INTERVENTION TIME SERIES ANALYSIS OF CRIME RATES:

THE IMPACT OF SENTENCE REFORMS IN VIRGINIA

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"Abstract:" *The Commonwealth of Virginia abolished parole and reformed sentencing for all felony offenders committed on or after January 1, 1995. We examine the impact of this legislation on reported crime rates using different time series approaches. In particular, structural time series models are considered as an alternative to the Box-Jenkins ARIMA models that form the standard time series approach to intervention analysis. Limited support for the deterrent impact of parole abolition and sentence reform is obtained using univariate modelling devices, even after including unemployment as an explanatory variable. Finally, the flexibility of structural time series models is illustrated by presenting a multivariate analysis that provides some additional evidence of the deterrent impact of the new legislation.*

KEY WORDS: INTERVENTION, STS MODELS, ARIMA MODELS, SENTENCE REFORM.

1. INTRODUCTION

The articles in a recent issue of the *Journal of Quantitative Criminology* (2001, Vol. 17, No. 4) have prompted an interesting debate on methodologies for time series analyses of crime rates. In this paper, we would like to contribute to this discussion in the context of intervention analysis. Various intervention time series approaches have been used in the evaluation of programs and policies in a number of criminal justice settings. Intervention time series analysis can be regarded as measuring a change in a coefficient at a particular time point in the time series. Standard approach when analysing time series in this framework aims at discriminating between the behaviour of the time series prior to the intervention and after the intervention. The typical research question is: did the intervention have an impact on the time series; did the intervention interrupt the trajectory of the time series?

The standard time series approach to intervention analysis is based on autoregressive integrated moving average (ARIMA) models (Box and Tiao, 1975). On the other hand, structural time series (STS) methodology provides an alternative approach to modelling intervention (Harvey, 1989), which has not yet been applied in criminal analysis setting. However, structural time series models have been applied in other policy and intervention analysis applications (Harvey and Durbin, 1986; Harvey, 1996; Balkin and Ord, 2001). Major advantages of the STS methodology over the ARIMA approach are: a) whereas trend and seasonal are explicitly modelled, in the ARIMA models they are removed from the series before any analysis is performed; b) in the ARIMA models the observed time series is differenced prior to the analysis, in order to obtain an approximation to stationary time series, while in the STS approach the time series is modelled directly in levels, whether stationary or not; c) missing data, stochastic explanatory variables, and multivariate data are easily incorporated into the STS methodology.

In this paper we investigate the impact of Virginia's parole abolition and sentence reform on reported crime rates. The Commonwealth of Virginia abolished parole and reformed sentencing for all felony offences committed on or after January 1, 1995. To examine the impact of Virginia's abolition of parole on reported crime rates, we consider different methods of intervention analysis. Preliminary results are based on simple regression methods. Then, autoregressive integrated moving average (ARIMA) models are applied, as the standard approach to intervention analysis. Finally, the analysis is carried out using the structural time series (STS) models, as an alternative to the ARIMA processes. The STS models are estimated both in the univariate and multivariate domains. In addition, the multivariate STS models provide a good framework for pursuing intervention analysis with control groups (Harvey, 1996). Examined crime rate series include burglary, larceny, motor vehicle theft,

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robbery, aggravated assault, murder, and rapes. Definitions of these crime categories are given in the extended version of this paper, see Sridharan et al. (2003).

The present paper is not intended to be a comprehensive evaluation of Virginia's legislation on abolition of parole and sentence reform. Instead, the focus of this paper is on the impact of the legislation on the reported crime rates. The 1990s were a period of considerable social and economic changes in the United States. There were declines in crime trends throughout the U.S. during the decade. Further, the middle to late nineties was an economically prosperous period in the United States. As an example, unemployment rates declined sharply through most of the period. Furthermore, it was also a time in which a number of innovative criminal justice programs and policies were enacted both at the State level and at the level of local communities. In addition, there were also favourable changes in patterns of drug use and access to guns. All of these factors could serve as alternative explanations for the decline in crime. Disentangling the impact of parole abolition on crime rates from other factors poses a considerable methodological challenge.

Despite the empirical intricacies, Virginia's experience with abolition of parole and sentence reform remains of interest for a few reasons. A number of States have abolished parole for specific felony offences, while Virginia abolished parole for all felony offences. Parole abolition was further accompanied by large-scale changes in the sentencing system. Further, the timing of this law occurred when the downward trends in crime had already begun both nationwide and in Virginia. It is therefore interesting to empirically investigate whether parole abolition and sentence reform in Virginia led to steeper declines in crime rates as compared to expected patterns based on past history. Additionally, the results and the techniques discussed in this paper could be potentially useful for policy analysts working in the Departments of Criminal Justice or the Juvenile Justice and other individuals interested in intervention analyses of crime rates. Last but not least, structural time series methods can be a useful addition to the policy analysts' tool box.

