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Contents of the project:	There is an increased interest in the safety effects of traffic enforcement measures. In Australia, monthly data of several types of enforcement and campaigns was gathered and analysed, together with background data and safety data. In this report, the Australian data has been reanalysed, using a slighly different method than the Australian one.

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Summary

There is an increased interest in the Netherlands in the safety effects of traffic enforcement measures. This regards the intermediate effect of enforcement on behaviour as well as the final effect on safety itself. In addition to these general safety effects, regional differences are also of concern. The current study was meant to identify a feasible and scientifically correct analysis of enforcement data for evaluation purposes. This was done using Australian data.
In Victoria, Australia, monthly data of several types of enforcement and campaigns was gathered, together with background data and safety data. These series of monthly data were analysed using Harvey's structural time-series technique. In cases like these, time-series analysis is superior to ordinary (log-linear) regression analysis, because it takes the developments of the traffic and safety systems into account.

In order to learn from the Australian experiences, their data has been reanalysed, also using structural time-series analysis, however, this time applied to all the regional series together. It was assumed that if common trends in the series were represented by common parameters in the joint model, a more stable solution would result from the total set of regional series than from the separate analyses for each series.
This study was carried out not to check the results and interpretation of the original study, but to see how such complicated multivariate time-series models, as intended to be used in the Netherlands, would work out on the Australian data.

Various models were applied, with various (combinations of) enforcement and campaign variables included. These models were applied to the regional data separately as well as jointly.
The model was applied to accident rates (accidents divided by vehicle kilometres). The basic structural model, consisting of trend, drift (Harvey, 1989), and monthly components, was extended by addition of alcohol sales and unemployment figures. To this extended basic model, (combinations of) enforcement variables were added. Chi-square tests were applied to measure the improvement of the model by the addition of enforcement variables.
It turned out that in general the residuals are considerable. However, this seems to be more a result of the variation in the individual measurements, caused by the small number of accidents per month, than by the uncertainty in the model as such.
It was also found that the monthly trends in accidents are different for different regions. Therefore, the number of parameters in the joint analyses was still considerable, because 11 monthly parameters were added for each series.
The results showed that only small (insignificant) effects of campaigns were found and almost no effects of enforcement. This can be explained partly as a result of the conservative way of testing: all effects of enforcement and campaigns that could be explained by other factors as well, were attributed to the other factors.

The outcomes of the combined analysis over regions were comparable to those of the separate regions. However, the effects of enforcement or campaigns were still not significant. This research shows that it is important to use rather long time-series to prove effects, especially if the number of accidents per region is low.

The major aim of the study was to see if the multivariate time-series models could be applied successfully to several series of traffic safety data as are expected to result from the Dutch experiment. From a technical point of view the outcomes were very promising. The authors hope that their experiences may stimulate others to use (multivariate) structural time-series analysis for similar research problems.

Contents

1. Introduction

In order to improve traffic safety in the Netherlands, a number of safety targets have been highlighted. Some of these targets are related to safe traffic behaviour of road users. It was therefore decided to intensify police enforcement on speed behaviour, drink-driving, red light negation, safety belt use, and the use of crash helmets (in order to improve safe behaviour). This programme which consists of several regional activities, started in 2000, provisionally for a period of four years.

An important decision criterion for continuation of this programme is the effectiveness of the enforcement efforts with regard to behaviour and safety. The current study was meant to identify a feasible and scientifically correct analysis of data for evaluation purposes. This was done using Australian data.

An extensive research programme was carried out by MUARC to evaluate the effects of police enforcement in the Australian state of Victoria. The results were reported in August 2000 (Monash University Accident Research Centre (MUARC) Report No. 172). The abstract of that report is given below.

> **Abstract of evaluation research on police enforcement in Victoria, Australia**
>
> "The Victoria Police requested MUARC to develop a procedure that would measure traffic enforcement outcome levels against expected levels for each Victoria Police Region. To achieve this objective, relationships were developed that connected monthly casualty crashes in each of the five Police Regions with monthly variations in variables representing exposure, enforcement activity and other factors measured in each Region for the period 1989-1997. These relationships were achieved using structural ('state-space') time-series regression modelling techniques.
>
> The models developed revealed the relative contribution of an increase in each enforcement operation to reducing the risk of casualty crashes in each Region after the effects of exposure changes and other factors had been taken into account. The coefficients (obtained from the regression models in most cases) measured the relative contribution of each enforcement operation, specific to each Region, and formed the basis of an index which allowed the overall contribution to traffic safety produced by the mix of enforcement activities in each Region to be assessed and compared between Regions.
>
> An index for each Region was developed for the months January-December 1998 using the monthly average during 1997 as the base period. There was some variation found in the monthly indices both between and within Regions. When considering the overall index (i.e. for all regions combined – based on the five regions' average), the estimated index has shown that relative to the previous year (1997), the Police performed better than average during the first quarter of 1998, but decreased their performance for the rest of the year.
>
> Although the Police performance, as reflected by the index, was below average for most of 1998, the index should still be considered as a valuable tool for Police. This is because the index specifies which enforcement operations Police should increase their resources in per Region, to reduce the risk of casualty crash in that Region.
>
> The indices developed for each Region during January-December 1998 were tested against actual road safety performance by comparing the observed crash frequencies per month with the expected levels (projected from the estimated models). This testing procedure appeared to work best when Police were performing better than average (as measured by the index), with reductions in casualty crash risk occurring in most cases. This was even more evident when the current month's index was compared with the next month's crash risk outcomes."

Because the evaluation research to be carried out by SWOV has a number of common features, it is interesting to learn from the Victorian experiences.

The central issue in the Australian study is the dependence of traffic safety on police enforcement. It is assumed that the development of traffic safety is also influenced by other factors, such as vehicle kilometres travelled, economic developments measured by unemployment rate, and safety campaigns, primarily concerning drink-driving and speeding. Therefore, these factors were taken into account as well. However, apart from this context of safety developments, it is also important to study the causal relations. Police enforcement is supposed to change road user behaviour and, as a result of that, to increase safety.
In the Dutch research, changes in traffic behaviour on the basis of police enforcement are studied together with changes in safety. From a scientific point of view, the behavioural change is an essential assumption for the effect of police enforcement on safety. However, also in the Netherlands, the ultimate link between police enforcement and safety is the major motivation for policy makers to improve traffic behaviour by enforcement.

In addition to the similarities and dissimilarities between the major aims of the studies, an important similarity between both evaluation studies is the interest in regional effects.

Most evaluation research is carried out using before-and-after studies with and without control groups or ordinary regression analysis. In such analyses, direct relations between the dependent variables and independent variables are assumed. From a modelling point of view, it is important to realise that the data concerned are time-related: they describe developments of systems in time. Although data for all variables are selected for individual time-points (e.g., the number of accidents, the traffic volume, the percentage of drivers with a blood alcohol level above the limit in year t, t+1, t+2 etc.), time itself, or better the development of processes over time, is ignored in ordinary regression analysis. I.e., the analysis is not controlled for the developments in the series themselves.

In time-series analysis developments of traffic safety are studied as a function of previous traffic safety levels, together with the influence of external factors on these developments. Ignoring time effects often results in misleading conclusions about the effects of safety measures. E.g., it is known that in developed countries, traffic risk steadily decreases over the years. However, in before-and-after studies as well as in regression analysis, data is seldom controlled for this general phenomenon, resulting in too optimistic estimates of safety effects of specific safety measures. Haight (1986) gives an example of such an erroneous effect stated by Nichols (1982). Nichols extrapolates the increasing trend in accidents in Victoria, Australia up to 1970 and compares this with the decrease after 1970, the year of introduction of the safety belt law. The difference between the extrapolated and observed numbers is interpreted as the effect of the safety belt law. Firstly, the number of accidents decreases in all developed countries in that period, secondly, the number decreases for all kinds of accidents, not only for car drivers and front passengers. Thirdly, the safety belt effect is not an effect that increases over time to that extent (see e.g., *Figure 1* below). However, most importantly, he ignores the general trend in

the accident rate, which together with the reduced increase in traffic volume, explains the general decrease in the number of accidents.
Even in cases of before-and-after studies with control groups it is recommended to use time-series analysis in order to check for changes in trends of control groups, especially when relatively long time periods are used. Time trends for the control groups may already differ from the experimental group in the before period. Or control groups that were acceptable in the before period need not be acceptable control groups in the after period.

Series of safety data in time should be regarded as the result of developments in the safety aspects of traffic systems. Changes in the state of a system depend not only on changes of external factors, but also on the state of the system before the change. E.g., a change in traffic behaviour of a road user, if confronted with a change in enforcement from level A to B, need not be the reverse of a behavioural change if enforcement changes from level B to A, as is assumed in ordinary regression. Therefore, in order to investigate such behavioural change, time-effects should be taken into account. Sequential data such as series of accidents contain information about the developments in the safety systems that should be used in the analysis.
Time-series models investigate changes of systems over time as a result of system developments together with the influence of external factors. A good example of this approach is given in Harvey and Durbin (1986). They modelled the accident data for killed and seriously injured car drivers in Great Britain before the introduction of the safety belt law, and predicted the casualty numbers after this introduction with and without an intervention effect (see *Figure 1*).

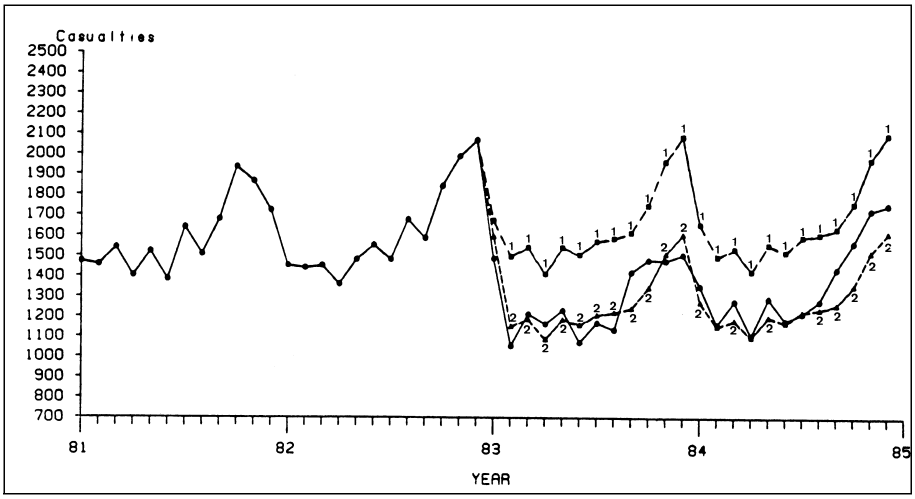

Figure 1.1*. Car drivers killed and seriously injured; unmarked dots: observed numbers; dots marked with '1': predictions with intervention effect removed; dots marked with '2': predictions with intervention effect included.*

Because a major part of the variation in casualty numbers in the after period can be 'explained' by a seasonal trend in the data, a much more precise effect of the safety belt law can be established than would have been possible if a simple before-and-after design had been used. E.g., given a monthly casualty number of some 1600 in the before period, an estimated gain based on the first six months of the after period would have been much greater than based on the second half of that same year, although the time-series forecast shows that the effects during these periods are largely the same.

This insight was the reason for the Monash University Accident Research Centre (MUARC) in Melbourne to change their analytical approach. This type of data had been analysed originally using log-linear regression models. However, the analysis of the police enforcement data was carried out by means of structural time-series analysis techniques as developed by Harvey (Harvey 1990). Such models, however, are less easily built and interpreted, especially in case of more than one series of accidents. Therefore, they used separate models for the five police regions.

As is the case in the Dutch situation, it would probably be more efficient to study the data for the five regions jointly. It was therefore recommended to use the rich data available from the Victorian study, to develop time-series models that can be used in the Dutch situation. Recent developments make it possible to use time-series models for more than one dependent variable. This means that the data from various regions can be analysed together in order to investigate common effects in addition to individual differences.
The data was reanalysed to investigate the new possibilities for multivariate modelling. Just as in the MUARC analysis structural time-series analysis was used. However in this case a joint analysis was performed on the data from the five police regions. The outcomes may result in a more parsimonious model with smaller error, because data in the different regions will share common characteristics, in addition to specific trends. Stochastic variations in the individual series will partly be cancelled in the joint analysis of all series. As a result of this, parameters that are not significant in the regional models may become significant in the total model, because of incremental effects in the larger total sample.
It is not our intention to reanalyse the Victorian data in order to check results and interpretations found by MUARC, but only to investigate how multivariate time-series analysis models can be used to analyse safety problems such as the establishment of enforcement effects. The models developed that way need not be restricted to the analysis of the relation between enforcement and safety alone. The same type of model can also be applied to the relation between enforcement and behaviour and many other problems where series of related trends should be studied. The results of these modelling exercises are reported here.

