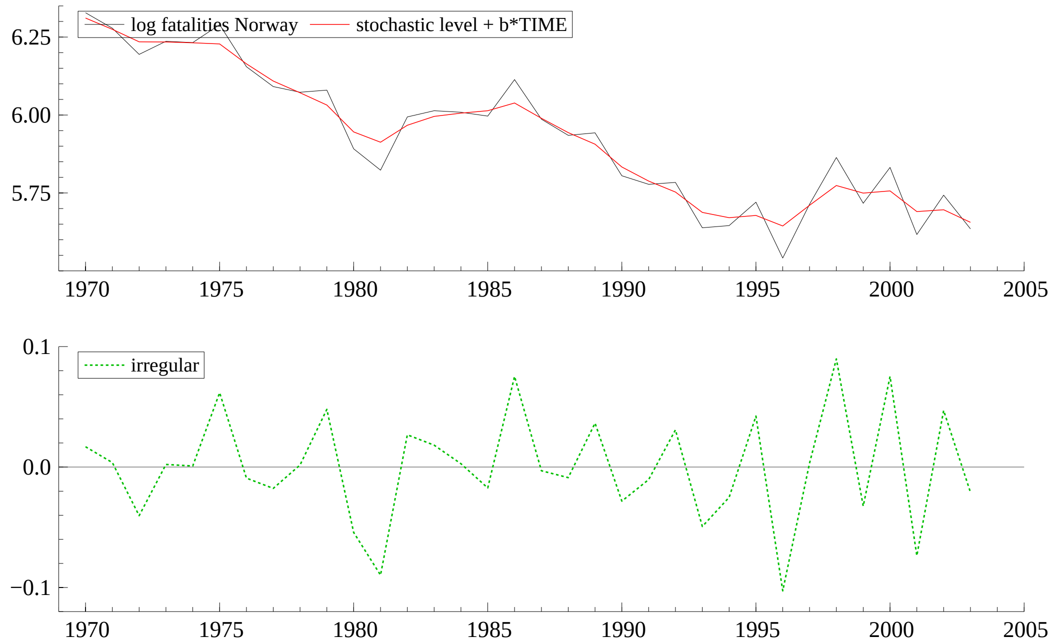


Figure 1.4: Correlogram of residuals of classical linear regression of the log of the Norwegian fatalities on time.

The first eight autocorrelations of the residuals in Figure 1.4 are shown in the correlogram in Figure 1.5 (see again Section 3.3.1 for the exact definition of the correlogram). None of these autocorrelations exceed the 95% limits of ±0.343. In contrast with classical linear regression, this indicates that the residuals of the state space analysis are independent of one another, and that the value of the *t*-test can now therefore be trusted.

In this case, the standard *t*-test for establishing whether the regression coefficient *b* = -0.019860 deviates from zero yields

$$t = \frac{-0.019860}{0.0106358} = -1.87.$$

Since the value of the latter *t*-test is associated with a *p*-value of 0.071, the relation between the Norwegian fatalities and time is no longer significant at the conventional 5% level. Moreover, since the values of the regression coefficient obtained with classical linear regression and with state space analysis are virtually identical, the large difference between the values of the two *t*-tests can be almost completely attributed to the large differences in their standard errors: 0.0017356 for classical regression versus 0.0106358 for time series analysis. See Durbin and Koopman (2001, par 6.2.4) for details on how to calculate the denominator of the *t*-statistic.

