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Intervention Time Series Analysis of Crime Rates

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Intervention time series analysis of crime rates: the impact of sentence reforms in Virginia

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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.

Some Keywords: ARIMA models; Intervention; Parole abolition; Regression models; Sentence reform; Structural time series models.

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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.

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1 Introduction

The articles in a recent issue of the *Journal of Quantative Crimonology* (Volume 17, No 4, 2001) with the noticeable contributions of Greenberg (2001) and Cantor and Land (2001) have prompted an interesting debate on methodologies for time series analysis of crime rates. In this paper we 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 (Loftin et al., 1983; McCleary and Hay, 1980; McDowall et al., 1995). The standard approach to time series analysis in this framework aims at discriminating between the behavior of the time series prior to the intervention and after the intervention (McCleary and Hay, 1980; Orwin, 1997). 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). In the ARIMA framework, non-stationary series need to made stationary prior to the analysis. The usual approach is to difference the series until it exhibits features of a stationary time series and then to fit the appropriate autoregressive moving average (ARMA) model to structure the remaining serial correlation in the series. Structural time series (STS) methods provide an alternative approach to the modelling of interventions (Harvey, 1989) which have 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, whereas within the ARIMA framework this is not so straightforward.

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 offenses 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 offenses and violent offenders. For non-violent offenses (and offenders) the new "truth-in-sentencing" attempted to preserve the time-served practices from the prior system (Virginia Criminal Sentencing Commission, 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 time series 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 an ideal framework for pursuing intervention analysis with control groups (Harvey, 1996). Examined crime rate series include burglary, larceny, motor vehicle theft, robbery, aggravated assault, murder, and rapes. Definitions of these crime categories are given in the Appendix.

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 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 local communities level. In addition, there were also favorable 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 complexities inherent in understanding the factors associated with the change in crime rates, 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 offenses, while Virginia abolished parole for all felony offenses. 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 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 Departments of Criminal Justice or 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 detail 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, respectively. 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.

2 Changes in Criminal Justice System of Virginia

The abolition of parole in Virginia was proposed during the 1993 George Allen's campaign for Governor. A key element of the campaign was to reduce the disparity between the sentence imposed in court and the actual time-served. This meant to eliminate or reduce "good-time" credit and abolish parole. As Governor, Allen established the Commission on Parole Abolition and Sentencing Reform. This Commission formed by crime victims, law enforcement professionals, judges, prosecutors, business and civil letters, and other state and local officials recommended a "plan to abolish parole, establish truth-in-sentencing, incarcerate violent and repeat offenders significantly longer, institute more productive and economical methods to punish non-violent criminals, and expand prison capacity"[1].

In September 1994 a special session of the Virginia General Assembly was held to take up the recommendations of the Governor's Commission. After days of deliberation and compromise, parole was abolished for offenders convicted of a felony committed on or after January 1, 1995. As specified in Code of Virginia $$53.1-202.2 and $$53.1-202.3 offenders would now have to serve at least 85% of any sentence imposed for a felony. An offender could still have a sentence reduction based on "good-time" credit or "earned sentence credit", but the credit was reduced from thirty days per thirty days served to a maximum of four and one-half days per thirty days served. Furthermore, it was envisioned that an offender would have to earn the reduction by participating and cooperating in programs in which they were assigned.

In addition to a significant reduction in "good-time" credit, the enabling legislation established criteria for developing discretionary felony guidelines. The newly created Sentencing Commission was required by $17.237 of the Code of Virginia (recodified to $17.1-805) to adopt sentencing guideline midpoints based on actual time-served "for similarly situated offenders, in terms of their conviction offense and prior criminal history, increased by 13.4 percent" (to account for earned-sentence credits) "and second, by eliminating the upper and lower quartiles"[2]. To address offenders who committed violent offenses, the sentence for first and second degree murder, forcible rape, forcible sodomy, object sexual penetration and aggravated sexual battery were increased by 125%. For voluntary manslaughter, robbery, aggravated malicious wounding, malicious wounding and any burglary of a dwelling or any burglary with a firearm the midpoint was increased by 100% over historical time-served. These increases were established for offenders with no previous violent offense conviction.