2. Data and models

2.1. Victoria data

The Victoria data consists of monthly measurements from 1987 till 1999 of the number of accidents during 'high alcohol' hours and 'low alcohol' hours for five police districts. In addition to that, the total number of vehicle kilometres, the number of new probationary car licences, the level of drink-driving, and speeding campaigns (Adstock) on television, and the level of alcohol sales per month for the whole of Victoria.are included in the data set. Furthermore, the unemployment rate, the number of (speed camera) traffic infringement notices (TIN's), six types of penalty notices (apart from drink-driving notices) and the number of random breath tests (RBT's) are given per month and per region.

2.2. The multivariate time-series model

Following Harvey's basic structural model (Harvey, 1990), the following representation of the structural state space model can be given for one series of quarterly log-rates of crashes:

$$z_t = \begin{pmatrix} w_t \\ d_t \\ q_t \\ q_{t-1} \\ q_{t-2} \end{pmatrix} = \begin{pmatrix} 1 & 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & -1 & -1 & -1 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \end{pmatrix} \begin{pmatrix} w_{t-1} \\ d_{t-1} \\ q_{t-1} \\ q_{t-2} \\ q_{t-3} \end{pmatrix} + \begin{pmatrix} \varepsilon_t \\ \delta_t \\ \theta_t \\ 0 \\ 0 \end{pmatrix} \qquad (1)$$

In this model w_t represents the level component, d_t the drift component and q_t the quarterly component at time t. These components may be subject to random disturbance, by the components ε_t, δ_t and θ_t. These components are sometimes called 'the hyper parameters'.
This state space model is combined with the following measurement equation for (in our case) the log-rate of crashes:

$$y_t = h' z_t + v_t \qquad (2)$$

with z_t the state space vector and h' = (1,0,1,0,0) the design vector. Equations (1) and (2) are together known as the Basic Structural Model (BSM, see Harvey,1989). The quarterly component is used in this example for practical reasons, but can of course be replaced by a monthly component, existing of 11 values m_t - m_{t-11} instead of q_t - q_{t-3}. These monthly components are in fact used in the model at hand.

Ignoring the random and seasonal components, it is clear that d_t is fixed and w_t increases or decreases each step by the value d_t. Therefore, if only d_t = d and w_0 = w are non-zero state space parameters, the model for y_t is an ordinary linear model, with intercept w, slope d and random error v_t.

Furthermore, we see that the sum of four succeeding q-values is equal to zero and thus represents a cyclic trend.
The random disturbance parameters of the state space model allow for temporary (random walk) shifts that will be passed on to the next value until the next shift. The term ε_t represents a temporary shift in the level parameter, while the term δ_t represents a temporary shift in the drift parameter.
The general idea is that over the period of analysis the log crash rate y_t develops roughly (and not completely, because of ε_t and δ_t) along a straight line, apart from seasonal deviations.
It can be shown that the hyper parameters ε_t, δ_t and θ_t will not interfere with the estimation of the general trend and also that the random error term v_t of the measurement equation will not take over (parts of the) role of the hyper parameters ε_t, δ_t and θ_t. Therefore all parameters can be interpreted independently.

This basic structure is easily generalised, e.g. for the joint estimation of different series of log crash rates. In our case the model is generalised to a joint model for the series of accidents during ‘high’ and ‘low’ alcohol hours for each region (the regional models) and to a joint model consisting of the 5 times 2 series for the five regions together (the total model). In these generalised (multivariate) models restrictions can be defined for the development of the series, e.g. by assuming equal seasonal trends for all regions and/or the two series within the regions.

In this basic model additional variables can be added to the state space equation as well as to the measurement equation. These additional variables are of course the enforcement and campaign variables - the effects of which are the target of the analysis - in the first place, but other adjustment factors can be added to the basic model as well. In our case the adjustment factors are traffic volume, alcohol sales, and unemployment rates.

If it is assumed that the effect of some variable is not only immediate, but will also last longer in time, and therefore influence the system, it is preferable to add these variables to the level components in the state space model. If only immediate effects are expected, then it is better to add the variables to the measurement equation.

In our case, only the enforcement variables are added to the state space equations. The parameters for speeding and drink-driving Adstock were added to the measurement equation instead of the system equations, because it was assumed that the time effect was already taken care of in the way these variables were calculated (see Diamantopoulou et al., 2000). Also the adjustment for traffic volume, alcohol sales, and unemployment rates was carried out adding these factors to the measurement equation.

2.3. Basic model

A series of analyses have been carried out on the data for each region separately, as well as on the data of all five regions together.

A shortlist of the abbreviations is given below:

alc = alcohol
dd = Adstock drink-driving
enf = police enforcement
RBT = random breath tests
TIN's = traffic infringement notices
un = unemployment.

prefixes:
out = measurement (output) equation
sys = system equation

suffixes:
1 = High alcohol hours
2 = Low alcohol hours

Each separate analysis for a region consisted of the two series of accident data to be analysed jointly: the accidents during ‘low’ and ‘high’ alcohol hours. These series were first corrected for the number of vehicle kilometres (Vkm’s). In the model it had to be assumed that the distribution of traffic over the regions did not change over time. This assumption is of course much too strong, but necessary because regional data is missing. Furthermore, because only the total number of Vkm’s is given and not the contribution for each region, the absolute risk level is unknown even under the assumption of a proportional distribution of traffic over the regions from time point to time point.

For the total analysis the same model was used as for the separate regions. In these analyses five times two series were analysed jointly.

The general idea behind the modelling was to describe the data as well as possible by internal and external developments, without the enforcement effects, and to see to what extent the addition of the enforcement variables improves the model. This is a conservative approach, because all effects that can be attributed to both enforcement and to other factors, will be attributed to the other factors first. We are interested in the importance of the enforcement after any alternative explanation, hence conservative approach. A model without enforcement effects will be called ‘the (extended) basic model’. The model with all enforcement effects included will be called ‘the complete model’.

After some preliminary analysis it was decided to use separate parameters for the trend, drift, and monthly effect in the basic model for the ‘low alcohol’ and ‘high alcohol’ series of accidents. Differences between the fit of models can be measured by the differences between the -2logL values, which are approximately Chi-squared distributed, and can be used to establish the significance of (sets of) parameters.
Two different models were applied to the two series of crashes for each region. The first model had different monthly parameters for the two series, the second model had common monthly parameters. The Chi-square values in the five regional models that represent the difference between basic models with different and with common parameters for the two series for each month (with 11 degrees of freedom) were 105.45, 152.91, 101.71,

108.22 and 103.59 respectively. These values are very high and in the same order of magnitude for all regions, except for region 2 whose value is considerably higher. For region 2 highly significant contributions were found for some enforcement parameters if a common monthly trend was used. These effects disappeared if different monthly trends were used for the two series. This suggests that particular monthly differences between the two series exist which, if ignored, result in apparent and not real effects of some enforcement variables.
It was therefore decided to use separate monthly trends for the two series of accidents in the total analysis. Thus, the basic model for each regional analysis has 2 parameters for trend and drift and 2 x 11 parameters for month. For the total analyses there are 5 x 2 parameters for trend and drift and 5 x 2 times 11 parameters for month.

2.4. Extended basic model

In addition to this basic model, alcohol sales and unemployment parameters were added to the measurement equations for each of the two accident series separately. The adjustment for alcohol sales and for unemployment has been made, in order to estimate a genuine effect of enforcement. The two variables were added to the measurement equations because their effects on traffic safety are considered to be instantaneous. In the total model, these parameters are common (shared) for the five regions. This means that the effects of alcohol sales and unemployment are supposed to be the same over regions if also the alcohol sales and the amount of unemployment are the same, but may differ if the alcohol sales and unemployment rates differ. For the actual model, in which alcohol sales are only known for the total of all regions together but the unemployment rates are known per region, this means that the effect of alcohol will be the same in each region, but the effect of unemployment may still differ (despite the one common parameter) because of differences in employment rates. These 2 x 2 parameters are denoted by ‘out-alc1’, ‘out-alc2’, ‘out-un1’ and ‘out-un2’ respectively.

The unemployment rates may have a genuine effect on the accident risk, but may also affect the risk indirectly via changes in traffic volume. If these last effects are present, these variables can adjust for regional traffic volume differences over time.
We will call the model with the alcohol sales and unemployment effects included, ‘the extended basic model’.

2.5. Complete model

A further extension of the basic model was the addition of parameters (r1 and r2) for over-dispersion in the two series. After some inspection it was decided not to use these parameters in the extended basic model, because it can be argued that it may reduce the effect of other parameters, as indeed it did. It would be preferable to use the over-dispersion parameters on the residuals of each model, in order to check afterwards whether variance that could be explained by other factors, still remains. This, however, has not been done.

The extended basic model is used as a starting point for further modelling. Parameters are added to the system equations of the extended basic model

for the effect of random breath tests (sys-rbt1 and sys-rbt2), for speed enforcement as measured by traffic infringement notices combined with all other safety enforcement effects measured by the sum of six types of penalty notices given to violators of traffic rules (sys-enf1 and sys-enf2). Parameters for campaigns, separately for drink/driving Adstock (out-dd1 and out-dd2) and speeding Adstock (out-spd1 and out-spd2) were added to the measurement equations. All possible combinations of these enforcement and campaign effects are used in separate models, to see to what extent effects add to each other and also to see to what extent they can replace each other.
The model with all these parameters added to the extended basic model is called the complete model.
The significance of the addition of each set of two parameters to a particular model was again measured by a Chi-square value with df=2.

3. Results

In a first series of analyses per region, the data from 1991 - 1996 was used to estimate the model parameters for the complete model and to forecast the data for 1997 for each region. This was primarily done to check whether a sensible model could be achieved.
Appendix 1 shows the graphs for the estimated and observed numbers of crashes (not the crash-rates) and the 95% error bound margins for the 'high and low alcohol' hours for each region. The expected values for each month of the modelling period are the forecasts of the number of crashes on the basis of the information up to the month just before the month concerned. It can be seen that the error is extensive, probably due to the small number of observations (crashes) per month. The error bound margins for the forecasts are not much wider than for the modelling period, suggesting that the model uncertainty is relatively small, compared with the uncertainty of each individual measurement. It was assumed that the crashes were Poisson distributed. No parameters for over-dispersion were added to the models as presented, but analyses that were carried out with over-dispersion parameters included, showed small, insignificant effects.
In the next series of analyses, data from 1997 was added to the model. The outcomes of these analyses were used as final results.

Appendix 2 shows the different components of the complete model leading to the predictions of the log-crash-rates for the 5 x 2 series. The trend component includes the influence of the drift and of RBT's and enforcement on the system equation, together with the smoothed error as estimated from the Kalman filter (Harvey, 1989). We see that the general trend is different for different regions and sometimes for the two series within a region. E.g., for the first region we see a downward trend during the first two and a half years for the 'high alcohol' hours, followed by an upward trend during three and a half years and again a downward trend during 1997. For the 'low alcohol' hours the downward trend lasts four years, followed by an upward trend for two years and again a downward trend for 1997. For region 2 the trend for the 'low alcohol' hours is similar to the one for region 1; however, the trend for the 'high alcohol' hours is rather different.

The drift component is smaller than 1, indicating a general decrease in the crash-rates over time. This decrease does not change over time; the hyper parameter for drift is therefore negligible for region 1. This result is also found for region 2, 3, and 4 but not for region 5. In region 5 we see that for both series the drift varies over time.

The seasonal trends show that there are consistent monthly patterns for each year, which seem to be different for both series. This suggests that each series needs its own monthly trend. This result was confirmed by test statistics.

The outcomes for the parameters and statistics of the extended basic model with additional parameters for (combinations of) enforcement variables are given in *Appendix 3* for each region. In order to make the interpretation of the results easier, mean parameter values were computed over regions for each model. The combined results for the regions are given in *Table 1* which gives an overview of the mean values of the parameters for the 16 models that were applied to the five regions. Columns 3-6 show whether the drink-driving, RBT, speed or enforcement variables were present (1) or not (0). All combinations are given, resulting in 24 = 16 models. Columns 7-10 show the parameter values for alcohol and Adstock variables which were always present. Columns 3-10 in the bottom part of the table show the parameter values for the other variables if present.