The remaining part of the paper is organised as follows. In section 2 we discuss in more details the criminal justice situation in Virginia and its recent changes and developments in the parole and sentence systems. Different time series methodologies for intervention analysis are considered in section 3. Additionally, this section gives plan and details of empirical intervention study, in particular using descriptive and regression approaches. Empirical results of our investigation of the effect of parole abolition and sentence reform on the crime rates in Virginia, using ARIMA and structural time series methods, are presented in sections 4 and 5. Section 6 offers discussion of the results, comparing different methodological approaches to intervention analysis. This section also concludes and raises questions that can be analysed in future. Section 7 gives a list of the referenced articles.

2. CHANGES IN CRIMINAL JUSTICE SYSTEM OF VIRGINIA

The Commonwealth of Virginia abolished parole and reformed sentencing for all felony offenders committed on or after January 1, 1995. This law was passed in a special legislative session in the fall of 1994. Parole abolition was accompanied with substantially enhanced sentences for both violent offences and violent offenders. For non-violent offences (and offenders) the new "truth-in-sentencing" attempted to preserve the time-served practices from the prior system (Virginia Criminal Sentencing Commission, 1995). The net result of the implementation of the legislation was a substantial increase in the sentences for the violent offences (especially rape and murder) and also for offenders with a violent past. Table 1 (adapted from the Virginia Criminal Sentencing Commission annual report of 1995), compares the median time-served (in years) for prisoners released in 1993 (in a system with parole) with a median expected time-served for two groups of offenders sentenced in 2001 a system without parole. Three groups of offenders sentenced in 2001 are described in Table 1: (a) group of offenders who did not have any prior offences; (b) group that had prior offences with a statutory maximum less than 40 years (roughly corresponding to non-violent prior offence); (c) group of offenders that had prior offences with a statutory maximum greater then 40 years (roughly corresponding to a prior record with violent offences).

Table 1: Comparison of median time-served (in years) in 1993 (system with parole) and anticipated median time-served for Offenders Sentenced in 2001 (system without parole)[3].

Offence	Released FY93[4]	Sentenced FY01			
	Median time	Median expected time			
		No prior	Prior < 40	Prior ≥ 40	All combined
Burglary	2.2	1.8	3.6	5.4	2.7
Larceny	1.3	1.1	1.8	2.3	1.4
Motor vehicle theft	1.3	1.3	1.8	2.7	1.4
Robbery	4.4	6.4	11	16.2	7.3
Aggravated assault	2.8	3.7	6.2	7.3	4.1
Murder (2nd degree)	5.7	13.6	22.7	20.0	16.3
Rape (forcible)	4.4	9.0	13.5	34.3	12.6

As can be seen from Table 1, increases in time-served were especially high after the implementation of the legislation for murder and rape. To the extent that severity of punishment serves as a deterrent to committing crimes, we would expect the reported crimes to drop especially for murder and rape. However, severity of punishment is only one explanation for a drop in crime. As discussed earlier, a number of alternative explanations can be used to explain a drop in crime. The recent book, *The Crime Drop in America* (Blumstein and Wallman, 2000) compiles a variety of explanations for the reductions in crime in the U.S. For example, alternative explanations for drops in crime from this compilation include: changes in drug use patterns, policing and community policing, growth in prison expansion, reductions in use of handguns, expanding economy, and changing demographics. Obtaining monthly time series data on these alternative explanations is difficult. Instead, in this paper, unemployment rate is used as a measure of expansion in the economy. Under a deterrence hypothesis, the effects of enhancements in severity of the sentence should be significant even after we control for unemployment rates. From Table 1, given the enhancements in time-served for the violent offences, we would anticipate these decreases in crime rates to be significant for the violent offences.

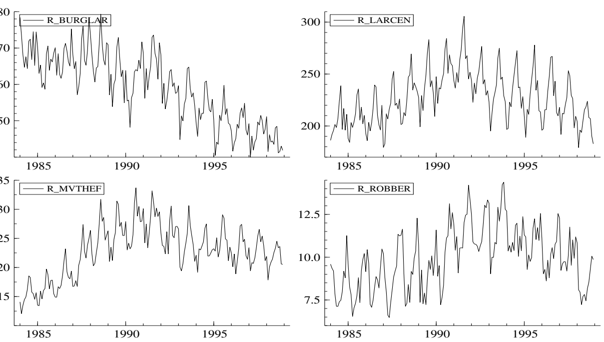
3. PLAN AND DETAILS OF EMPIRICAL INTERVENTION STUDY

3.1 DATA DESCRIPTION

The data was collected from the Uniform Crime Reports collected by the Virginia State Police. Monthly time series on unemployment rates were collected from the Bureau of Labour Statistics web site. The pre-intervention period corresponded to the period between 1984 January to December 1994. The choice of years for the pre-intervention period was driven primarily by data availability. The earliest period for which we were able to access data on reported crimes from the UCR was 1984. Starting 1999, the Virginia State Police changed their system of reporting (they moved towards an incident based reporting system). In order to ensure consistency of data for the post-intervention period, it was restricted to observations until the end of 1998.

Figures 1 and 2 present the reported crimes rates for property and violent crimes respectively[5]. Rather interestingly, it can be observed from the graphs that most of these crimes were already declining when parole was abolished in January 1995.