Offenders with prior convictions for violent felonies were also recommended for additional enhancements over historical time-served. The General Assembly established by statute the offenses that would constitute violent offenses. As expected murder, rape, robbery and felony assault charges were included. In addition some offenses not usually thought of as violent (e.g., burglary, obscenity and possession of weapons offenses) would increase the sentencing guidelines recommendation[3]. An offender with a prior conviction for a violent offense with a statutory maximum of forty years or more would have a guidelines recommendation increased by 300% to 500% over historical time-served. A prior violent felony with a statutory maximum of less than forty years increased the guidelines recommendation by 100% to 300%[4].

[1]Governor's Commission on Parole Abolition and Sentencing Reform, Final Report, August 1994.

[2]Code of Virginia.

[3]See Code of Virginia §17.1-805(C) or Sentencing Guidelines Manual 7th Edition Table A.

[4]Virginia Criminal Sentencing Commission, 1995 Annual Report, page 10-11 Note: First and second degree

Discretionary sentencing guidelines were developed based on the statutory requirements and were implemented for any offender who committed a felony offense on January 1, 1995 or after. In many non-violent cases, judges would need to impose a sentence that seemed significantly lower than the sentences handed down under the parole system. Even though, the reality was that the offender would serve at least the same amount of time as he or she would under the parole system. After the first year of truth-in-sentencing, judges were in agreement with the guidelines in 75% of the cases. Judges went above the guidelines 15% of the time and below the guidelines recommendation in 10% of the sentencing. At the end of fiscal year 2001, judges continue to sentence within the guidelines recommendation in eight out of ten cases. Judges were more likely to sentence within the guidelines recommendations for non-violent offenses such as larceny, drug and traffic than for violent offenses of rape, murder and robbery.

The net result of the implementation of the legislation was a substantial increase in the sentences for the violent offenses (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 offenses; (b) group that had prior offenses with a statutory maximum less than 40 years (roughly corresponding to non-violent prior offense); (c) group of offenders that had prior offenses with a statutory maximum greater then 40 years (roughly corresponding to a prior record with violent offenses).

As can be seen from Table 1, increases in time-served were especially high after the imple-

murder, rape, forcible sodomy, object sexual penetration and aggravated sexual battery midpoints were increased by 125% for no prior violent felony, 300% for prior violent felony with statutory maximum less than forty years and 500% with prior violent felony with a maximum of 40 years of more. A first degree murder conviction in combination with a prior violent felony with a maximum of forty years or more is recommend for a life sentence. Voluntary manslaughter, robbery, aggravated malicious wounding, malicious wounding, burglary of a dwelling, burglary with a weapon midpoints were increased by 100% for no prior violent offense, 300% for prior violent felony with less than forty year maximum, and 500% with prior violent felony with forty or more maximum. Sale etc. of a Schedule I/II drug midpoints were increased only for offenders with a prior violent felony; a 200% increase for prior felony with maximum of less than 40 years and 400% increase for violent felonies with maximum of 40 years or more. Midpoints were increased for all other felonies by 100% for prior felony with maximum of less than forty and 300% for prior felony with a maximum of forty years or more.

[5]FY93 Used because parole was an issue in the 1994 campaign and parole grant rates began to change prior to the abolition of parole.

[6]Virginia Criminal Sentencing Comission 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 Comission.

Offense	Released FY93[5] Median time	Sentenced FY01 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

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).[6]

mentation 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. As example, 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 (Johnson, Golub and Dunlap, 2000), policing and community policing (Eck and Maguire, 2000), growth in prison expansion (Spelman, 2000), reductions in use of handguns (Blumstein and Wallman, 2000), expanding economy (Grogger, 2000) and changing demographics (Fox, 2000). 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 offenses, we would anticipate these decreases in crime rates to be significant for the violent offenses.

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. 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 data until the end of 1998. The monthly unemployment rates that we will be using in the analysis are obtained from the U.S. Bureau of Labor Statistics.