It turned out that there was a consistent effect of alcohol sales and of unemployment on both series in all models; an increase in alcohol sales and an increase in unemployment both result in less accidents. The averaged values over models are –0.076 and –0.169 for out-alc1 and out-alc2 respectively, with standard deviations of 0.031 and 0.027; for out-un1 and out-un2 these values are much smaller, –0.008 and –0.003 respectively, with sd-values of 0.001. This unexpected result suggests an indirect effect on risk, via regional traffic volumes: if alcohol sales and unemployment increase, the risk decreases (as a result of a decrease in traffic volume, not measured in the total amount of Vkm's given). Whether it is likely that the alcohol sales are correlated with traffic volume is something to be investigated.

In general the results of these analyses, as well as of the analyses to be discussed below, are difficult to interpret. This is not only due to the problems just mentioned, but is also related to a number of methodological and statistical issues.
In order to compute the log-likelihood values, an initial estimate of parameters must be given. For these initial estimates values equal to zero are assumed with a high degree of uncertainty. In fact the uncertainty is infinite, but this cannot be programmed in the Kalman filtering procedure used. A diffuse Kalman filtering procedure, which recently became available, can solve this statistical problem. The impact of this shortcoming on the final estimates, however, will be small.

A second problem is caused by the model specification. One restriction in the model is that at this moment, only linear and log-linear models are possible. In our case a log-linear model is used for the accident rates (number of accidents in a series, divided by the number of Vkm's). In such a log-linear model it is not possible to combine a linear model on the log-rates with linear assumptions on the Vkm's themselves. However, it would be useful to restrict estimates of the Vkm's for regions such that the sum of the Vkm's over regions is equal to the total of the Vkm's. Therefore, it would be interesting to investigate to what extent mixed (non-linear) models can be developed to overcome these problems.

Other methodological difficulties also exist. E.g., it is possible (as it is in ordinary regression analysis) that variables correct the effect of other variables and therefore should be evaluated together. It is also possible that variables have an effect that is not genuine, but which is caused by a correlation with the real underlying cause.
The first kind of problem is investigated for the enforcement effect by making all sorts of combinations of variables in the model and to see how parameter values change over models. This is however not done for the combination of variables used in the extended basic model. It was argued, that even if effects of the extended basic model interfere with parameter estimates of

enforcement effects, the effects should still be addressed to the extended basic model parameters and not to enforcement.
The second type of problem, the correct specification of the model needs to be solved in advance, by analysis of the problem by experts in the field.
Two aspects are important for the interpretation: the direction of the effect and its significance. The direction of the effect can be deduced from the signs of the parameters. However, the significance is not based on error bound margins of the parameters directly, but is measured by comparing the Chi-square values of different models. Specifically, to ascertain the significance of enforcement variables A and B, first the two models are fitted only including either enforcement variables A or enforcement variables B. Then the best fitting of these two models is compared with the model including both enforcement variables A and B.
The major reason for the analyses carried out here is to understand how multivariate analysis problems in traffic safety like the Victorian one should be solved, using the rather unexplored time-series techniques that became available recently for data such as collected in Victoria. Therefore no definite interpretation of the results will be given, but the effects will be discussed as they appear from the analysis.

Coming back to *Table 1*, the out-un2 parameter seems to be decreasing if sys-enf is added to the model; the opposite seems to be the case with out-un1. We see that the parameters of sys-enf1 and sys-enf2 have reversed signs as well. A relation between unemployment and enforcement could be explained by the underlying (but unknown) regional differences in traffic volume. An explanation for the joint effect might be that unemployment results primarily in less traffic (and less notices and accidents) during ‘low alcohol’ hours, which effect is partly annihilated during ‘high alcohol’ hours because of a relatively higher risk. The negative value of the out-alc1 parameter becomes larger when enforcement variables are added to the extended basic model, especially if sys-rbt is added to the model. This indicates a relation between alcohol sales and the number of RBT’s, which seems reasonable. For out-alc2 this effect is only present with regard to sys-rbt. Although addition of sys-rbt to the model has a relatively large effect on out-alc, the sys-rbt parameters themselves are almost zero. With fixed out-alc parameters the values of the sys-rbt parameters may have become negative, indicating a positive safety effect.
Drink-driving and speeding Adstock do not seem to have such obvious effects, which might be partly due to the fact that they are part of the measurement equations and not of the system equations.

For drink-driving Adstock there is a consistent positive parameter value over models for the ‘high alcohol’ hours, with an average of 0.019, and sd-value of 0.001, but not for the ‘low alcohol’ hours (an average of 0.000, with sd of 0.000). This suggests a small negative safety effect of drink-driving Adstock during ‘high alcohol’ hours.

For speed Adstock the parameter value is negative for both series, with a more negative value for ‘low alcohol’ hours (equal to -0.006, sd=0.002) than for ‘high alcohol’ hours (-0.003, sd=0.002). This suggests a small positive safety effect of speed Adstock on the number of accidents especially in the ‘low alcohol’ hours.

Re-gion	Model	Out-dd	Sys-rbt	Sys-enf	Out-spd	Out-alc1	Out-alc2	Out-un1	Out-un2
1-5	1	0	0	0	0	-0.032	-0.162	-0.009	-0.002
1-5	2	0	0	0	1	-0.041	-0.172	-0.009	-0.002
1-5	3	0	0	1	0	-0.029	-0.168	-0.007	-0.005
1-5	4	0	0	1	1	-0.044	-0.177	-0.007	-0.005
1-5	5	0	1	0	0	-0.069	-0.193	-0.009	-0.001
1-5	6	0	1	0	1	-0.082	-0.207	-0.008	-0.001
1-5	7	0	1	1	0	-0.073	-0.201	-0.005	-0.003
1-5	8	0	1	1	1	-0.090	-0.215	-0.006	-0.003
1-5	9	1	0	0	0	-0.073	-0.128	-0.010	-0.003
1-5	10	1	0	0	1	-0.078	-0.142	-0.010	-0.003
1-5	11	1	0	1	0	-0.065	-0.128	-0.009	-0.005
1-5	12	1	0	1	1	-0.075	-0.137	-0.009	-0.005
1-5	13	1	1	0	0	-0.115	-0.157	-0.009	-0.001
1-5	14	1	1	0	1	-0.121	-0.174	-0.009	-0.002
1-5	15	1	1	1	0	-0.112	-0.165	-0.007	-0.004
1-5	16	1	1	1	1	-0.125	-0.176	-0.007	-0.004
Average over models:						-0.076	-0.169	-0.008	-0.003
Sd-value:						0.031	0.027	0.001	0.001
Total model (complete):						-0.138	-0.156	-0.005	-0.006

--- Extension of table --- *)

Re-gion	Model	Out-dd1	Out-dd2	Sys-rbt1	Sys-rbt2	Out-spd1	Out-spd2	Sys-enf1	Sys-enf2
1-5	1								
1-5	2					-0.001	-0.009		
1-5	3							0.001	-0.001
1-5	4					-0.003	-0.006	0.001	-0.001
1-5	5			0.000	0.000				
1-5	6			0.000	0.000	-0.001	-0.009		
1-5	7			0.000	0.000			0.001	-0.001
1-5	8			0.000	0.000	-0.003	-0.006	0.001	-0.001
1-5	9	0.019	-0.001						
1-5	10	0.017	-0.001			-0.003	-0.006		
1-5	11	0.019	-0.001					0.000	-0.001
1-5	12	0.018	-0.001			-0.005	-0.003	0.000	-0.001
1-5	13	0.020	0.000	0.000	0.000				
1-5	14	0.019	0.000	0.000	0.000	-0.003	-0.006		
1-5	15	0.020	0.000	0.000	0.000			0.001	-0.001
1-5	16	0.019	0.000	0.000	0.000	-0.006	-0.003	0.001	-0.001
Average over models:		0.019	0.000	0.000	0.000	-0.003	-0.006	0.001	-0.001
Sd-value		0.001	0.001	0.000	0.000	0.002	0.002	0.000	0.000
Total model (complete):		0.003	0.010	0.001	0.000	-0.012	0.005	0.001	0.000

Table 1. *Averaged parameter values for the regional models. The second part of the table (*) is an extension of the first part of the table.*

The enforcement effects seem to be practically absent. The absolute value of the parameters in a certain solution is not the only relevant factor. Parameter values can change considerably if other factors are added to the model, because of their correlation. Therefore, whether a (set of) variable(s) has a significant contribution is better evaluated using the Chi-square distributed difference between the –2logL values with and without these variables added to the model. Given a specific model, the direction of the effect depends on the sign of the parameter, but we have seen that the sign may also change if the model changes. Given the extended basic model however, we do not see a change in the enforcement parameters over models with or without other enforcement or Adstock variables added. This is not the case with the Adstock parameters; if other variables are included then their parameters change. If the sys-tin variables are added to a model with the speed Adstock variable included, then the out-spd1 parameter becomes more negative and the out-spd2 parameter less negative. The same is the case when the drink-driving Adstock variable is added. For drink-driving Adstock and speed Adstock there seems to be some compensating effect between both parameters; for speed Adstock and TIN's the effect might be caused again by traffic volume as an underlying cause: speed Adstock may become relatively less effective in the 'low alcohol' hours if the number of TIN's and therefore the traffic volume increases.

The results from the total analysis with the complete model (given in the bottom line of *Table 1*) are rather similar to the averages of the regional analyses with the complete model (model 16). A much lower positive value for out-dd1 (0.003 instead of 0.019) and a much higher positive value for out-dd2 (0.010 instead of 0.000) are found, suggesting a larger negative effect on safety during the 'low alcohol' hours than during 'high alcohol' hours. As said before, there is a relation between the out-alc parameters and the drink-driving Adstock parameters that might explain the fact that the out-dd parameters are not negative.The out-spd1 parameter is two times more negative and the out-spd2 parameter has a reversed (now positive) sign. The other parameters are still small.

Table 2 gives the Chi-square values for the parameters of the regional models. These values are the sum of the contributions of the five values for the two parameters for the regions. The extended basic model is represented at the bottom line. Reading the table from the bottom up, it can be seen that the contribution of out-dd (with 5 x 2 degrees of freedom) is significant at the 1%-level (Chi-square=28.460, df=10), but the other effects are not significant. The major contributions (if only one particular factor is present and there are no other effects) are relatively high, ranging from 8.369 to 11.674, but not significant. The addition of extra factors to existing factors results in relatively small additional contributions, suggesting that different variables explain partly the same effects on accidents.

Region	Sys-rbt	Sys-enf	Out-dd	Out-spd	Mean diff.	Chi-square	Significance Chi-square (df=10)	
1-5	1	1	1	1	0.294	1.469		
1-5	0	1	1	1	0.381	1.905	15.99	10%
1-5	1	0	1	1	0.626	3.128	18.31	5%
1-5	0	1	0	1	0.635	3.175	23.21	1%
1-5	0	0	1	1	0.735	3.676		
1-5	1	1	0	1	0.772	3.862		
1-5	1	1	1	0	0.943	4.716		
1-5	1	1	0	0	1.099	5.493		
1-5	1	0	1	0	1.248	6.242		
1-5	1	0	0	1	1.614	8.071		
1-5	1	0	0	0	1.674	8.369		
1-5	0	1	1	0	1.690	8.452		
1-5	0	1	0	0	1.998	9.989		
1-5	0	0	0	1	2.335	11.674		
1-5	0	0	1	0	5.692	28.460		
1-5	0	0	0	0	114.377	571.886		

Table 2. *Different regional models and the significance of parameters for the combined effect of regions.*

Figures 2 and 3 show the effect of all enforcement and Adstock variables on the series for the five regions. The figures are based on the results of the complete model over the full period. It can be seen from *Figure 2* which represents the ‘high alcohol’ hours, that the value in general is smaller than 1, which indicates a small but positive effect on safety: the accident rate is multiplied by a number smaller than 1. This is not the case for *Figure 3*; here we see a small negative effect. However, we should be aware that when other explanatory variables are added to the extended basic model, a change in the level or drift parameter can be compensated by a reversed change in one of the enforcement or Adstock parameters resulting in series in which both effects are positive or negative. Therefore, it is necessary to adapt the analysis technique such that this interchange of values is not possible anymore, and effects can be interpreted directly.

