Statistical Modelling of Traffic Safety development

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This thesis is submitted to the Technical University of Denmark (DTU) in partial fulfillment of the requirements for the PhD degree.

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The thesis is concerned with modelling of past and future road traffic safety developments. The main contribution of this paper is a discussion of how statistical analysis techniques can improve the evaluation of potential countermeasures

The work was supervised by Poul Thyregod at IMM, DTU and Ass. Professor and Research Director, Kurt Petersen, at DTF

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Abstract

Road safety is a major concern for society and individuals. Although road safety has improved in recent years, the number of road fatalities is still unacceptably high. In 2000, road accidents killed over 40,000 people in the European Union and injured more than 1.7 million. In 2001 in Denmark there were 6861 injury traffic accidents reported by the police, resulting in 4519 minor injuries, 3946 serious injuries, and 431 fatalities.

The general purpose of the research was to improve the insight into aggregated road safety methodology in Denmark. The aim was to analyse advanced statistical methods, that were designed to study developments over time, including effects of interventions. This aim has been achieved by investigating variations in aggregated Danish traffic accident series and by applying *state of the art* methodologies to specific case studies.

The thesis comprises an introduction to accident data, and influential factors such as changing traffic volumes and demographic and economic trends. It highlights the limitations in the influential factors data-structure, in particular, their strong covariance and slow development over time.

An important issue in this thesis was to investigate the temporal dependency in the accident series. The thesis shows that the monthly observations of accidents are serially correlated and that this correlation can only partly be explained by the explanatory variables. One should therefore use dynamic modelling techniques to analyse variations in accident series. The thesis demonstrates that the general decreasing tendency in the accident series has its own slow pattern, not explicable by recorded descriptive variables.

In addition, as a result of the research projects carried out during the preparation of this thesis, I have published the following papers:

- Statistisk modellering af trafik uheld, Trafikdage på Ålborg Univeristet, 2001.
- Sociale karakteristika hos trafikofre, Danish Transport Research Institute, 2001.
- Models for traffic accidents, FERSI Young Researchers' Seminar, 2001.
- Evaluation of the Danish Automatic Mobile Speed Camera Project Experiment: A State-space intervention analysis, symposium i anvendt statistik, 2003.

Resumé

Trafiksikkerhed er et stort problem, som vedrører samfundet og det enkelte individ. Selvom trafiksikkerhed er gradvis forbedret gennem de seneste år, er antallet af dræbte i trafikken stadig uacceptabelt højt. I 2000 dræbte trafikuheld over 40.000 i EU og skadede over 1.7 millioner. I Danmark i 2001 var der 6861 politirapporteret trafikuheld med tilskadekomst. De resulterede i 4519 lettere tilskadekomne, 3946 alvorligt tilskadekomne og 431 dræbte.

Det generelle formål med dette forskningsarbejde er at forbedre indsigten i trafiksikkerhedsarbejdet på aggregeret niveau. Formålet er at analysere advancerede statistiske metoder, som er udviklet til at analysere udvikling over tid inklusiv bestemmelse af interventioner. Dette formål er opfyldt ved at undersøge variationer i tidsrækker af aggregeret danske trafikuheld og ved at anvende *state of the art* metoder til bestemmelse af specifikke tiltag til forbedring af trafiksikkerheden.

Nærværende afhandling begynder med en introduktion af uheldsdata, betydningsfulde faktorer som varierende trafik volume og demografiske og økonomiske tendenser, og fremhæver begrænsninger i deres datastruktur. Navnlig deres stærke kovarians og langsomme udvikling over tid.

Et vigtigt emne i denne afhandling er undersøgelse af den tidslige afhængighed i observationer af trafikuheld. Afhandlingen påviser, at antallet af uheld er korreleret over tid, og at denne korrelation kun delvis kan forklares ved hjælp af de forklarende variable. Derfor bør man anvende dynamiske modelleringsmetoder til at analysere variationer i tidsrækker af trafikuheld. Denne afhandling demonstrerer desuden, at den generelle aftagende tendens i antallet af trafikuheld har sin egen langsomme udvikling, som ikke kan beskrives ved hjælp af registreret descriptive variable.

Foruden afhandlingen er der tillige publiceret følgende:

- Statistisk modellering af trafik uheld, Trafikdage på Ålborg Univeristet, 2001.

- Sociale karakteristika hos trafikofre, Danish Transport Research Institute, 2001.
- Models for traffic accidents, FERSI Young Researchers' Seminar, 2001.
- Evaluation of the Danish Automatic Mobile Speed Camera Project Experiment: A State-space intervention analysis, Symposium i anvendt statistik, 2003.

Contents

CHAPTER 1

Introduction

This thesis deals with the field of traffic safety research. While some mathematical statistics are needed, the emphasis is on the methods and their conceptual underpinnings rather than their theoretical properties. As a result, this thesis will hopefully appeal not only to the statisticians but also to the broad spectrum of researchers and practitioners in the field of traffic safety.

1.1 Background

Traffic safety is a major concern for society and the individual. Although traffic safety has improved in recent years, the number of road fatalities is still unacceptably high. It is estimated that by 2020, road traffic accidents will have moved from ninth to third in the world disease burden ranking, and second in the developing countries (Bunn et al., 2003). In 2000 road accidents killed over 40,000 people in the European Union and injured more than 1.7 million. In Denmark in 2001 there were 6861 police reported traffic accidents with injuries, resulting in 4519 minor injuries, 3946 serious injuries, and 431 fatalities (Statistics-Denmark, 2002).

Compared to most other OECD countries, the Danish traffic accident fatality rate is low, but compared to its nearest neighbours in Scandinavia and the northern part of Europe, Denmark has a high fatality rate. (Sweden 6.7 deaths per 100,000 inhabitants, Norway: 6.8, Netherlands: 6.8, United Kingdom: 6.0, Germany: 9.1 and Denmark: 9.3) (IRTAD, 2002).

In the OECD countries traffic accidents are the leading cause of death among the 3-34 year age group. Traffic accidents are among the 4 leading causes of lost life-years in Denmark (Sundhedsministeriet, 97) and are ranked even higher if measured in disability adjusted life-years.

For many years, strategies and actions to reduce this unacceptable social burden have been devised and implemented by national governments, but until the early 1980s they were mainly based on a reactive approach, i.e. aiming to slow down the existing negative developments. In the last two decades, however, some governments, including the Danish government, have begun to take the more progressive approach of planning for future safety improvements by building on the knowledge acquired in the past. The Danish Commission of Traffic Safety has set up action plans for traffic safety in Denmark for the periods 1986-2000 and 2000-2012. The plans include overall targets, focused areas and suggested countermeasures.

In order to develop realistic quantitative safety targets, and then to design effective strategies and plans, one has to be able to measure safety developments and to understand the underlying processes and their causes. This, in turn, requires extensive and reliable data recorded over a long period of time, and modelling techniques that are suitable for describing, interpreting and, ideally, forecasting safety developments.

1.2 End-user objectives

The end-user objectives of the work described in this thesis are to investigate methodologies for the analysis of previous and future traffic safety developments. this thesis focuses on following three areas.

- To be able to determine which safety developments could be anticipated from changes in influential factors such as changing traffic volumes and demographic and economic trends.
- To be able to attribute a change in the accident counts to a particular countermeasure taken, the influence of other sources of variation must be established. Modern statistical modelling techniques can be very effective in sorting out the influence of other sources of variation.
- To review and discuss a number of modelling methodologies, with a view towards developing a sound methodology for describing changes in traffic safety.

1.3 Outline of the thesis

The thesis is organized into two separate parts:

Part 1 consists of chapters 2- 3, which introduce and discuss traffic safety research, its measures and statistical modelling methods, exemplified by Danish accident series.

Chapter 2 presents traffic safety data and potential exposure data. It discusses problems when relating changes in road safety to changes in the surroundings. Simple explorative modelling techniques are used to extract relevant information from the data.

A brief *State of the Art* review is given in chapter 3. Various non-dynamic and dynamic modelling techniques are discussed and applied to the aggregated traffic safety data.

In **Part 2** three different aspects of the modelling methods described in part 1 are applied to relevant Danish traffic accident scenarios.

Chapter 4 is an evaluation of an area-wide speed reducing experiment for preventing traffic related injuries. The Chapter is based on Christen (2003), which investigates traffic calming through speed camera enforcement. The study applies dynamic basic structural models within the state space framework.

Chapter 5 analyses the impact of an imprecise description in police reporting manual '*Vejledning til indberetning om færdselsuheld*' on the reported number of accidents through state space models with time dependent parameters. Time dependent parameters are a natural extension of the model in chapter 4. This method is also applied to analyze whether the influence of traffic exposure remains constant over time.

The aim of chapter 6 is to set up a method for assessing the ability of detecting a shift, caused by a countermeasure, in a given traffic safety times series study. This so-called power is calculated through simulation.

The summary and conclusions are given in chapter 7.

CHAPTER 2

Accident data

Traffic accidents may be explained by examining influences at different levels of causality such as lifestyle influences (individual behaviour), environmental influences, and the social structure at the national level. Explaining traffic accidents at a macro level has occupied the attention of many transport and social scientists for the past three decades.

In order to analyze road accidents and monitor the safety of the road transport system, the availability and quality of accident data is of major importance. Equally important is the availability and quality of the potential explanatory data, such as the volume of traffic. To facilitate international comparisons, it is important that data are recorded consistently across nations.

This chapter presents and discusses the traffic safety data in Denmark. Furthermore, an explorative analysis of the relationship between the variation in traffic safety and variation in explanatory variables is given.

2.1 Description of data

The data source in this thesis is primarily the official Danish traffic accident statistics maintained until 31 December 2002 by Statistics Denmark. The Danish Road Directorate has from 1 January maintained the accident statistics Since 1930 the official accident statistics have been based on police reports. The advantage of the police reports is that, in principle, they are recorded consistently on a national level. Studies have shown that this reporting is almost complete when it comes to collecting the numbers of people killed in traffic accidents. However, the reporting of injury and property damage only accidents is incomplete (see 2.1.2).

Other sources of traffic accident data are available in Denmark. One is hospital admission statistics and another is statistics from insurance companies. Even though, hospital admission statistics and insurance statistics have a higher level of reporting of injury accidents and property damage only accidents, this thesis is based on the official traffic accident statistic, i.e. based on police reports. This is because, both hospital and insurance statistics suffer from temporal inconsistency as well as and lack of information about the location of the road accidents and of other parties involved in the accidents. Furthermore, gaining access to insurance data is not without problems.

2.1.1 The official accident statistics

A traffic accident in the official Danish traffic accident statistics is defined as an accident on a public road, where at least one of the involved parties is driving or bicycling.

All injury accidents and all property damage only accidents with damage exceeding 10,000 DKK are supposed to be reported to the police. A police traffic report contains information about the specific accident (e.g. time, location and a classification of the accident type and severity), the elements (e.g. vehicle specification , pedestrians and obstacles) and road users involved (e.g. age, sex and intoxication).

Injury accidents are accidents where at least one of the involved persons requires medical attention. Injuries are categorized as follows: Fatal, serious injuries and slight injuries. Accidents victims that die from their injuries within 30 days are labelled fatal. Persons dying as a result of an accident after 30 days are categorized as seriously injured.

To facilitate international comparisons it is important that the national reporting systems ideally operate to a common standard. Initiatives have been taken to propose common definitions for the basic road accident concepts at an international level, for example as in the Geneva Convention.

The definition of a traffic accident stated in the Geneva Convention is very similar to the Danish definition and is as follows:

" An accident which occurred or originated on a way or street open to public traffic which resulted in one or more persons being killed or injured and in which at least one moving 'vehicle' was involved."

Comparisons between countries show that the most common classification of casualties in accident statistics is 'fatal injury', 'serious injury' and 'slight injury' Cost

329 (in press). But the national definitions of these terms differ widely. For IRTAD, the OECD road accident database, the term 'hospitalized' has also been introduced, covering "accident victims admitted to hospital as in-patients, excluding all killed." This term coincides more or less with the term 'seriously injured' in many countries, including Denmark.

2.1.2 Source of error

Incomplete accident reporting, also called 'under-reporting', is a problem in all motorized countries (Elvik and Mysen, 1999). Since 1996, Statistics Denmark has investigated the level of reporting nationwide and the results are updated annually. By comparing hospital admission statistics with the accident statistics based on police reports, the level of reporting of various categories (e.g. severity, age, and means of transport) is estimated. The overall level of reporting in the official accident statistics is only around 20% and since 1996 this reporting level has decreased slightly. In general, the level of reporting increases as the accident severity increases. Very few (0-5) killed in traffic are not reported by the police. The level of police reporting is lowest for injuries to children, bicyclists and people involved in single accidents (13%, 9% and 11%) (Statistics-Denmark, 2002).

A survey by Odense University Hospital (Ulykkes-Analyse-Gruppen, 1997) has shown that only 45% of the traffic accident injuries treated by the hospital were included in the police reports. Additionally, the level of coverage varies with police jurisdictions. Accidents occurring in rural areas are more not reported than urban accidents (Statistics-Denmark, 2002).

International studies have shown the same relationship between location, severity and means of transport (Elvik et al., 1997). However, studies also show that the level of reporting in Denmark is lower than in countries such as Sweden, Norway, and Great Britain- countries to which Denmark is normally compared (Elvik and Mysen, 1999).

There are two major problems with underreporting. First of all, since the official measure of traffic safety is the number of fatalities and serious injuries, (Statistics-Denmark, 2002) Danish road safety is overestimated. Underreporting might also lead to an underestimation of the actual cost to society of road accidents, Thus making it difficult for a political prioritizing of the traffic safety work.

Second, the inconsistency in the level of reporting in respect to temporal and spacial resolutions makes it difficult to establish targets and evaluate traffic safety work retrospectively (e.g. when one compares traffic safety over time, one should bear in mind that the level of reporting has decreased from 23% in 1996 to 20% in 2000). Similar considerations are appropriate when comparing safety across modes of transport or across police jurisdictions. Unfortunately, there exists only scarce data on the variations in levels of reporting. Varying levels of reporting contribute extra un accounted variations in the accident models.

2.2 Measure of traffic safety

traffic safety is usually stated in terms of numbers of accidents or numbers of victims. Occasionally, the safety effects are expressed as financial losses. In this project, only numbers of accidents will be used to measure traffic safety, or rather the opposite, road unsafety. (See subsection 2.2.1 for explanation)

The principle data source used for the analysis in this thesis is monthly police reported observations of (i) the number of accidents with killed (AK), (ii) the number of accidents with killed or seriously injured AKSI, and (iii) the number of accidents with injuries (AI). All police reported accidents occuring between 1 January 1978 and 31 December 2001 are included in this study. By selecting a relatively long series, one is better able to investigate potential sources of variation.

The patterns of the 3 different series can be seen in figure 2.1

It may be of interest to subdivide the total number of accidents into various categories; for example, by road-user type and/or age-group. However, the initial analysis is focused on the broad picture with aggregated data for the purpose of developing a sound method for the analysis of time dependent data.

2.2.1 Number of injuries versus number of injury accidents

Choosing the number of injuries as the dependent variable in order to explain variations in traffic safety can introduce a source of systematic bias. This is because the number of injuries is conditional on there first being an injury accident. If the numbers of injuries per accident (injury rate) changes over time (Andreassen, 1991), then traffic safety is incorrectly estimated. This may be a problem with any definition of injury. From figure 2.2 it can be seen that both the rate of people killed per accident with fatalities and the rate of seriously injured per serious injury accident changes over time. Furthermore, a decreasing trend in the serious injury rate is visible.

An injury accident can be thought of as a single event, independent of other accidents. (Although some of the injured may be involved in more than one injury accident in their lifetime).

2.2.2 Potential explanatory variables

In order to understand developments in traffic and safety,it is not only the direct traffic safety indicators such as the number of accidents or injuries that should be

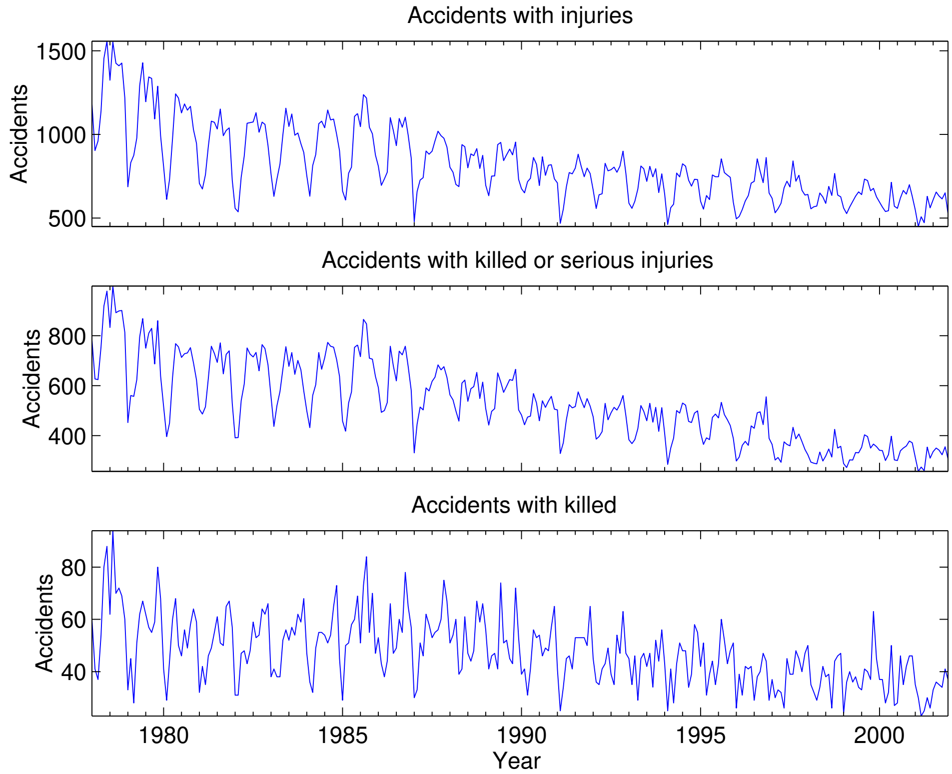

Figure 2.1: *Monthly observations of accidents with injuries (AI), with killed or serious injuries (AKSI), and with killed (AK) from 1978 to 2001.*

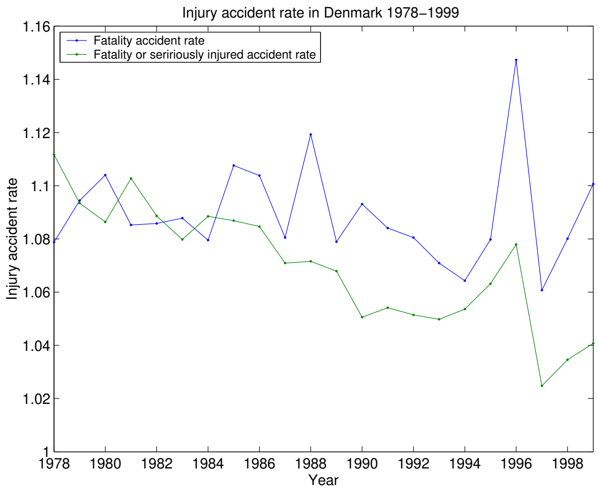

Figure 2.2: *The rate of people killed per fatal accident and the rate of serious injuries per serious injury accident.*

monitored, but also major changes in traffic, demography and economic activity. These three sets of factors are mainly outside the direct control of traffic safety; However, to effectively increase traffic safety, one has to establish the relationship between safety and these factors.

In addition to traffic, demography and economic activity many other influential factors can explain variations in the number of accidents. In an OECD (1997) report a range potential factors besides accident-countermeasures are listed:

- Weather, technological developments, oil prices, population size and composition, -factors that cannot be influenced by road safety policy makers.
- Public transportation, modal split, fuel taxes, vehicle taxes, vehicle park composition, types of driver's license etc. Many of these factors have an indirect association with safety through the amount of exposure.
- Socio-economic changes: recorded as percentage of unemployed, prosperity, consumption patterns, mobility needs, etc.

As in most areas of social sciences, there is no firm economic theory indicating which explanatory variables can explain changes in the accidents counts. The focus in this thesis is on the aggregated level, therefore, attempts to associate changes in the number of accidents with variations in the following factors/explanatory variables will be conducted:

Exposure variables

The amount of traffic is an accepted indicator of exposure to accidents [Broughton (1991), Robertson (1996)]. Previous studies have found the amount of traffic to be the single most determinant factor in accident models OECD (1997). Other indicators of exposure may include the number of hours spent in traffic, number of trips, number of vehicles, or size of population. Because there is a direct causal relationship between vehicle kilometres and the risk of accident, the number of vehicle kilometres (in 10 million kilometres) is used. Distance travelled (traffic) is recorded by the Danish Road Directorate. When analysing risk across modes of transport, the choice of exposure is highly relevant (e.g. comparisons between car kilometres and bicycle kilometres are perhaps not as relevant as car time and bicycle time).

Alcohol consumption

According to Bernhoft and Behernsdorff (2000) alcohol is involved in approximately 20% of all road fatalities in Denmark. In this analysis the amount of pure alcohol, given in litre per person over 14 years is chosen. Other different measures might also be relevant, e.g. the total number of beers consumed etc. The amount of alcohol is recorded by the Statistics Denmark

Economic factors

Economic variables have the potential to inderectly influence the amount of traffic accidents through the quantity and quality of travel (Christens, 2001a). Relevant factors could be unemployment rates and gross national product. Both unemployment (unemp) and gross national product (gnp) are recorded by the Statistics Denmark, independently of the accident statistics.

Population factors

Average risk differs considerably between age groups, [Christens (2001a), Statistics-Denmark (2002)], consequently demographic changes will have a substantial influence on traffic safety and risk. Therefore, factors such as, e.g. the proportion of young drivers (less than 25 years of age), should be taken into account when explaining variations in the total number of accidents. Another example is the impact on traffic safety of the increasing number of elderly people over the next two decades. The the total population (Pop) and the proportion of young people (young) are recorded by the Statistics Denmark.

Data collection procedure

Changes in the police reporting system have a huge impact on the reported number of accidents (OECD, 1997), which is also seen in section 2.1.2. An imprecise description in the police accident reporting manual concerning head injuries lead, in 1997 and onwards, to the misclassification of a group of serious head injuries as minor injuries (Lund and Hemdorff, 2002). This is denoted as HI

Seasonality and trend

As seen in figure 2.1 there is a clear seasonal variation in the accident counts. Additionally, one sees a decreasing trend in the accident series over the time period.

traffic safety legislation

Other potential factors that may explain variations in road accidents include road safety and transportation legislation. In this analysis the legislation of 1 October 1985 (Speed), where the speed limit in urban areas was reduced from 60 km/h to 50km/h, is included. This had a very strong effect on reducing the number of traffic accidents (Engel and Thomsen, 1998).

2.3 Explorative analysis

In the following section simple explorative methods are used in order to help to understand and predict the accident process. Focus will be on identifying and evaluating those (causal) factors with a potential influence on the accident processes. In section 2.2, 21 variables were identified; 7 quantitative variables illustrated in figure B.1 in appendix B, 12 dummy variables capturing seasonal variation (e.g. Jan.dummy equals 1 if the month is January and 0 otherwise) and finally 2 dummy variables describing the change in reporting system (hi) and urban speed limit (speed).

Unfortunately, the explanatory factors identified above are measured on different frequencies. The population factors and alcohol consumption are yearly observations. Gross national product is reported quarterly, whereas the unemployment rate and traffic index are monthly observations. While being aware that interpolation techniques can impose an artificial correlation structure between the dependent variable and the variable itself, simple linear interpolation is used in order to adjust for inadequate monitoring. Since the monthly variation in the population, the proportion of young people, and alcohol consumption is very limited, this will not impose a problem.

Illustrations of the accident processes in figure 2.1 clearly show temporal decreasing trends and seasonal variation. The trend varies across the three different accident series, but over time, road safety has improved significantly.

It would also have been natural to use scatter-plot to illustrate the relationship between explanatory variables and the accident series, if the correlation with time was not as high. This almost linear relationship between time and the explanatory variables is seen in figure B.1 and table B.1 in appendix B.1. Table B.1 shows the pairwise correlation of the 21 explanatory variables. Particularly strong correlations are seen between time and gnp, traffic, pop, young. In other words these variables tend to change simultaneonusly over time.