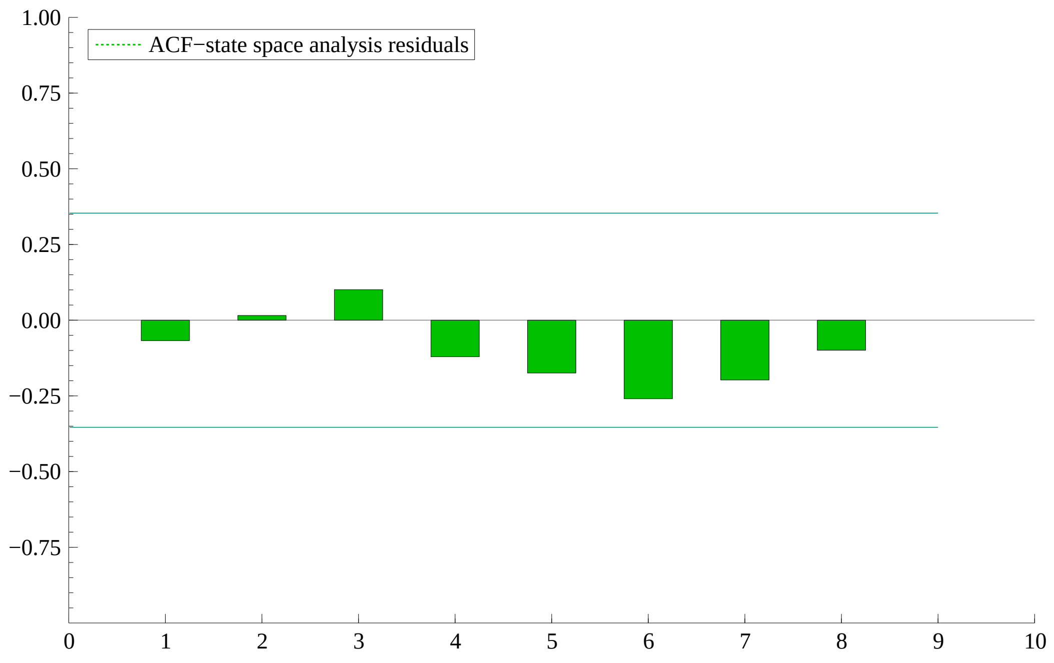


Figure 1.5: Correlogram of the residuals of state space analysis of the log of the Norwegian fatalities.

Generally, time series analysis can serve three purposes. First, time series analysis can be used to obtain an adequate *description* of the time series at hand, as we have illustrated for the log of the Norwegian fatalities series. Second, explanatory variables other than time can be added to the model in order to obtain *explanations* for the development in the time series at hand. In SafetyNet, these explanatory variables are national exposure data (as collected in WP2), national safety performance indicators (as collected in WP3), and national road traffic safety measures. A third important application of time series analysis is the ability to *predict* or *forecast* further developments of a series into the (unknown) future. In traffic safety research, such forecasts can be used to assess whether future national safety targets are likely to be met, for example.

In order to obtain adequate forecasts from a modelled time series it is crucial that the chosen model is itself appropriate. We therefore end this section by illustrating the differences between forecasts obtained with a misspecified model, and with a more appropriately specified model.

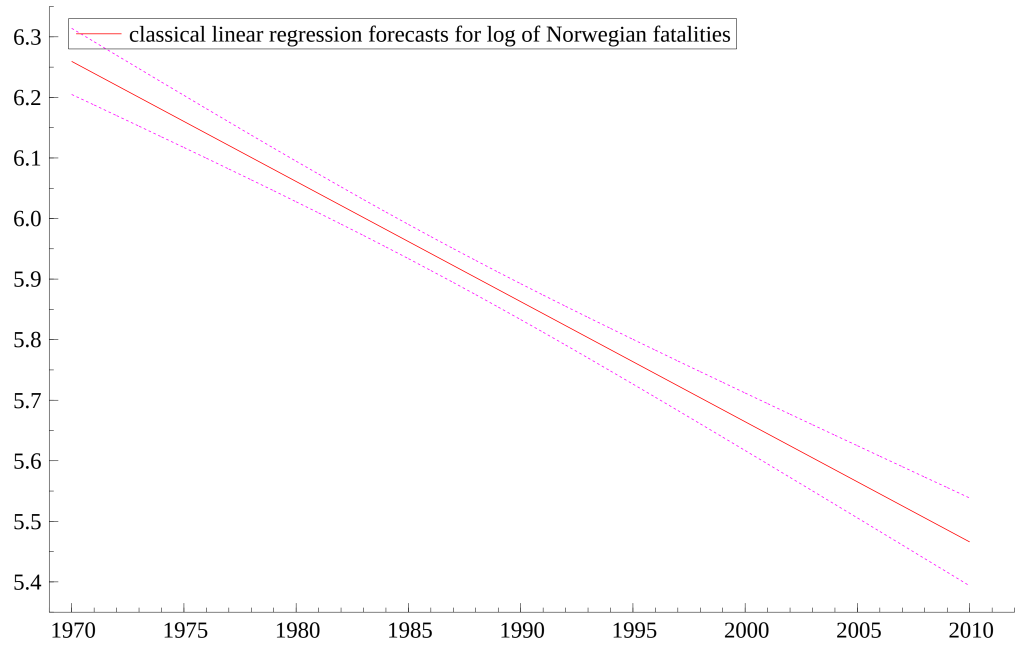


Figure 1.6: Classical linear regression analysis forecasts for Norwegian fatalities.

Applying the incorrect classical regression model (1.1) to the log of the Norwegian fatalities series, the forecasted number of fatalities in Norway for the years 2004 through 2010 are those shown in Figure 1.6, together with their 90% confidence limits.

For the years 2004 through 2010 the forecasts in Figure 1.6 are 5.5851, 5.5653, 5.5454, 5.5256, 5.5058, 5.4859, and 5.4661, respectively. Thus, according to classical linear regression the number of road traffic fatalities in Norway will show a steady decline, resulting in a predicted number of exp(5.4661) = 237 fatalities in the year 2010.