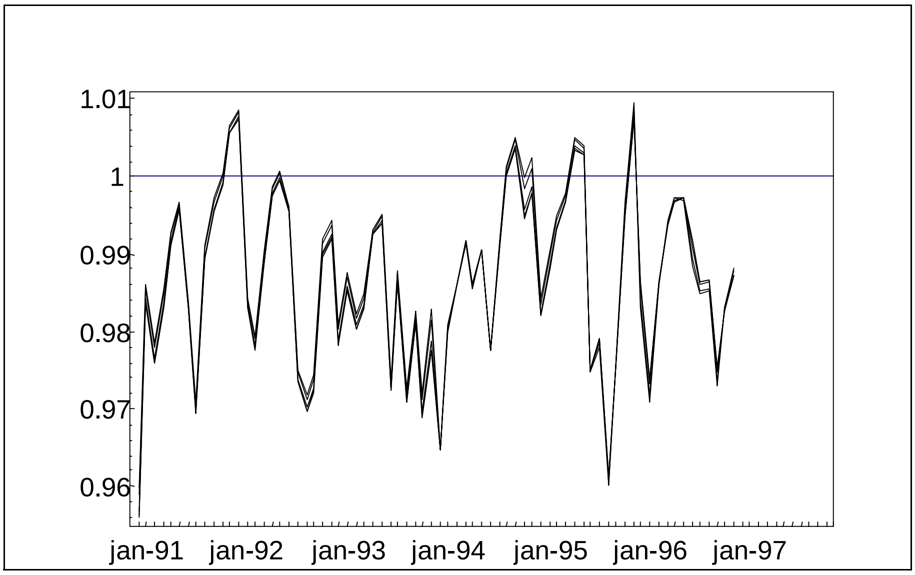

Figure 2. *Influence of enforcement on crashes during 'high alcohol' hours for five police regions*

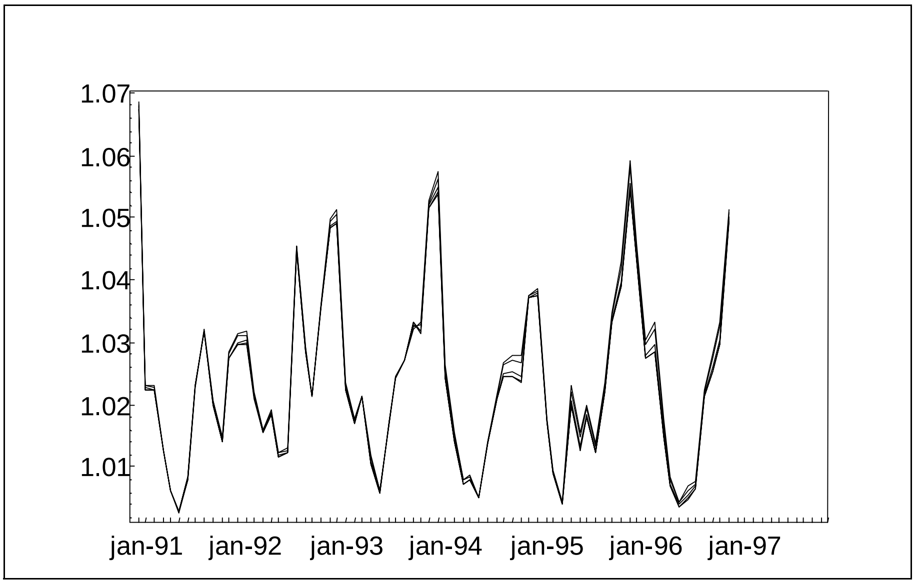

Figure 3. *Influence of enforcement on crashes during 'low alcohol' hours for five police regions*

For the 'high alcohol' as well as the 'low alcohol' hours there is hardly any difference between the effects in the regions. This must be caused by the fact that the enforcement variables hardly differ between regions.

Figures 4 and 5 show that there is a considerable regional effect of unemployment. In these figures the effect of unemployment is added to the Adstock and enforcement variables. There are only two parameters for unemployment in the complete model which are equal for the five regions. However, the unemployment rates are different in the five regions and therefore show different effects of unemployment for each region.

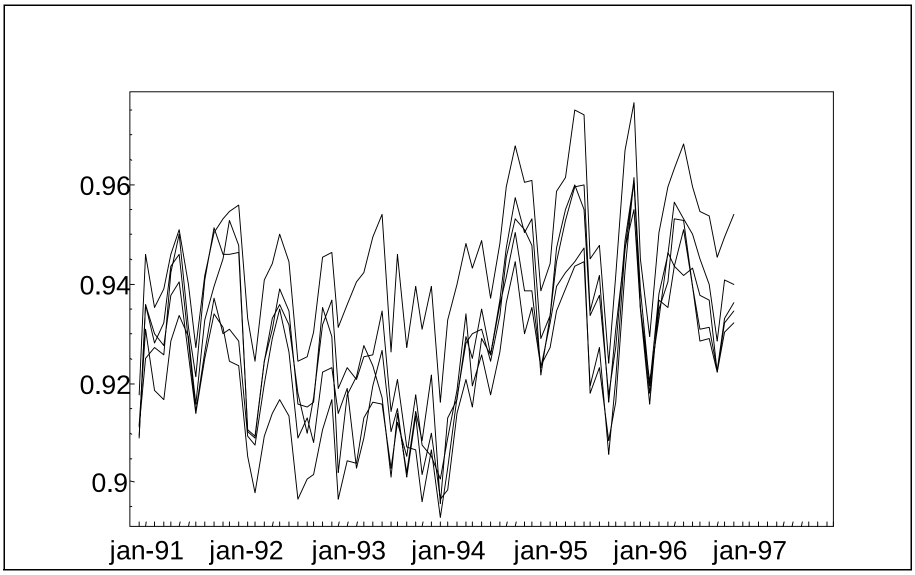

Figure 4. *Influence of enforcement and employment on crashes during 'high alcohol' hours for five police regions*

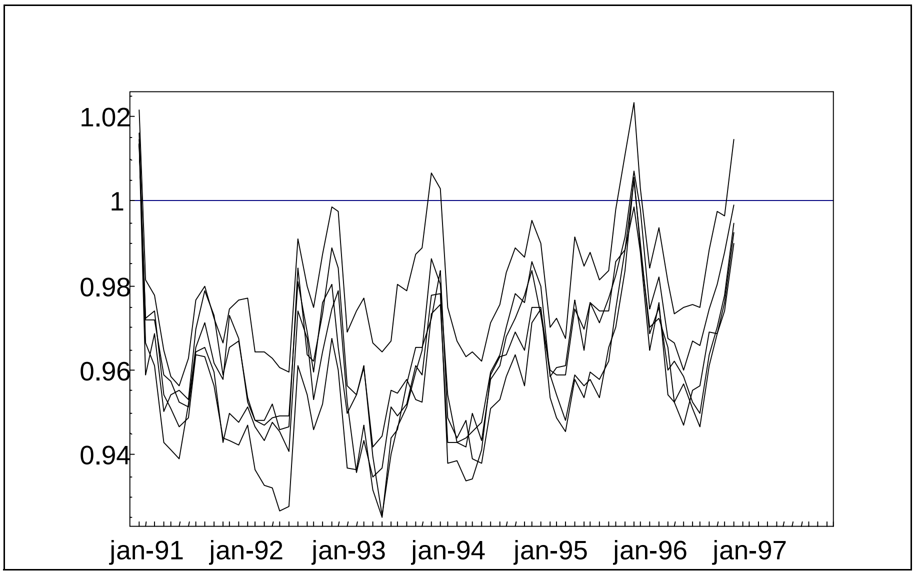

Figure 5. *Influence of enforcement and employment on crashes during 'low alcohol' hours for five police regions*

4. Concusions

Multivariate analyses of safety developments in ordinary regression analysis and especially in time-series analysis are seldom applied, although the total is often supposed to be more than the sum of the parts. Therefore, this exercise has been carried out primarily to study the application of such newly developed techniques to real world situations.

Analyses have been made for five individual police regions in Victoria, Australia, separately as well as for these five regions together. The data were not totalled over the regions, but the original ten series of data were analysed jointly in the total analysis. The model for this analysis will be called 'the complete model'.
In the original study, all series were only analysed individually. Effects that are too small to detect in each study separately, may turn out to be significant if all series are combined. The multivariate technique makes it possible to distinguish between separate and common trends. The number of parameters is reduced, because common trends are represented by only one parameter in the complete model. This makes the complete model more parsimonious.
Another difference in approach was the application of a multi-stage procedure. The series were 'corrected' for effects of mobility, before the effects of intervention or campaigns were established. The idea behind this is that the risk reduction is of concern, and not the total number of casualties. In principle this procedure can have a positive or a negative influence on the estimation of intervention and campaign effect. If the amount of intervention correlates positively with mobility and also with the number of casualties, then taking out the effect of mobility first may prevent intervention from showing a spurious negative effect on the number of casualties. If it correlates negatively, a spurious positive effect is corrected. The disadvantage is therefore that it is a conservative approach, because effects that are related to mobility as well as enforcement are rightly or wrongly attributed to mobility. The advantage is that only those effects that cannot be explained otherwise are attributed to intervention or campaigns, preventing us from possibly having too high expectations for the safety measures.
Finally, contrary to the original analysis, the method applied incorporates developments in time. E.g., effects of enforcement or campaigns that last in time can be traced by a single time-dependent parameter. In regression analysis, it is difficult to model such effects. Furthermore, analyses of trends over time, if present, are interesting on their own account. They can tell which intervention procedures are the most promising (a one-shot approach, superimposition of measures etc.).

To avoid an extremely complicated total model, it was tested to what extent a simple basic model could be used with common monthly trends for crashes during 'high alcohol' and 'low alcohol' hours for five police regions. It was found that the assumption of a common monthly trend for the two series in the five regions was too strong and that separate monthly trends were necessary for all ten series. This finding supports the idea that summation over regions results in loss of information.

Separate parameters for enforcement effects were used in the total analysis for ‘high’ and ‘low alcohol’ hours, but these parameters were supposed to be the same for regions.

In general, the outcomes of the complete model and those of the separate regional models were in agreement with each other. One of the findings was that the effect of enforcement in the regional, as well as the complete analysis, was smaller than expected on the basis of the outcomes from the MUARC analysis. In the present study, the only significant effect was found not for an enforcement variable, but for drink-driving campaigns. In general, there were indications for effects of all enforcement and campaign variables if they were added to the (extended) basic model without other variables, but no significant effects other than for drink-driving campaigns were found. If, in addition, one other variable was added to such a model, the contribution of that second variable was small, suggesting that there were compensating effects. In the complete model, these effects were also not significant. An explanation for this difference in findings between our analysis and the MUARC analysis might be our conservative model approach in which we tested effects against the extended basic model. Especially the correction for traffic volume in our analysis, which was not applied by MUARC but used as an additional explanatory factor, may have caused these effects. When changes in traffic volume are correlated with enforcement activities, effects addressed to enforcement may partly disappear if correction for traffic volume is applied.

A general reason for the fact that none of the enforcement variables was significant, although small systematic positive tendencies could be noticed, can be the relatively small number of crashes in the regional series. As can be seen from *Appendix 1*, the uncertainty in the model predictions is rather high. This seems to be due to the individual measurements more than to the model uncertainty: the uncertainty of the forecasts for 1997 is only slightly greater than for the years 1991 - 1996.
A second reason might be, that, although the effect of enforcement is part of the systems equations, the assumption of an instantaneous effect of enforcement on safety is not optimal, and should be modelled with a time lag. This means that these variables do not change the system from the next month onwards, but from a later point in time onwards.

A possible explanation for the lack of a significant enforcement effect could also be that this variable was a combination of the effect of TIN’s and notices for all other kinds of traffic violations. However, an analysis with these two variables separated, hardly changed the situation.

As said before, the major object of the study was not primarily to describe the data and interpret the results, but to learn how to apply multivariate time-series analysis techniques to problems similar to the one in Victoria. Such problems are foreseen in the near future for ongoing SWOV research, not only for the evaluation of enforcement effects, but also in other areas. A special warning against too rapid conclusions about the final results of the analyses, regards the crude mobility data available. To draw firm conclusions, high quality mobility figures comparable to the quality of the intervention and campaign figures are necessary.

The analyses carried out helped greatly to understand how to specify models, how to understand and interpret model parameters, and how to define statistics for such models. The authors concluded that the technique used had great advantages over the analysis as originally used by MUARC. In discussions with researchers from MUARC, it was generally agreed that the merits of these new techniques have been proven. This resulted in a close cooperation on the application and development of such models for traffic safety analysis. The authors hope that the application of these techniques to road safety problems in the future will benefit from these experiences.