Figures 1 and 2 present the reported crimes rates for property and violent crimes respectively[7]. Rather interestingly, it can be observed from the graphs that most of these crimes were already declining when parole was abolished in January 1995.

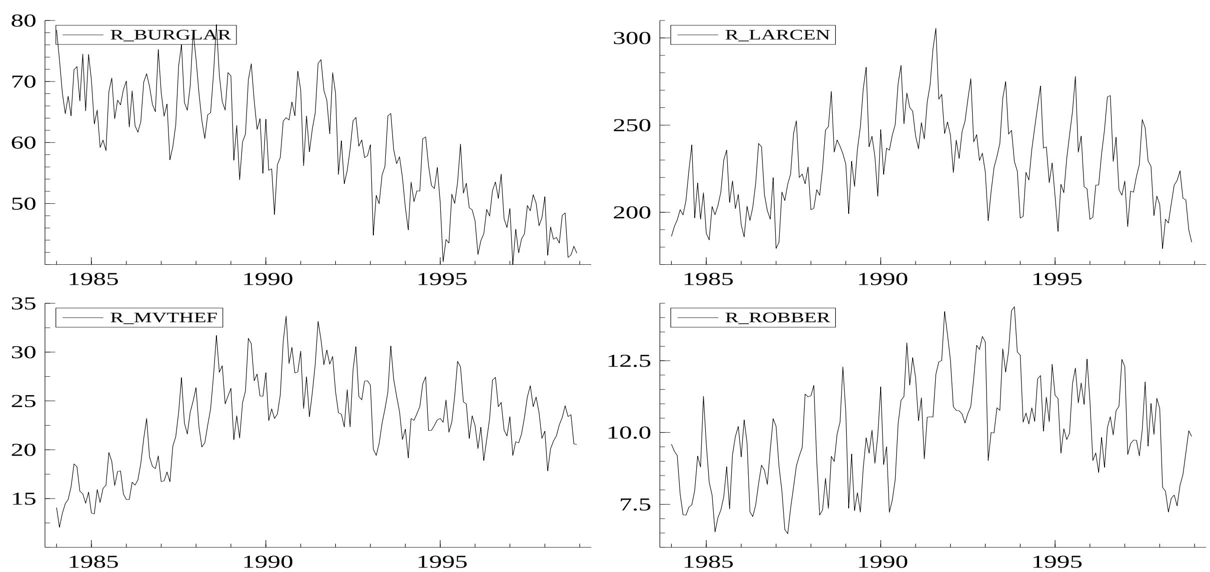

Figure 1: Crime Rates for Property

3.2 Software

The computations for the regression models (with and without ARMA errors) are done by PcGive of Hendry and Doornik (2001). The intervention ARIMA models are implemented

[7]Following the UCR categorization scheme, robberies were included together with the property crimes.