2.3.1 Multicollinearity between the explanatory variables

Correlation beetween the explanatory variables is called multicollinearity. When multicollinearity is present between 2 explanatory variables e.g. time and gnp, it is difficult to estimate the effect of gnp adjusting for time. This is because adjusting for time means fixing the level of time and then estimating the effects of gnp from observations whose time is at that particular level.

Multicollinearity has two potentially serious consequences :

- The estimated parameters tend to have large uncertainty.
- The interpretation of the parameter as the change in the predicted outcome per unit change in the explanatory variable, when all other variables are held constant, becomes questionable, since high correlation among the explanatory variables means that as one variable changes, the others tend to change as well.

The first point concerns model assessment: having chosen a final model, estimating its prediction error (generalization error) on new data. Whereas the second point is about model selection: estimating the performance of different models in order to choose the 'approximate best one'.

2.4 Techniques to handle multicorrelation

To be able to attribute a change in the accident series to a change in a particular factor one has to investigate the correlation structure in the set of different explanatory variables. In this thesis principal component analysis and Shrinkage methods will be applied.

2.4.1 Principal Component Analysis

Principal component analysis was originated by Pearson (1901) and later developed by Hotelling (1933). It is a multivariate technique for examining relationships among several quantitative variables. Principal component analysis can be used to summarize data and detect linear relationships. It can also be used for exploring polynomial relationships and for multivariate outlier detection (Gnanadesikan, 1997).

Principal component analysis summarizes high dimensional data into a few dimensions. Each dimension is called a principal component and represents a linear combination of the variables. The first principal component accounts for as much variation in the data as possible. Each succeeding principal component accounts for as much of the variation unaccounted for by preceding principal components as possible.

When applying principal component analysis to the seven quantitative explanatory variables from section 2.2.2, 94% of the variation among these variables can be explained by the first three principal components.

A biplot of the first few components can show useful information about the distribution of the data, eg, it can identify different groups of data or or it can identify observations with extreme values (possible outliers). A biplot consists of two elements. The data points are first displayed in a scatter plot of the principal components together with the approximated Y variables. The Y variable axis is generated from the regression coefficients of the Y variables on the principal components. The lengths of the axes are approximately proportional to the standard deviations of the variables. A closer parallel between a Y variable axis and a principal component axis indicates a higher correlation between the two variables.

The biplot B.2 in appendix B shows that the variables time (year), pop, gnp and traffic are highly correlated and also correlated with the first principal component. Alcohol and unemployment are highly correlated with each other and the second principal component. Finally, 'young' has a negative correlation with the first principal component.

The scatter-plot matrix B.4 in appendix B shows that many of the explanatory variables are highly correlated with time. Therefore, it appears appropriate to investigate the correlation structure in the explanatory variables after adjusting for time. Time itself, is not the driving factor in the different processes, but it could easily be argued that the other explanatory variables vary very slowly with time.

Adjusting for one variable corresponds to making all the other variables linearly independent of that variable. This means that, in the principal component analysis the adjusting variable gets its own principal component. In the principal component analysis of the time adjusted variables, time and the 3rd component are identical. Adjustment for time also appears to make the observations less systematic, which is seen from illustrations of the variables and the scatter-plot B.3 and in the simple adjusted scatter-plot matrix B.7 in appendix B. Now it takes 5 principal components to explain 95% of the variation among the time adjusted explanatory variables.

A temporal association in the accident processes has been established. Visual inspections of figures B.5 and B.6 in appendix B show a relatively strong association between traffic and accidents after adjusting for time. Associations are also seen with gnp, unemployment and seasonal variation. It appears that increasing traffic or increasing gnp increases the number of accidents. Unemployment appears to have a negative correlation with the number of accidents.

Alcohol, pop and young do not appear to be associated with the accident processes.

2.4.2 Shrinkage methods

So-called 'Shrinkage' methods were developed for the purpose of reducing the prediction error when predicting future observations, whats more these methods can sometimes also alter estimated coefficients and give more realistic values of the estimated parameters.

Shrinkage methods reduce the impact of predictors in a smooth way, by reducing the magnitude of their coefficients. The most common method is called ridge regression (Hoerl and Kennard, 1970). A newer method, called the 'Lasso,' tends to shrink some coefficients all the way to zero (Tibshirani, 1996). A brief introduction to Shrinkage methods is given in appendix A.

The Gauss-Markow theorem implies that the least squares estimator in Generel Linear Models has the smallest variance among all unbiased linear estimators. Being unbiased and having the smallest variance is convenient for testing hypotheses about the coefficients. However, smallest variance does not imply smallest mean-square error (prediction error). An estimator would trade a little bias for a large reduction in variance and selecting the right model amounts to creating the right balance beetween bias and variance.

Data preparation

The explanatory data consists of the 21 variables (see section 2.2.2), which form the basis for predicting the response, the number of accidents with killed or seriously injured during the period 1978 - 2001. Shrinkage methods are also applied to two other accident series: accidents with killed and accidents with injuries. Note, that the explanatory variables are exactly the same for the three different accident series.

The effect of shrinkage depends of the size of predictors (x-variables), so these are standardized to have unit variance. They are also standardized to have zero means, so that the intercept in the model can be estimated separately, without shrinkage.

The standardized x-variables were computed as:

$$x_{\text{standardized}} = \frac{x - \bar{x}}{S_x}, \tag{2.1}$$

where $\bar{x}$ is the mean and S_x the standard deviation of x.

The 12 dummy regressors (Jan, ...,Dec) representing the seasonal pattern in the accident series are defined arbitrarily. For the accidents with killed or seriously injured, December was selected as the reference month for the other seasonal parameters. The value for December itself is the difference between the general level (set to zero) and the level of December.

Discussion of shrinkage methods and accident data

By dividing the dataset into a training set of size 264 (1978-1999) and a test set of size 24 (2000-2001), a platform for evaluating the various shrinkage methods was constructed.

It is noted that these shrinkage techniques assume independent observations of the response variable, but as usually seen in accident data, the observations are not temporally independent. Therefore, one can enhance the predictive performance of the various shrinkage and selection methods by choosing the test dataset randomly in the existing dataset, but then the scenario is not applicable to real traffic safety work.

Accidents with killed or seriously injured

A linear model was fitted to the mean adjusted log-transformed number of accidents with killed or seriously injured after first standardizing the predictors to have zero means and unit variance. Least squares estimation was applied to the training set, producing the estimates, standard errors, t-test statistics, variance inflation factor, and tolerance shown in table B.2 in appendix B.

The tolerance (T) and the variance inflation factor (VIF) measure the impact of collinearity among the predictors in a regression analysis on the precision of estimation. It can be shown that the variance of parameter estimates is proportional to VIF. As a 'rule of thumb', predictors with tolerance above 10 or equivalent variance inflation factor below 0.1 should be treated carefully (Belsley et al., 1980).

It should be noted that these measures are applicable to quantitative regressors in linear models. Dummy regressors require a more general approach, because correlation among regressors in related sets are affected by nonessential changes in the model (such as changes in a baseline category for a set of dummy regressors). Since the focus in this shrinkage study is on the quantitative regressors and not the seasonal variation, no further action is taken.

The predictors, time, traffic and gnp, show the strongest effect, with HI also being significant, while young and the unemployment rate are merely significant at a 5 % significant level. However, all significant variables have too high a tolerance. Additionally, a very strong seasonal variation is present.

Table B.3 in appendix B shows the coefficients from a number of different selection and shrinkage methods. They are subset selection (by including all variables and excluding stepwise all non-significant (5%) terms), backward selection, ridge regression, the lasso, principal components regression and partial least squares. Excluding all the non-significant terms at once, alcohol, pop, speed and 6 seasonal regressors) using F-statistics has a p-value of F(1.72,9,243)=0.0848, and hence, is not significant.

Each method except subset and backward selecting has a complexity parameter, and this parameter was chosen to minimize an estimate of the prediction error based on random tenfold cross-validation (Hastie et al., 2001).

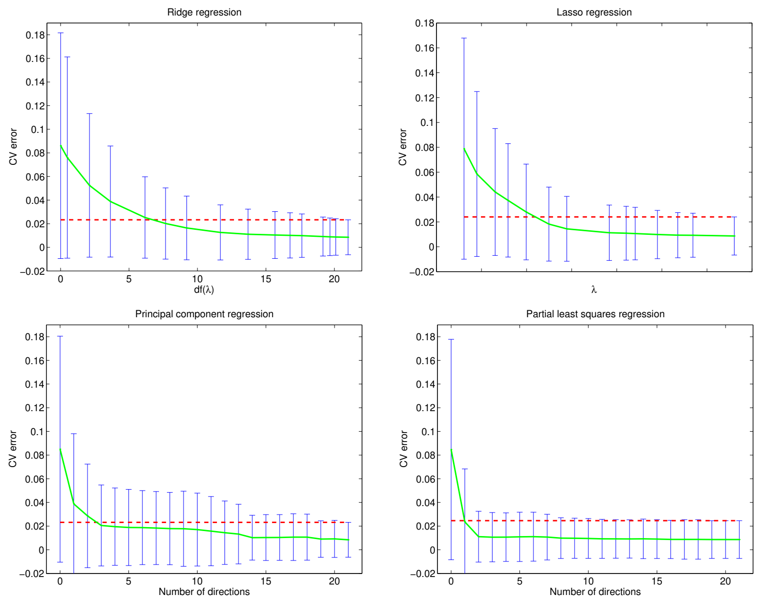

Figure 2.3: *Estimated prediction error curves and their standard errors for the various shrinkage methods. The least complex model within one standard error of the best is chosen. (broken line)*

The estimated prediction error curves are shown in figure 2.3. Many of the curves are very flat over large ranges near their minimum. The estimated standard error bands for each estimated error rate based on the ten error estimates computed by cross-validation are included. The complexity parameter for the various shrinkage methods was chosen by the "one-standard error" rule - one chooses the most parsimonious model within one standard error of the minimum.

The "lasso" estimates have two main advantages over subset selection models: first, they can be computed by standard continuous optimization procedures; second, the estimate varies smoothly with the learning set and with the hyper-parameter setting. As a result, the method is stable with respect to slight changes in data and with respect to errors in the hyper-parameter tuning.

Figure 2.4 demonstrates that the "lasso" algorithm, for this road accident data, as in general, leads to parameter estimates of which some are zero while others are quite large compared to ridge regression estimates, hence giving interpretable models.

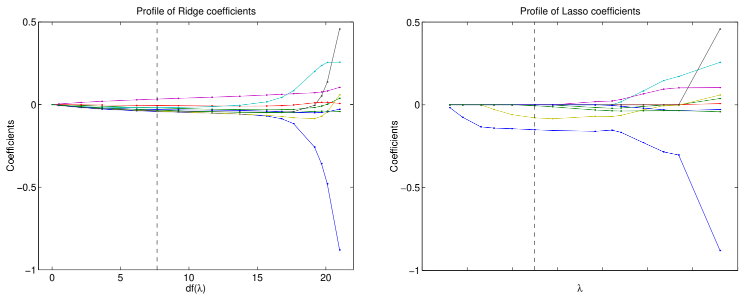

Figure 2.4: *Profiles of ridge and lasso coefficients except season regressors for the road accident data as the tuning parameter λ is varied. A vertical line is drawn at the value of the chosen tuning parameter.*

A comparison of the different shrinkage methods and subset selections should be based on the computed average prediction error (test error) and standard error, shown in table 2.1. It is seen that all the shrinkage methods and the stepwise methods deal with the over-fitting of the least squares regression, and therefore give better predictions. The "lasso" predictions are clearly the best in terms of test error and standard error. The test errors for the "lasso" predictions are about 50% of least squares and 75% of best subset selections. Partial least squares prediction is the second best, followed by ridge regression.

The "lasso" algorithm shrinks the coefficients with small variability. Still, it is a surprise that the only predictors left in the model besides seasonal regressors are time, HI and pop. In stepwise selection methods the pop had a very small t-statistic. This shows that model selection through choosing the best model and model assessment are two different aspects.

The validation of the various methods shows that both "lasso" and partial least

Predictor	LS	Subset	Backward	Ridge	Lasso	PCR	PLS
Test error	0.0200	0.0152	0.0160	0.0126	.0091	0.0181	0.0110
Std error	0.0316	0.0244	0.0239	0.0164	0.0137	0.0235	0.0165

Table 2.1: *Estimated test error results for different subset and shrinkage methods applied to the data with accident with killed or seriously injured.*

squares regression perform very well compared to the least squares regression. The "lasso" regression may be preferred because it shrinks smoothly, rather than in discrete steps.

Accidents with injuries

When applying these shrinkage and subset selection methods to the accidents with injuries, gives very similar results. However, evaluation of the test set showed that the shrinkage methods were not able to enhance the predictions. It is seen in table 2.2 that best subset selection only marginally improved the prediction error (test error). Partial least squares regression is the best shrinkage method, but only at the same level as the model with all variables included.

Predictor	LS	Subset	Ridge	Lasso	PCR	PLS
Test error	0.0106	0.0090	0.0131	0.0156	0.0228	0.0102
Std error	0.0160	0.0126	0.0189	0.0216	0.0270	0.0107

Table 2.2: *Estimated test error results, for different subset and shrinkage methods applied to the data with accidents with injuries.*

Accidents with killed

It can be seen from figure 2.5 that the variance in the prediction error for the 'best' model on the training data set is very large when predicting accidents with killed. In fact, it is so large, that when the complexity parameter for the shrinkage methods is selected by the 'one-standard error' rule, the minimal model (a model with just one intercept) is chosen. In other words, the predictions of accidents with killed through the four different shrinkage methods are equivalent and equal to the predictions from the minimal model.

The various prediction methods are again evaluated on the test set, and the comparison between the resulting three methods are seen in table 2.3. The relatively best model is the least squares model with all explanatory variables.

Predictor	LS	Subset	Minimal model
Test error	0.0267	0.0598	0.1283
Std error	0.0272	0.0708	0.1322

Table 2.3: *Estimated test error results, for different subset methods applied to the data with accidents with killed.*

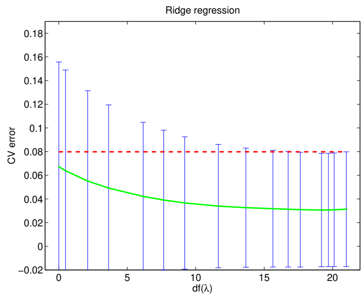

Figure 2.5: *Estimated prediction error curves and their standard errors for the ridge regression method. The least complex model within one standard error of the best is chosen (broken line).*

Conclusion drawn from use of shrinkage methods

In this section, in the light of multi-correlation, the same set of explanatory variables have been used to predict AKSI, AK , and AI through selection and shrinkage methods. For accidents with killed or seriously injured, the shrinkage methods appears to provide good predictions. It appears that there is no gain from using shrinkage methods on accidents with injuries. Finally, it is not possible to improve predictions of the number of accidents with killed through shrinkage with this set of explanatory variables. The variables have simply too little information about the accident process.

Therefore, it is concluded that in order to benefit from the various shrinkage methods, the explanatory variables need to be correlated and they need to provide information about the accident process. The ability to predict the number of accidents varies substantially across the different accident series. Only 40% of the variation accident with killed was accounted for by least squares regression. Whereas, 80% and 90% of the variations were explained in the AI and AKSI, respectively.

2.5 Conclusion

This chapter shows that variations in the accident series can partly be explained by variations in the explanatory variables, but pinpointing the source of variation to particular factors is troublesome. This is due to strong multicorrelation among the explanatory variables, especially correlation with time.

Principal component analysis is not able to disentangle the strong correlation. This is because traffic, gnp, pop, and young vary almost simultaneously with time.

The explanatory variables, ability to make linear predictions of the accidents series was also evaluated. The predictive power of the variables varies across the different series. In the series AKSI and AI the predictions are relatively good, whereas the explanatory variables can not predict the number of accidents with killed. It is mainly the temporal variables that determine the predictions.

The most important feature extracted from this chapter is the temporal dependency in accident series. This will be investigated more thoroughly in the following chapters. Additionally, there is some indication that changes in traffic, unemployment and gnp can also explain some of the variations in the number of accidents.

CHAPTER 3

Modelling variations in accident data

Traffic accidents are unwanted events. They are unpredictable in the sense that, had the particular accident been anticipated, it would most likely not have happened. Even though accidents are unpredictable at a micro level, the number of accidents at a macro level is subject to causal explanation or policy intervention. Through changes in the behaviour of the road users and through the design of the transport system, the probability of an accident occurring can be influenced, thereby altering the long-term accident frequency.

To a large extent, this randomness at the micro level together with ethical considerations precludes the use of perfectly controlled experimental designs, where the traffic safety researcher can include the factors systematically and measure the effect of the factor of interest.

Therefore, to gain insight into the causal relationship governing the accident generation process, one has to use statistical models that take developments over time into account. Such models essentially involve repeated observation of the same physical or institutional object. The unit of observation is a point or period in time (hour, day, month, year).

The purpose of this chapter is to review various modelling techniques, which were designed to understand and predict the accident process. The idea of this chapter is not to rewrite various textbooks, but simply to give a brief introduction to the various models that will be applied in this thesis.

Peltzman (1975) gave one of the first examples of a traffic safety analysis on the basis of accident risk, taking developments over time into account. Annual observations were analyzed in an additive model on the log scale. It was clear from the study that when analyzing data over a long period of time, changes over time should be accounted for.

An extensive review of the literature by Hakim et al. (1991) and several original articles on "macro models for road accidents" were published in a special issue of the journal, *Accident Analysis and Prevention* (Haight, 1991). A recent literature review is presented in Scuffham (2001) and in Cost329 (1999) a historical review is given. These reviews were used as a starting point for this thesis.

A major issue in this research is the time perspective of the different accident modelling techniques. Models that take developments over time into account can be separated into two major classes: models that use time as an index set (non-dynamic models) and models in which developments of processes over time are described (dynamic models). In the following non-dynamic models (linear and log-linear models) and dynamic models (arima and state space models) will be discussed and their ability to adapt to the traffic accident series will be investigated.

3.1 Non-dynamic models

Non-dynamic modelling techniques are widely used in the analysis of traffic safety data and for estimating and testing models for evaluation of countermeasures at an aggregated level and at the site-specific environment. In this section general linear regression and generalized linear regression models are discussed and applied. The temporal variables are entered as a simple index set, eg, as regressors or quantitative factors.

3.1.1 Log linear models

Rather compelling arguments can be found in support of the assertion that accident counts must follow the Poisson probability law (Griffin, 1989). Traffic accidents seem to occur at random in time and space. In addition, the probability of an accident occurring at a site during a short period of time (e.g. a second) is constant within this period of time. These assumptions match the properties of the Poisson probability distribution.

The Poisson regression model belongs to the class of generalized linear models (GLM), that extend the classical regression models in two ways. First, the assumption of normal errors is widened to that of errors of an exponential family. This allows, for example, Poisson, binomial, gamma and inverse Gaussian errors as alternatives.

Second, the assumption that the mean μ is linear in the explanatory variables is replaced by the assumption that some (monotonic) function of μ is linear. Familiar quantities in regression analysis have their analogies in GLM analysis; for instance, the residual sum of squares, which measures the discrepancy of the data with respect to the model, is replaced by the deviance $D = \sum d_i$, where

$$d_i = 2\int_{\mu_i}^{y_i} \frac{y_i - \mu}{V(\mu)} d\mu. \tag{3.1}$$

and where $V()$ is the variance function of the distribution assumed for the errors, thus for Poisson, the $V(\mu) = \mu$. Since, in general, the variance changes with the mean, the definition of residuals should allow for this.

Since accident occurrences are necessarily discrete, positive, often sporadic and more like random events, the Poisson regression model appears to be more suitable than the Gaussian linear regression model. The Poisson process as the binomial limit seems to fit exactly the sense of the word 'accident' as a completely fortuitous event (Haight, 1967). In a number of studies in recent years [Fridstrøm (1991), Klit (1994), Kulmala (1995), Greibe (1999)] Poisson regression models have been used to establish statistical relationships between traffic accidents and the contributing factors of their surroundings.

Danish accident series

Analyses of the accident data from section 2.2.2 through Poisson regression are performed separately according to the three different outcomes, AKSI, AI and AK. All explanatory variables, except time and dummy variables, are in logs. This means that the explanatory variables are modelled in the following additive structure on the log scale.

$$\begin{aligned} \log(\mu_i) &= \beta_0 + \beta_1 \mathrm{jan}_i + \cdots + \beta_{12}\mathrm{dec}_i + \beta_{13}\mathrm{time} + \beta_{14}\log(\mathrm{unemp}) + \\ &\quad \beta_{15}\log(\mathrm{alcohol}) + \beta_{16}\log(\mathrm{traffic}) + \beta_{17}\log(\mathrm{young}) \\ &\quad \beta_{18}\log(\mathrm{pop}) + \beta_{19}\log(\mathrm{gnp}) + \beta_{20}\mathrm{speed} + \beta_{21}\mathrm{hi} \end{aligned} \tag{3.2}$$

A thorough discussion of this choice of transformation of the explanatory variables is given in chapter 5. At this stage it is noted that the logarithmic form has a nice interpretation as elasticities and that the logarithmic form may eliminate some types of non-linearities of explanatory variables.

The estimated coefficients, standard errors and test-statistics for accidents with killed or seriously injured are given in table C.1 in appendix C. The Poisson model fit indicates strong over-dispersion ($p<0.0001$), which means that extra variation, not explained by the model, is present in the data.

Poisson regression models have some potential limitations. One important constraint is that the variance must be equal to the mean [McCullagh and Nelder (1989), Thyregod (1998)]. If this assumption is not valid, the standard errors of the estimates, usually estimated by the maximum likelihood (ML) method, will be biased and the test statistics derived from the model will be incorrect. Many researchers have modified the Poisson assumption simply by assuming that

$$\mathrm{var}(Y_i) = \sigma^2 \mathrm{E}(Y_i), \tag{3.3}$$

where σ^2, the dispersion parameter, is assumed to be constant over the estimation sample. The dispersion parameter is estimated from either the Pearson or the Devians residuals. In a number of studies [Christens (2001a) and Fridstrøm et al. (1995)] accident data were found to be significantly over-dispersed, i.e. the variance is much greater than the mean.

Over-dispersed data can arise in a number of different ways, for example, when there is inter-subject variability, which is common in behaviour studies and in studies of accident-proneness (McCullagh and Nelder, 1989).

If the precise mechanism that produces the over-dispersion or the under-dispersion is known, specific methods can be used to model the problem. In the absence of such knowledge it is convenient to assume, as an approximation, that $\mathrm{var}(Y) = \sigma^2\mathrm{E}(Y)$ for some constant σ^2. This assumption can and should be checked, but even relatively substantial errors in the assumed functional form of $\mathrm{var}(Y)$ generally only have a small effect on the conclusions. An alternative method is to assume that the variance function is quadratic instead of linear (see section 6.2). At this point a dispersion parameter is included in the Poisson model for AKSI.

Prior to interpretation and finding parsimonious linear predictors through standard modelling reduction schemes, evaluation of the validity of the underlying assumption are performed.

Residual plots for model checking in GLM

McCullagh and Nelder (1989) derive several types of residuals for GLMs, and Pierce and Schafer (1986) show that the deviance residual is almost the optimum normalizing transformation for any GLM distribution. One may thus proceed as if the deviance residuals were normal, with mean zero and common variance, irrespective of the distribution postulated for y_i (Lee and Nelder, 1998). Consequently, two important model checking plots can help with the analysis, namely, those of standardized Studentized residuals against fitted values on the constant-information scale (Nelder, 1990), and the plot of the absolute residuals against fitted values on the constant-information scale. Neither of the two residual plots in figure 3.1 indicate obvious departures from the model.