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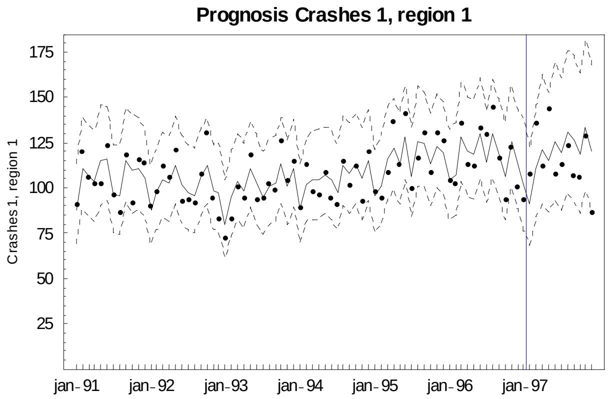
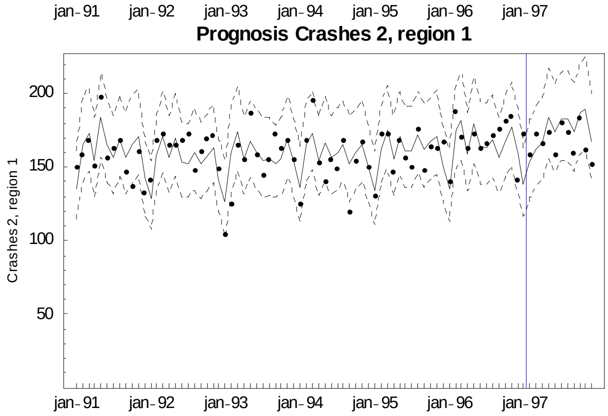
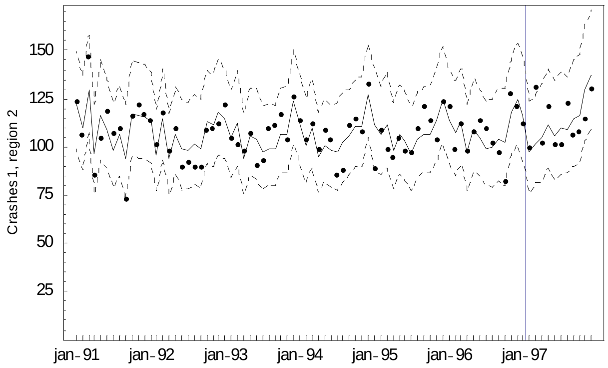
Appendix 1 Observed and expected numbers of crashes

Observed and expected numbers of crashes for 5 x 2 series of crashes, as computed from the complete model, using data from 1991 - 1996 and forecasting 1997.

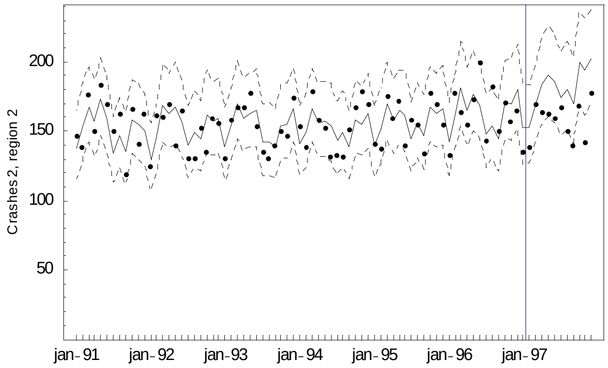




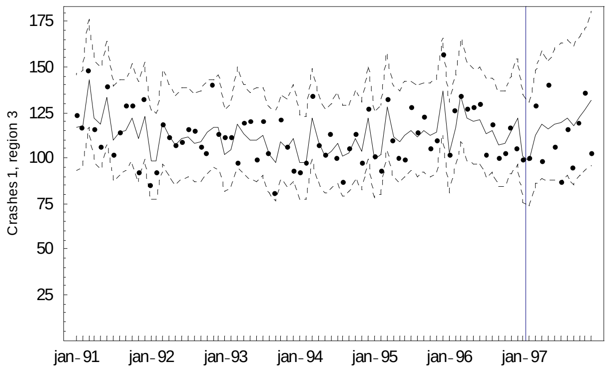
Prognosis Crashes 1, region 2



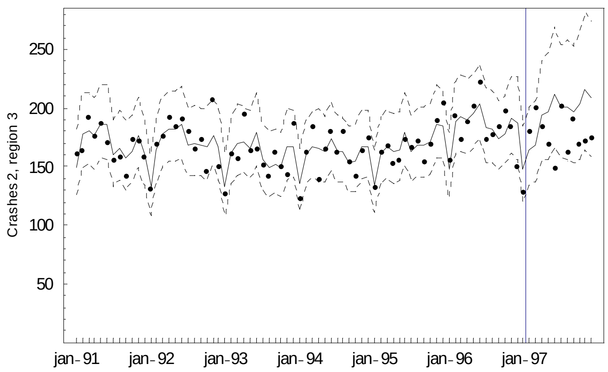
Prognosis Crashes 2, region 2



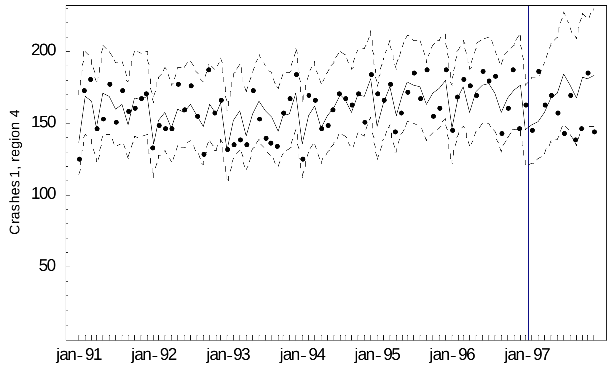
Prognosis Crashes 1, region 3



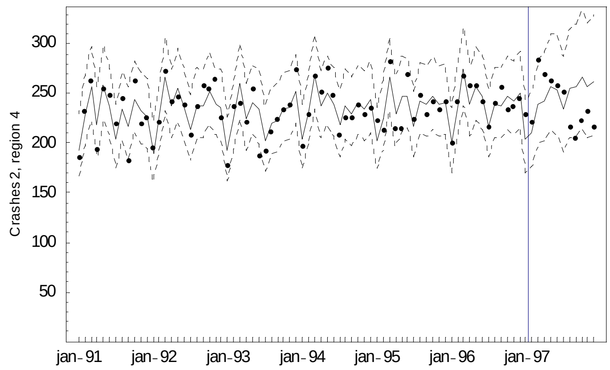
Prognosis Crashes 2, region 3



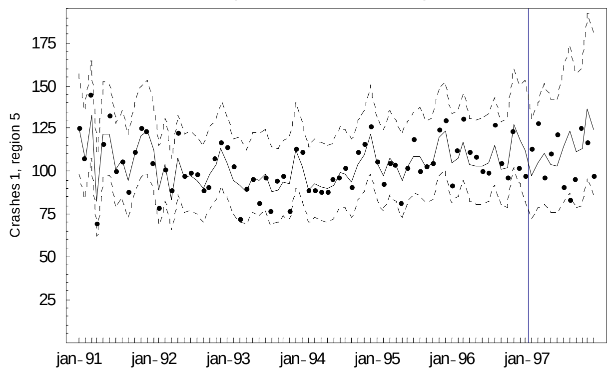
Prognosis Crashes 1, region 4



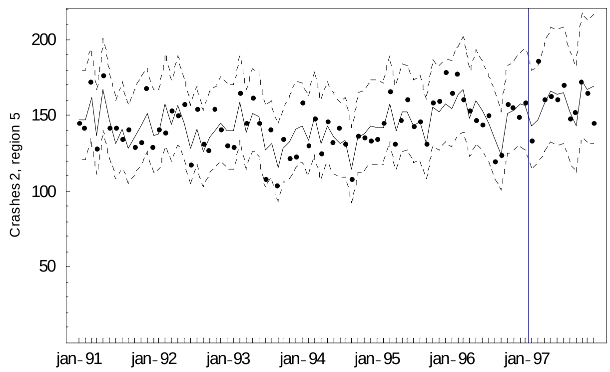
Prognosis Crashes 2, region 4



Prognosis Crashes 1, region 5



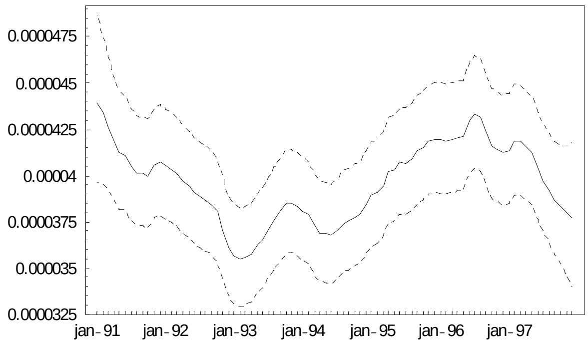
Prognosis Crashes 2, region 5



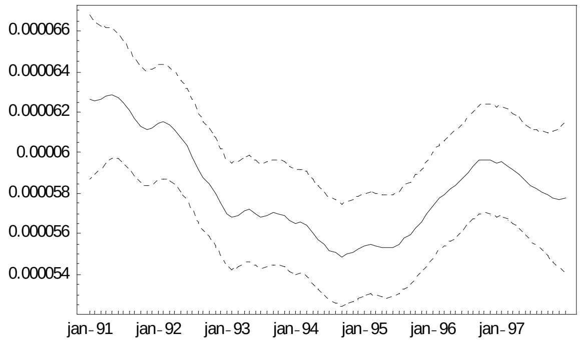
Appendix 2 Contribution of trend, drift and monthly components

Contribution of trend, drift and monthly components of the basic model for 5 x 2 series of log-crash rates, to the prediction of the complete model, using data from 1991 - 1997.