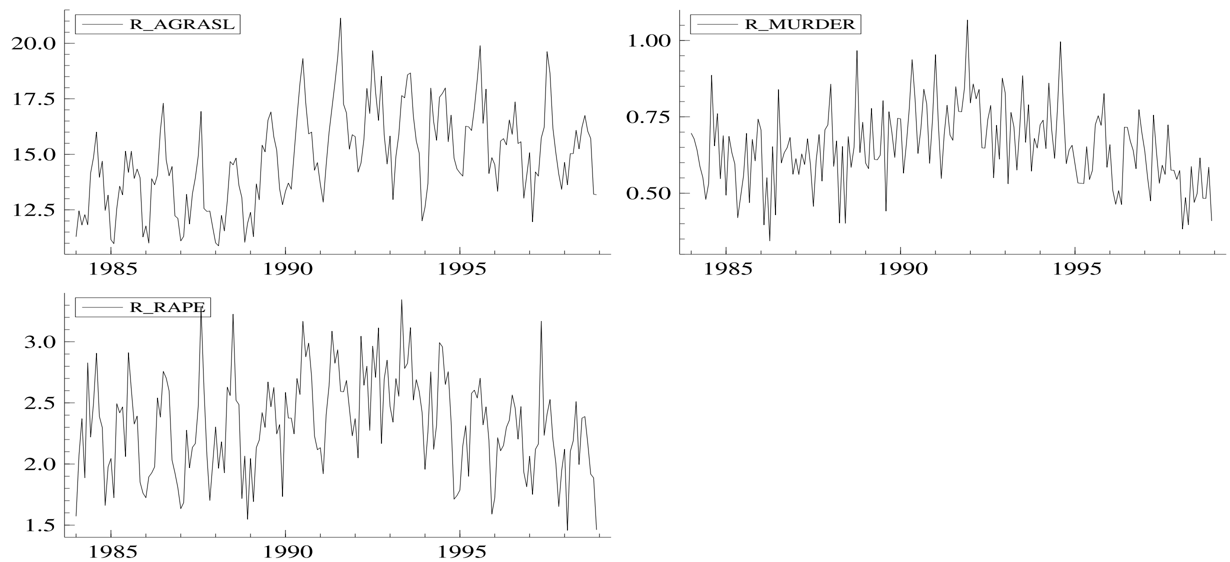

Figure 2: Crime Rate for Violent Crimes

using a combination of the SCA software of Liu et al. (1992) and the ITSM2000 software of Brockwell and Davis (2002). The structural time series models (univariate and multivariate) are estimated using STAMP of Koopman et al. (2000).

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 modeled as the level shift or step intervention, where the value of the level of the time series instantly changes at the time point when the intervention takes place, and where the level change is permanent after the intervention. The impact of

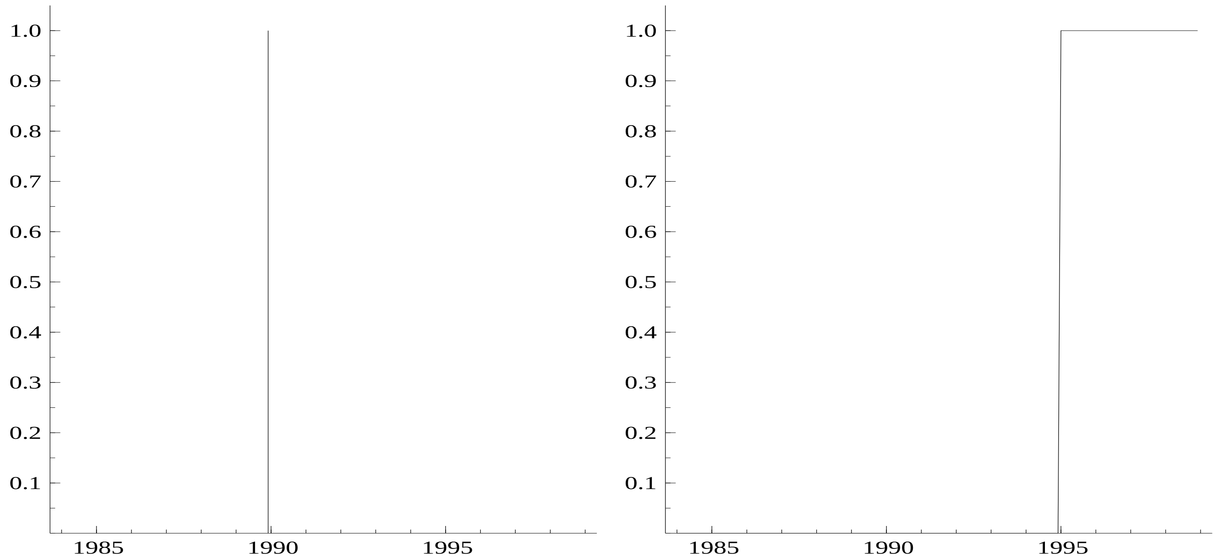

Figure 3: Intervention effects

the intervention is assumed to start instantaneously from January 1995 since Governor Allen was elected in November 1993 on a platform whose primary focus was parole abolition and sentence reform. Even before parole was formally abolished, there was considerable focus in the media on changes in criminal justice sentencing. When parole was formally abolished in a special legislative session in September-October 1994, there was considerable media coverage of this session and often the focus was on the enhancement in time-served of violent offenses. The reality was that a majority of offenders (mostly non-violent) would not be serving additional enhancements over the time served. However, this fact was not stressed in the media coverage. In the months preceding January 1st 1995, there was considerable focus in the media on the "severity" of the new parole abolition system. Hence it was assumed that the deterrent impact of the legislation would occur very soon after January 1st, 1995.