The first plot shows a running mean that is approximately straight and flat, showing

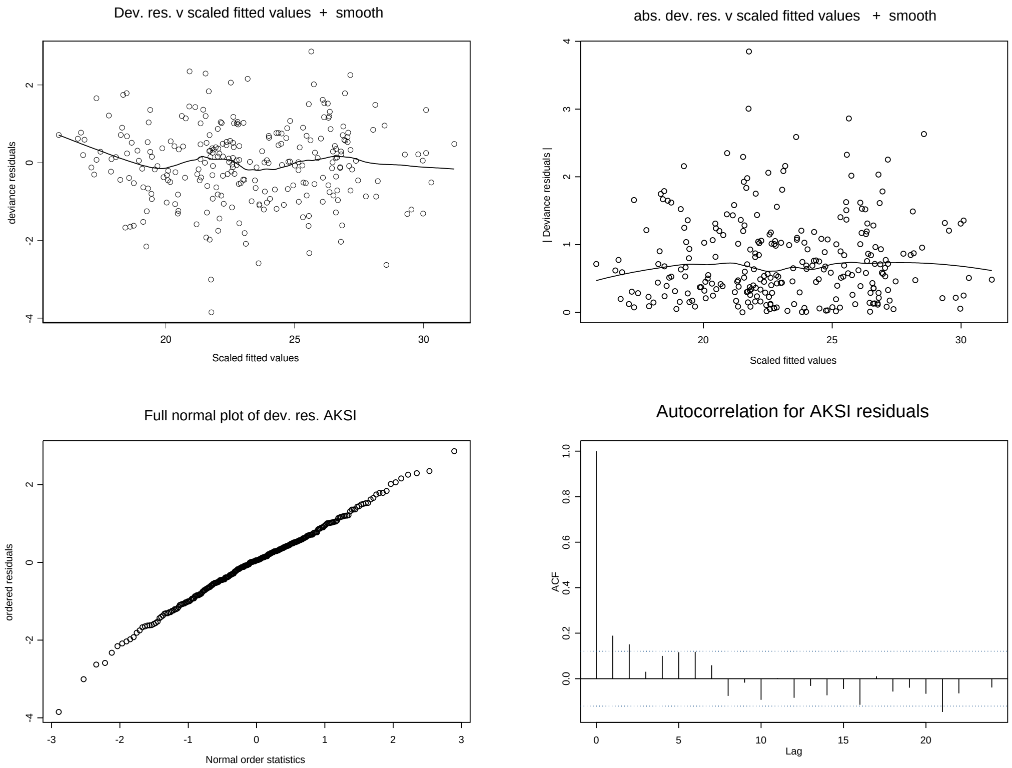

Figure 3.1: *Model-checking residual plots for accidents with killed or seriously injured.*

that the mean of the residuals is independent of the fitted values. If there is marked curvature, this indicates an unsatisfactory link function or linear predictor. Since the first plot is sufficiently flat, the second plot may be used to check the variance function $V(\mu_i) = \sigma^2 E(\mu_i)$. Again the plot is approximately straight and flat, which means that the choice of variance function is vindicated. A rising trend in the absolute residuals suggests using a variance function, $V(\mu) = \mu^2$.

Another useful plot is the full-normal plot of the residuals. (See figure 3.1). This can show isolated discrepant points as extreme points not following the trend of the remainder. Figure 3.1 shows some outliers.

The residual plots above indicate that a satisfactory variance and link function have been found. Further, diagnostics of another underlying assumption should be validated, namely, that no serial correlation is present.

Figure 3.1 shows the autocorrelation function (acf) of the standardized Studentized residuals. From looking at the acf, it is clear that there is some significant serial autocorrelation left in the residuals. It is noted, that the interpretation of the correlation between individual residuals in GLMs differs from the acf in time series models, where the correlation of the residuals is assumed to be zero (Thyregod, 1998). Due, to the model design in a GLM, the correlation of the standardized Studentized residuals $\tilde{r}_j$ and $\tilde{r}_k$ is as in equation 3.4.

$$\mathrm{corr}(\tilde{r}_j, \tilde{r}_k) = \frac{-h_{j,k}}{\sqrt{(1-h_{j,j})(1-h_{k,k})}}, \tag{3.4}$$

where $h_{j,k}$ is the element of the local hat matrix, which can be viewed as a local projection matrix, similar to the hat matrix from the linear models.

If the correlations 3.4 are small, then one often uses an significant level as if the residuals were a white noise process (uncorrelated identical random variables with mean zero and constant variance), stemming from a dynamic time series model. The estimated acf in a white noise process is asymptotic Gaussian with zero mean and variance $\frac{1}{N}$ (Madsen, 1998).

When autocorrelation in the error terms of the Poisson regression is present, reliable inferences cannot be made. Therefore, searching further for a parsimonious Poisson regression model does not appear to be relevant. A discussion of autocorrelated residuals is given in 3.1.3

The Poisson regression of accidents with injuries is very similar to the above analysis and is given in figure C.1 and table C.2 in appendix C. Again it is noted that there is some autocorrelation left in the residuals and therefore reliable inferences cannot be made. The estimated over-dispersion is 30% larger than for fit of AKSI. This additional dispersion is probably partly due to a lower level of accident reporting consistency (see section 2.1.2).

When analyzing accidents with killed through Poisson regression, all model diagnostics show no obvious departure from the model's assumptions, as seen in figure 3.2.

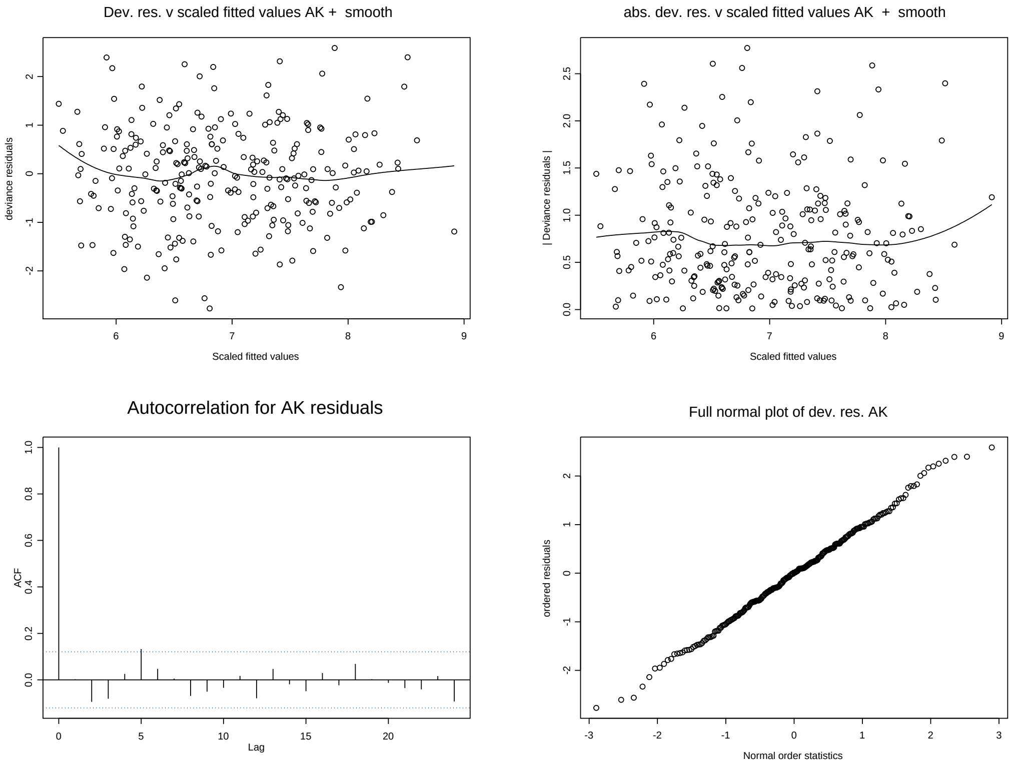

Figure 3.2: *Model-checking plots for accidents with killed.*

Table 3.1 present the results of the Poisson regression fit, excluding the highly significant seasonal parameters. The seasonal parameters are given in table C.3 in appendix C. There is only some over-dispersion in the model (p-value=0.0251), which can partly be explained by a very high recording consistency (see section 2.1.2) .

From table 3.1 it can be seen that traffic is the only explanatory variable which is highly significant and that the variation explained by one of the socio-economic variables can be explained by the other variables. Simple backward elimination of all non-significant variables, except seasonal variables, results in a model with only season, time, traffic, gnp and speed. however, due to multicorrelation (see section 2.3.1), a different end model would be achieved, if another model reduction strategy was selected.

Table 3.2 lists the estimated significant coefficients in three different end-models

Explanatory variables	Coefficient	Std. error	F-statistic	p-value
Time	-0.0889	0.0433	4.23	0.0407
logunemp	0.0338	0.1270	0.07	0.7905
logalc	0.1094	0.7587	0.02	0.8854
logtraffic	1.5909	0.2777	32.95	<.0001
logyoungpct	1.1551	0.8888	1.69	0.1951
logpop	2.1389	9.9070	0.05	0.8292
loggnp	0.5026	0.4752	1.12	0.2907
speed	-0.1411	0.0640	4.82	0.0291
HI	0.0547	0.0650	0.71	0.4002

Table 3.1: *Poisson regression fit to accidents with killed (1978-1999). F-test statistic is used due to significant over-dispersion (σ^2=1.1876, p-value = 0.0251).*

for accidents with killed. It is difficult to say which model is the most effective at pinpointing the influences of the explanatory variables, but traffic, time and speed are recurrent variables in all three models.

expl. var.	model 1 coef.	model 2 coef.	model 3 coef.
time	-0.1155	-0.0434	-0.0332
logunemp			-0.1747
logalc			1.2629
logtraffic	1.4474	1.5153	1.6111
logyoungpct		1.7381	
logpop			-14.8601
loggnp	0.9499		
speed	-0.1174	-0.1828	-0.1420
hI			
F-test statistic	0.6829	0.4051	0.1643

Table 3.2: *Poisson regression coefficients, except seasonal coef., in different end-models for accidents with killed (1978-1999) and F-test statistic for reducing all non-significant at once. Blank entries correspond to variables omitted.*

The aim of this model reduction is to achieve a model with a relatively small number of parameters and, other things being equal, a simpler model is preferred to a complicated one (principle of parasimony or Occam's razor). Therefore, one chooses either model 1 or model 2, but a further selection within these two models is not relevant. This is because the two models, due to strong multicorrelation between gnp and young (see section 2.4.1) explain almost the same changes in the accident numbers. The individual effect of gnp and young is therefore impossible to disentangle, but changes in these variables are associated with changes in number of accidents. Note that much of variation of young can be explained by gnp, whereas gnp is significant in model with both gnp and young.

During the model reduction the coefficient for the influence of speed was found to be in consistent. In a model with just temporal variables and traffic, the effect of the speed changed and had a positive association (non-significant) with accidents.

This may make the interpretation of the change in speed less strong. The variable speed is a dummy variable, which means that the effect of the speed change is modelled a sudden 11 % (1-exp(0.1174)) decrease in the number of accidents in October 1985. Visual inspection of figure 3.3, which illustrates the predicted values from model 1 and AK, indicates that the decrease is not sudden, but gradual beginning in 1987. (This also gives also autocorrelation in the residuals). A similar pattern is also reported in Pedersen (1999).

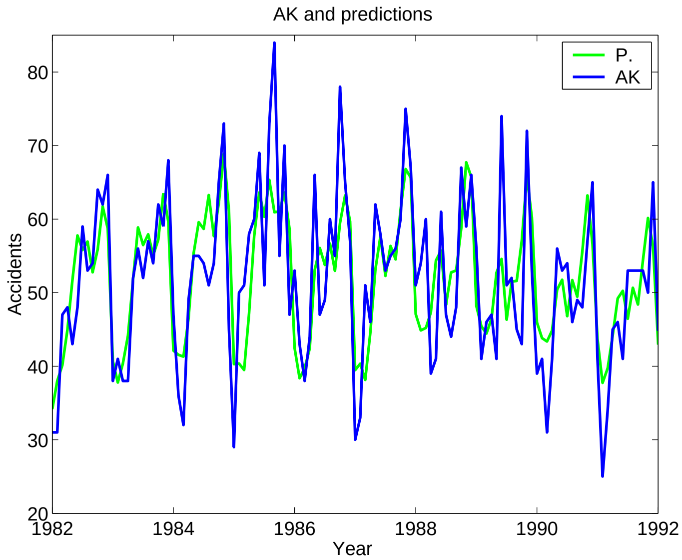

Figure 3.3: *Poisson predictions of AK from model 1 (1982-1992).*

Therefore, it is problematic to quantify the effect of the changing speed limit by this approach, but an estimate could be obtained from a model with both gnp and young in addition to the temporal variables and traffic. The estimated coefficient is then 13.52% [1.95%-23.81%] (p-value = 0.0215). Other studies have found that urban accidents were significantly reduced by the speed limit reduction (Engel and Thomsen, 1998).

The amount of traffic is highly significant and has an estimated coefficient 1.51 [1.03-1.99] found in the above model. This means that a 1% increase in traffic would lead to a 1.51% increase in the number of accidents with killed. The temporal variables are highly significant with a growth rate on -9.58% per year and a seasonal variation given in table 3.3, adjusted for traffic, gnp, young. As seen, November and December are high risk months. The limiting distribution of the Poisson is Gaussian with variance

J	F	M	A	M	J	J	A	S	O	N	D
1.06	0.93	0.87	0.90	0.95	0.95	0.85	0.92	0.94	1.08	1.28	1.37

Table 3.3: *Seasonal variation for accidents with killed*

equal to the mean. For large accident counts, therefore, one might as well model the number of accidents by Gaussian regression techniques after some variance stabilizing transformation.

3.1.2 Linear models

(Recht, 1965) was probably the first to use regression techniques in the history of the description of traffic safety developments. He attempted to explain accident rates by means of general linear models (LM). Linear models (LM) were the predecessors of GLM and have been used widely in traffic accident studies [Zlatoper (1984), Jovanis and Chang (1986), Joshua and Garber (1990)]. However, a number of researchers, [Jovanis and Chang (1986),Zlatoper (1987)], have highlighted limitations in LM to describe adequately discrete, non-negative and sporadic accident data.

The result of using LM regression on the three accident series AKSI, AI and AK do not differ much from the Poisson regression results. Since, LM regression assumes that the observations have constant variance (homeoskedasticity), a transformation of the accident counts are required. From the validation of the variance-function in section 3.1.1, one sees that the variance of accident counts appears to be $\mathrm{var}(Y_i) = \sigma^2 \mathrm{E}(Y_i)$ and therefore a square-root transformation is appropriate. However, in order to get exactly the same specification of the mean structure as in section 3.1.1, and thereby comparable coefficients, logarithmic transformation has been carried out. The two transformations do not differ much and graphical validation of the residuals plot of the log transformed model do not show any departure from the constant variation assumption.

Tables C.4 , C.5 and C.6 in appendix C show the fit of the LM regression for AKSI, AI and AK. The fit of LM and the GLM are very similar, as are the predictions made by these non-dynamic models.

The autocorrelation functions of the residuals from the LM model look similar to those from the log linear regression models, thus inferences based on LM are questionable. Therefore, one may prefer the log-linear to the LM.

3.1.3 Autocorrelated residuals

When modelling data, one must always check to make sure that all the assumptions of the model are satisfied. One of the assumptions is independent disturbance (error) terms.

The correlation between any pair of error terms of the least squares (LS) equation must not exceed the level given in equation 3.4. Should this not hold, then the residuals are said to be autocorrelated and a relationship between present and past values can be observed. Serial autocorrelation therefore refers to the existence of a linear equation involving the residuals of the regression.

There are many causes of serial autocorrelation in regressions involving time series data. Models based on monthly time series often have dependent error-term structures, stemming mainly from seasonality and trend effects and also from some momentum, not explained by other observable variables. Annual time series models usually have errors that are not autocorrelated (Zlatoper, 1984).

If the correlation of the errors Σ were known, then the formulas of the LS estimates of $\hat{\beta}$ and $\mathrm{var}(\hat{\beta})$ are

$$\hat{\beta} = (X'\Sigma^{-1}X)^{-1}X'\Sigma^{-1}Y \qquad \mathrm{var}(\hat{\beta}) = \hat{\sigma}^2(X'\Sigma^{-1}X)^{-1}, \tag{3.5}$$

As a result, estimates of β and inference procedure based on equations 3.5, where Σ are incorrectly assumed to be equal to one, will be biased. If the explanatory variables are uncorrelated with the error correlation then the usual LS estimates of β will generally still be consistent and asymptotically normally distributed. However, they will not be efficient. High levels of autocorrelation change the 'effective' number of independent observations dramatically so that observed values may provide a poor estimate of the error term [Bayley and Hammersley (1946), Nelson and kang (1984)].

Inference and estimation in the generalized linear regression models (McCullagh and Nelder, 1989) suffer from the same problems when autocorrelation is present.

There is a large body of literature on tests for serial autocorrelation. However, the standard test included in most software packages is the Durbin-Watson test (Durbin and Watson, 1950). This test is applicable for first order serial correlation. A general test for serial dependence is the pormanteau Box-Ljung Q-statistic, which is based on the first s residual autocorrelations (Ljung and Box, 1978).

It is important to produce a realistically small estimate of noise in order to establish a relationship between the accident series and the explanatory variables in question. One way to do this in the presence of serial autocorrelation is to develop autocorrelation consistent estimates of the asymptotic variance of β (Newey and West, 1987). Another, and more natural, way is to model the serial autocorrelation by means of dynamic modelling techniques. For such models, well developed software exists, allowing the researcher to specify complicated error structures.

3.2 Dynamic models

To produce an unbiased estimator of the error variance and of the coefficients of explanatory variables in the presence of serially correlated observations, statistical procedures that involve the use of transfer functions are often used. Box and Jenkins (1976) auto-regressive integrated moving average (arima) approach is an example of such a procedure. Another example is the state space models (Harvey and Durbin, 1986). In this section both arima modelling and state space models will be discussed and applied.

3.2.1 Arima models

In the arima approach one explicitly models the autocorrelation in the errors. This is done by designing a filter able to obtain all the information from the time-series. All the structure and interrelations of the process, Y_t, are to be captured by the filter. The resulting residuals should behave as a white noise process. Illustrated graphically:

$$Y_t \Longrightarrow \boxed{\text{Filter}} \Longrightarrow \text{white noise}$$

These models are based on the stationarity of the time series, that is to say, on a stable relationship between the observation at time t and the previous observations. The assumption is therefore, that the values at succeeding points in time are correlated. Hence, one can forecast values of a variable, utilizing only the information contained in the past values of the time series. These models were popularised in the 1970s in the work of Box and Jenkins (1976). Now, the expressions, arima models and Box-Jenkins focus, are considered to be practically synonymous.

The univariate arima representation of a time series matching a variable Y_t could be generalised to incorporate one or more explanatory variables. In this context, the resulting model is known as a transfer function model.

Arima modelling has been widely used in traffic accident studies [Wagenaar (1984), Scott (1986), Bergel (1992), Rebello (1999)]. These models are flexible and allow a large number of explanatory variables. They aim both at describing and forecasting traffic safety developments.

In the paper by Christens (2001b), changes in the two accident series, AKSI and AK (1978-1999), were examined in relation to changes in the following three variables: traffic, the number of young people (18-24 years) and speed. A one to one comparison with the non-dynamic models from section 3.1 is not feasible due to a smaller monitoring period (24 months) and a different explanatory factor, namely the number of young people. However, a comparison can provide information about similarities and dissimilarities in the broad picture. This is particulatly so since the development in the accident counts over time and the influence of traffic seem to be the two most important features when describing the aggregated number of accidents in Denmark.

In order to obtain a stationary series for AKSI, transformations were necessary. The visual inspection of the original series (see figure 2.1) and the analyses using the regression models recommend certain transformations. First of all, due to the non-stationary-variance observed in the series, a logarithmic transformation has been carried out. With respect to the mean, the need to transform the variable is supported by the analysis of the estimated simple autocorrelation coefficients. Seasonal differencing and regular first differencing are applied. The behaviour of the estimated coefficients for the simple and partial autocorrelation function of the transformed series, $\Delta_1\Delta_{12}$logaksi, suggests using the so-called airline model arima(0,1,1)(0,1,1)$_{12}$ (Box and Jenkins, 1976). Time series with a large number of accidents are often successfully modelled by the airline model (Harvey and Durbin, 1986).

The estimated coefficients for the airline model for AKSI are highly significant. The model can be written as:

$$\Delta_1\Delta_{12}\log(\mathrm{AKSI}) = (1 - 0.7143B)(1 - 0.7969B_{12})a_t, \tag{3.6}$$

where a_t is white noise.

The simple and partial autocorrelation functions of the residuals show signs of autocorrelation in the residuals and the portmanteau Box-Ljung Q-statistic is not accepted. Adding log traffic as a simple regressor to the airline model improves the fit, and the diagnostics of the residuals indicate no obvious departure from the model assumptions.

Table 3.4 shows the estimated coefficients, std. error, t-test and p-value from the airline model with the three explanatory variables. Traffic is the only explanatory variable which is found to be significant.

Model parameter	Estimate	Std. error	T-test	p-value
Moving average, Lag 1	0.766	0.041	18.86	<.0001
Moving average, Lag 12	0.885	0.055	16.13	<.0001
Log traffic	1.511	0.183	8.227	<.0001
No. of young	0.000	0.015	0.023	0.9810
Speed	-.089	0.055	-1.616	0.1070

Table 3.4: *Estimated coefficients, std.error, t-test and p-value for arima airline model for log AKSI*

The input variables are differenced similarly to the dependent series prior to their inclusion in the model. Investigations of the cross correlation function of the prewhited input variables did not indicate any dependencies in the lag values of the input variables.

Modelling AK within the arima framework is very similar. Again visual inspections of the different autocorrelation functions recommend using the airline model.

Table 3.5 shows the estimated coefficients, std. error, t-test and p-value from the airline model with the three explanatory variables. Traffic is the only explanatory variable found to be significant. Note, that the estimate of the changing speed limit (speed) is very similar to the estimate from the non-dynamic section, but the error is larger, giving a non-significant p-value (0.0808) The study by Christens (2001b)

Model parameter	Estimate	Std. error	T-test	p-value
Moving average, Lag 1	0.939	0.029	32.01	$<.0001$
Moving average, Lag 12	0.964	0.115	8.36	$<.0001$
Log traffic	1.483	0.273	5.43	$<.0001$
No. of young	0.015	0.011	1.39	0.1655
Speed	-.132	0.075	-1.75	0.0808

Table 3.5: *Estimated coefficients, std.error, t-test and p-value for arima airline model for log AK*

concludes that there is some difference in the performance of the arima models compared to the performance of the Poisson regression models. Log linear regression of the accidents with killed or seriously injured indicated that inferences might not be reliable, since autocorrelation is present in the residuals. Due to the autocorrelation not being accounted for, the estimated coefficients are all significant in the log linear model, whereas only traffic is significant in the arima model, which models the autocorrelation. It should be noted, that the changing speed limit is almost significant at 5% significant level in the arima model for accidents with killed.

The forecast for 1999 and the fit of the models measured in mean error and test error are almost identical with a small advantage to the Poisson regression models.

Arima models have some potential limitations. One important constraint is that the appropriate way to deal with trend and seasonal components is to eliminate them by differencing. This prevents the researcher identifying the main observable features of the accident series under study. Another potential problem is the model selection approach advocated by Box and Jenkins (1976). This approach may lead the model builder into a fairly wide range of possible arima models, when it is not likely that any of these would be a suitable model (Harvey and Durbin, 1986).

3.2.2 State space models

The distinguishing feature of state space time series models is that observations are regarded as being made up of distinct components such as trend, seasonal, regression and disturbance elements, each of which is modelled by a separate dynamic process. Thus, the state space models, also called structural models, are based on the traditional intuitive representation of a regression model:

$$Observed\ series = trend + seasonal + regression + irregular,$$

However, the trend and seasonal components and perhaps the regression coeffecients are not assumed to be constant, but allowed to vary over time. The "irregular" component reflects non-systematic movements in the series. This is in sharp contrast to the philosophy underlying Box Jenkins arima models, where the trend and seasonality are removed by differencing prior to detailed analysis.

The Kalman filter (kalman, 1960) plays a key role in the statistical treatment of state space models as least squares estimation in linear models. The Kalman filter is a recursive estimation algorithm that minimises the mean square error and decomposes the one-step-ahead prediction errors.