[3] Virginia Criminal Sentencing Commission Annual Report 1995 p7 for FY93; Actual Time Served and Annual Report 2001, pp. 66-71; Burglary, Motor Vehicle Theft and all combined data is from unpublished data maintained by the Sentencing Commission.
[4] FY93 Used because parole was an issue in the 1994 campaign and parole grant rates began to change prior to the abolition of parole.
[5] Following the UCR categorization scheme, robberies were included together with the property crimes.



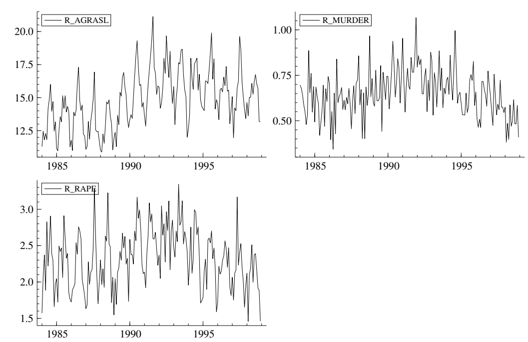


Figure 1. Property crime rates **Figure 2. Violent crime rates**

3.3 INTERVENTION ANALYSIS

Examples of intervention effects are given in graphical form in Figure 3. The first graph is a so-called *pulse intervention* and is used to capture single special events in a month such as a special holiday or a strike. Such events may cause outlying observations within the time series and the pulse regression variable can take such observations outside the general model. The second graph shows a so-called *step intervention* that enables breaking the single time series into two distinct segments with two different overall means, one consisting of all pre-intervention observations and one consisting of all post-intervention observations. The step intervention is introduced in the model to capture events such as the introduction of new policy measures or changes in regulations. The analysis of intervention in a time series focuses on a test of the null hypothesis, that is, did the intervention have an impact on the time series? In the case of a step intervention the null hypothesis can be tested by comparing means of the pre- and post-intervention parts of the time series.

In our case the intervention is modelled as the level shift or a step type of intervention, where the value of the level of the time series suddenly changes at the time point when the intervention took place, and where the level change is permanent after the intervention. The deterrent impact of the new legislation is assumed to start instantaneously from January 1st, 1995.

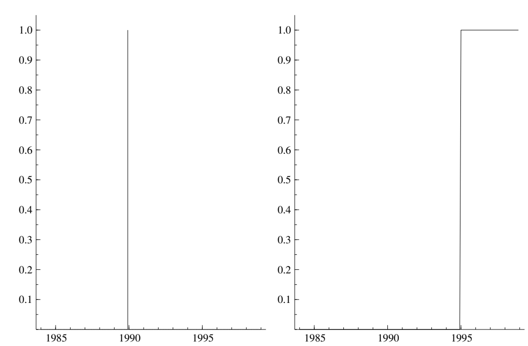


Figure 3. Intervention effects

The intervention analysis of the impact of parole abolition and sentence reform on crime rates is assessed in two steps. In the first step, we assess the effect of the intervention using different time series models including regression, ARIMA and structural time series models. In all three different models, the intervention is introduced as a step type of intervention. In the second step we examine the impact of the legislation by modelling a group of crime rates time series simultaneously where one sub-group is used as a control group for the intervention effect[6].

[6] Ideally we would have liked access to monthly time series measures of a number of factors that could serve as explanations for changes in crime rates. However, obtaining monthly time series of explanatory variables such as changes in access to guns or changes in drug use is difficult. The only time series that was readily available at a monthly time-interval was unemployment rate. However, linkages between unemployment and crime can be

3.4 DESCRIPTIVE ANALYSIS

We first compare the changes in the means of the entire pre-intervention period (1984-1994) with the post-intervention period (1995-1998). In Figures 4 and 5, the two different means are presented for the property crime series and the violent crime series. It appears that property crime rates are not affected by the abolishment of the parole system apart from the burglary series. In the case of violent crimes, the murder and rape series seem to be affected by the change. Strong decreases are observed for reported burglary, murder and rape crime rates. Since this analysis considers a fairly long pre-intervention period that potentially corresponds to multiple temporal regimes, a better understanding of the change in crime rates may be obtained by restricting the sample to four years before the introduction of the law. In this analysis, all reported crime rates besides aggravated assaults show a decrease.

The results so far may potentially provide a misleading picture of change because no information on trends is incorporated in the calculations of changes in the crime rates in the two periods. When trends are considered, the differences between the means of the pre- and post-intervention periods are larger and appear more dramatic (Figures 6 and 7) with exception of burglary. This preliminary analysis shows that measurements of intervention effects can be rather different and the need for an elaborate analysis based on time series models becomes imminent.