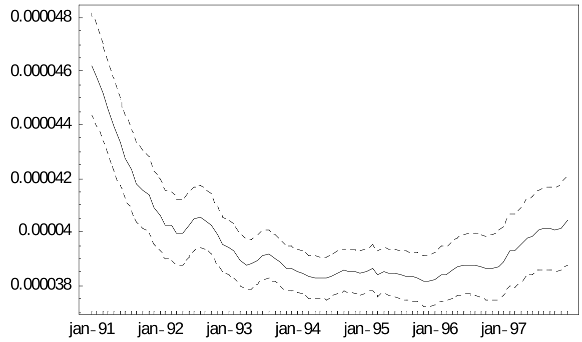
Trend Crashes 1, region 1 full period



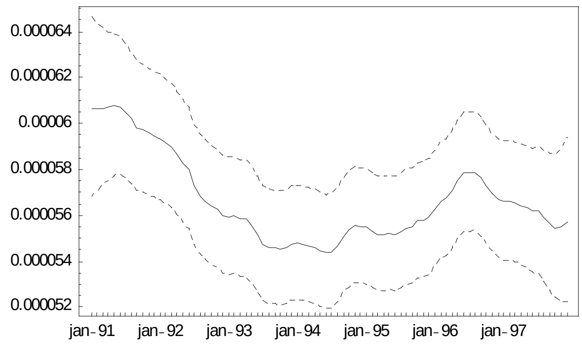
Trend Crashes 2, region 1 full period



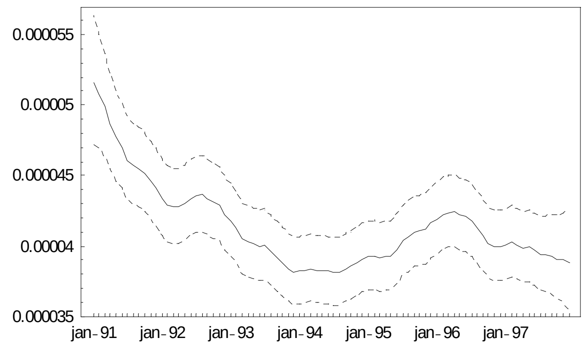
Trend Crashes 1, region 2 full period



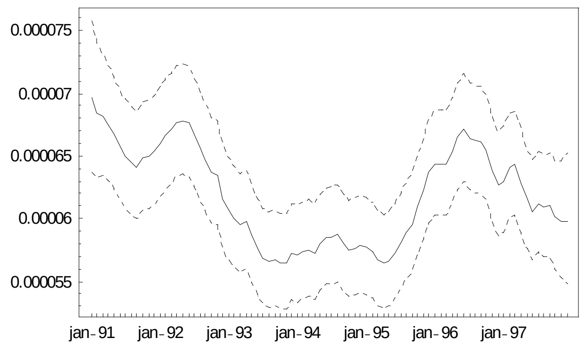
Trend Crashes 2, region 2 full period



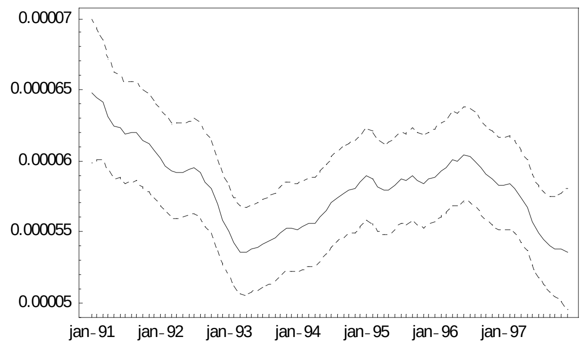
Trend Crashes 1, region 3 full period



Trend Crashes 2, region 3 full period

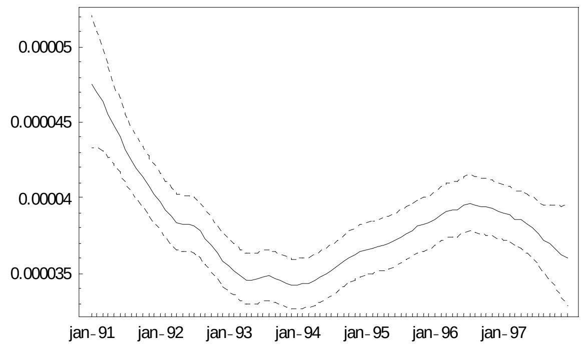


Trend Crashes 1, region 4 full period

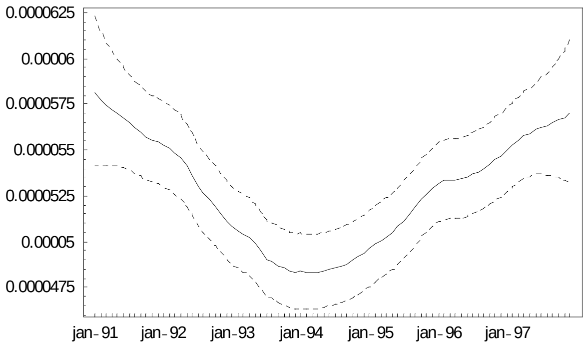


Trend Crashes 2, region 4 full period

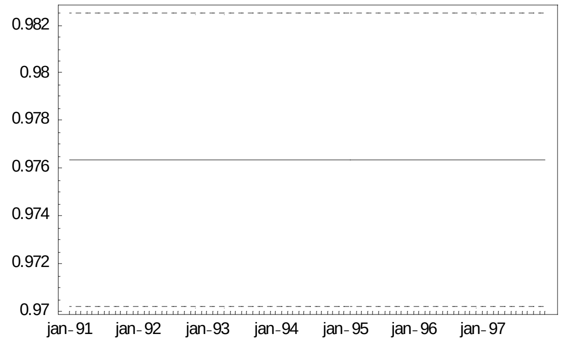
Trend Crashes 1, region 5 full period



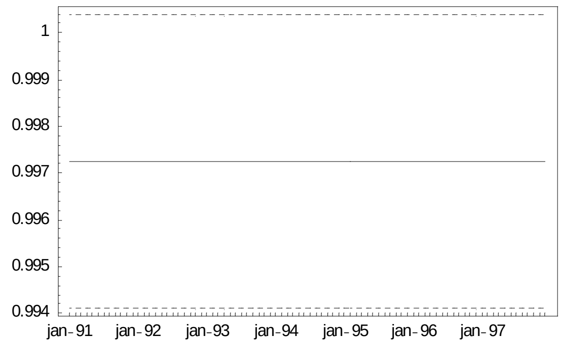
Trend Crashes 2, region 5 full period



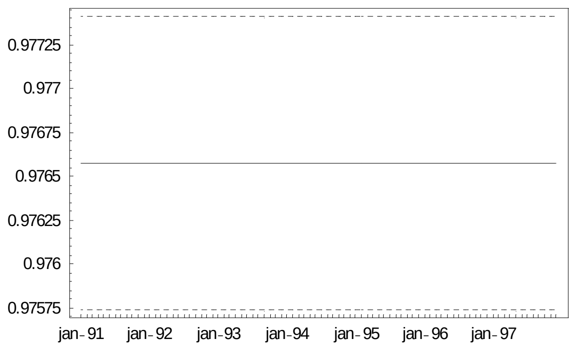
Drift Crashes 1, region 1 full period



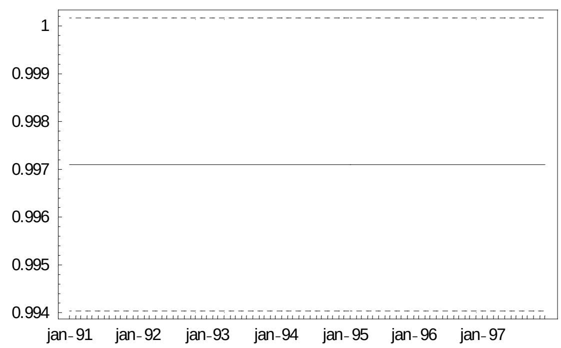
Drift Crashes 2, region 1 full period



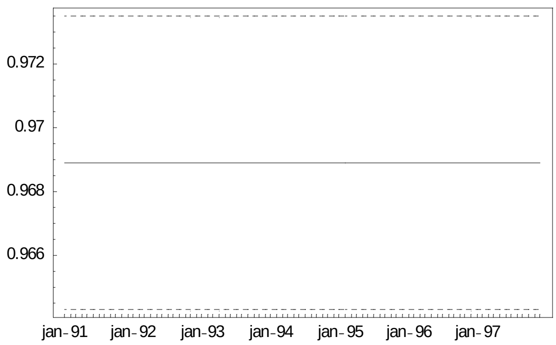
Drift Crashes 1, region 2 full period



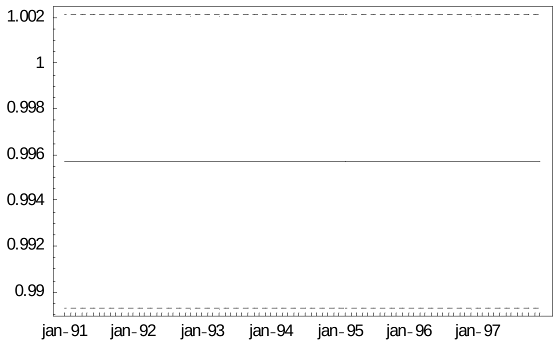
Drift Crashes 2, region 2 full period



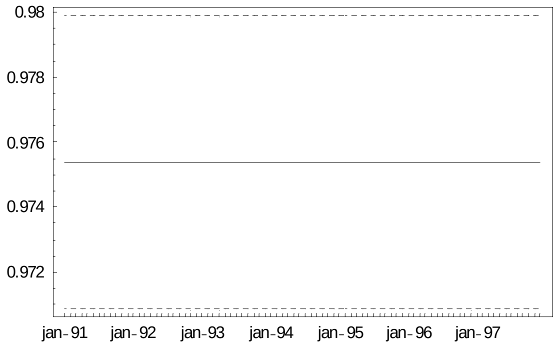
Drift Crashes 1, region 3 full period



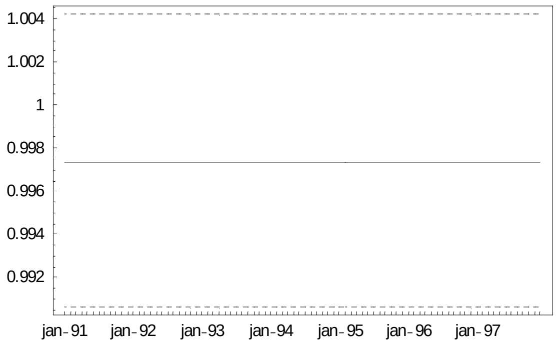
Drift Crashes 2, region 3 full period



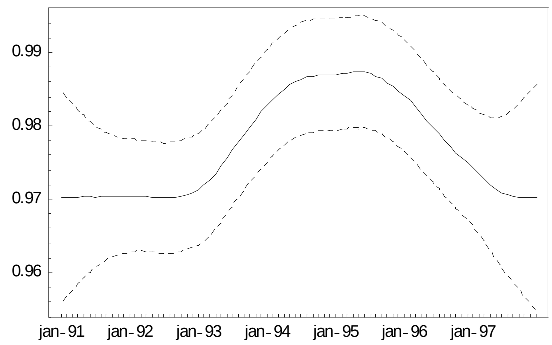
Drift Crashes 1, region 4 full period



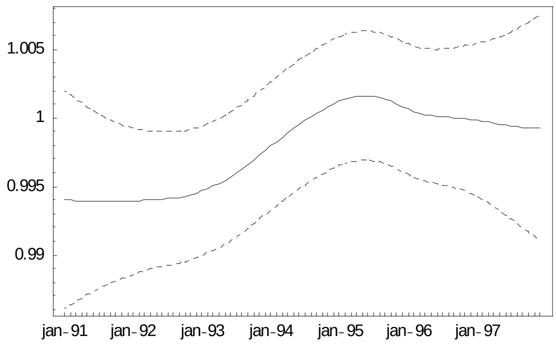
Drift Crashes 2, region 4 full period



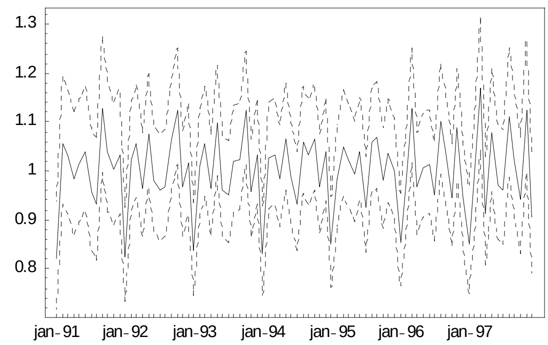
Drift Crashes 1, region 5 full period



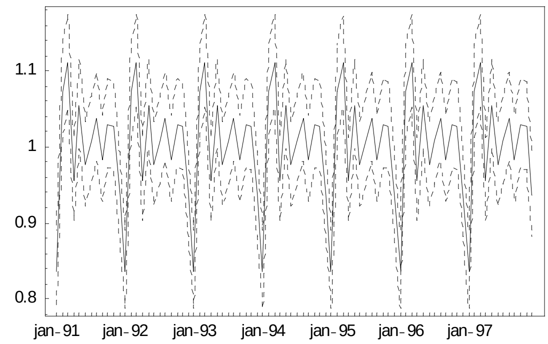
Drift Crashes 2, region 5 full period



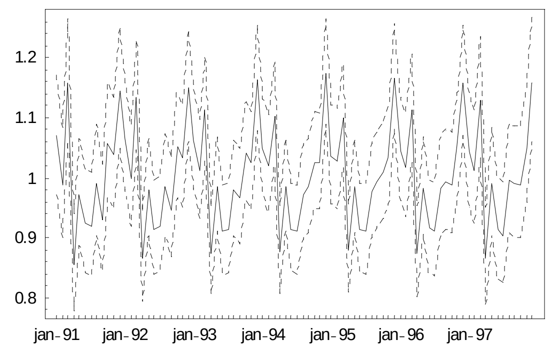
Seasonal Crashes 1, region 1 full period



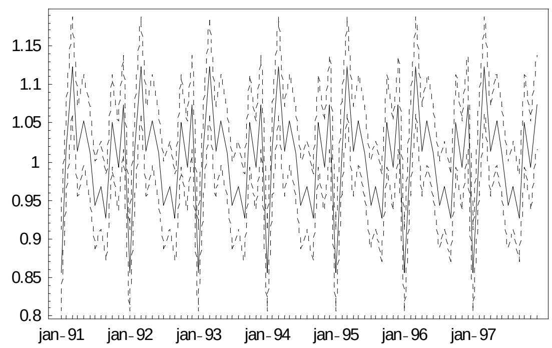
Seasonal Crashes 2, region 1 full period