The first attempt at estimating the relationship between accidents and explanatory variables using state space models was performed by Harvey and Durbin (1986). Recently, these models have been widely used in accident research to examine variations in monthly, quarterly and annual observations of traffic safety [Diamantopoulou et al. (1999), Scuffham (2001), Scuffham and Langley (2002), Lassarre (2000)]. Oppe and Bijleveld (1999) used the state space approach to simultaneously model the amount of traffic and accident risk (injuries per accident). Thereby separating the trends and seasonal variations in exposure (traffic) and risk.

Harvey and Durbin (1986) proposed a state space model, named basic structural model (BSM), where the trend and seasonality are modelled as a local linear trend and a seasonal random walk. This model is adopted to the study of AKSI, AI and AK. The model can be described as follows:

$$\begin{aligned}
y_t &= \mu_t + \gamma_t + \epsilon_t \\
\mu_t &= \mu_{t-1} + \beta_{t-1} + \eta_t \\
\beta_t &= \beta_{t-1} + \zeta_t \\
\gamma_t &= -\left(\sum_{i=1}^{s} \gamma_{t-i} \right) + \omega_t,
\end{aligned} \tag{3.7}$$

where y_t denotes the log transformed number of accidents. s is the number of seasons. All disturbances, ϵ_t, η_t, ζ_t and ω_t, (so-called hyper-parameters) are independent Gaussian distributed with zero mean and variances σ^2_ϵ, σ^2_η, σ^2_ζ, and σ^2_ω. If $\sigma^2_\eta = \sigma^2_\zeta = \sigma^2_\omega = 0$ then the model collapses to a simple non-dynamic LM with a global trend and fixed seasonal variation, as in section 3.1.2.

Figure 3.4 illustrates a moving trend estimated in the BSM for AKSI. The disturbance components for this BSM fit are $\sigma_\epsilon^2 = 0.006246$, $\sigma_\eta^2 = 0.00097$, $\sigma_\zeta^2 = 0$, and $\sigma_\omega^2 = 0$, meaning that the model estimates a moving level, but the slope and seasonal variation remain constant over time. A BSM with fixed season and slope corresponds to the so-called airline model (in the arima framework) with a seasonal moving average parameter close to one. From tables 3.4 and 3.5 it is seen that the seasonal parameter is close to one, particularly the parameter for accidents with killed.

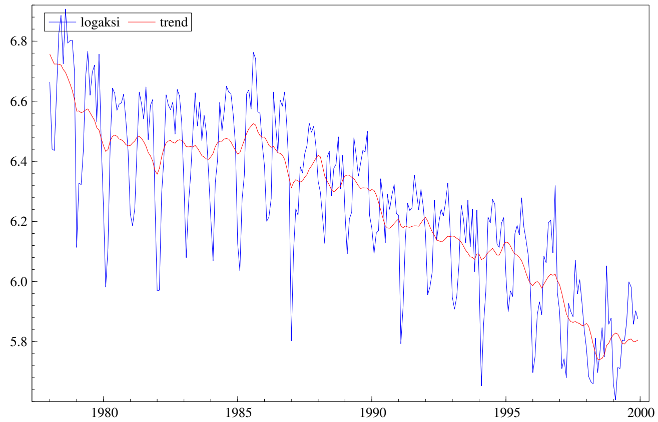

Figure 3.4: *Log transformed AKSI and the estimated trend in the corresponding basic structural model.*

Illustrations of the residuals and the smoothed irregular disturbance component showed that the number of accidents in January 1987 was extremely low, which is also indicated in figure 3.4. This finding is explained by unusually cold weather conditions (Statistics-Denmark, 1988). By adding a dummy variable for that particular observation, the diagnostics of the model are improved.

Non-dynamic modelling techniques (section 3.1) indicated that some of the movements in the series can be accounted for by the explanatory variables. In order words, the explanatory varibles reduce the variance of the hyper parameter in the three accident series. For accidents with killed the hyper parameters are equal to zero when some of the explanatory variables (trend, season, traffic and gnp) are included.

Explanatory variables are all entered as in the classical linear regression models, but one should note that since the (relative) variances are not known, the traditional t-value does not follow a t-distribution. This is not a problem in large samples, since the regression parameters converge to normal distribution (Harvey and Durbin, 1986).

Table 3.6 lists a range of diagnostics tests to verify an appropriate model specification. The first two test for serial correlation: The Durbin-Watson is the statistic for first-order autocorrelation approximately assymptotic normal (2,4/T). Box-Ljung is the pormanteau Box-Ljung Q-statistic, which is based on the first s residual autocorrelations (Ljung and Box, 1978), tested against a χ^2_{s-p} distribution. Normality tests for skewness and kurtosis of the residuals (Bowman and Shenton, 1975) are assumed to be χ^2_2 distributed. Finally, a $F_{m,m}$ test is undertaken for heteroskedasticity, known as the H-test (Harvey and Durbin, 1986).

Variable	Estimate	p-value
Durbin Watson	1.8958	0.3953
Box-Ljung	15.223	0.1725
Normality	1.5339	0.5665
Heteroskedasticity	1.2269	0.1776
Pred. error var.	0.0062	
R^2_s	0.4415	

Table 3.6: *Summary diagnostics for the full state space model for AKSI (1978-1999), adjusted for an outlier in January 1987.*

The coefficients of determination, R^2_s, used in this study are based on first differences around the seasonal mean. The usual coefficient of determination, R^2, will often be close to unity if the model is only able to detect the trend in the accident data. Therefore R^2_s better reflects a good description of the data.

None of the diagnostic test indicate obvious departures from the model assumptions and investigations of the residuals showed nothing unusual. The prediction error variance is the variance of the one step ahead prediction errors. A larger prediction error variance reflects a less accurate fit.

Table 3.7 lists the estimated coefficients of the explanatory variables together with standard deviations, test statistics and the p-value. The coefficient for traffic is the only significant variable. Unemployment and HI are nearly significant at a 5% significant level. The estimated coefficients of these are very similar to those from the non-dynamic models (see section 3.1). The estimated coefficients for the variance of the state disturbance components are: $\sigma^2_\epsilon = 0.0047$, σ^2_η = 3.40e-5, $\sigma^2_\zeta = 0$ and σ^2_ω = 2.23e-5. These indicate that the trend is changing over time, a fixed slope and, a minor changing seasonal pattern. The changes in the seasonal pattern over the period are non-significant (p = 0.5598). This is assessed by a likelihood ratio test.

Stepwise reductions of all non-significant explanatory variables resulted in the model with summary diagnostics given in table 3.8. At all stages in the model reduction, the model was checked using the diagnostics described in the previous section, and the coefficients of the explanatory variables were examined. Once a parsimonious end model was obtained, a reduction in the state disturbance components was performed. The variance of the level component is σ^2_η = 2.59e-5, slope and seasonality are fixed and the irregular component is $\sigma^2_\epsilon = 0.0050$.

Variable	Coefficient	R.m.s.e.	Test statistic	p-value
logunemp	0.1882	0.1037	1.8142	0.0708
logalc	0.3683	0.6328	0.5821	0.5610
logtraffic	1.5768	0.2057	7.6643	<.0001
logyoungpct	0.3517	1.2045	0.2920	0.7705
logpop	0.4309	11.5930	0.0371	0.9704
loggnp	0.2204	0.2998	0.7352	0.4628
speed	-0.0763	0.0543	-1.4032	0.1618
HI	-0.0925	0.0537	-1.7210	0.0865

Table 3.7: *Estimated coefficents for the explanatory variables in the full state space model for AKSI (1978-1999), adjusted for an outlier in January 1987.*

Variable	Estimate	p-value
Durbin Watson	1.9160	0.4965
Box-Ljung	14.2690	0.3552
Normality	0.7667	0.6816
Heteroskedasticity	1.1015	0.3265
Pred. error var.	0.0059	
R_s^2	0.4648	

Table 3.8: *Summary diagnostics for the end state space model for AKSI (1978-1999), adjusted for an outlier in January 1987.*

The coefficients of the explanatory variables in the end model are listed in table 3.9. Because the variables traffic and unemployment are in logs the coefficients may be interpreted as elasticities. Thus a 1% increase in the traffic index gives a 1.61% [1.27%- 1.97%] increase in the number of accidents with killed or seriously injured, while a 1% increase in the number of unemployed gives a 0.20% [0.04% - 0.36%] increase in the number of accidents. The change in the reporting routine (HI) decreased the reported number of accidents by 1-exp(-0.0945) = 9.02% [-0.01% - 17.61%]

In addition to these three explanatory variables, a strong significant seasonal variation (see table 3.10) and a decreasing trend were found.

As it can be seen, the main adverse seasonal effects occur during the October, November, December, and January, when taking unemployment, trend, and traffic into account. The growth rate is -7.68% per year

Model assessment of the number of accidents with injuries (AI) was similarly performed. Summary diagnostics of the full model and the end model are given in table 3.11. No obvious departures from the model assumption ares found.

Variable	Coefficient	R.m.s.e.	Test statistic	p-value
logunemp	0.2037	0.0802	2.5394	0.0117
logtraffic	1.6194	0.1756	9.2199	$<$.0001
HI	-0.0945	0.0496	-1.9047	0.0579

Table 3.9: *Estimated coefficients for the explanatory variables in the end state space model for AKSI (1978-1999), adjusted for an outlier in January 1987.* σ_ϵ^2*=0.0050549,* σ_η^2 *= 0.0002597 and signal to noise ratio =0.0512*

J	F	M	A	M	J	J	A	S	O	N	D
1.06	0.87	0.88	0.91	1.03	0.94	0.92	0.99	1.03	1.08	1.14	1.21

Table 3.10: *Seasonal variation for accidents with killed or seriously injured*

Traffic was the only explanatory variable that was found to be significant when modelling the number of accidents and, as for AKSI, slope and seasonal variations were fixed. The variance of the level component is $\sigma_\eta^2 = 0.000164$ and the irregular component is $\sigma_\epsilon^2 = 0.00409$. A 1% increase in the traffic index gives a 1.55% [1.27%-1.83%] increase in the number of accidents with injuries. The growth rate is -7.38% per year. The seasonal variation is also very similar to the variation of AKSI (see table 3.12).

A state space model of AK with the explanatory variables is identical to the linear regression model. This is because, when including either traffic and gnp or traffic and young in the BSM, the variances of disturbance components are not significantly different from zero. In other words, the dynamics in the number of accidents with killed can be explained by the development in the above variables, together with a fixed trend and seasonal variation.

Predictive power of state space models

Table 3.13 compares the predictive power of the models from this chapter to the shrinkage methods from section 2.4.2. It shows the prediction error of the predicted number of accidents in 2000 and 2001 for the best shrinkage method and the regression predictions. The predictions of future accidents in state space models are approximately 50% better than predictions from shrinkage methods. This is because the state space model utilizes the serial autocorrelation in data when predicting future events. However, if no serial correlation is present, there is much to be gained by using shrinkage methods on accident data where the coefficient of determination is relatively high, as it is for AKSI and AI.

Diagnostics	Estimate	p-value	Estimate	p-value
Durbin Watson	1.7925	0.0919	1.8087	0.1055
Box-Ljung	16.3360	0.2936	20.8580	0.1211
Normality	0.16050	0.9231	0.5741	0.7520
Heteroskedasticity	1.1122	0.3108	1.0530	0.4051
pev	0.0048		0.0047	
R_s^2	0.4805		0.4960	

Table 3.11: *Summary diagnostics for the full and the end state space model for AI (1978-1999), adjusted for an outlier in January 1987.*

J	F	M	A	M	J	J	A	S	O	N	D
1.06	0.87	0.88	0.93	1.00	0.95	0.92	1.02	1.02	1.07	1.10	1.16

Table 3.12: *Seasonal variation for accidents with injured*

3.3 Conclusion

Only few socio-economic variables were found to be significant when modelling the three accident series. This is because the socio-economic variables are strongly multicorrelated. In other words these variables seem to vary simultaneously with time, and therefore they can only contribute a little additional explanation of the accident series when temporal dependencies and traffic are taken into account. Strong multicorrelation also makes interpretation of the significant explanatory variables problematic.

The amount of traffic has been found to be the single most important factor in all three accident series, not taking temporal variables into account. The estimate of traffic is large for all three series, but due to the strong multicorrelation with time, gnp, young, and pop, the interpretation of this coefficient should be conducted with care. However, across the wide range of modelling techniques ,non-dynamic and dynamic, the influence of traffic was very consistent.

Summaries of the seasonal effect for the three accident series is best viewed through a graphic presentation (see figure 3.5).

Figure 3.5 indicates that January, October, November and December are high risk months. The number of accidents with killed in November and December is extremely high.

The general decreasing trend in the accidents with killed or seriously injured and in the accidents with injured varies over the estimation period. However, the growth rate is approximately -7% per year. The growth rate for accidents with killed is

Accident	Error	Shrinkage	Log linear	Linear	State space
AKSI	Test	0.0110	0.0482	0.0386	0.0072
	Std	0.0165	0.0342	0.0306	0.0126
AI	Test	0.0090	0.0202	0.0169	0.0044
	Std	0.0126	0.0187	0.0170	0.0074
AK	Test	0.0267	0.0275	0.0275	0.0275
	Std	0.0272	0.0316	0.0319	0.0319

Table 3.13: *Estimated test error results for non-dynamic models, state space models and the best shrinkage method (section 2.4.2) for the three accident series. State space model predictions of AK are identical to LM*

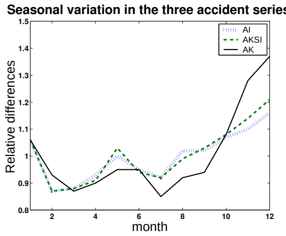

Figure 3.5: *Seasonal effects for AK, AKSI, and AI (1982-1992).*

approximately -10% per year.

The variation in unemployment is weakly positively associated with changes in the number of accidents with killed or seriously injured. The change in police reporting practices is associated with a small decrease in the reported number of accidents with killed or seriously injured.

Increasing gnp is associated with additional accidents with killed and the reduction in the urban speed limit is associated with a decrease in the total number of fatal accidents.

An important issue in this chapter was to investigate the temporal dependency in the accident series. It was shown that the monthly observations of accidents was serially correlated and that this correlation could only partly be explained by the explanatory variables for accidents with killed or seriously injured and for accidents with injured. The basic structural model (Harvey and Durbin, 1986) is constructed to model temporal dependencies in a very flexible manner, where level, slope and seasonality may change over the estimation sample. However, the dynamics in the three accident series is relatively slow and can be captured by a simple model, where only the level is allowed to change over time and the slope and seasonality are fixed. A deterministic model, such as the regression model, may adequately describe the variations in accidents with killed. Dynamic modelling techniques should be used when assessing the traffic safety through the use of accident series, since non-dynamic models, in the presence of serial correlation, are only able to provide a rough indication of the road traffic safety situation. The non-dynamic approach is likely to describe short accident series satisfactorily.

Chapter 4

Evaluation of the Danish Automatic Mobile Speed Camera Experiment: A State-Space Intervention Analysis

Chapter 4 is an evaluation of an area-wide traffic calming experiment for preventing traffic related injuries. The Chapter is based on Christen (2003), which investigates traffic calming through speed camera enforcement. The study applies dynamic basic structural models within the State Space framework using disaggregated accident data.

4.1 Introduction

There is a general consensus that even modest speed reductions can prevent many collisions, and reduce the severity of damage and injuries that result when accidents do occur [Leaf and Preusse (1998), Stuster and Coffman (1998), Elvik (2001)]. Speed reductions are particularly effective at reducing injuries to pedestrians and cyclists. A literature study (Elvik et al., 1997) showed that a reduction of just 5% in the mean speed leads, in general, to a reduction in the number of accidents. Out of 8 studies, only one reports a negative effect in reducing speed, and on average, in that study the number of accidents with injuries was reduced by approximately 15%. Finch et al. (1994) showed that a reduction in speed of only 1 mile per hour reduces accidents by 5%. This figure has now been validated in a more recent study by Taylor et al. (2000). In several studies speed cameras have been shown to be associated with decreases in the average speed and in the frequency of reported accidents [Cameron et al. (1992), Diamantopoulou et al. (2000), Diamantopoulou and Cameron (2002)].

The Danish automatic mobile speed camera experiment was initiated to evaluate the effect of speed cameras on the number of speeding violations in urban areas. The hypothesis was that speed cameras would reduce the incidence of speeding and consequently reduce the number of accidents correspondingly. The experiment was also intended to provide information about how to operate the speed cameras, as well as, to test the judicial and administrative processes. To reduce the number of accidents as much as possible, sections of road with high accident rates and many speeding offences were primarily selected for automatic mobile speed camera enforcement. The speed camera experiment was conducted in 6 different urban areas, including areas of Copenhagen and Odense, from April 6th, 1999 to March 31st, 2000.

The areas selected for the speed camera experiment were signposted. By placing the speed camera in mobile unmarked vehicles, a reduction in speed throughout the entire experiment areas was anticipated.

The experiment surveyed an average of 19000 vehicles per week and discovered that approximately 3000 vehicles per week were exceeding the legal speed limit. Due to the photo quality and legal aspects only 2000 out of 3000 offenders received fines. At the start of the experiment, approximately 18% of the surveyed vehicles were violating the speed limit and by the end of the experiment this number had dropped to 14%.In order to assess the speed camera experiment's effect on the vehicles' average speed, similar urban areas in Jutland were selected as control sites. During the experiment the average speed in the experimental areas on urban roads with a 50 km/h speed limit was reduced by 1.2 km/h, compared to the control sites. Through the 12 month experiment this speed reduction varied from 0.3 km/h to 2.4 km/h (Agustsson et al., 2000).

Following the experiment new Danish legislation was passed that introduced automatic mobile speed camera enforcement nationwide. Enforcement started in October 2002.

The purpose of this paper is to assess the effect of the Danish automatic speed camera experiment on accident counts. The Danish Road Directorate undertook to monitor the effect of the experiment on traffic accidents and as part of this monitoring exercise they invited the Danish Transport Research Institute to conduct an independent technical assessment of the statistical evidence.

The chapter is organised as follows: In section 2 data is introduced and a brief presentation of the statistical models is given. The results are presented in section 3 and the methods and results are discussed in Section 4.

4.2 Data and statistical modelling

4.2.1 Data

To investigate the variation in accident counts in the areas where the experiment was conducted (treatment series), and compare them to variations in accident counts in other urban areas (control series), monthly observations of urban traffic accidents occurring between 1 January, 1990, and 31 December, 2001 were included for analyses. A relatively long series enables one to better adjust for other explanatory, variables e.g. the amount of traffic. The main data source used for the analysis in this paper is monthly police reported observations of (i) the number of urban accidents with killed and seriously injured road users, (ii) the number of urban accidents with injuries (iii) the number of urban accidents with injuries and vulnerable road users (pedestrians and bicyclists). The speed camera experiment started ob 6 April, 1999 and ended on 31 March, 2000. It was conducted in Frederiksberg, Gentofte, Gladsaxe, Svendborg, Odense and parts of Copenhagen.

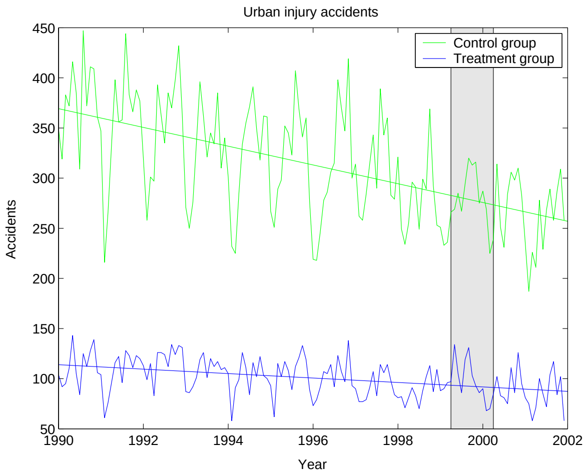

Figure 4.1: *Accident with injuries in urban areas with and without automatic speed camera control. The camera experiment is highlighted in grey*

The accident data series is presented in figure 4.1. It shows monthly observations of all Danish urban injury accidents from 1 January, 1990 to 31 December, 2001.

The accidents are divided into 2 groups - A treatment group and a control group. The treatment group consists of accidents from the areas where the speed camera experiment was conducted for 12 months in 1999 and 2000. The control group is accidents from all other urban areas. The patterns in the 2 series / groups are different with respect to trend and seasonality on this scale. The variation over months seems to change over time for the control series, whereas the seasonality of the treatment series is more steady. Figure 4.1 indicates that there is no clear reduction in the number of accidents in the areas with automatic speed camera control.

To investigate whether patterns in the series can be accounted for by observable explanatory variables, some relevant variables were identified.

Two changes in the police reporting system took place during the monitoring period. Both changes are known to have had an influence on the distribution of reported accident severity. During the years 1998 to 2000 all police stations switched from manual recording to electronic reports. This change led in Copenhagen to an artificial increase in the recorded number of accidents with injuries and a decrease in damage only accidents (Kjeldsen and Rosenkilde, 2001). This change has not found to effect the accident severity distribution outside Copenhagen. This is properly because police reporting in Copenhagen was maintained centrally until the time of the electronic reporting, where as reporting outside Copenhagen has always been done by the officer on the accident site.

What's more, an imprecise description in police reporting manual *'Vejledning til indberetning om færdselsuheld'* concerning head injuries led, in 1997 and onwards, to the misclassification of serious head injuries as minor injuries (Lund and Hemdorff, 2002). The change to electronic reporting is modelled as an intervention with a gradual change corresponding to the actual ratio of electronic and manual recordings. The changing police reporting practice was modelled by an invention variable.

As exposure variables, two different vehicle traffic indices are included. The first measures the traffic in Copenhagen and the second measures the total traffic in Denmark. Furthermore, gnp, the total size of the population, the proportion of young people (18-24 year old), the unemployment rate and alcohol consumption are included. Unfortunately only the unemployment rate is available on a monthly basis. Gross national product is measured quarterly and the remaining explanatory variables are only available on a annual basis. This problem is discussed in section 4.

4.2.2 Statistical modelling

In this study the number of accidents is modelled by the basic structural model (BSM) Harvey and Durbin (1986)

The model can be described as follows:

$$
\begin{aligned}
y_t &= \mu_t + \gamma_t + \epsilon_t \\
\mu_t &= \mu_{t-1} + \beta_{t-1} + \eta_t \\
\beta_t &= \beta_{t-1} + \zeta_t \\
\gamma_t &= -\left(\sum_{i=1}^{s} \gamma_{t-i}\right) + \omega_t,
\end{aligned}
$$

where y_t denotes log transformed number of accidents, s is the number of seasons, ϵ_t, η_t, ζ_t and ω_t are independent Gaussian distributed variables with zero mean and variances σ_ϵ^2, σ_η^2, σ_ζ^2, and σ_ω^2

Explanatory, exposure and police intervention variables are all entered as in the classical linear regression models.

Multiplicative Poisson regression with independent observations within the generalized linear model framework (McCullagh and Nelder, 1989) has also been applied to evaluate the performance of the dynamic structure in the state space modelling. If the relative variances are equal to zero in the above state space model, the mean structure collapses to the multiplicative Poisson mean.

The assessment of the effect of automatic mobile speed cameras raises further issues of model selection. These issues are described in section 4. One approach was to concentrate on selecting an adequate model for the 3 different series of accident counts based on data from January 1990 to December 1996, i.e. before the speed camera experiment started. The basic idea was to fit the model with observations prior to January 1997 and then use the 1997 data for post-sample predictive tests.

The first model fitted was a local linear and seasonal random walk model on the series of accidents with injuries in urban experiment areas excluding Copenhagen. Maximum likelihood estimation resulted in a model with a nonrandom slope and seasonality, which expressed the relatively slow dynamic, given the short series with just 96 observations. Various model diagnostics and parameters indicate good model performance. Re-estimating the model with data up to December 1997 only alters the parameters slightly.

This analysis was also performed on the other 2 accident series. The model for injury accidents with vulnerable road users performed acceptably, but the post-sample predictive test failed for the accident series of serious injuries. Residual plots indicate a clear decrease in the level of accidents from January 1997. This decrease in the reported number of accidents has also been found in other Danish studies and is associated with the changing police reporting practice (Lund and Hemdorff, 2002). By allowing the state space model shift in level in January 1997, the various model diagnostics show no departures from the model assumptions.