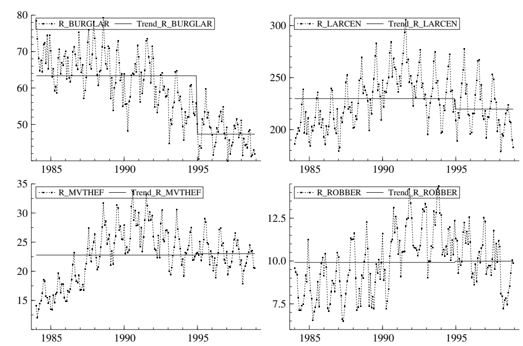


Figure 4. Mean change in property crime rates

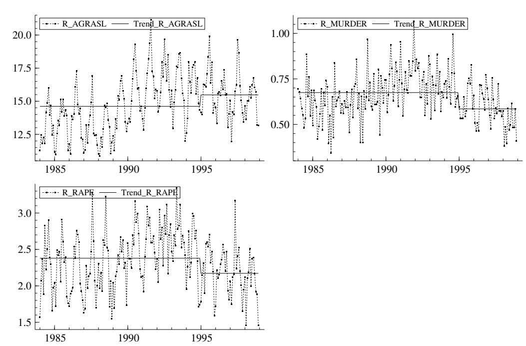


Figure 5. Mean change in violent crime rates

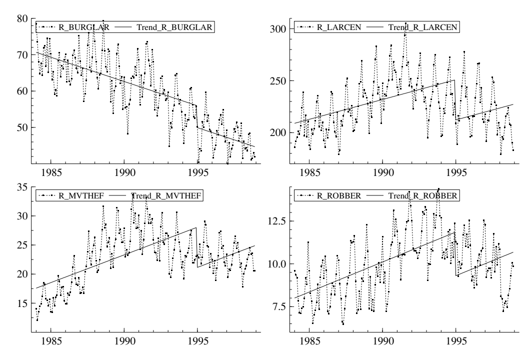


Figure 6. Trend change in property crime rates

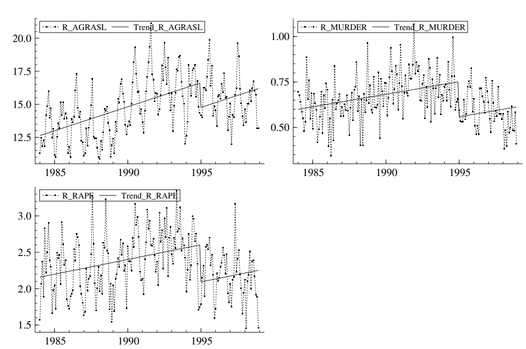


Figure 7. Trend change in violent crime rates

3.5 REGRESSION ANALYSIS

The typical regression approach of studying the impact of an intervention is to consider the standard regression model

$$y_t = x_t'\beta + \delta I_t + \varepsilon_t, \qquad \varepsilon_t \sim N\left(0, \sigma_\varepsilon^2\right), \tag{1}$$

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complex. As described by Cantor and Land (1985), both motivation and opportunity components need to be modelled when relating unemployment to crime. Although this will not be the focus of this paper, we do consider unemployment measures as a potential confounder in the relationship between parole abolition and crime in the next sections.

for $t = 1,\ldots,n,$ where y_t is a time series of crime rates, x_t is a $k \times 1$ vector of explanatory variables (covariates), and β is a $k \times 1$ vector of regression coefficients. The variable that measures the intervention effect is defined as a dummy variable I_t which equals zero before a fixed time point and equals one on and after this time point. The intervention coefficient δ measures the change in the mean of crime rates time series after the intervention period. In our empirical study, the intervention variable is zero for the period before 1995 and is coded one for the period on and after January 1995. The disturbances ε_t are normally and independently distributed with mean zero and variance σ_ε^2 for all time points $t = 1,\ldots,n.$ A constant, trend, and seasonal dummies can be included in the vector of covariates x_t together with other explanatory variables that may have an influence on crime rates. For this regression model, ordinary least squares can be used to estimate β and δ.

Table 2 in the extended version of the paper (Sridharan et al., 2003) presents the estimation results of the intervention effects of the crime rate series based on single regression models with only a constant (level), only a trend (trend) and with trend and seasonal explanatory variables. The estimated coefficient δ for the intervention effect is reported together with its *t*-test[7]. In most cases significant intervention effects are reported, but the diagnostic test statistics, and in particular the *Q* statistics, are not satisfactory. This indicates that the regression errors are serially correlated and therefore the regression effects are not reliable.

3.6 REGRESSION MODELS WITH ARMA ERRORS

Since time series are by nature subject to serial correlation, the standard errors of OLS parameter estimates are *biased*. As a result of this bias, *t*-tests that are used to test the null hypothesis may overstate the statistical significance of an impact. For this reason, the time series should not be analysed by means of ordinary least squares regression methods. On the assumption that the time series corrected for fixed trend and seasonal effects is stationary, we may consider autoregressive moving average (ARMA) processes for the explicit modelling of the serial dependence. The regression model with ARMA disturbances is given by

$$y_t = x_t{}'\beta + \delta I_t + u_t, \tag{2}$$

where u_t is modelled by the ARMA model that can be represented as

$$u_t = \phi_1 u_{t-1} + \ldots + \phi_p u_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \ldots + \theta_q \varepsilon_{t-q}, \tag{3}$$

for fixed integers *p* and *q*. The disturbance ε_t is a white noise term (serially uncorrelated across time) and will be assumed normally distributed.