As will be discussed in more detail in Section 3 of Deliverable 7.3 the most appropriate state space model for describing the log of the Norwegian fatalities series is actually a so-called local level model (see Section 3.6). The forecasts obtained with the local level model for the years 2004 through 2010 are shown in Figure 1.7, together with their 90% confidence limits. The values of the forecasts in Figure 1.7 are all equal to 5.6627. In contrast with the forecasts obtained with classical linear regression, therefore, according to state space analysis the future number of road traffic fatalities in Norway will not decline, but remain at a constant level of exp(5.6627) = 288 fatalities per year. Moreover, the 90% confidence limits of the state space model in Figure 1.7 indicate a much larger (and more realistic) uncertainty about these predicted values than the confidence limits associated with the forecasts obtained with classical linear regression (see Figure 1.6).

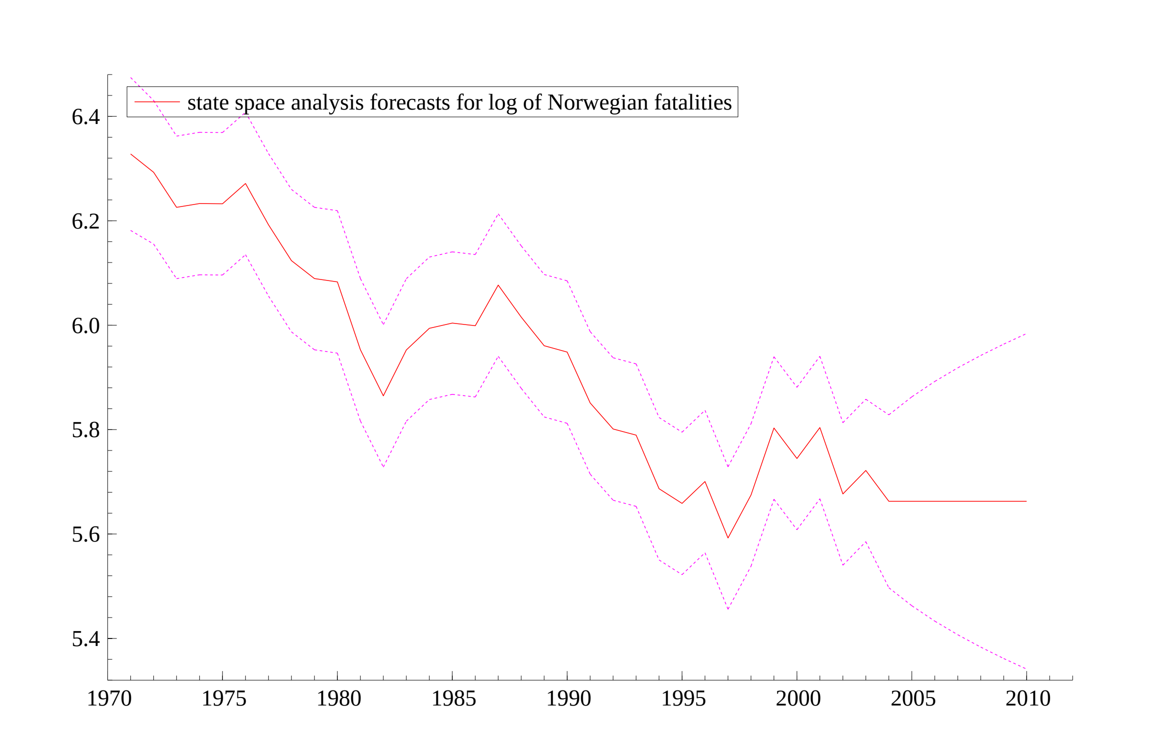


Figure 1.7: State space analysis forecasts for log of Norwegian fatalities, See Section 3 for details .

Summarising, when dealing with repeated measurements over time, statistical tests based on standard techniques like classical linear regression easily result in overoptimistic or even plain incorrect conclusions, due to the fact that the residuals obtained with these techniques usually do not satisfy the model assumptions. This is true irrespective of whether the interest lies in descriptive analysis, in explanatory analysis, or in forecasting.

Dedicated time series analysis techniques, 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. This is not only true for the state space methods illustrated in the present section, but also applies to other dedicated time series techniques like ARIMA and DRAG models.

Since many data collected in the SafetyNet project consist of repeated measurements over time, it is essential that the relations between developments in accident data (WP1), exposure data (WP2), and safety performance indicators (WP3) in the EU are investigated with dedicated time series analysis techniques.

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