4.3 Results

The 3 different experiment series, accidents with injuries (AI), accidents with killed or serious injuries (ASI) and injury accidents with vulnerable road users (AIV) are analysed separately in the following section.

It is seen in figure 4.2 in the appendix at the of this chapter, that accidents with injuries in Copenhagen differ in frequency and in trend from the other series. Due to the fact that the change from manual to electronic reporting only affected the distribution of accident severity in Copenhagen, it was decided to model the accident series from Copenhagen separately. Because of the small numbers in the treatment series, excluding Copenhagen, and their similarity in pattern, it was decided to aggregate these series and analyse the resulting serie separately.

Accidents with injuries and vulnerable road users (AIV) show a very similar pattern and therefore it was decided to separate the accident counts into 2 series as was done with the AI series. See figures 4.4 and 4.5 in the appendix.

Illustrations of the accidents with killed or serious injuries (ASI) in 6 areas again highlights the need for a separate analysis of the accidents in Copenhagen: see Figures 4.6 and 4.7 in the appendix. Note that all the series have an evident decrease in the number of reported accidents due to the changing police reporting practice concerning head injuries. Though the police reporting manual with the imprecise description was introduced in January 1997, Copenhagen accident counts are not affected till January 1998. This finding is also reported in another study (Kjeldsen and Rosenkilde, 2001).

Prior to aggregation of the accident counts in the treatment areas excluding Copenhagen, tests for equal trend and seasonality in an over-dispersed Poisson model were performed. No significant differences in the 5 treatment areas were found. The Poisson distribution was chosen due the small numbers.

Table 4.1 summarizes the results from the models that were finally selected for the various accident series. The models were selected through inclusion of all variables and subsequent standard stepwise elimination of all insignificant variables, both explanatory variables and noise components. For each category of accidents, the estimated percentage change in the number of accidents attributed to the speed camera experiment, are given and 95% confidence interval, values of diagnostic statistics and the significant explanatory variables are also shown.

The model diagnostic statistics shown in 4.1 indicate rather good model performance. Examination of plots of the residuals for the various models also suggests that the models describe the accident data adequately.

The effect parameter for the speed camera experiment was found not to be significant in any of the series and parameters across the various series did not tend to be either positive or negative. Therefore it is concluded that this study can not document either positive or negative effects of the speed camera experiment.

The estimated parameters of the explanatory variables in the models reported in table 4.1 have some interesting features. The change to electronic reporting in Copenhagen led to a 14% [2% ;28%] artificial increase in the reported number of accidents with injuries. For injury accidents with vulnerable road users, this figure was 23% [8%;40%]. The misleading reporting manual led to a 23 % [24%;32%] artificial decrease in the number of accidents with killed or seriously injured in Copenhagen. In the 5 other urban areas the number of accidents with killed or seriously injured was reduced by 35% [21%;47%] due to the misleading manual.

None of the socio-economic explanatory variables were found to be significant. The exposure measure of the traffic in Copenhagen (Copenhagen traffic index) was also not significant. One reason for this could be that the measure is not very accurate and does not take into account changes in traffic flows due to the opening of a new motorway in 1997.

This study finds that the traffic index of the total vehicle traffic in Denmark is significant. The estimated elasticities of the various accidents with respect to the total traffic index ranges from 2.1 to 2.7. The elasticity for accidents with injuries in Copenhagen indicates that a 1% increase in the traffic index leads, other factors being equal, to a 2.1% [0.5%;3.5%] increase in the number of accidents.

4.4 Discussion

In this chapter univariate state space modelling has been applied in order to estimate the effect of the speed camera experiment on accident rates. The study could not document any significant effect of the speed camera experiment on the 3 different accident series.

Accidents	change %	95% CI	R_s^2	H(43)	Box-Ljung	Norma-litity	Varia-bles
AI Cph.	6%	[-6% ; 19%]	0.45	2.09	14.75	0.67	T E
AI Others	-3%	[-15% ; 11%]	0.47	0.92	7.42	2.75	T
AIV Cph.	2%	[-10% ; 17%]	0.46	1.72	12.66	2.72	T E
AIV Others	5%	[-10% ; 23%]	0.49	0.76	5.25	2.38	T
ASI Cph.	-1%	[-13% ; 12%]	0.48	1.06	7.80	4.69	T M
ASI Others	4 %	[-12% ; 22%]	0.47	1.34	6.33	0.39	T M
5% Signif. Points				0.54/ 1.83	15.51	5.99	

Table 4.1: *Percentage changes in injury rates and values of diagnostic statistics. AI=accidents with injuries, AIV=accidents with injuries and vulnerable road users, ASI=accidents with killed or serious injuries, T=traffic index, E=electronic reporting, M=Changing reporting practice*

It was decided to model the speed camera effect as an intervention parameter that caused a shift in the series during the speed camera experiment. This decision was of course based on a prior consideration. The speed camera experiment had massive media attention from the very start and the police enforcement was relatively constant throughout the experiment. If information about the police operating level was available on a monthly basis e.g. number of speeding tickets and operating hours, the intervention effect could have been modelled in more detail. If there was found to be significant effects of the speed camera experiment, it would have been natural to measure the effect of the speed camera experiment as a function of the monthly average speed reduction.

It could be argued that the assessment of the speed camera effect should be based on data from April 1999 and onwards and not only on the 12 month duration of the official speed camera experiment. This is because, even though the experiment ended officially on the 31 March 2000, police continued using the cameras in the treatment areas. Unfortunately no record of the level of enforcement are available. Using 33 months starting 1 April 1999, to estimate the speed camera effect does not alter the results.

Prior to the start of the official experiment, a pilot speed camera experiment was conducted in Copenhagen and Odense. Since the enforcement level in the pilot experiment was very low, it was decided not to take this into account. Leaving Copenhagen and Odense out of the analysis does not alter the results and no significant shift in level of accidents due to the pilot experiment was found when modelling accident counts for Copenhagen and Odense separately.

During the study the question of whether to use annual or monthly data was raised. Using annual data seemed more reliable because annual observations tend to average out the irregularities in monthly observations. However, as pointed out by Harvey and Durbin (1986) "Discounting can be quite considerable" due to the loss in efficiency that arises in large samples when estimating a step intervention effect from annual, rather than monthly, observations.

A simulation study was conducted to assess the power in this study. (See chapter 6 for a further description). If accident trends develop along the same path as the injury accidents in this study, then the probability of detecting a true 15% shift in level is about 67%. This means that in order to detect a significant change in the accident rate, the effect of speed camera should be relatively high. Nine out of ten studies would find a 20% shift in the trend. Using annual data instead of monthly data reduces the power significantly.

Even though the effect of the Danish speed camera experiment on mean speed reduction was moderate, 1.2 km/h on average, varying from 0.3 to 2.4km/h in the 12 month experiment (Agustsson et al., 2000), a moderate reduction in the accident rate would have been expected.

One might also consider using a before-and-after design with a control group. Here, changes in the ratio of the number of urban accidents in the treatment group and the numbers in the control group are investigated. Such a design assumes that the accident counts in the control group have a similar pattern to the ones in the treatment group. A more sophisticated method is to model the treatment group and the control group simultaneously. If observations in the control group are highly correlated with the experiment group, one would achieve a more precise estimate of the effect in question. Elvik (2002) has recently investigated other disadvantages with the use of before-and-after studies.

Multivariate state space modelling was carried out for the different accident series in order to investigate whether the trend or the seasonality in the control series changed during the speed camera experiment. If changes were found, then the assessment of the speed camera effect should take this into account. No evidence of changes in the control group was found.

As is often seen with socio-economic factors, some of the explanatory variables are measured on different frequencies. One way of dealing with this is to interpolate series from one frequency to another with smaller time units. However, it is important to note that such interpolation can lead to an artificial autocorrelation structure on the interpolated series. Since the series in question, e.g., the proportion of young people (18-24 year old) have, change rather slowly simple linear interpolation is chosen.

Using the Poisson regression method for the different accident series only changes the speed camera effect parameter slightly and again the effect parameters are not significantly different from zero. (See table 4.2 in the Appendix). However, diagnostics of the residuals show significant autocorrelation and therefore these non-dynamic models are not used to assess the effect of the speed camera experiment.

It could be argued that the level of enforcement in the Danish mobile speed camera experiment was too low to achieve a positive correlation with reductions in the accident rates. International studies (Vulcan et al., 1996) show that the enforcement level in the Danish experiment should have been approximatively 8 times higher to obtain a positive effect. One study found that when increasing the level of enforcement to surveying 66% of all vehicles per month, the number of speed violations was reduced from 12% to 3% (Bodinnar, 1994).

4.5 Conclusion

The hypothesis was that speed cameras would reduce the speed and consequently reduce the number of accidents correspondingly. This study can document neither positive nor negative effects of the speed camera experiment on the number of accidents.

4.6 Appendix

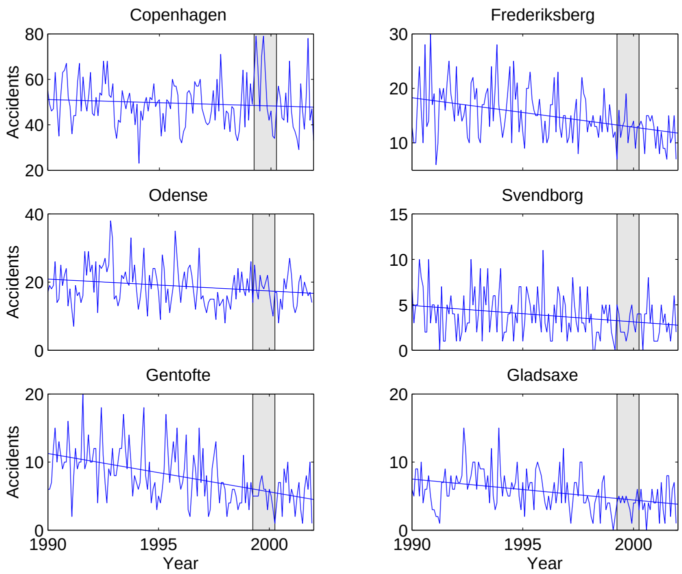

Figure 4.2: *Monthly injury accidents in 6 treatment areas. The experiment is highlighted in grey*

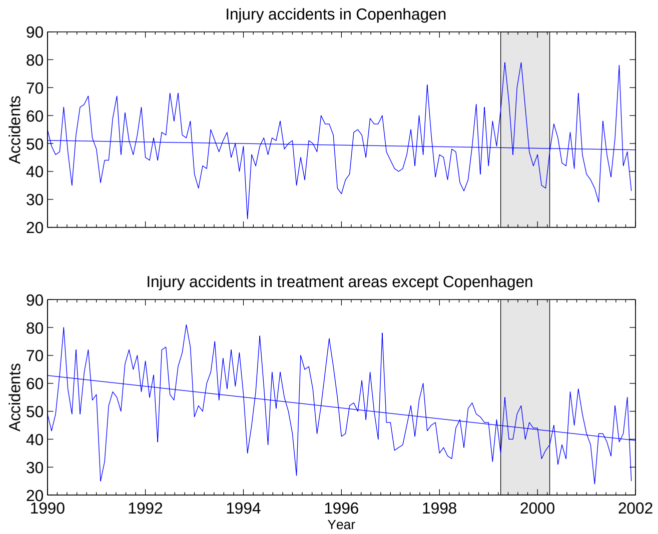

Figure 4.3: *Monthly injury accidents in Copenhagen and the 5 other treatment areas aggregated. The experiment is highlighted in grey*

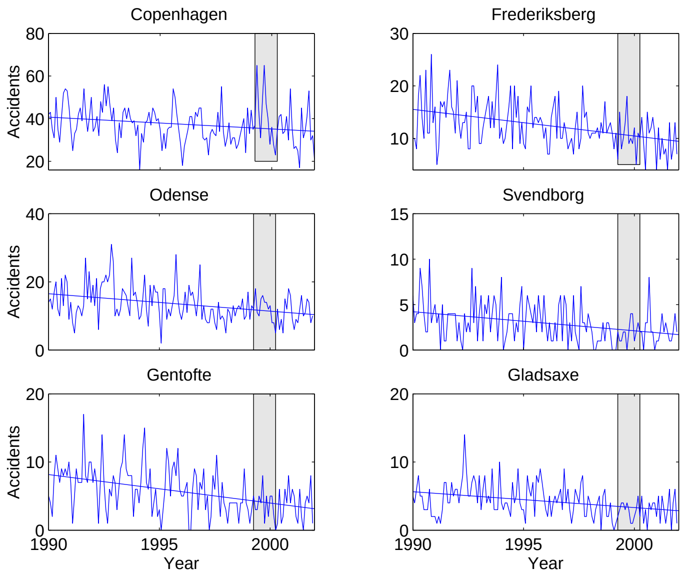

Figure 4.4: *Monthly injury accidents with vulnerable road users in the 6 treatment areas. The experiment is highlighted in grey*

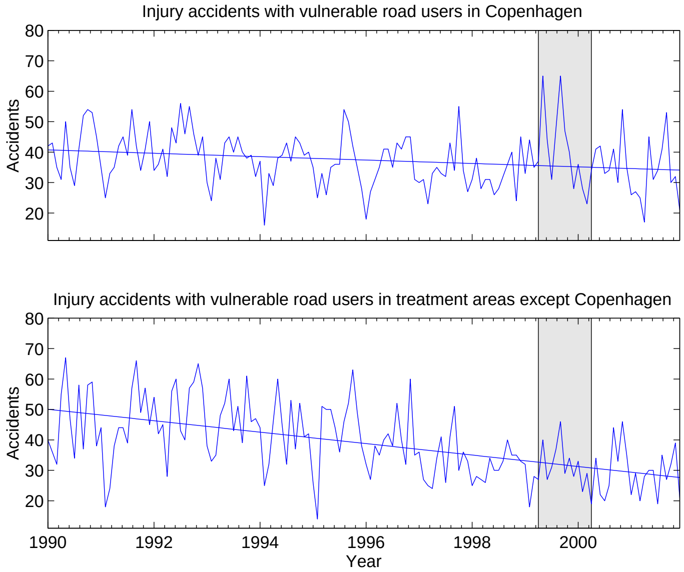

Figure 4.5: *Monthly injury accidents with vulnerable road users in Copenhagen and the 5 other treatment areas aggregated. The experiment is highlighted in grey*

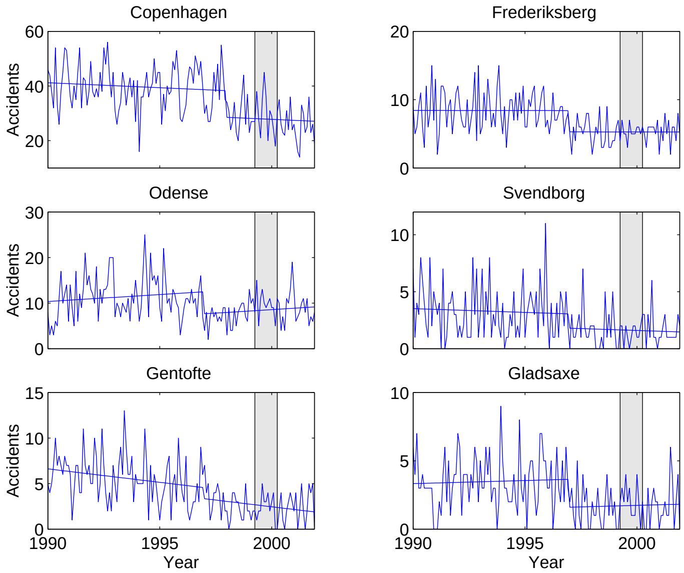

Figure 4.6: *Monthly accidents with killed or serious injuries in the 6 treatment areas. The experiment is highlighted in grey*

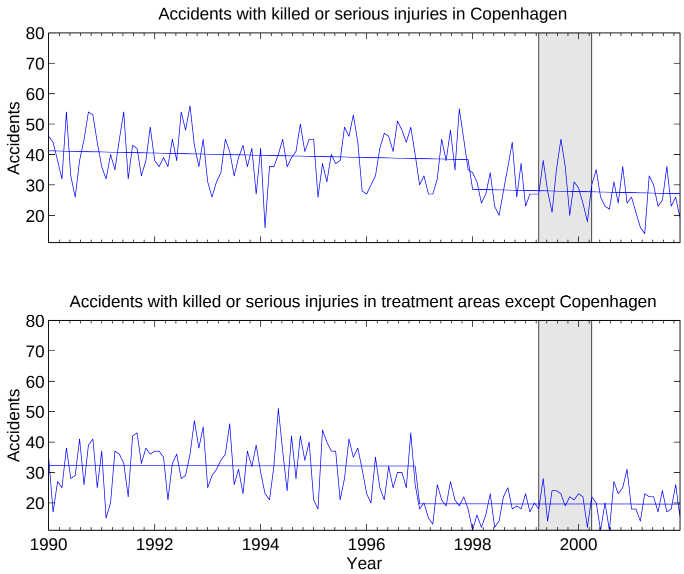

Figure 4.7: *Monthly accidents with killed or serious injuries in Copenhagen and the 5 other treatment areas aggregated. The experiment is highlighted in grey*

Accidents	change %	95% CI
Injury Cph.	8%	[-4% ; 21%]
Injury Others	-4%	[-14% ; 8%]
Injury, Vulnerable Cph.	5%	[- 7% ; 20%]
Injury, Vulnerable Others	1%	[-14% ; 13%]
Serious injuries Cph.	0%	[-12% ; 14%]
Serious injuries Others	6%	[-10% ; 25%]

Table 4.2: *Percentage changes in injury rates and confidence intervals estimated through over-dispersed Poisson regression.*

CHAPTER 5

Time dependent regression parameters in state space models

This chapter has two aims. The primary aim is to assess the impact of a change in the police accident reporting routine on the reported number of accidents. A secondary aim is to investigate the underlying assumption, that parameters of the explanatory variables are constant over the estimation sample. This assumption is verified by the use of time dependent parameters in state space models.

Unfortunately, there was an imprecise description the police accident reporting manual *'Vejledning til indberetning om færdselsuheld'* updated in 1997. According to the new reporting routine, injured people with concussion were to be classified as having suffered a minor injury. Previously, this injury was classified as a serious injury.

The effect of this change is particularly interesting since 1998 serves as the reference year for which target values for the national traffic safety plan (Færdselssikkerhedskommisionen, 2000). This change is also interesting from a traffic safety research point of view, because the AKSI series serves as an important tool in assessing the effect of different countermeasures on an aggregated and disaggregated level. The two other accident series, AK and AI, suffer from either having too few observations or being recorded too inconsistently.

During the summer of 2003 the police reporting practice will again be altered so it is consistent with the routine prior to 1997. Therefore, this study can also make an educated guess about the expected increase in the reported number of accidents.

5.1 Introduction

A natural starting point for the assessment of the effect of the changing police reporting practice on the number of accidents with killed or seriously injured is the final model from chapter 3.

$$\begin{aligned} y_t &= \mu_t + \beta \text{time} + \gamma_t + \delta_1 \text{logtraffic} + \delta_2 \text{logunempl} + \delta_3 \text{Hi} + \delta_4 \text{Jan87} + \epsilon_t \\ \mu_t &= \mu_{t-1} + \eta_t \end{aligned} \tag{5.1}$$

where y_t denotes log transformed AKSI, ϵ_t and η_t are independent Gaussian with zero mean and variances σ^2_ϵ and σ^2_η, γ_t describes the seasonal variation modelled by dummy variables and Jan87 is a dummy variable for the outlier in January 1987. This model is in fact a local level model with explanatory variables.

Table 3.9 lists the maximum likelihood estimates from model 5.1. It is seen that traffic is highly significant, whereas the change in reporting practice is nearly significant at a 5% significance level. Since exp(-0.0945) = 0.9098, the estimated reduction in the reported number of accidents was approximately 9%.

In Christen (2003) the estimated reduction was found to differ in size across the different urban areas, ranging from 23% to 35%. In addition, the effect was immediate in most areas, whereas the effect in Copenhagen was delayed one year. Other studies have also found that the effect varies across areas and road user category (Lund and Hemdorff, 2002).

In model 5.1 the most straightforward hypothesis was adopted, ie, that the introduction of the police reporting manual *'Vejledning til indberetning om færdselsuheld'* in January 1997 induced an one-off downward shift in the level of the series of AKSI. However, the effect of Hi (the police manual) can be assumed to cause changes in the dependent series in numerous ways. Prior to investigating the effect of Hi, which may be thought of as an intervention variable, an analysis of the other explanatory variables, mostly traffic, is performed. This is to reduce some of the biase by trying to account for the variation caused by the other explanatory variables.

5.2 Specification of the effect of traffic

In this study the effect of traffic (exposure) on the number of accidents was also found to be the single most important factor, not taking temporal variables into account. Exposure variables are often modelled as elasticities. As a result, one achieves an interpretable description of the effect of exposure and some non-linearities are included in the model specification.

In real life, effects are often not linear. Techniques that apply predefined basis functions to achieve nonlinearities of the explanatory variables are often used. That way, one may continue to operate in the attractive simple regression framework. Generalized additive models are a more automatic flexible statistical method that can be used to identify and characterize non-linear regression effects (Hastie and Tibshirani, 1990). In the regression setting, a simple generalized additive model for identifying the effect of traffic may have the form:

$$\mathrm{E}(Y|\text{traffic,time}, X) = \alpha + X^T\beta + f_1(\text{time}) + f_2(\text{traffic}), \tag{5.2}$$

where Y is log AKSI and X represents the explanatory variables (season, hi, unemp) to be modelled in a linear form. f_1(time) and f_2(traffic) are unknown functions of time and traffic. The building block for fitting non-linear effects in generalized additive models is a scatterplot smoother (e.g. a cubic smoothing spline or a kernel smoother), which for the model 5.2 fits the function f_1, f_2 simultaneously with the linear effects.

Here, focus will be on f_2(traffic), but a non-linear function of time is also used in order to adjust for the generally increasing safety level, which could not be explained by a simple linear trend (see chapter 3). Generalized additive models provide an illustrative graphical representation of the partial effects, taking all other variables into consideration. Figure 5.1 illustrates the partial effect of traffic and logtraffic on the log of the number of accidents. The scatterplot smoother, here a spline smoother, has a tendency to choose a logarithmic form for traffic and log accidents, whereas the relationship between log traffic and log accident is almost linear. Thus, the log specification of traffic appears to be very reasonable.

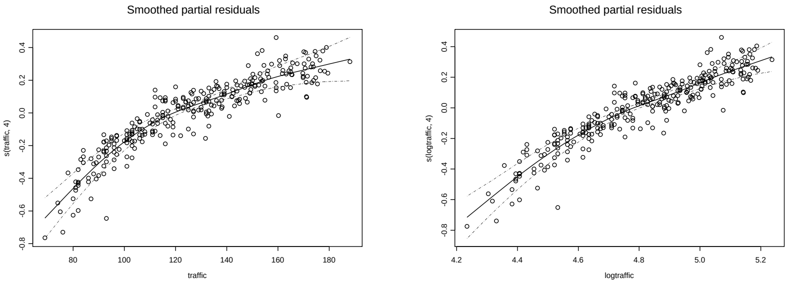

Figure 5.1: *Partial effect of traffic and log traffic.*

A formal test of the functional specification of effect may be conducted within the generalized additive models, but for the present investigation a graphical presentation is sufficient. In addition, the serial correlation in the observations makes inference non-reliable.

5.3 Structural stability

Model 5.1 assumes that the parameters of the model, δ, are constant over the estimation sample. A simple and intuitive way to investigate parameter constancy is to compute recursive estimates of δ; that is, to estimate the model recursively to $t = k+1, \ldots, T$ giving $T-k$ recursive estimates $(\hat{\delta_{k+1}}, \ldots, \hat{\delta_T})$ (Zivot and Wang, 2003). If δ is constant, then the recursive estimates of $\hat{\delta_t}$ should quickly settle down near a common value. If some of the elements in δ are not constant, then the corresponding estimates would show instability. Hence, a simple graphical technique for uncovering parameter instability is to plot the recursive estimates, $\hat{\delta_{it}}$, and look for instability in the plots.