Table 3 describes the results of regression models with trend and seasonal explanatory variables, but with autoregressive errors of orders one and two. These results show estimated effects which are not all statistically significant. Strong negative effects of the legislation are found for murder and rape. No statistically significant effects are found for the property crimes and aggravated assault. It may therefore be concluded that regression results with weak diagnostic statistics can easily produce spurious results.

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[7] Further, two diagnostic test statistics are given, that is *N* for the Bowman and Shenton normality test (χ^2 distributed with two degrees of freedom) and the pormanteau Box-Ljung *Q*(*p*) test statistic consisting of the sum of the first *p* autocorrelation coefficients of the standardised regression residuals (χ^2 distributed with approximately *p* degrees of freedom). Finally, two goodness-of-fit criteria are reported, that is the one-step ahead prediction error variance (p.e.v.) and the R^2 value corrected for seasonal means (R_s^2). For seasonal data with a trend, the value corrected for seasonal means is a more appropriate measure of goodness-of-fit than the traditional coefficient of determination. This requires the sum of squares, *SSDSM*, obtained by subtracting the seasonal means from the data's first differences (Δy_t). The coefficient of determination is then $R_s^2 = 1 - SSE / SSDSM$, where *SSE* is the residual sum of squares. Any model that has R_s^2 negative can be rejected (Harvey, 1989).

Results are also reported for models that include the explanatory variable unemployment and the dummy outlier variable for December 1989 that has shown to result in significant effect in many series. The series that have shown a significant response to unemployment are aggravated assault (*t*-value 4.98), murder (*t*-value 2.89), rape (*t*-value 3.83) and robbery (*t*-value 4.27). It is interesting that unemployment has a significant positive effect on all violent crime rates and the most violent property crime rate. Although such results have to be taken with care since the relationship between crime and unemployment is complex, these results are interesting. On the other hand, the interventions for parole legislation do not change significantly whether explanatory variables are included or not. For the series where unemployment is significant, the effect of the legislation becomes less pronounced, except for robbery.

Table 3. Estimated interventions for a regression plus AR error models

		coeff	*t*-test	*N*	*Q*(20)	p.e.v.	R_s^2
	trseas + ar1	-5.37	-3.13	5.09	28.18	8.93	0.21
BURGLAR	trseas + ar2	-5.3	-2.82	3.6	27.64	8.74	0.22
	trseas + ar2 + expl	-4.8	-2.44	0.39	29.00	7.89	0.27
	trseas + ar1	-18.76	-2.28	48.41	43.01	79.47	0.069
LARCEN	trseas + ar2	-10.48	-1.38	21.9	22.44	65.82	0.23
	trseas + ar2 + expl	-7.83	-1.09	0.76	18.37	56.00	0.34
	trseas + ar1	-1.11	-0.73	0.84	28.8	2.34	0.042
MVTHEF	trseas + ar2	0.26	0.18	1.22	22.38	2.22	0.089
	trseas + ar2 + expl	0.46	0.31	1.34	22.38	2.19	0.099
	trseas + ar1	-1.99	-3.59	0.95	16.75	0.72	0.15
ROBBER	trseas + ar2	-1.06	-1.63	1.02	13.41	0.68	0.2
	trseas + ar2 + expl	-1.21	-2.51	4.09	9.95	0.63	0.25
	trseas + ar1	-1.58	-3.18	0.098	35.97	0.912	0.22
AGRASL	trseas + ar2	-1.3	-2.23	0.46	22.02	0.866	0.26
	trseas + ar2 + expl	-0.8	-1.92	1.27	16.04	0.796	0.29
	trseas + ar1	-0.19	-5.85	0.94	18.47	0.012	0.44
MURDER	trseas + ar2	-0.18	-4.87	1.66	14.35	0.0117	0.45
	trseas + ar2 + expl	-0.14	-3.91	2.66	14.99	0.0112	0.46
	trseas + ar1	-0.5	-6.35	3.69	13.96	0.0604	0.39
RAPE	trseas + ar2	-0.5	-6.28	3.77	13.93	0.0604	0.39
	trseas + ar2 + expl	-0.4	-5.30	2.64	11.92	0.0556	0.41

4. BOX-JENKINS ARIMA MODEL APPROACH

The most popular model within the class of seasonal ARIMA models has become known as the '*airline model*' since it was originally fitted to a monthly series on UK airline passenger totals. The model is of order $(0,1,1)\times(0,1,1)_s$ with no constant and it is written as

$$(1-B)(1-B^s)u_t = (1-\theta B)(1-\Theta B^s)\varepsilon_t, \tag{4}$$

where s is the seasonal length (s = 4 for quarterly data and s = 12 for monthly data). The model has been found extremely useful in practice, because it has only a few parameters to estimate and fits data with pronounced seasonal effect generally well.