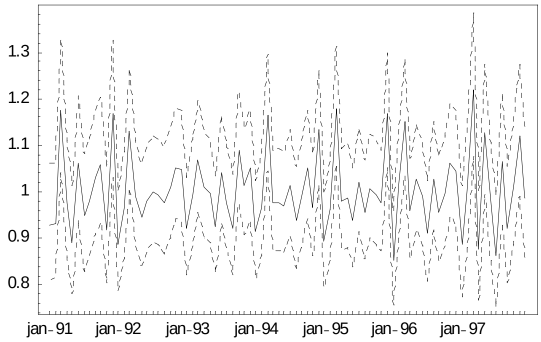
Seasonal Crashes 1, region 2 full period



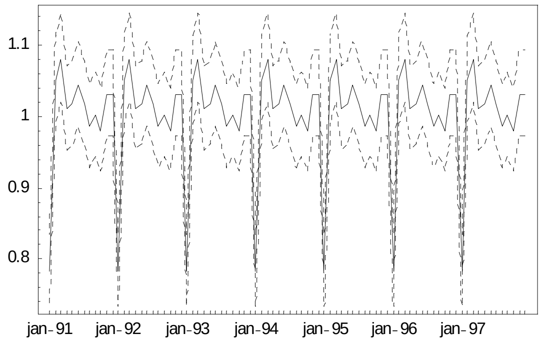
Seasonal Crashes 2, region 2 full period



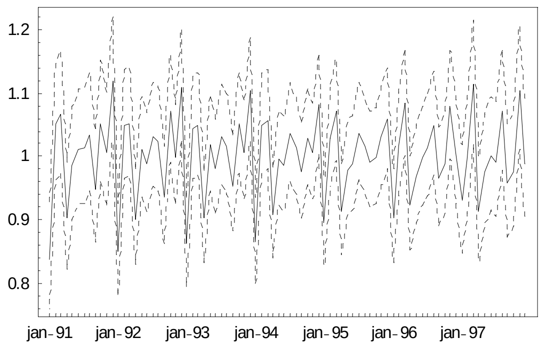
Seasonal Crashes 1, region 3 full period



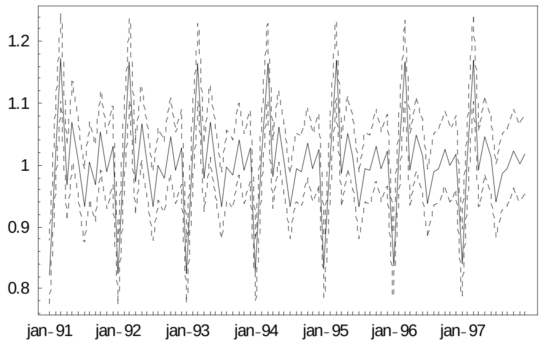
Seasonal Crashes 2, region 3 full period



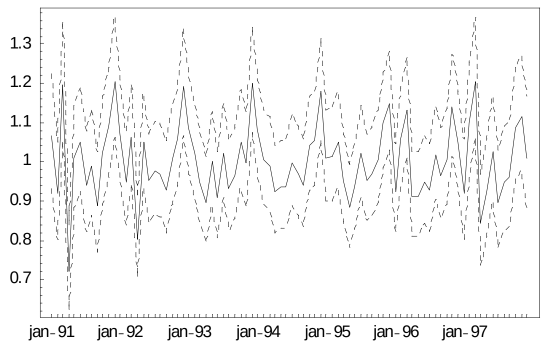
Seasonal Crashes 1, region 4 full period



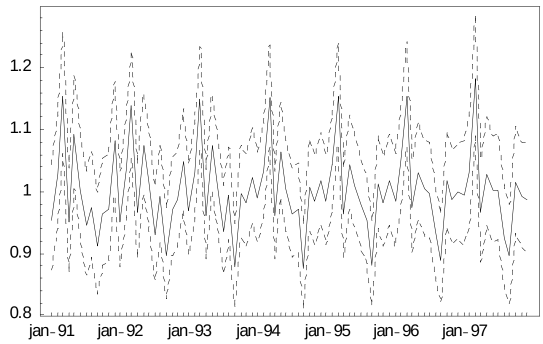
Seasonal Crashes 2, region 4 full period



Seasonal Crashes 1, region 5 full period



Seasonal Crashes 2, region 5 full period



Appendix 3 Goodness of fit measures for different models per region.

Re-gion	Month	Sys -rbt	Sys -tin	Sys -enf	Out-dd	Out-spd	Over-disp	2logL	Delta 2logL	Mean delta
1	0	0	0		0	0	0	-294.118		
2	0	0	0		0	0	0	-263.308		
3	0	0	0		0	0	0	-262.027		
4	0	0	0		0	0	0	-337.801		
5	0	0	0		0	0	0	-276.867		
1	0	0	0		0	0	1	-294.440	0.323	13.740
2	0	0	0		0	0	1	-322.796	59.489	
3	0	0	0		0	0	1	-269.224	7.197	
4	0	0	0		0	0	1	-339.198	1.397	
5	0	0	0		0	0	1	-277.162	0.295	
1	0	0	0		0	1	0	-295.713	1.595	1.164
2	0	0	0		0	1	0	-266.310	3.002	
3	0	0	0		0	1	0	-262.321	0.294	
4	0	0	0		0	1	0	-338.252	0.451	
5	0	0	0		0	1	0	-277.347	0.480	
1	0	0	0		0	1	1	-296.035	0.322	0.259
2	0	0	0		0	1	1	-322.885	0.089	
3	0	0	0		0	1	1	-269.334	0.110	
4	0	0	0		0	1	1	-339.748	0.550	
5	0	0	0		0	1	1	-277.571	0.223	
1	0	0	0		1	0	0	-294.170	0.053	15.274
2	0	0	0		1	0	0	-323.760	60.453	
3	0	0	0		1	0	0	-268.033	6.006	
4	0	0	0		1	0	0	-338.167	0.366	
5	0	0	0		1	0	0	-286.360	9.493	
1	0	0	0		1	0	1	-294.486	0.046	1.485
2	0	0	0		1	0	1	-324.528	0.767	
3	0	0	0		1	0	1	-274.745	5.522	
4	0	0	0		1	0	1	-339.500	0.302	
5	0	0	0		1	0	1	-287.148	0.788	
1	0	0	0		1	1	0	-295.807	0.093	0.242
2	0	0	0		1	1	0	-323.840	0.080	
3	0	0	0		1	1	0	-268.186	0.152	
4	0	0	0		1	1	0	-338.668	0.416	
5	0	0	0		1	1	0	-286.829	0.469	

Re-gion	Month	Sys -rbt	Sys -tin	Sys -enf	Out-dd	Out-spd	Over-disp	2logL	Delta 2logL	Mean delta
1	0	0	0		1	1	1	-296.100	0.065	0.207
2	0	0	0		1	1	1	-324.589	0.061	
3	0	0	0		1	1	1	-274.815	0.069	
4	0	0	0		1	1	1	-340.088	0.340	
5	0	0	0		1	1	1	-287.647	0.499	
1	0	0	1		0	0	0	-294.570	0.452	12.753
2	0	0	1		0	0	0	-323.477	60.170	
3	0	0	1		0	0	0	-262.555	0.528	
4	0	0	1		0	0	0	-337.961	0.160	
5	0	0	1		0	0	0	-279.324	2.456	
1	0	0	1		0	0	1	-294.776	0.207	0.530
2	0	0	1		0	0	1	-324.358	0.881	
3	0	0	1		0	0	1	-270.241	1.017	
4	0	0	1		0	0	1	-339.413	0.215	
5	0	0	1		0	0	1	-279.655	0.331	
1	0	0	1		0	1	0	-296.704	0.991	0.577
2	0	0	1		0	1	0	-323.846	0.369	
3	0	0	1		0	1	0	-262.830	0.275	
4	0	0	1		0	1	0	-338.406	0.154	
5	0	0	1		0	1	0	-280.420	1.096	
1	0	0	1		0	1	1	-296.996	0.292	0.240
2	0	0	1		0	1	1	-324.695	0.337	
3	0	0	1		0	1	1	-270.287	0.046	
4	0	0	1		0	1	1	-339.996	0.248	
5	0	0	1		0	1	1	-280.695	0.275	
1	0	0	1		1	0	0	-294.622	0.053	0.959
2	0	0	1		1	0	0	-325.303	1.543	
3	0	0	1		1	0	0	-268.835	0.801	
4	0	0	1		1	0	0	-338.331	0.164	
5	0	0	1		1	0	0	-288.594	2.233	
1	0	0	1		1	0	1	-294.811	0.034	0.738
2	0	0	1		1	0	1	-326.104	0.801	
3	0	0	1		1	0	1	-276.543	1.798	
4	0	0	1		1	0	1	-339.718	0.218	
5	0	0	1		1	0	1	-289.431	0.837	
1	0	0	1		1	1	0	-296.871	0.167	0.370
2	0	0	1		1	1	0	-325.672	0.369	
3	0	0	1		1	1	0	-268.906	0.071	
4	0	0	1		1	1	0	-338.821	0.154	
5	0	0	1		1	1	0	-289.682	1.088	

Re-gion	Month	Sys -rbt	Sys -tin	Sys -enf	Out-dd	Out-spd	Over-disp	2logL	Delta 2logL	Mean delta
1	0	0	1		1	1	1	-297.133	0.137	0.336
2	0	0	1		1	1	1	-326.455	0.352	
3	0	0	1		1	1	1	-276.552	0.008	
4	0	0	1		1	1	1	-340.332	0.244	
5	0	0	1		1	1	1	-290.620	0.938	
1	0	1	0		0	0	0	-296.879	2.761	13.390
2	0	1	0		0	0	0	-325.222	61.915	
3	0	1	0		0	0	0	-263.822	1.795	
4	0	1	0		0	0	0	-338.033	0.231	
5	0	1	0		0	0	0	-277.114	0.247	
1	0	1	0		0	0	1	-297.179	0.300	0.935
2	0	1	0		0	0	1	-326.534	1.312	
3	0	1	0		0	0	1	-271.683	2.459	
4	0	1	0		0	0	1	-339.485	0.287	
5	0	1	0		0	0	1	-277.482	0.320	
1	0	1	0		0	1	0	-298.579	1.700	0.522
2	0	1	0		0	1	0	-325.284	0.061	
3	0	1	0		0	1	0	-264.191	0.369	
4	0	1	0		0	1	0	-338.466	0.214	
5	0	1	0		0	1	0	-277.613	0.266	
1	0	1	0		0	1	1	-298.896	0.317	0.214
2	0	1	0		0	1	1	-326.562	0.028	
3	0	1	0		0	1	1	-271.873	0.191	
4	0	1	0		0	1	1	-340.007	0.259	
5	0	1	0		0	1	1	-277.887	0.274	
1	0	1	0		1	0	0	-296.883	0.004	0.992
2	0	1	0		1	0	0	-327.088	1.865	
3	0	1	0		1	0	0	-270.772	2.738	
4	0	1	0		1	0	0	-338.398	0.230	
5	0	1	0		1	0	0	-286.484	0.123	
1	0	1	0		1	0	1	-297.187	0.008	1.049
2	0	1	0		1	0	1	-328.228	1.140	
3	0	1	0		1	0	1	-278.373	3.628	
4	0	1	0		1	0	1	-339.789	0.289	
5	0	1	0		1	0	1	-287.328	0.180	
1	0	1	0		1	1	0	-298.596	0.018	0.132
2	0	1	0		1	1	0	-327.125	0.038	
3	0	1	0		1	1	0	-271.023	0.251	
4	0	1	0		1	1	0	-338.880	0.213	
5	0	1	0		1	1	0	-286.969	0.140	