An alternative approach to investigate parameter instability is to compute estimates of the model's parameters over a rolling window of a given fixed length. The parameters should be constant across the different windows. Such rolling analysis can provide a simple pseudo time dependent parameter model.

For this study the width, n, of the rolling window is set to 48 because the width, n, has to be greater than the number of parameters in the model, and furthermore, due to the 12 seasonal parameters in the model n should equal 24, 36, 48, ... It is noted, that rolling regression is not really appropriate to investigate parameter stability of dummy variables, ie the effect of Hi, since the rolling window should contain both values of the dummy variable.

Figure 5.2 is an illustration of the recursive and rolling estimates of the coefficients associated with the explanatory variables in model 5.1. For simplicity reasons the recursive and rolling estimates were calculated for every 12 months and a rolling window of 60 monthly observations. The recursive and rolling coefficients do not seem to vary too much compared to their variances.

Stability of the parameters can also be analysed through the use of time dependent parameters in state space models. By allowing the parameters associated with the explanatory variables in model 5.1 to be random walks, as the level and slope component in Harvey and Durbin (1986) basic structural model, one achieves time varying parameters. If the parameter δ associated with logtraffic is allowed to follow a random walk the model may be written as

$$
\begin{aligned}
y_t &= \mu_t + \gamma_t + \delta_t \text{logtraffic} + \delta_2 \text{logunemp} + \delta_3 \text{hi} + \delta_4 \text{Jan87} + \epsilon_t \\
\delta_t &= \delta_{t-1} + \omega_t,
\end{aligned}
$$

where μ_t and γ_t are defined as in 5.1 and ω_t is Gaussian $(0, \sigma^2_\omega)$.

Testing for time variation in the coefficients of the explanatory variables is subject to problems, as when testing for reduction of the hyperparameters in the basic structural model (Harvey, 1989). In addition, the way the time dependent parameters are introduced into the model is important for estimation stability, but a quick and rough

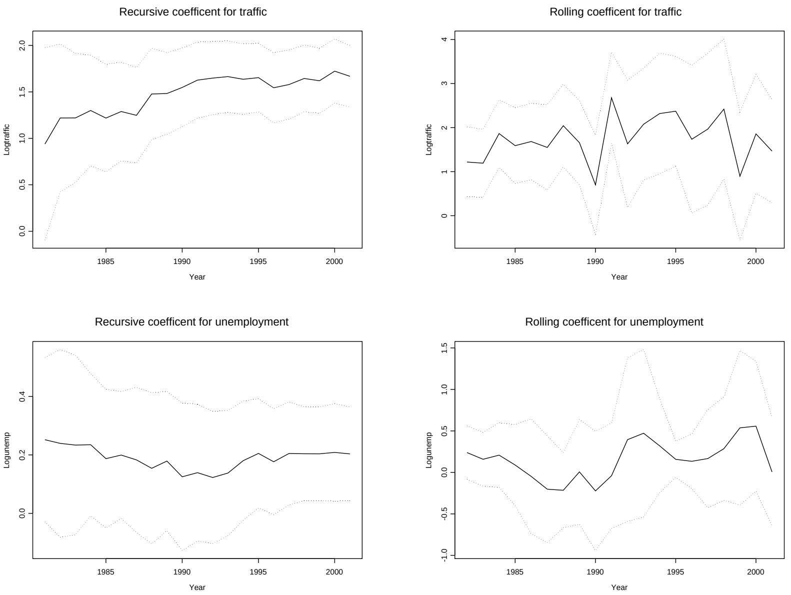

Figure 5.2: *Recursive and rolling coefficients for the the explanatory variables.*

estimation gives a rather small variance of ω =4.575604e-005 , the hyperparameter associated with traffic. Figure 5.3 illustrates the smoothed estimates of δ_t (Durbin and Koopman, 2001). From a graphic diagnostic of figure 5.3, one sees that the parameter associated with traffic can be assumed to be constant over the sample period, relative to the root mean square error for logtraffic in table 3.9.

The smoothed estimates of the time dependent coefficient associated with unemployment varies even less over the sample period.

These analyses find that there are no obvious departures from the assumption that the effect of traffic and unemployment can be modelled as constant elasticities. This is also in accordance with the satisfactory model diagnostics in chapter 3.

5.4 Assessment of the changing reporting practice

The assessment of the changing reporting practice can be thought of as an intervention analysis. Intervention analysis is concerned with making inferences about the effect of known events. These effects are measured by including intervention, dummy variables to the dynamic regression model (e.g. Hi and Jan87 in model 5.1).

If the model contains trend and seasonal component then the effect of the intervention

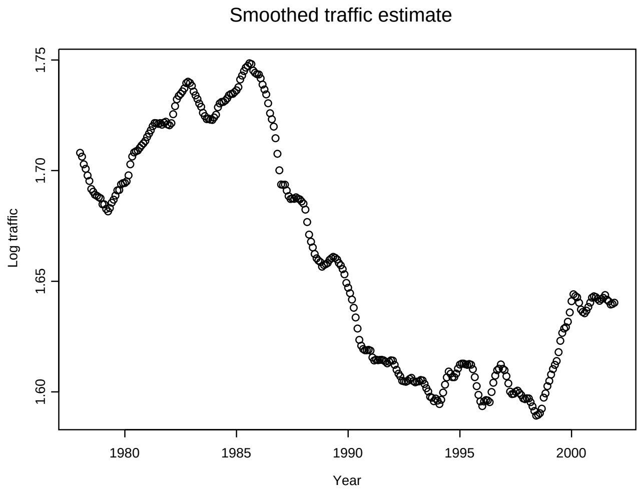

Figure 5.3: *Smoothed estimates of the log of trafffic.*

can assume 4 different shapes: 1) a transitory effect as the outlier in January 1987, 2) a structural break in the level of the series, 3) a structural break in the slope of the series (e.g. a change in the gradual movement in the series), 4) or a change in the seasonal pattern.

It is possible for an intervention to influence the pattern of the series in a combination of the forms listed above. In addition the intervention may also give a dynamic response, where, for example, the effect gradually decreases.

According to Harvey (1989) it is extremely difficult to determine whether the intervention is an outlier, a step or a slope change. This is particularly difficult when the effect of the changing reporting practice is relatively small compared to the variance of the hyperparameter in the level, which is also seen in the p-value in table 3.9

In the non-dynamic models the coefficient associated with an intervention can be estimated consistently and the variance of coefficients decreases when the sample period increases. However, in dynamic state space models only observations recorded immediately after the intervention took place can be used to measure the effect. This is because the relative variance of the hyperparameter in the level determines how quickly the series will move on to a new level. When the relative variance of the level's hyperparameter is approximately 0.05, as it is for the model 5.1 (see table 3.9), then the estimated effect is only influenced by the first 10 observations recorded following the time of the intervention (Harvey, 1989).

Since assessment of an intervention variable in dynamic modelling is only based on few observations, one should construct a form of intervention based on as much a priori knowledge as possible and then submit it to diagnostic checking of the model. The form of the intervention in a specific countermeasure assessment is highly dependent on the willingness of traffic users to change their behaviour and the awareness of the forthcoming intervention. In such situations a logit function may be a better description of the response of road users to the intervention than a simple step-function (e.g. a logit function of the road users' speed may be a well-specified intervention for analysing changes in safety due to speed reduction countermeasures). Unfortunately, such informative data are often not available and one has to rely on a priori assumptions.

It could easily be argued that diffent police stations would respond differently to a change in the reporting practice. This is also seen in Christen (2003) and Lund and Hemdorff (2002). Table 5.1 lists the effect of the changing reporting practice starting in January 97, ..., May 97. It seems that the estimated effect depends on the assumed starting point of the intervention.

These investigations indicated a slow dynamic response to the changing reporting practice. The effect seems to have reached its maximum three months after the intervention was introduced. Analyses with only one observation after the time of intervention show the same result.

Variable	Change in %	95 % CI	p-value
Hi Jan 97	-0.0945	[0.0047; -0.1937]	0.0579
Hi Feb 97	-0.1236	[-0.0252; -0.2219]	0.0129
Hi Mar 97	-0.1283	[-0.0302; -0.2264]	0.0094
Hi Apr 97	-0.1280	[-0.0295; -0.2264]	0.0099
Hi May 97	-0.0640	[0.0351; -0.1639]	0.2010

Table 5.1: *Estimated effect in logscale for the changing police reporting practice for different intervention dates.*

The change in reporting practice occurs near the end of the sample. A suitable model could be constructed on the basis of observations prior to the intervention. Thus the estimation of the hyperparameters will be unaffected by any misspecification in the intervention. The intervention variable is then added and the model specification is subjected to various diagnostics. The diagnostics should be based on the residuals immediately after the intervention, otherwise possible distortion could be diluted in the full set of residuals.

Brown et al. (1976) utilize the generalized recursive residual to produce two simple tests for parameter instability. These two tests, known as the CUSUM and

CUSUMSQ tests, are based on the standardized 1-step ahead recursive residuals.

$$\hat{w}_t = \frac{\hat{f}_t}{\hat{\epsilon}_t} = \frac{\hat{f}_t}{y_t - \hat{\beta}'_{t-1}x_t} \tag{5.3}$$

where $\hat{f}_t^{\,2}$ is an estimate of the recursive error variance.

CUSUM and CUSUMSQ are best regarded as a diagnostic rather than formal test procedure (Harvey, 1989). One should, therefore, through the use of graphic illustrations of CUSUM and CUSUMSQ, check for systematic tendencies to underpredict or overpredict immediately after the intervention rather than just checking whether the CUSUM and CUSUMQ exceed their confidence bands.

Figure 5.4 illustrates of predicted values of log AKSI, residuals and CUSUM from the model with the intervention starting March 97. These visual diagnostics together with post intervention test statistics show no obvious misspecification of the intervention occurring with a 2 month delayed response.

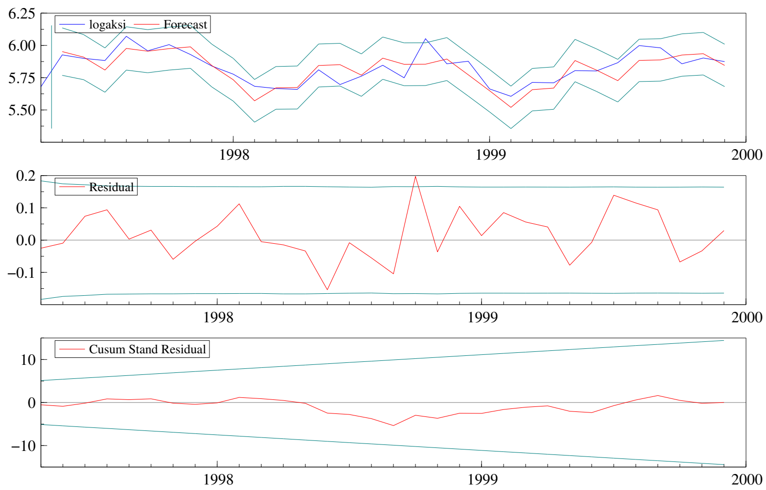

Figure 5.4: *Predicted values, log AKSI, residuals and CUSUM immediately after intervention.*

Diagnostics and test statistics for intervention models taking place in January, February and April 1997 show similar results. Therefore, selecting a given form of the intervention by excluding models, where diagnostics indicate significant misspecification is not possible. As argued previously, one could also assume that the intervention could be modelled as a gradually increasing function over the first month in 1997, but the estimate of such an approach is also highly dependent on the specific form of the function.

Here a conservative selection approach is used due to no a priori knowledge about how accident series would respond to such a change. This means that the assessment of the effect of the changing reporting practice is based on the official assumption that states that the reporting practice should be changed immediately on 1 January, 1997. From table 5.1 one sees that under this assumption the effect is then 9%. The estimated effects of the other intervention models listed in table 5.1 are not that different compared to their relative confidence intervals. The relationship between the normal and the log-normal distributions suggests the use of $\exp[\hat{\delta} + 1/2\text{var}(\hat{\delta})]$ instead of $\exp[\hat{\delta}]$. Adjustment for the log-normal reduces the estimated effect of the changing reporting practice to 6.7%.

5.5 Conclusions

The change in the police reporting practice in 1997 lead to a 6.7% decrease in the reported number of accidents with killed or seriously injured. A realistic estimate of the actual traffic safety in 1998, measured by the number of accidents with killed or seriously injured could be the reported number corrected by $(1/0.933)$-1 = 7.2%, which is approximately 285 additional accidents. The national safety plan (Færdselssikkerhedskommisionen, 2000) is based on the number of killed and the number of seriously injured but a similar approach may be used here.

Even though the reasons for sudden changes in an accident series may be known, it is possible to use the series to describe the effect of a given countermeasures or exposure, when one adjusts for the changes. Even if changes are not accounted for by observable explanatory variables, one can still utilize the series if the changes are absorbed by a dynamic model structure.

Assessment of the effects of a specific countermeasure can be problematic and should be based on as much a priori knowledge as possible. This is because the effective number of observations used to estimate the effects are highly dependent on the dynamics in the accident series. Extending the post intervention period does not necessarily improve the estimated effect associated with the countermeasure.

Using time dependent coefficients in state space models to assess the instability of the parameters associated with explanatory variables has, in this study, been effective. Analysis showed that the influence of traffic is stable over the estimation sample and that the influence of traffic can be modelled as an elasticity. Time dependent coefficients may also help to characterize and model non-linear effects as the generalized additive models for non-dynamic observations.

CHAPTER 6

Power

The aim of this chapter is to set up a method for assessing the ability of detecting a shift, caused by a countermeasure, in a given traffic safety time series study. Knowledge of this so-called power prevents the researcher from rejecting potentially important ideas because a small study fails to confirm them. “Experts have been warning about the dangers of underpowering studies for over 40 years.” Matthews (2003).

In statistical theory, power is the probability that a test results in rejection of a hypothesis, H_0 say, when some other hypothesis, H say, is valid. This is termed the power of the test “with respect to the alternative hypothesis H.” If there is a set of possible alternative hypotheses, the power, regarded as a function of H, is termed the power function of the test. When the alternatives are indexed by a single parameter θ, simple graphical presentation is possible.

If the power function is denoted by $\beta(\theta)$ and H_0, then the value of $\beta(\theta)$ - the probability of rejecting H_0 when it is in fact valid - is the significance level.

The basis of this study is the dataset of a Danish mobile speed camera experiment (see chapter 4 for a detailed description). From this study monthly observations of urban injury accidents occurring from 1 January, 1990 to 31 December, 2001 in five Danish municipalities (Frederiksberg, Gentofte, Gladsaxe, Svendborg and Odense) were selected. An illustration of the aggregated accidents is given in figure 4.3 in chapter 4. The mean structure of these accidents, estimated in an acceptable Poisson regression analysis, was chosen as the initial values for the simulations. The initial values consisted of a decreasing trend, seasonal variation and a positive elasticity of the amount of traffic.

Countermeasures can affect the number of accidents differently. For this simulation study it was assumed that the countermeasure influenced the accident counts as a step function, meaning that initial values were reduced uniformly during the period of the countermeasure. It was decideedto simulate a countermeasure that would influence the accident counts for 12 months, which corresponds to the duration of the Danish speed camera experiment.

This simulation study consists of two scenarios: the first simulates Poisson distributed accidents; in the second approach accidents are generated from a Poisson gamma distribution in order to have over-dispersed data, as seen in many traffic accidents series.

6.1 Simulated Poisson distributed accidents

Figure 6.1 provides an overall impression of the data. The simulated accidents in figure 6.1 indicate a large decrease in the number of accidents during 1999 and the estimated decrease is also highly significant ($p<0.0001$).

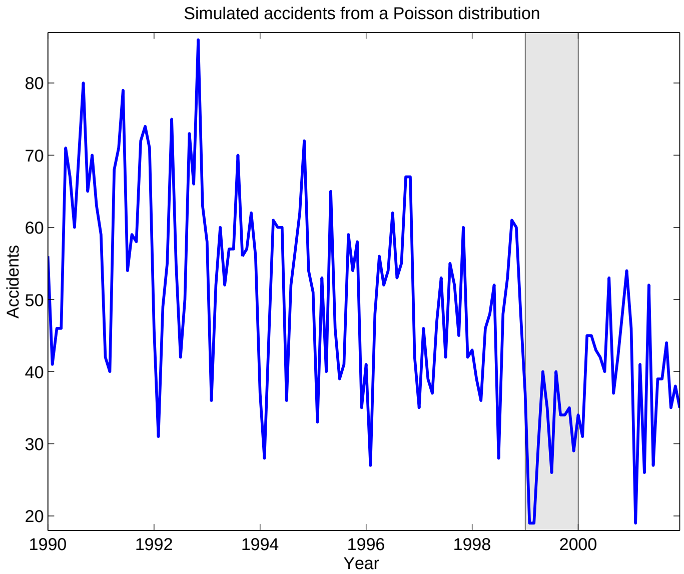

Figure 6.1: *Poisson simulated accidents with a 30% decrease in the accident counts in 1999 (highlighted in grey)*

Figure 6.2 is a graphical presentation of the power for different values of the valid alternative hypothesis [0%; 30%], calculated through 10000 simulations. Additionally, figure 6.2 shows the power calculated from monthly and annual data. For example, if the number of accidents varies, as in the speed camera experiment, then the probability of detecting a valid 15% decrease is approximately 83% when using monthly data.

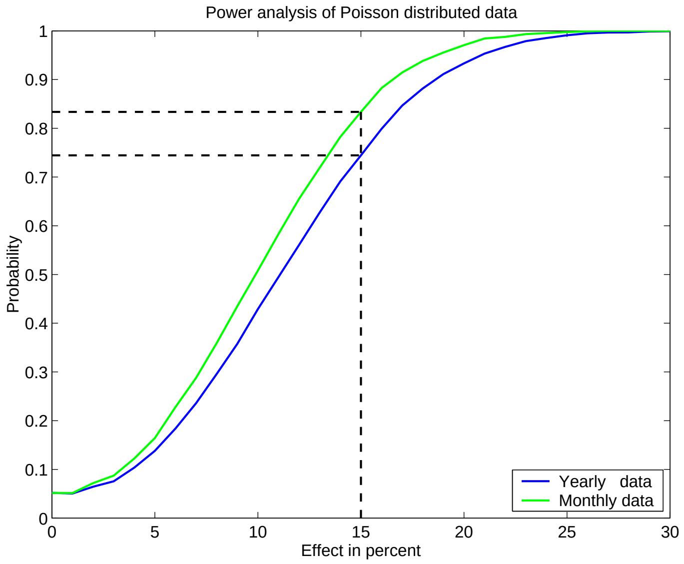

Figure 6.2: *Power analysis of Poisson distributed data.*

During the project the question of whether to use annual or monthly data was raised. Using annual data seemed more reliable because annual observations tend to average out the irregularities in the monthly observations. However, as mentioned earlier Harvey and Durbin (1986) point out that the loss in efficiency which arises in large samples when estimating a step intervention effect from annual, rather than monthly, observations, can be quite considered.

A simulation study was conducted to verify this efficiency loss. The results are illustrated in Figure 6.2. The difference depends on the level of the true effect parameter, but the possibility of finding a truely significant effect is higher when using monthly data. One should note, that the power $\beta(\theta) = \beta(-\theta)$.

Another disadvantage of using annual data when the intervention period only lasts 12 months is that one only has a single data point to measure the effect and to conclude whether the significant estimated effect is not an artifact due to an outlier.

6.2 Simulated over-dispersed accidents

It is frequently found in practice that the estimated dispersion parameter, after fitting an otherwise acceptable Poison regression model, exceeds 1. This means that the standard Poisson approach is not able to model the variation in the observations. Two approaches are commonly used for dealing with such over-dispersion (Lee and Nelder, 2000): the first is to use a quasi-likelihood function (QL) (McCullagh and Nelder, 1989), having a variance of Y with an adjustable dispersion parameter, e.g. var(Y)=$\sigma^2\mu$ with $\sigma^2 > 1$ for the over-dispersed model; the second approach is to use a random effect at the bottom level. If one uses a two-stage Poisson gamma model with random effect u, so that $E(y|u) = \mu' = \mu u = \mu'$, $\mathrm{var}(y|u) = \mu'$, $E(u) = 1$ and $\mathrm{var}(u) = \lambda$, then var(y)=$\mu + \lambda\mu^2$. Thus, the variance function of the approaches, $\sigma^2\mu$ and $\mu + \lambda\mu^2$ are functionally different and hence potentially distinguishable through diagnostics of the residuals (see section 3.1.1). The Poisson gamma model belongs to the class of hierarchical generalized linear models, which is often used to model traffic safety at an aggregate level and micro level (intersections, road sections, etc.) [Vistisen (2002) , Hauer (2001), Fridstrøm (1991)].

The over-dispersed accident counts were generated through a compound Poisson gamma model. Again initial values were obtained from estimation of the speed camera experiment data. The significant over-dispersion parameter was found to be $\sigma^2 = 1.49$.

Even though the simulated over-dispersed accidents were generated through the Poisson-gamma model, the assessment of the power assumed the QL function approach. This choice was made because even relatively substantial errors in the assumed functional form of $\mathrm{var}(Y)$ generally have only small effects on the conclusions (McCullagh and Nelder, 1989). Furthermore, if the wrong specification of $\mathrm{var}(Y)$ had influenced the assessment of the power, then a 5% significant level was not obtained, as seen in figure 6.3.

The over-dispersion reduces the power in the study as seen in figure 6.3. The probability of detecting a significant countermeasure when the valid effect is 15%, is approximately 67%. The difference between using monthly or annual data is highly increased compared to modelling Poisson distributed data. This is due to an uncertain estimation of the over-dispersion based on only 1/12 of the number of monthly observations.

6.3 Conclusion

Ideally, one should always include an analysis of the power in a given investigation. It enables the researcher to evaluate whether the particular study design is efficient in detecting the effect of the countermeasure in question and the limitations in the

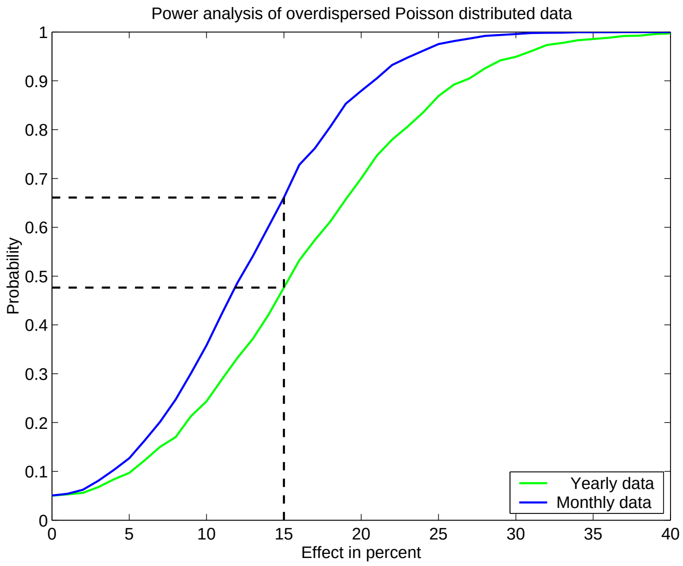

Figure 6.3: *Power analysis of over-dispersed Poisson distributed data.*

design become visual.

In this simulation study the power was relatively low compared to the expected reduction in the number of accidents. This means that the possibility of finding a significant effect is small.

The study does not take into account the serial correlation in the accidents that is often seen in accident studies with monthly observations. Though serial correlation dilutes the test statistics (see section 3.1.3), this simulation study may give a rough impression of the power in a study.

Chapter 7

Summary and conclusions

This chapter summarizes the work presented in the thesis and outlines the conclusions. At the end of the chapter some suggestions for future work are provided.

The general purpose of the study was to improve the insight into the aggregated traffic safety methodology in Denmark. The aim was to investigate contemporary statistical methods, that haved been designed to study developments over time, including effects of interventions. This aim has been achieved by investigating variations in aggregated Danish traffic accident series and by applying *state of the art* methodologies to specific case studies.

This thesis deals with statistical modelling of the aggregated traffic safety developments. The thesis consists of two parts. The first part introduces accident data and influential factors such as changing traffic volume and demographic and economic trends, and highlights the limitations in their data-structure: in particular the influential factors strong covariance and slow development over time. A number of modelling methodologies are reviewed and discussed with a view towards developing a sound methodology for describing changes in traffic safety.