Table 4 in the extended version of the paper (Sridharan et al., 2003) describes the results of the ARIMA models, based on the airline model specification. In addition, the iterative ARIMA model building approach as described in Liu et al. (1992) is also implemented using SCA. Since a range of multiplicative seasonal ARIMA models are considered, we report in addition the results of the ARIMA $(0,1,1)\times(0,1,1)_{12}$ models which we regard, together with the results of the airline model, as representative. Similar to the regression results with ARMA errors described in Table 3, a statistically significant negative effect of the legislation is found for murder and rape, but when the Airline model is considered, no significant intervention is detected. No statistically significant effects are found for the property crimes (except for burglary) and aggravated assault.

5. STRUCTURAL TIME SERIES MODELS

5.1 THE BASIC STRUCTURAL TIME SERIES MODEL

The basic model for representing a time series is the additive model:

$$y_t = \mu_t + \gamma_t + \varepsilon_t, \qquad t = 1, \ldots, n, \tag{5}$$

where μ_t is a *trend* component, γ_t is a *seasonal*, and ε_t is irregular component called the *error*. If we consider a simple form of model (5) in which μ_t is a random walk, no seasonal is present and all random variables are normally distributed, then we obtain the *local level model*[8] as given by

$$\begin{aligned} y_t &= \mu_t + \varepsilon_t, \qquad \varepsilon_t \sim N\left(0, \sigma_\varepsilon^2\right), \\ \mu_{t+1} &= \mu_t + \eta_t, \qquad \eta_t \sim N\left(0, \sigma_\eta^2\right), \end{aligned} \tag{6}$$

for $t = 1, \ldots, n$, where the ε_t's and η_t's are mutually independent and are independent of μ_1. The local level model is a simple example of a *linear Gaussian state space model*. In state space methods, time series data are assumed to be stochastic, and thus the measurement errors are included in both equations. The variable μ_t is called the *state* and is unobserved. The object of the methodology is to study the development of the state over time using the observed values $y_1, \ldots, y_n$. Hence, the first equation is called the *observation equation*.

The local level model is a simple form of a structural time series model. By adding a slope term ν_t, which is generated by a random walk, we can derive the *local linear trend model*:

$$\begin{aligned} y_t &= \mu_t + \varepsilon_t, \qquad \varepsilon_t \sim N\left(0, \sigma_\varepsilon^2\right), \\ \mu_{t+1} &= \mu_t + \nu_t + \xi_t, \qquad \xi_t \sim N\left(0, \sigma_\xi^2\right), \\ \nu_{t+1} &= \nu_t + \varsigma_t, \qquad \varsigma_t \sim N\left(0, \sigma_\varsigma^2\right) \end{aligned} \tag{7}$$

The local linear trend model contains two state equations: one for modelling the level, and one for modelling the slope. If $\xi_t = \varsigma_t = 0$, then $\nu_{t+1} = \nu_t = \nu$, and $\mu_{t+1} = \mu_t + \nu$, so that the trend is exactly linear and (7) reduces to the deterministic linear trend plus noise model. The form (7) with $\sigma_\xi^2 > 0$ and $\sigma_\varsigma^2 > 0$ allows the trend level and slope to vary over time.

In the structural time series methodology, a seasonal component can be modelled by adding it either to the local level model or to the local linear trend model. Various specifications for the seasonal component γ_t exist. For our empirical analysis we adopt a trigonometric specification since the statistical properties imply a smooth seasonal process and its parameterisation is flexible.

[8] In this model the *level* of the estimated "true" development is allowed to vary over time, i.e., the *level* is only fixed *locally*. Hence, the name of the model.

Intervention effects can be incorporated in the structural time series model framework. To account for the change in level due to an intervention at time τ, we add the intervention regression effect to model (5) and we obtain

$$y_t = \mu_t + \gamma_t + \lambda I_t + \varepsilon_t, \qquad t = 1,\ldots,n, \tag{8}$$

Obviously, the STS models gain in flexibility as compared to other models because the stochastic formulation allows mean, trend and seasonality to evolve over time. More details on the state space approach to modelling time series data can be found in Harvey (1989), and Durbin and Koopman (2001), among other available literature.

The estimation results for the structural time series model are described in Table 5. The impact coefficients of parole abolition on crime rates match the ones obtained by regression models with ARMA errors and by the Box-Jenkins ARIMA models for six of the seven crimes. Statistically significant impacts of the legislation on crime rates are found for murder and rape. No statistically significant impacts are obtained for burglary, larceny, robbery and aggravated assaults. However, the one difference from the earlier models is that a positive impact of parole abolition is found for motor vehicle theft. This result is somewhat surprising given that this effect was not significant in either the regression (the coefficient was positive in the regression model though not significant) or the ARIMA model. We explore this phenomenon further in the next section.

5.2 INCLUSION OF UNEMPLOYMENT AS AN EXPLANATORY VARIABLE

Explanatory variables can also be incorporated in the structural time series modelling framework. Suppose we have *k* regressors $x_{1t},\ldots,x_{kt}$ with unknown regression coefficients $\beta_1,\ldots,\beta_k$ which are constant over time. By adding the regression effects into model (8) we obtain

$$y_t = \mu_t + \gamma_t + \sum_{j=1}^{k} \beta_{jt} x_{jt} + \lambda I_t, \qquad t = 1,\ldots,n, \tag{9}$$

where the β_{jt}'s are unknown regression coefficients. The state space representation of this model is discussed in Harvey (1989).