Re-gion	Month	Sys -rbt	Sys -tin	Sys -enf	Out-dd	Out-spd	Over-disp	2logL	Delta 2logL	Mean delta
1	0	1	0		1	1	1	-298.909	0.013	0.130
2	0	1	0		1	1	1	-328.245	0.017	
3	0	1	0		1	1	1	-278.536	0.163	
4	0	1	0		1	1	1	-340.348	0.260	
5	0	1	0		1	1	1	-287.845	0.197	
1	0	1	1		0	0	0	-297.525	0.646	0.700
2	0	1	1		0	0	0	-327.280	2.057	
3	0	1	1		0	0	0	-264.401	0.579	
4	0	1	1		0	0	0	-338.227	0.194	
5	0	1	1		0	0	0	-279.347	0.024	
1	0	1	1		0	0	1	-297.787	0.262	0.533
2	0	1	1		0	0	1	-328.587	1.307	
3	0	1	1		0	0	1	-272.400	0.717	
4	0	1	1		0	0	1	-339.794	0.310	
5	0	1	1		0	0	1	-279.724	0.070	
1	0	1	1		0	1	0	-299.806	1.228	0.443
2	0	1	1		0	1	0	-327.642	0.363	
3	0	1	1		0	1	0	-264.814	0.413	
4	0	1	1		0	1	0	-338.666	0.200	
5	0	1	1		0	1	0	-280.433	0.013	
1	0	1	1		0	1	1	-300.428	0.622	0.303
2	0	1	1		0	1	1	-328.922	0.335	
3	0	1	1		0	1	1	-272.545	0.146	
4	0	1	1		0	1	1	-340.385	0.379	
5	0	1	1		0	1	1	-280.730	0.035	
1	0	1	1		1	0	0	-297.526	0.001	0.532
2	0	1	1		1	0	0	-329.158	1.879	
3	0	1	1		1	0	0	-271.347	0.575	
4	0	1	1		1	0	0	-338.600	0.203	
5	0	1	1		1	0	0	-288.596	0.003	
1	0	1	1		1	0	1	-297.796	0.009	0.419
2	0	1	1		1	0	1	-330.226	1.068	
3	0	1	1		1	0	1	-279.061	0.688	
4	0	1	1		1	0	1	-340.106	0.312	
5	0	1	1		1	0	1	-289.449	0.018	
1	0	1	1		1	1	0	-299.893	0.086	0.175
2	0	1	1		1	1	0	-329.540	0.381	
3	0	1	1		1	1	0	-271.552	0.205	
4	0	1	1		1	1	0	-339.084	0.203	
5	0	1	1		1	1	0	-289.682	0.000	

Re-gion	Month	Sys -rbt	Sys -tin	Sys -enf	Out-dd	Out-spd	Over-disp	2logL	Delta 2logL	Mean delta
1	0	1	1		1	1	1	-300.582	0.155	0.186
2	0	1	1		1	1	1	-330.580	0.354	
3	0	1	1		1	1	1	-279.138	0.077	
4	0	1	1		1	1	1	-340.726	0.341	
5	0	1	1		1	1	1	-290.624	0.004	
1	1	0	0		0	0	0	-399.572	105.454	114.377
2	1	0	0		0	0	0	-416.218	152.911	
3	1	0	0		0	0	0	-363.738	101.711	
4	1	0	0		0	0	0	-446.021	108.220	
5	1	0	0		0	0	0	-380.458	103.590	
1	1	0	0		0	0	1	-406.279	6.707	6.305
2	1	0	0		0	0	1	-420.202	3.984	
3	1	0	0		0	0	1	-377.305	13.568	
4	1	0	0		0	0	1	-447.354	1.333	
5	1	0	0		0	0	1	-386.389	5.931	
1	1	0	0		0	1	0	-402.550	2.978	2.335
2	1	0	0		0	1	0	-422.711	6.492	
3	1	0	0		0	1	0	-365.164	1.426	
4	1	0	0		0	1	0	-446.045	0.024	
5	1	0	0		0	1	0	-381.211	0.753	
1	1	0	0		0	1	1	-407.923	1.643	1.132
2	1	0	0		0	1	1	-425.496	2.785	
3	1	0	0		0	1	1	-378.107	0.802	
4	1	0	0		0	1	1	-447.360	0.005	
5	1	0	0		0	1	1	-386.814	0.425	
1	1	0	0		1	0	0	-399.807	0.234	5.692
2	1	0	0		1	0	0	-428.584	12.365	
3	1	0	0		1	0	0	-373.038	9.300	
4	1	0	0		1	0	0	-446.468	0.447	
5	1	0	0		1	0	0	-386.571	6.114	
1	1	0	0		1	0	1	-406.450	0.171	3.602
2	1	0	0		1	0	1	-430.576	1.992	
3	1	0	0		1	0	1	-385.204	7.899	
4	1	0	0		1	0	1	-447.731	0.376	
5	1	0	0		1	0	1	-394.143	7.571	
1	1	0	0		1	1	0	-403.170	0.620	0.735
2	1	0	0		1	1	0	-430.426	1.842	
3	1	0	0		1	1	0	-373.436	0.398	
4	1	0	0		1	1	0	-446.523	0.055	
5	1	0	0		1	1	0	-387.332	0.761	

Re-gion	Month	Sys -rbt	Sys -tin	Sys -enf	Out-dd	Out-spd	Over-disp	2logL	Delta 2logL	Mean delta
1	1	0	0		1	1	1	-408.443	0.520	0.537
2	1	0	0		1	1	1	-432.141	1.566	
3	1	0	0		1	1	1	-385.355	0.150	
4	1	0	0		1	1	1	-447.738	0.007	
5	1	0	0		1	1	1	-394.583	0.441	
1	1	0	1		0	0	0	-400.224	0.652	1.998
2	1	0	1		0	0	0	-419.745	3.527	
3	1	0	1		0	0	0	-363.860	0.122	
4	1	0	1		0	0	0	-447.697	1.676	
5	1	0	1		0	0	0	-384.470	4.013	
1	1	0	1		0	0	1	-406.411	0.132	1.607
2	1	0	1		0	0	1	-423.042	2.840	
3	1	0	1		0	0	1	-377.737	0.432	
4	1	0	1		0	0	1	-448.795	1.098	
5	1	0	1		0	0	1	-389.923	3.534	
1	1	0	1		0	1	0	-404.038	1.488	0.635
2	1	0	1		0	1	0	-423.937	1.227	
3	1	0	1		0	1	0	-365.417	0.253	
4	1	0	1		0	1	0	-447.808	0.111	
5	1	0	1		0	1	0	-384.567	0.097	
1	1	0	1		0	1	1	-408.432	0.509	0.494
2	1	0	1		0	1	1	-426.569	1.073	
3	1	0	1		0	1	1	-378.820	0.713	
4	1	0	1		0	1	1	-448.888	0.093	
5	1	0	1		0	1	1	-390.004	0.081	
1	1	0	1		1	0	0	-400.410	0.186	1.690
2	1	0	1		1	0	0	-431.786	3.203	
3	1	0	1		1	0	0	-373.599	0.561	
4	1	0	1		1	0	0	-448.133	0.436	
5	1	0	1		1	0	0	-390.639	4.067	
1	1	0	1		1	0	1	-406.546	0.096	1.444
2	1	0	1		1	0	1	-433.473	1.687	
3	1	0	1		1	0	1	-386.832	1.627	
4	1	0	1		1	0	1	-449.156	0.362	
5	1	0	1		1	0	1	-397.591	3.448	
1	1	0	1		1	1	0	-404.583	0.546	0.381
2	1	0	1		1	1	0	-432.376	0.590	
3	1	0	1		1	1	0	-374.120	0.521	
4	1	0	1		1	1	0	-448.264	0.131	
5	1	0	1		1	1	0	-390.756	0.118	

Re-gion	Month	Sys -rbt	Sys -tin	Sys -enf	Out-dd	Out-spd	Over-disp	2logL	Delta 2logL	Mean delta
1	1	0	1		1	1	1	-408.882	0.440	0.290
2	1	0	1		1	1	1	-433.942	0.469	
3	1	0	1		1	1	1	-387.096	0.264	
4	1	0	1		1	1	1	-449.249	0.093	
5	1	0	1		1	1	1	-397.772	0.182	
1	1	1	0		0	0	0	-402.897	3.325	1.674
2	1	1	0		0	0	0	-419.202	2.983	
3	1	1	0		0	0	0	-365.207	1.469	
4	1	1	0		0	0	0	-446.411	0.390	
5	1	1	0		0	0	0	-380.660	0.202	
1	1	1	0		0	0	1	-408.933	2.654	1.955
2	1	1	0		0	0	1	-423.999	3.797	
3	1	1	0		0	0	1	-379.745	2.439	
4	1	1	0		0	0	1	-447.797	0.442	
5	1	1	0		0	0	1	-386.831	0.442	
1	1	1	0		0	1	0	-405.875	2.978	1.614
2	1	1	0		0	1	0	-426.059	3.348	
3	1	1	0		0	1	0	-366.716	1.509	
4	1	1	0		0	1	0	-446.452	0.041	
5	1	1	0		0	1	0	-381.406	0.195	
1	1	1	0		0	1	1	-410.822	1.888	1.315
2	1	1	0		0	1	1	-429.460	3.401	
3	1	1	0		0	1	1	-380.561	0.817	
4	1	1	0		0	1	1	-447.821	0.024	
5	1	1	0		0	1	1	-387.278	0.446	
1	1	1	0		1	0	0	-402.977	0.080	1.248
2	1	1	0		1	0	0	-431.645	3.062	
3	1	1	0		1	0	0	-375.441	2.403	
4	1	1	0		1	0	0	-446.894	0.427	
5	1	1	0		1	0	0	-386.842	0.270	
1	1	1	0		1	0	1	-408.982	0.048	1.406
2	1	1	0		1	0	1	-433.967	2.322	
3	1	1	0		1	0	1	-389.104	3.900	
4	1	1	0		1	0	1	-448.225	0.428	
5	1	1	0		1	0	1	-394.474	0.332	
1	1	1	0		1	1	0	-406.212	0.337	0.626
2	1	1	0		1	1	0	-433.643	1.997	
3	1	1	0		1	1	0	-375.883	0.441	
4	1	1	0		1	1	0	-446.960	0.066	
5	1	1	0		1	1	0	-387.619	0.287	

Re-gion	Month	Sys -rbt	Sys -tin	Sys -enf	Out-dd	Out-spd	Over-disp	2logL	Delta 2logL	Mean delta
1	1	1	0		1	1	1	-411.107	0.285	0.503
2	1	1	0		1	1	1	-435.691	1.724	
3	1	1	0		1	1	1	-389.243	0.139	
4	1	1	0		1	1	1	-448.242	0.017	
5	1	1	0		1	1	1	-394.932	0.348	
1	1	1	1		0	0	0	-403.747	0.850	1.099
2	1	1	1		0	0	0	-423.289	3.544	
3	1	1	1		0	0	0	-365.470	0.264	
4	1	1	1		0	0	0	-448.327	0.630	
5	1	1	1		0	0	0	-384.675	0.205	
1	1	1	1		0	0	1	-409.107	0.174	0.952
2	1	1	1		0	0	1	-427.216	3.217	
3	1	1	1		0	0	1	-380.155	0.411	
4	1	1	1		0	0	1	-449.560	0.766	
5	1	1	1		0	0	1	-390.116	0.193	
1	1	1	1		0	1	0	-407.546	1.671	0.772
2	1	1	1		0	1	0	-427.651	1.592	
3	1	1	1		0	1	0	-367.124	0.408	
4	1	1	1		0	1	0	-448.405	0.078	
5	1	1	1		0	1	0	-384.787	0.112	
1	1	1	1		0	1	1	-411.627	0.806	0.595
2	1	1	1		0	1	1	-430.881	1.421	
3	1	1	1		0	1	1	-381.152	0.591	
4	1	1	1		0	1	1	-449.629	0.069	
5	1	1	1		0	1	1	-390.207	0.090	
1	1	1	1		1	0	0	-403.783	0.036	0.943
2	1	1	1		1	0	0	-435.598	3.812	
3	1	1	1		1	0	0	-375.785	0.344	
4	1	1	1		1	0	0	-448.762	0.435	
5	1	1	1		1	0	0	-390.727	0.089	
1	1	1	1		1	0	1	-409.137	0.030	0.567
2	1	1	1		1	0	1	-437.504	1.905	
3	1	1	1		1	0	1	-389.529	0.425	
4	1	1	1		1	0	1	-449.938	0.378	
5	1	1	1		1	0	1	-397.688	0.098	
1	1	1	1		1	1	0	-407.801	0.254	0.294
2	1	1	1		1	1	0	-436.170	0.572	
3	1	1	1		1	1	0	-376.321	0.439	
4	1	1	1		1	1	0	-448.870	0.108	
5	1	1	1		1	1	0	-390.852	0.095	

Re-gion	Month	Sys -rbt	Sys -tin	Sys -enf	Out-dd	Out-spd	Over-disp	2logL	Delta 2logL	Mean delta
1	1	1	1		1	1	1	-411.806	0.179	0.212
2	1	1	1		1	1	1	-437.997	0.494	
3	1	1	1		1	1	1	-389.736	0.207	
4	1	1	1		1	1	1	-450.018	0.081	
5	1	1	1		1	1	1	-397.874	0.102	