In Part 2 two different aspects of the modelling methods described in part 1 are applied to relevant Danish traffic accident scenarios. One scenario is the assessment of an area-wide speed reducing experiment, through the use of mobile speed cameras, for preventing traffic related injuries. Another scenario is the evaluation of the impact of an unintended imprecise description in police reporting manual *' Vejledning til indberetning om færdselsuheld'* on the reported number of accidents.

General effects

One of the objectives for this work was to determine how traffic safety may be affected by changes in the influential factors such as, changing traffic volumes and demographic and economic trends in Denmark. Investigations showed that the socio-economic variables were highly multicorrelated. In other words these variables seem to vary simultaneously with time, which makes it difficult to pinpoint the source of variation to particular factors.

Only a few socio-economic variables were found to be significant when modelling the various accident series. This is because the socio-economic variables are strongly multicorrelated and they can, therefore, only contribute with a little additional explanation of the accident series when temporal dependencies and traffic are taken into account. Strong multicorrelation also makes interpretation of the significant explanatory variables problematic.

Among the socio-economic factors, the amount of traffic is found to be the single most determinant factor in the accident series, not taking temporal variables into account. The estimate of the traffic volume is large for all three series, but due to the strong multicorrelation, interpretation of this coefficient should be conducted with care. However, across the wide range of modelling techniques (non-dynamic and dynamic), the influence of traffic volume was very consistent. With the use of graphic illustrations and time dependent coefficients in state space models, the influence of traffic is investigated. Analysis shows that the influence of traffic is stable over the estimation sample and that the influence of traffic can be modelled as an elasticity. Time dependent coefficients may also help to characterize and model non-linear effects.

Variations in unemployment is weakly associated with changes in the number of accidents with killed or seriously injured and increasing gross national product is associated with additional accidents with killed. Again, one should interpretate the coefficients with care because of the strong multicorrelation.

The reduction in the speed limit in urban areas in 1985 was associated with a decrease in the number of accidents with killed.

Summaries of the seasonal effect for the accidents series indicate that January, October, November and December are high risk months. The number of accidents with killed in November and December is extremely high.

The general decreasing tendency in the series of accidents with killed or seriously injured and accidents with injured can not be modelled as a global trend. However, it can be described as a local linear movement, where the slope is fixed and the level or intercept has its own slow moving pattern. The slope represents the growth rate, which is approximately -7% per for accidents with killed or seriously injured and accidents with injuries. The growth rate for accidents with killed is approximately

-10% per year.

Modelling methods

An important issue in this thesis was to investigate the temporal dependency in the accident series. It was shown that the monthly observations of accidents were serially correlated and that this correlation could only partly be explained by the explanatory variables for accidents with killed or seriously injured and with accidents with injured. The basic structural model (Harvey and Durbin, 1986) is designed to model temporal dependencies in a very flexible manner, where level, slope and seasonal patterns may change over the estimation sample. However, the dynamic in the accident series is relatively slow and can be captured by a simple model, where only the level is allowed to change over time and the slope and seasonal pattern are fixed. A deterministic model, such as a regression model, may adequately describe the variations in the accidents with killed. Dynamic modelling techniques should be used when assessing traffic safety through the use of accident series. Although non-dynamic models, in the presence of serial correlation, might provide an adequent description of the variations in the accident series, inferences are not reliable. The non-dynamic approach may be able to describe short accident series satisfactorily.

The focus was to investigate methodologies for the analysis of previous and future traffic safety developments. An important measure of model fit is the model's ability to predict future observations. The predictions of future accidents in state space models are approximately 50% better than predictions from shrinkage methods, which are designed to obviate overfitting in regression models. This is because the state space model utilizes the serial autocorrelation in data when predicting future events. However, if no serial correlation is present, there is much gain when using shrinkage methods on accident data, where the coefficient of determination is relatively high.

Assessment of the effects of countermeasures

An important contribution is the demonstration and discussion of models that take developments over time into account when assessing how a change in the accident series is related to a particular countermeasure taken.

An example of an application, that aims to detect changes in the accident numbers is the mobile speed camera experiment. This study is also an example of a study of disaggregated data.

The hypothesis in the speed camera experiment was that speed cameras would reduce the speed and consequently reduce the number of accidents correspondingly. This thesis can document neither positive nor negative effects of the speed camera experiment on the number of accidents.

Another aspect examined in this thesis is the potential ability of a given study to detect a change in the number of accidents, caused by a countermeasure. Knowledge of the ability to detect changes prevents the analyst from setting up under-powered studies, where important ideas are rejected due to the design of the study.

Another example of studies that aim to detect changes due to a specific countermeasure or intervention is the study of the changing police reporting routine.

The thesis finds that the change in the police reporting practice in 1997 lead to a 6.7% decrease in the reported number of accidents with killed or seriously injured. In addition, the thesis finds that even though the reasons for sudden changes that appear in an accident series may be known, one may use the series to describe the effect of a given countermeasure or exposure when one adjusts for the changes. Even if changes are not accounted for by observable explanatory variables, one may still utilize the series if the changes are absorbed by the dynamics in the model.

It is also argued that assessment of the effects of a specific countermeasure can be problematic and should be based on as much a priori knowledge as possible. This is because the effective number of observations used to estimate the effects is highly dependent on the dynamic in the accident series. Extending the post intervention period does not necessarily improve the estimated effect associated with the countermeasure.

The main result from this research is the verification of the importance of dynamic models to describe variations in traffic accident series. Furthermore, the thesis demonstrates that the general decreasing tendency in the accident series has its own slow pattern, not explicable by recorded descriptive variables.

Assessment of the relationship between socio-economic variables and variations in Danish accident series does not seem to be worthwhile investigating further. This is because socio-economic variables in Denmark are highly muliticorrelated and have a slow simultaneous or almost deterministic development. As the traffic safety management plans often aim at improving the situation for certain groups of road users, it might be more appropriate to focus on evaluation of specific interventions in disaggregated accident series.

Appendix A

Brief intro to shrinkage methods

The idea of shrinkage methods in regression analysis is to shrink regression coefficients towards zero in order to overcome the problem of correlated x-variables. The different shrinkage methods that will be applied are very briefly described in the following:

A.1 Ridge regression

When normal linear regression is applied, the parameter estimates are computed by solving the normal equations given by

$$\hat{\boldsymbol{\beta}}_{\text{ols}} = (\boldsymbol{X}^T\boldsymbol{X})^{-1}\boldsymbol{X}^T\boldsymbol{Y}. \tag{A.1}$$

If one or more of the x-variables are correlated, it means that the columns in the $\boldsymbol{X}$-matrix are correlated and the matrix $\boldsymbol{X}^T\boldsymbol{X}$ is not invertible. To overcome this numerical problem, ridge regression (Hoerl and Kennard, 1970) can be applied, and the parameter estimates are given by

$$\begin{aligned}\hat{\boldsymbol{\beta}}_{\text{ridge}} &= \text{argmin}_{\beta} = \sum_{i=1}^{N}(y_i - \beta_0 - \sum_{j=1}^{p} x_{ij}\beta_j)^2 \\ &\quad \text{subject to } \sum_{j=1}^{p}\beta_j^2 \leq s \end{aligned} \tag{A.2}$$

or equivalently by

$$\hat{\boldsymbol{\beta}}_{\text{ridge}} = (\boldsymbol{X}^T\boldsymbol{X} + \lambda\boldsymbol{I})^{-1}\boldsymbol{X}^T\boldsymbol{Y}. \tag{A.3}$$

It is seen in (A.3) that a constant λ is added to the diagonal elements of $\boldsymbol{X}^T\boldsymbol{X}$, thereby making $\boldsymbol{X}^T\boldsymbol{X}$ invertable. The bigger λ is, the more the shrinkage. If the columns of X are highly co-linear, then some coefficients, obtained through least squares estimation, may be misleadingly negative. With ridge regression, as coefficients shrinks toward zero, their signs become meaningful.

The solution to a Ridge regression is still a matrix times Y, where the matrix is a function of X. Hence, the solution is still linear but biased. Typically the bias is less than the decrease in variance caused by the constraint on the estimates.

Ridge regression can also be derived as the mean or mode of a posterior distribution, with a suitable chosen prior to distribution.

A.2 The Lasso

Instead of a constraint on the sum of the squared parameters, we could use a constraint on the sum of the absolute values of the parameters. This shrinkage method is called lasso (Tibshirani, 1996), and is given by

$$\begin{aligned}\hat{\boldsymbol{\beta}}_{\text{lasso}} &= \text{argmin}_{\beta} = \sum_{i=1}^{N}(y_i - \beta_0 - \sum_{j=1}^{p} x_{ij}\beta_j)^2 \\ &\quad \text{subject to } \sum_{j=1}^{p}|\beta_j| \leq s. \end{aligned} \tag{A.4}$$

For small values of the shrinkage factor, s, the lasso sets a number of parameters equal to zero, while ridge regression only pulls the parameters towards zero .

A.3 Principal component regression

The idea of principal component regression is to compute a number of linear combinations of the original inputs, and use these as inputs to the regression analysis (Pearson, 1901). The linear combinations are, in this case, the principal components of the x-variables. The principal components are found by

$$\boldsymbol{z}_m = \boldsymbol{X} v_m, \tag{A.5}$$

and are afterwards used as inputs in the regression analysis. Predictions of the response are computed as

$$\hat{y}_{\mathrm{pcr}} = \bar{y} + \sum_{m=1}^{M} \hat{\theta}_m \boldsymbol{z}_m \tag{A.6}$$

where $\hat{\theta}_m = \langle \boldsymbol{z}_m, \boldsymbol{y} \rangle / \langle \boldsymbol{z}_m, \boldsymbol{z}_m \rangle$.

A.4 Partial least squares regression

Partial least squares regression is very similar to principal component regression. It was introduced by Wold (1975). However, instead of computing linear combinations based on the x-variables, it makes the computation based on both x and y. The first step of the partial least squares algorithm is to perform univariate regressions of $\boldsymbol{y}$ on each $\boldsymbol{x}_j$, thereby computing univariate regression coefficients $\hat{\varphi}_{1j}$, where 1 in the index indicates that it belongs to the first partial least squares direction. The first partial least squares direction is then computed as

$$\boldsymbol{z}_1 = \sum \hat{\varphi}_{1j} \boldsymbol{x}_j. \tag{A.7}$$

Afterwards the original inputs $\boldsymbol{x}_1, \cdots, \boldsymbol{x}_p$ are orthogonalized with respect to $\boldsymbol{z}_1$. This is done for each of the chosen partial least squares directions, M. Notice that if we chose M equal to the number of input variables, p, partial least squares regression is equivalent to the usual least squares estimates. This is also the case for principal component regression.

Appendix B

Descriptive statistics

In this chapter illustrations and tables from data descriptions in the text are presented.

B.1 Descriptive

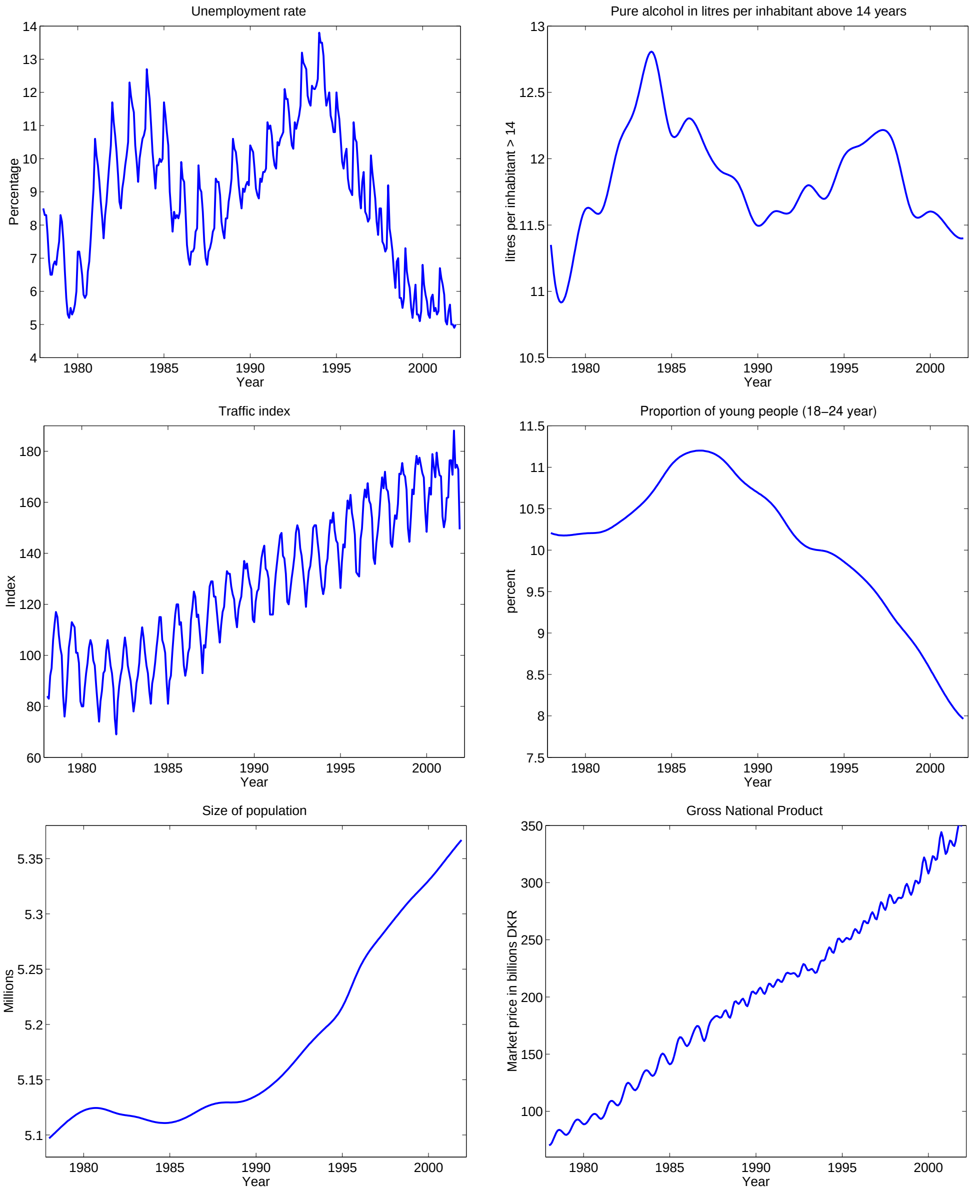

Figure B.1: *Explanatory variables against time.*

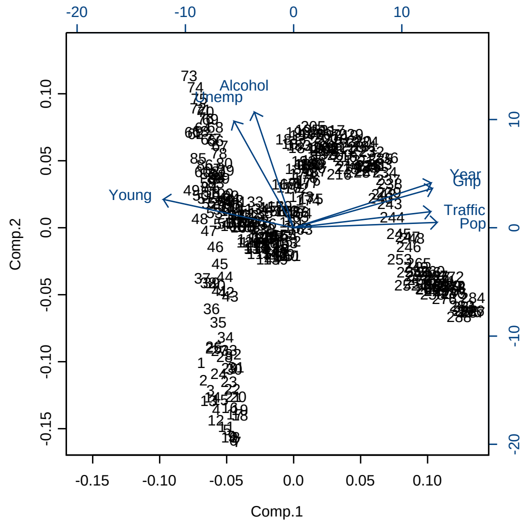

Figure B.2: *Principle Component Analysis of the quantative explanatory variables.*

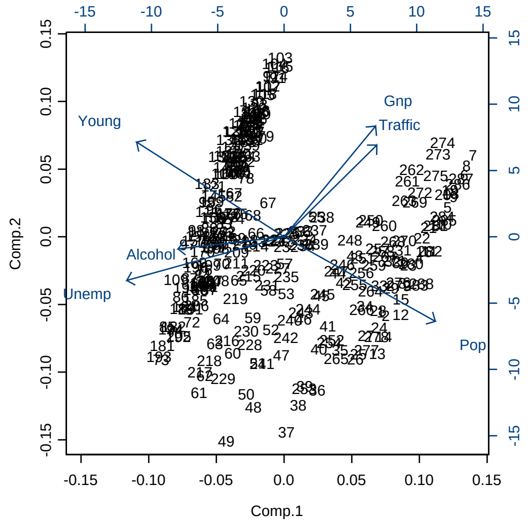

Figure B.3: *Principle Component Analysis of the quantitative explanatory variables adjusted for time.*

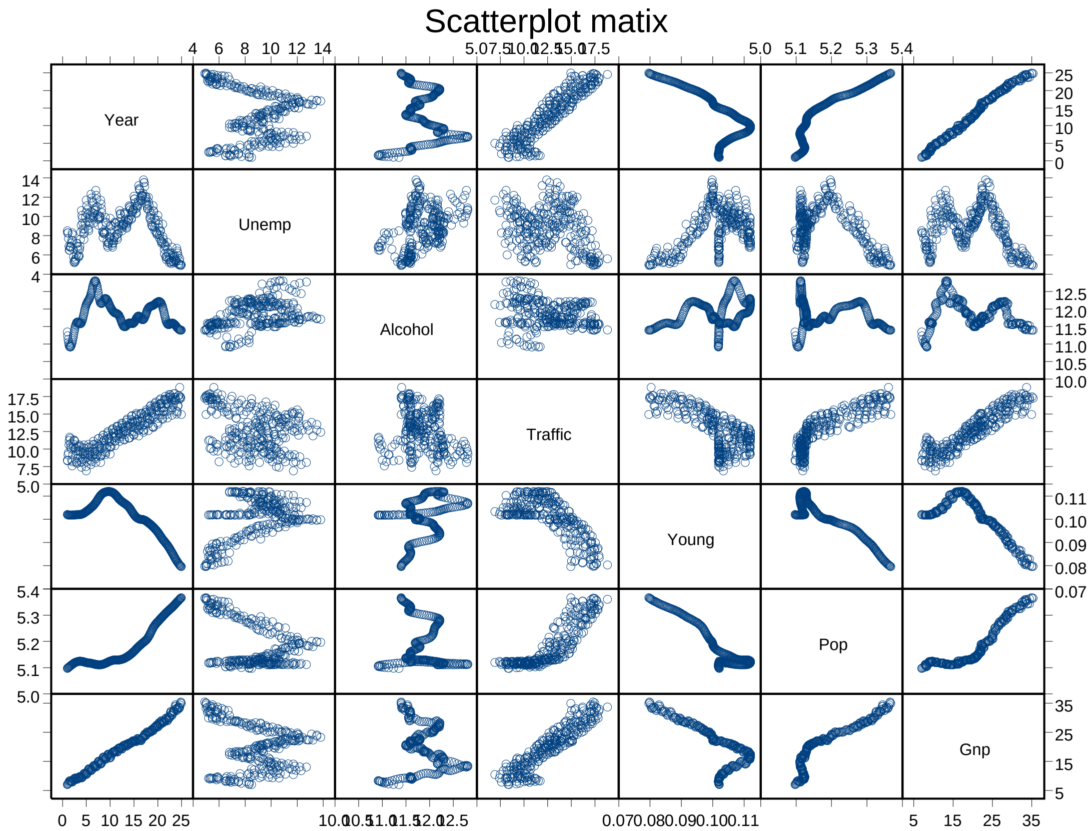

Figure B.4: *Scatterplot of the quantitative dependent variables and explanatory variables.*

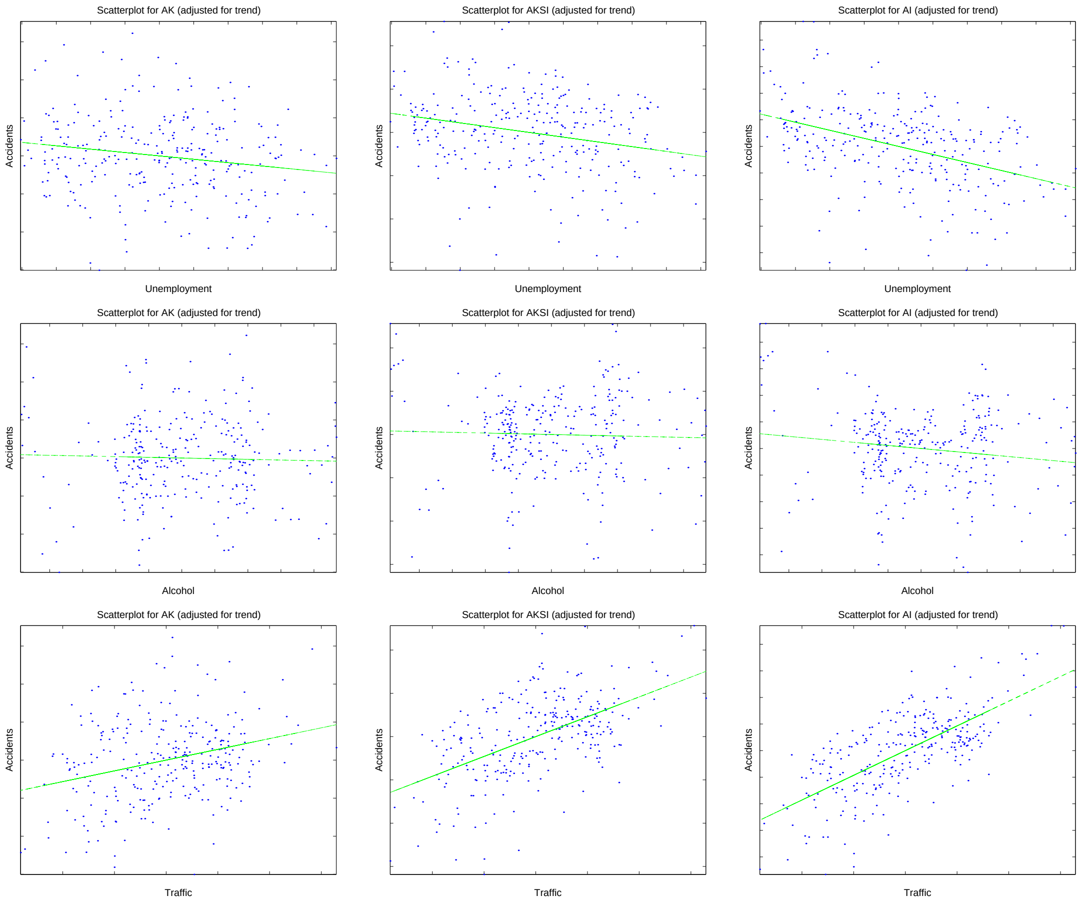

Figure B.5: *Scatterplot of the dependent variables and explanatory variables. Variables are adjusted for time.*