Table 5 also describes the estimation results for the structural time series models with the inclusion of parole abolition and unemployment rates as explanatory variables. For both the rape and murder series the intervention effect is no longer significant. The impact of parole abolition on motor vehicle theft still continues to be positive. To study the impact of parole abolition on motor vehicle theft, murder and rape in more detail, we analyse the impact of the intervention graphically in Figure 8 that presents the data together with estimated trends (including the regression effects), see Sridharan et al. (2003). For the case of motor vehicle theft it can be seen from the trend without explanatory variables that there is a small increase of motor vehicle thefts in 1995. On the other hand, murder and rape trends show a slight decline after 1995 although for the rape series the decline had begun before 1995. Since these declines are subtle and relatively small, it is obvious that the graphs in Figure 8 do not provide much support for statistically significant impacts of the legislation on reported crime rates generally.

5.3 MULTIVARIATE STRUCTURAL TIME SERIES MODELS

Until now, we have discussed univariate structural time series models, which means that we modelled only one time series at the time. In the case of structural time series models, we can easily generalise the analysis of one time series to the simultaneous analysis of two or more time series (say *p*). The basic structural model (5) still applies although the trend, seasonal and irregular components have become vectors because y_t has become a vector too in a multivariate analysis. Further, the disturbances associated with the components are vectors with variance matrices. These extensions imply that trends and seasonals of individual series can be correlated. For example, the trend of one series also applies to another series after appropriate scaling. When correlations are high, it means that components will be estimated with the combined use of more time series. Hence, a more precise estimate of the unobserved trend is obtained as a result. In the limiting case of perfect correlations (equal to one) between trends of individual series, the trend component is an equally weighted sum of the individual series. In the perfect correlation cases, the trend is said to be common. The same argument holds for the seasonal component.

We will not present a further technical discussion on multivariate models. The interested reader is referred to Harvey (1989) and Harvey and Koopman (1997). Explanatory and intervention variables can be added in the same way as for a univariate regression models.

Table 5. Estimated interventions for structural time series model

		coeff	*t*-test	*N*	*Q*(20)	p.e.v.	R_s^2
	level + seas	-4.67	-1.86	18.15	22.92	10.2	0.1
BURGLAR	trend + seas	-3.97	-1.59	18.82	21.94	10.04	0.11
	level + seas + unempl	-3.51	-1.50	0.80	18.17	8.76	0.23
	level + seas	-6.58	-1.02	34.64	19.1	68.62	0.2
LARCEN	trend + seas	-4.24	-0.68	27.92	20.9	68.67	0.2
	level + seas + unempl	-5.20	-0.84	1.75	20.07	54.72	0.37
MVTHEF	level + seas	2.19	1.66	0.76	24.87	2.15	0.12
	trend + seas	2.64	2.12	1.54	29.31	2.15	0.12
	level + seas + unempl	2.25	1.67	0.99	28.31	2.14	0.13
ROBBER	level + seas	0.51	0.8	4.44	18.17	0.73	0.14
	trend + seas	0.63	0.96	4.88	19.07	0.74	0.13
	trend + seas + unempl	0.68	1.06	4.85	15.20	0.72	0.15
AGRASL	level + seas	0.33	0.52	4.61	17.4	0.82	0.3
	trend + seas	0.27	0.41	4.1	17.9	0.82	0.3
	trend + seas + unempl	0.32	0.49	4.37	14.11	0.82	0.31
MURDER	level + seas	-0.1	-1.93	2.41	13.1	0.0117	0.45
	trend + seas	-0.09	-1.68	1.81	14.43	0.0118	0.45
	level + seas + unempl	-0.08	-1.74	2.55	12.56	0.0115	0.46
RAPE	level + seas	-0.15	-1.16	2.78	10.48	0.06	0.4
	trend + seas	-0.3	-2.99	1.27	14.98	0.06	0.39
	level + seas + unempl	-0.14	-1.12	2.32	11.56	0.057	0.42

The multivariate structural time series model for crime series can be used to assess the effect of parole abolition and reformed sentencing in Virginia. The results can be more convincing than the results from a univariate state space approach because more time series are involved simultaneously in the analysis. Since the new legislation seems to affect murder and rape convicts, but not so much burglary and robbery convicts, the former series can be considered as *treatment* series, while the latter series can be used as a proxy to a *control* series. Therefore, if we can show that the treatment series were significantly affected by the new legislation, while the control series were not affected by the intervention, we have an even stronger case in favour or against the effect of this law than before. The results are presented in Table 6. It is surprising that whether or not unemployment is considered as an explanatory variable, the parole abolition interventions appear to be significant. This is surprising since all series have a negative trend in early 1990s which does not help in the identification of a negative intervention. It does illustrate that the simultaneous consideration of a set of time series can lead to a more effective intervention analysis. Finally, we note that for all equations, unemployment as an explanatory variable is not estimated significantly. The maximum *t*-value is obtained for murder and equals 1.47.

Table 6. Estimated interventions for multivariate STS model

		coeff	t-test	N	$Q(20)$	p.e.v.	R_s^2
BURGLAR	multi			0.94	17.50	8.62	0.24
	multi + unempl			1.25	17.58	8.54	0.25
LARCEN	multi			4.33	11.74	0.65	0.23
	multi + unempl			3.28	12.07	0.65	0.24
MVTHEF	multi	-0.089	-4.31	1.91	8.14	0.010	0.49
	multi + unempl	-0.081	-3.33	2.01	8.21	0.010	0.49
ROBBER	multi	-0.22	-4.25	2.22	10.54	0.055	0.45
	multi + unempl	-0.22	-3.89	2.21	10.37	0.055	0.45

6. DISCUSSION AND CONCLUSIONS

Proposed models for analysing the intervention effects of parole abolition and sentence reform in Virginia clearly favours ARIMA or STS approaches to modelling intervention. Results using regression approaches are biased and the measured effects are not reliable because of the serially correlated errors. In addition to this, the intervention does not have to be obvious due to trend, seasonality and random effects. Together with the fact that adjacent error terms tend to be correlated and that the proposed model has to account for this type of noise as well, ARIMA and STS models are much better approaches in analysing the time series intervention design. Once the sources of variance in the series have been controlled for, the impact of an intervention can be tested and measured with greater reliability. Therefore, we should concentrate on discussing the estimation results obtained using ARIMA and STS models. All estimation results are reviewed in Table 7.

Consequently, we do find some support for the deterrent impacts of the increases in time-served sentences for both rape and murder crimes, but not for the property crimes and aggravated assault. This can be justified by the fact that implemented legislation affected considerably more violent than non-violent crimes, as we have argued in section 2. However, after including unemployment rates in the models, there is very limited support for the deterrent impacts of the intervention on any of the offences. Specifically, we still find the impact of the intervention to be negative on the reported rape and murder rates but the effect is no longer significant. This might indicate that in order to give a sound answer on whether the parole abolition and sentence reform in Virginia has or has not an impact on reported crime rates, a variety of other factors that can be expected to influence reported crime rates need to be explicitly controlled for in the models. In particular, together with unemployment, these other factors are income, age structure, demographics, or other social factors. Since we were unable to have access to such a wide data-set, future analysis in this direction would necessarily need to encompass these other factors as well.

Virginia's abolition of parole and reform of the sentencing system provides a useful social experiment to study. First the legislation was very sweeping and impacted all felonies. Further, such sweeping legislation was enacted at a time in which there were very large (and favourable) changes in a number of social and economic indicators. Finally, the 1990s also saw the implementation of a number of initiatives focused on reducing crime at the Federal, State and Community levels. Disentangling the impact of parole abolition from the other factors poses multiple design and analytical challenges that this paper attempted, but did not solve completely.

We also view the present paper as a potential contribution to time series methodology in criminology. Structural time series approaches have not yet been used to model intervention in criminal analysis setting. On the other hand, the regression and especially the ARIMA models have been widely used in the criminal justice literature. From our perspective, the STS methodology can contribute significantly in explaining the violent-crime drop of the 1990s, not only in Virginia but the rest of the United States as well.

Table 7. Intervention results for different models

		Reg	RegAr	Airline	Tr + Sea	Multiv
BURGLAR	coef (*t*)	-5.5 (-5.5)	-5.3 (-2.8)	-4.0 (-1.6)	-3.7 (-1.6)	
	fit	-0.2	0.22	0.09	0.22	0.24
LARCEN	coef (*t*)	-37. (-9.1)	-8.0 (-1.1)	-4.4 (-0.7)	-4.1 (-0.7)	
	fit	-1.6	0.34	0.09	0.36	
MVTHEF	coef (*t*)	-6.7 (-8.2)	0.3 (0.2)	2.2 (1.6)	2.6 (2.1)	
	fit	2.64	0.089	0.071	0.12	
ROBBER	coef (*t*)	-2.4 (-8.1)	-1.1 (-1.6)	0.7 (1.0)	0.63 (1.0)	
	fit	-0.45	0.2	0.1	0.13	0.23
AGRASL	coef (*t*)	-1.8 (-5.8)	-1.3 (-2.2)	0.3 (0.4)	0.3 (0.4)	
	fit	-0.08	0.26	0.24	0.3	
MURDER	coef (*t*)	-0.2 (-6.3)	-0.2 (-4.9)	-0.1 (-1.6)	-0.1 (-1.7)	-0.1 (-4.1)
	fit	0.43	0.45	0.58	0.45	0.49
RAPE	coef (*t*)	-0.5 (-7.4)	-0.5 (-6.3)	-0.1 (-0.9)	-0.3 (-3.0)	-0.1 (-4.1)
	fit	0.37	0.39	0.69	0.39	0.45

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