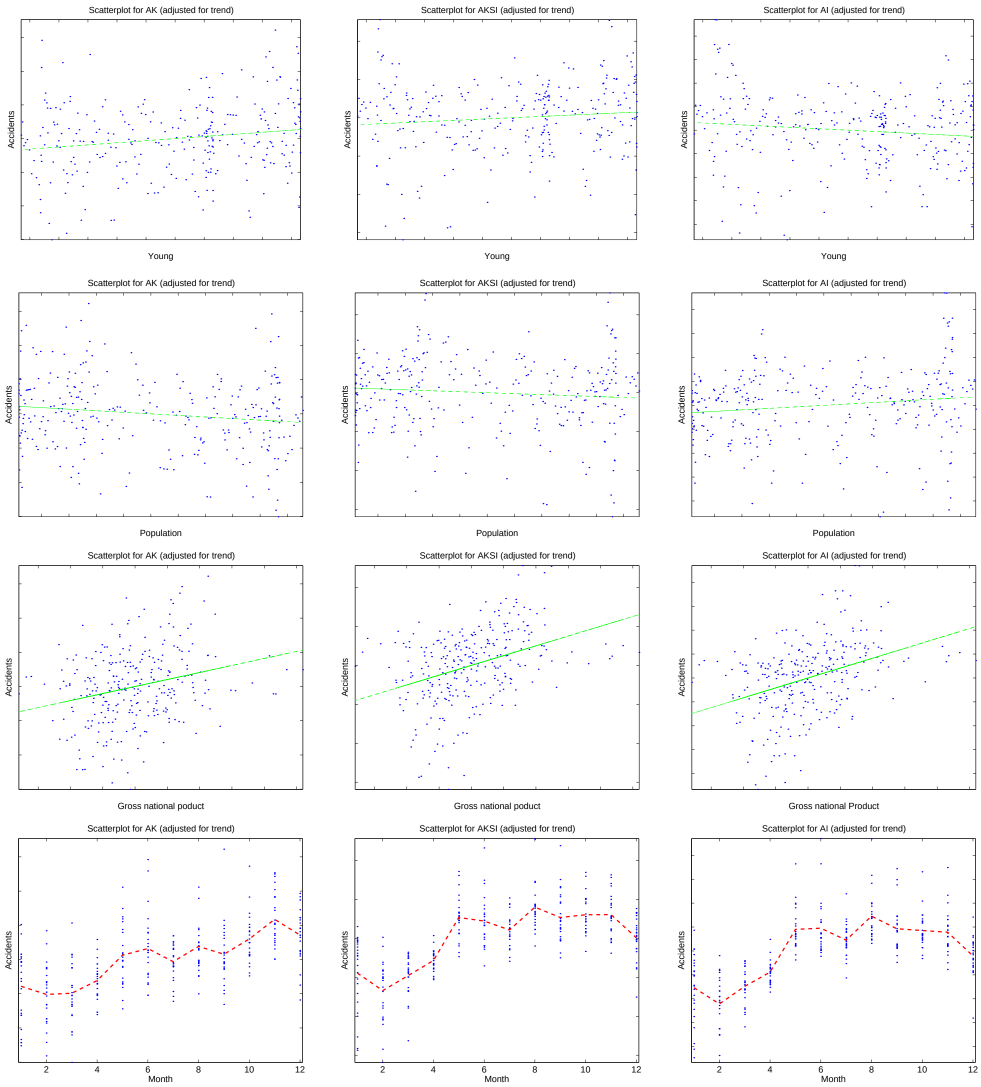

Figure B.6: *Scatterplot of the dependent variables and explanatory variables. Variables are adjusted for time.*

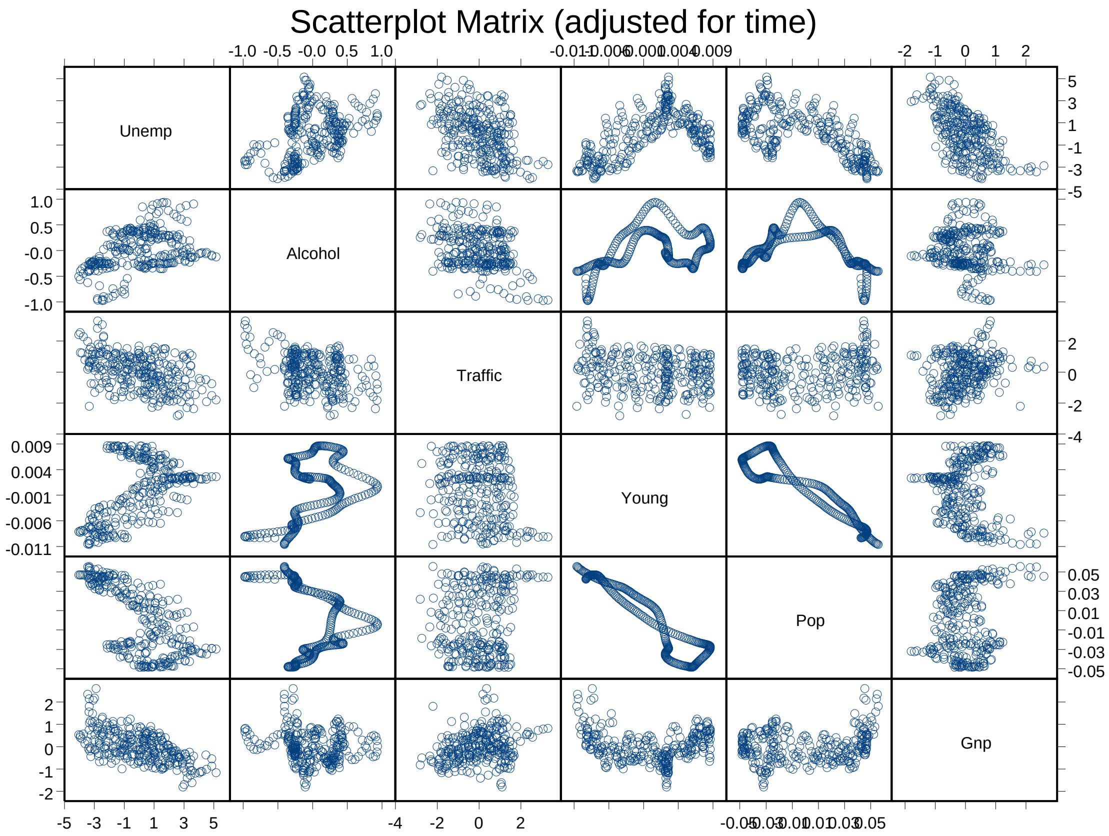

Figure B.7: *Scatterplot of the quantitative dependent variables and explanatory variables. Variables are adjusted for time.*

	Year	Unemp	Alcohol	Traffic	Young	Pop	Gnp	Speed
Year								
Unemp	-0.1316							
Alcohol	-0.0674	0.3993						
Traffic	0.9170	-0.3007	-0.2037					
Young	-0.7264	0.4485	0.3492	-0.7193				
Pop	0.9088	-0.3960	-0.1730	0.8623	-0.9263			
GNP	0.9958	-0.1866	-0.0809	0.9222	-0.7312	0.9127		
Speed	0.8099	0.0060	-0.1297	0.7476	-0.3115	0.5693	0.8036	
Hi	0.7034	-0.5760	-0.1797	0.6768	-0.8337	0.8668	0.7244	0.3542
Jan	-0.0199	0.2065	0.0037	-0.1999	0.0152	-0.0189	-0.0365	-0.0067
Feb	-0.0163	0.1473	0.0013	-0.1345	0.0124	-0.0154	-0.0301	-0.0067
Mar	-0.0126	0.1171	-0.0005	-0.0672	0.0099	-0.0122	-0.0187	-0.0067
Apr	-0.0090	0.0515	-0.0017	-0.0305	0.0070	-0.0087	-0.0079	-0.0067
May	-0.0054	-0.0567	-0.0024	0.0509	0.0043	-0.0053	-0.0044	-0.0067
Jun	-0.0018	-0.1105	-0.0025	0.1161	0.0014	-0.0017	-0.0040	-0.0067
Jul	0.0018	-0.1070	-0.0022	0.1264	-0.0013	0.0016	-0.0005	-0.0067
Aug	0.0054	-0.0419	-0.0015	0.1436	-0.0041	0.0051	0.0105	-0.0067
Sep	0.0090	-0.0804	-0.0005	0.0685	-0.0070	0.0087	0.0232	-0.0067
Oct	0.0126	-0.0603	0.0007	0.0464	-0.0098	0.0121	0.0295	0.0201
Nov	0.0163	-0.0472	0.0021	0.0009	-0.0127	0.0157	0.0246	0.0201
Dec	0.0199	-0.0182	0.0037	-0.1209	-0.0154	0.0191	0.0144	0.0201

Table B.1: *Correlations of predictors in the Road Accident data. 1978-2001. Variables Speed, HI, Jan, ..., Dec. are dummy regressors*

Predictor	Coefficient	Std. Error	T-stat	p-value	VIF	TOL
Jan	-0.0463	0.0084	-5.51	<.0001	0.4157	2.4053
Feb	-0.0888	0.0078	-11.28	<.0001	0.4729	2.1142
Mar	-0.0775	0.0084	-9.18	<.0001	0.4108	2.4339
Apr	-0.0655	0.0089	-7.31	<.0001	0.3657	2.7338
May	-0.0233	0.0109	-2.14	0.0336	0.2461	4.0621
Jun	-0.0397	0.0135	-2.92	0.0038	0.1588	6.2935
Jul	-0.0522	0.0140	-3.71	0.0003	0.1482	6.7437
Aug	-0.0294	0.0138	-2.12	0.0346	0.1532	6.5234
Sep	-0.0273	0.0110	-2.49	0.0136	0.2422	4.1272
Oct	-0.0166	0.0101	-1.65	0.1002	0.2875	3.4771
Nov	-0.0032	0.0088	-0.37	0.7099	0.3791	2.6375
Dec	-0.0069	0.0063	-1.09	0.2758	0.7288	1.3720
Year	-0.8798	0.1470	-5.98	<.0001	0.0015	634.3933
Unemploy	0.0382	0.0190	2.01	0.0454	0.0926	10.7909
alcohol	0.0074	0.0124	0.59	0.5524	0.1863	5.3676
Traffic	0.2564	0.0490	5.23	<.0001	0.0137	72.8178
Young	0.1043	0.0419	2.49	0.0136	0.0256	38.9976
Pop	0.0593	0.0768	0.77	0.4405	0.0069	144.1464
Gnp	0.4574	0.1311	3.49	0.0006	0.0020	478.5030
Limit50	-0.0282	0.0177	-1.59	0.1133	0.0887	11.2678
Hi	-0.0420	0.0140	-2.99	0.0031	0.1997	5.0052

Table B.2: *Linear model fit to accidents with killed or serious injuries (1978-1999). T-test statistic is the coefficient divided by it's standard error.*

Predictor	LS	Subset	Backward	Ridge	Lasso	PCR	PLS
Jan	-.0463	-.0487	-.0493	-.0233	-.0328	-.0608	-.0463
Feb	-.0888	-.0850	-.0849	-.0376	-.0619	-.0428	-.0706
Mar	-.0775	-.0676	-.0669	-.0237	-.0340	-.0272	-.0446
Apr	-.0655	-.0523	-.0513	-.0136	-.0126	-.0126	-.0252
May	-.0233			0.0129		0.0131	0.0241
Jun	-.0397	-.0119		0.0115		0.0334	0.0230
Jul	-.0522	-.0229	-.0196	0.0069		0.0364	0.0150
Aug	-.0294			0.0214	0.0037	0.0301	0.0406
Sep	-.0273			0.0137		0.0184	0.0263
Oct	-.0166			0.0164		0.0131	0.0309
Nov	-.0032			0.0150		0.0011	0.0276
Dec	-.0069			0.0030		0.0341	0.0015
Year	-.8798	-.8775	-.9110	-.0422	-.1508	-.0551	-.0577
Unemploy	0.0382	0.0316	0.0326	-.0203		-.0440	-.0452
Alcohol	0.0074			-.0057		0.0006	-.0140
Traffic	0.2564	0.1376	0.1226	-.0188		-.0193	-.0162
Young	0.1043	0.0408	0.0352	0.0334		0.0376	0.0449
Pop	0.0593			-.0402	-.0784	-.0467	-.0542
Gnp	0.4574	0.5552	0.6020	-.0377		-.0510	-.0507
Limit50	-.0282			-.0302		-.0474	-.0399
Hi	-.0420	-.0395	-.0416	-.0337	-.0053	-.0342	-.0452
Test error	0.0200	0.0152	0.0160	0.0126	.0091	0.0181	0.0110
Std error	0.0316	0.0244	0.0239	0.0164	0.0137	0.0235	0.0165

Table B.3: *Estimated coefficients and test error results for different subset and shrinkage methods applied to the data for accidents with killed or serious injuries. The blank entries correspond to variables omitted.*

Appendix C

Non-dynamic analysis of accident data

In this appendix the results of non-dynamic regression modelling are given.

Explanatory variables	Coefficient	Std. error	F-statistic	p-value
Intercept	-10.8902	7.4317		
Jan	-0.1441	0.0274		
Feb	-0.3218	0.0273		
Mar	-0.2946	0.0280		
Apr	-0.2549	0.0291		
May	-0.1080	0.0317		
Jun	-0.1781	0.0369		
Jul	-0.2455	0.0388		
Aug	-0.1480	0.0380		
Sep	-0.1176	0.0322		
Oct	-0.0749	0.0304		
Nov	-0.0200	0.0271		
Dec	ref.		30.00	$<.0001$
Time	-0.1087	0.0218	25.03	$<.0001$
logunemp	0.1637	0.0651	6.32	0.0126
logalc	0.1565	0.3807	0.17	0.6814
logtraffic	1.2972	0.1404	85.61	$<.0001$
logyoungpct	1.3471	0.4583	8.63	0.0036
logpop	10.0213	5.0334	3.96	0.0476
loggnp	0.4583	0.2391	3.68	0.0562
speed	-0.0743	0.0325	5.21	0.0233
HI	-0.0512	0.0350	2.14	0.1444

Table C.1: *Poisson regression fit to accidents with killed or serious injured (1978-1999). The F-test statistic is used due to significant over dispersion (σ^2=3.51 p-value $<$0.001). The F-test value for December is the test for no seasonal variation*

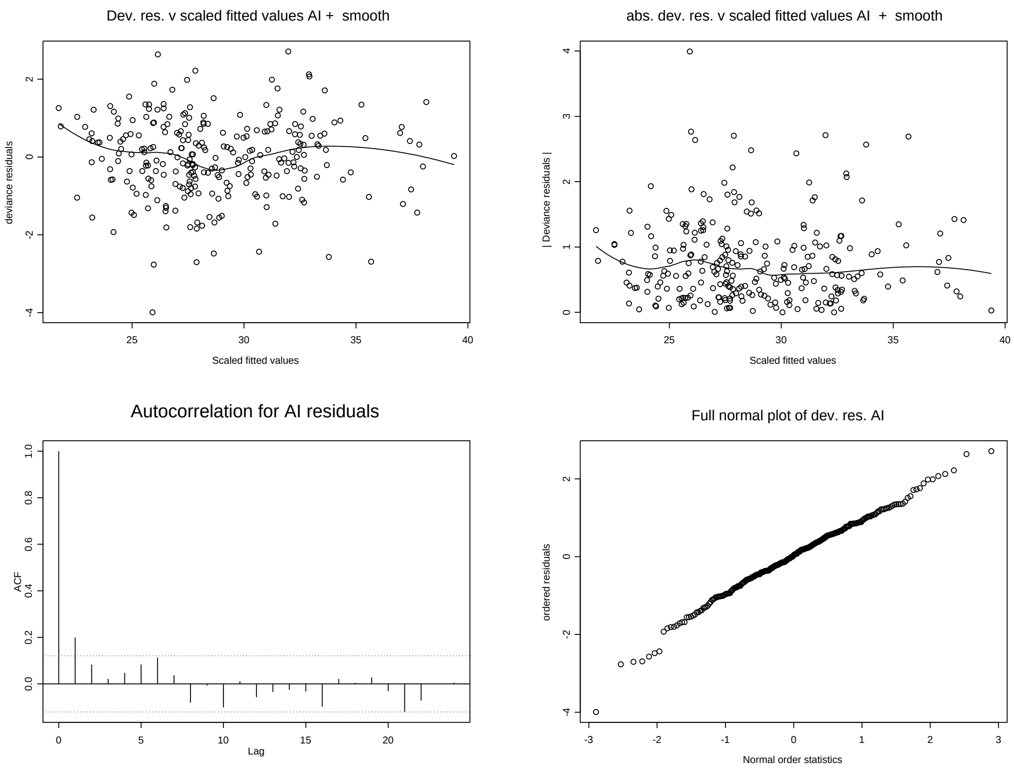

Figure C.1: *Model-checking plots for accidents with injuries.*

Explanatory variables	Coefficient	Std. error	F-statistic	p-value
Intercept	-10.2793	6.5022		
Jan	-0.1278	0.0244		
Feb	-0.3173	0.0243		
Mar	-0.2825	0.0247		
Apr	-0.2488	0.0256		
May	-0.1123	0.0279		
Jun	-0.1747	0.0323		
Jul	-0.2609	0.0340		
Aug	-0.1480	0.0333		
Sep	-0.1174	0.0283		
Oct	-0.0893	0.0268		
Nov	-0.0369	0.0240		
Dec	ref.		35.50	<.0001
Time	-0.0946	0.0192	24.41	<.0001
logunemp	0.0912	0.0562	2.63	0.1058
logalc	0.5379	0.3375	2.54	0.1124
logtraffic	1.5475	0.1225	160.22	<.0001
logyoungpct	1.0179	0.4038	6.35	0.0124
logpop	8.9470	4.4090	4.12	0.0435
loggnp	0.1989	0.2108	0.89	0.3462
speed	-0.0807	0.0292	7.61	0.0062
HI	0.0511	0.0294	3.02	0.0837

Table C.2: *Poisson regression fit to accidents with injuries (1978-1999). The F-test statistic is used due to significant over dispersion (σ^2=4.17 p-value $<$ 0.0001). The F-test value for December is the test for no seasonal variation.*

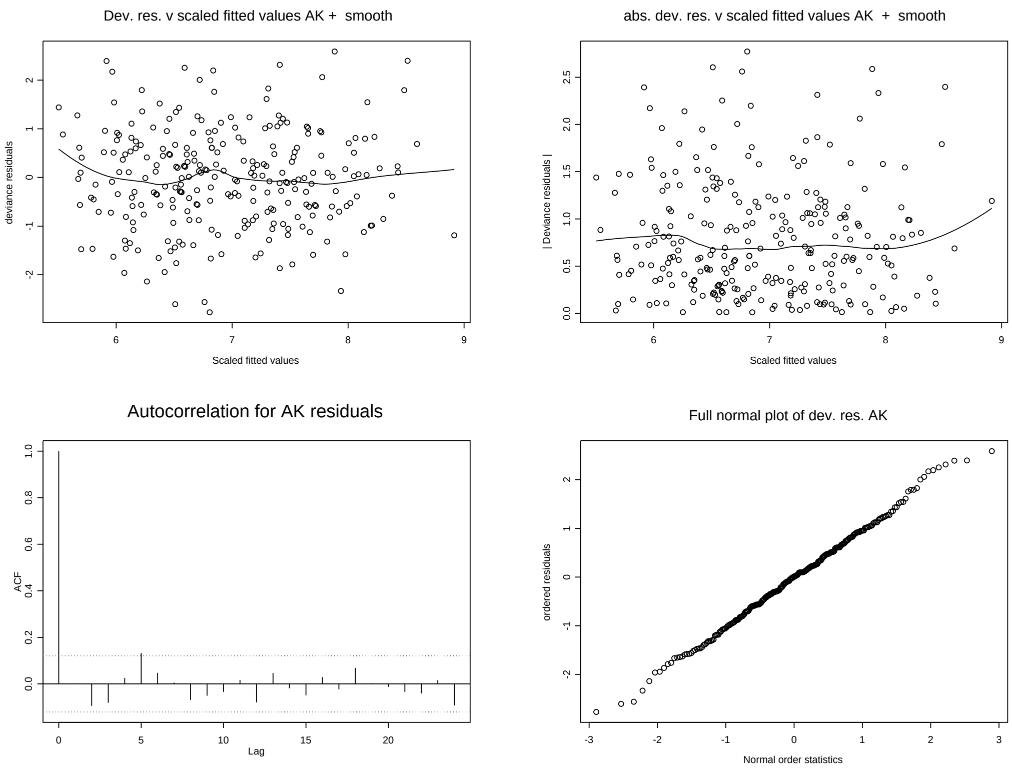

Figure C.2: *Model-checking plots for accidents with killed.*

Explanatory variables	Coefficient	Std. error	F-statistic	p-value
Intercept	-1.2753	14.6278		
Jan	-0.2531	0.0522		
Feb	-0.4037	0.0513		
Mar	-0.4653	0.0536		
Apr	-0.4373	0.0553		
May	-0.3723	0.0612		
Jun	-0.3915	0.0710		
Jul	-0.5082	0.0749		
Aug	-0.4289	0.0735		
Sep	-0.3772	0.0620		
Oct	-0.2494	0.0577		
Nov	-0.0775	0.0503		
Dec	ref.		15.61	<.0001
Time	-0.0889	0.0433	4.23	0.0407
logunemp	0.0338	0.1270	0.07	0.7905
logalc	0.1094	0.7587	0.02	0.8854
logtraffic	1.5909	0.2777	32.95	<.0001
logyoungpct	1.1551	0.8888	1.69	0.1951
logpop	2.1389	9.9070	0.05	0.8292
loggnp	0.5026	0.4752	1.12	0.2907
speed	-0.1411	0.0640	4.82	0.0291
HI	0.0547	0.0650	0.71	0.4002

Table C.3: *Poisson regression fit to accidents with killed (1978-1999). TheF-test statistic is used due to significant over dispersion (σ^2=1.181 p-value = 0.0251). The F-test value for December is the test for no seasonal variation.*

Explanatory variables	Coefficient	Std. error	F-statistic	p-value
Intercept	-8.1369	7.4865		
Jan	-0.1434	0.0267		
Feb	-0.3196	0.0255		
Mar	-0.2918	0.0270		
Apr	-0.2597	0.0283		
May	-0.1227	0.0319		
Jun	-0.1960	0.0369		
Jul	-0.2476	0.0381		
Aug	-0.1536	0.0380		
Sep	-0.1292	0.0324		
Oct	-0.0823	0.0306		
Nov	-0.0297	0.0275		
Dec	0		27.55	$<.0001$
Time	-0.1114	0.0225	22.61	$<.0001$
logunemp	0.1285	0.0658	3.51	0.0623
logalc	0.2708	0.3967	0.43	0.5131
logtraffic	1.3242	0.1412	80.96	$<.0001$
logyoungpct	0.9407	0.4625	3.81	0.0522
logpop	7.5080	5.0794	2.01	0.1574
loggnp	0.5325	0.2454	4.33	0.0384
speed	-0.0752	0.0346	4.35	0.0381
HI	-0.0629	0.0314	3.69	0.0559

Table C.4: *Linear regression fit to accidents with killed or serious injured (1978-1999). The F-test value for December is the test for no seasonal variation.*

Explanatory variables	Coefficient	Std. error	F-statistic	p-value
Intercept	-9.2121	6.5745		
Jan	-0.1259	0.0234		
Feb	-0.3150	0.0224		
Mar	-0.2795	0.0237		
Apr	-0.2491	0.0249		
May	-0.1234	0.0280		
Jun	-0.1902	0.0324		
Jul	-0.2643	0.0335		
Aug	-0.1554	0.0334		
Sep	-0.1287	0.0285		
Oct	-0.0965	0.0269		
Nov	-0.0452	0.0242		
Dec	ref.		33.03	<.0001
Time	-0.0988	0.0197	23.03	<.0001
logunemp	0.0793	0.0578	1.73	0.1894
logalc	0.6277	0.3484	2.99	0.0851
logtraffic	1.5975	0.1240	152.78	<.0001
logyoungpct	0.7782	0.4062	3.38	0.0673
logpop	7.6978	4.4607	2.74	0.0991
loggnp	0.2578	0.2155	1.32	0.2522
speed	-0.0796	0.0304	6.33	0.0126
HI	0.0493	0.0276	2.94	0.0878

Table C.5: *Linear regression fit to accidents with injuries (1978-1999). The F-test value for December is the test for no seasonal variation.*

Explanatory variables	Coefficient	Std. error	F-statistic	p-value
Intercept	1.5047	14.5627		
Jan	-0.2602	0.0519		
Feb	-0.4044	0.0497		
Mar	-0.4669	0.0524		
Apr	-0.4380	0.0550		
May	-0.3836	0.0620		
Jun	-0.3977	0.0718		
Jul	-0.5010	0.0742		
Aug	-0.4317	0.0740		
Sep	-0.3866	0.0630		
Oct	-0.2523	0.0596		
Nov	-0.0775	0.0535		
Dec	0.0000	0.0000	14.02	$<.0001$
Time	-0.0887	0.0437	3.79	0.0529
logunemp	0.0094	0.1280	0.00	0.9439
logalc	0.3690	0.7716	0.21	0.6468
logtraffic	1.6044	0.2747	31.41	$<.0001$
logyoungpct	0.7956	0.8997	0.72	0.3970
logpop	-0.4826	9.8805	0.00	0.9627
loggnp	0.5252	0.4773	1.11	0.2922
speed	-0.1309	0.0673	3.49	0.0630
HI	0.0517	0.0611	0.66	0.4171

Table C.6: *Linear regression fit to accidents with killed (1978-1999). The F-test value for December is the test for no seasonal variation.*

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