In the present context, the intervention analysis of the impact of parole abolition and sentence reform on crime rates is assessed from various time series approaches. The effect of the intervention are estimated using regression, ARIMA and structural time series models[8]. In all three different models, the intervention is introduced as a step type of intervention. The results do not lead to conclusive evidence and therefore more elaborate models are considered. First, we consider the inclusion of monthly unemployment rates for Virginia in the regression and structural time series models[9]. Second, we present an analysis of a selected group of

[8]Techniques based on intervention analysis using structural time series models have not yet been applied in criminological settings, to our knowledge.

[9]Ideally we would have liked access to monthly time series measures of a number of factors that could serve

crime rates simultaneously using a multivariate extension of the structural time series model. Taken the various approaches together we can conclude that some deterrent impact of the new legislation is noticeable for crime series with a violent nature.

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 are 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.

3.5 Regression analysis

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

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

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 (or covariates) and β is a $k \times 1$ vector of regression coefficients. The variable that

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 complex. As described by Cantor and Land (1985), both motivation and opportunity components need to be modeled 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.

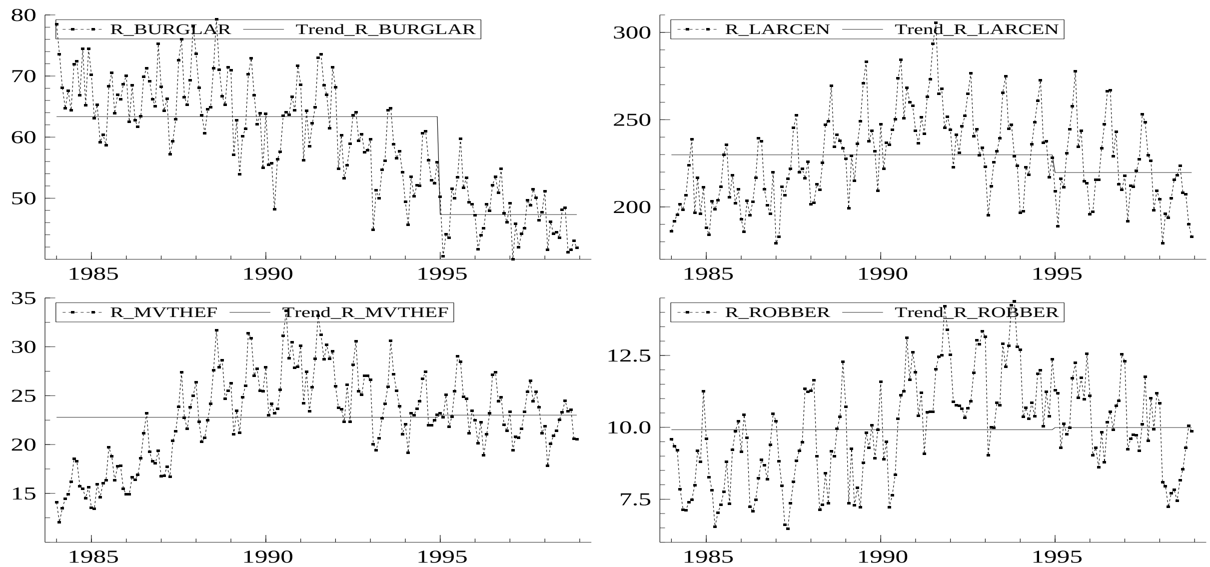

Figure 4: Mean Change in Property Crime Rates

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 $t = 1, \ldots, n$. 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 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. 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)[10].

[10]For seasonal data with a trend, the R^2 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 substracting the seasonal means from the data's first differences (Δy_t). The coefficient of deter-

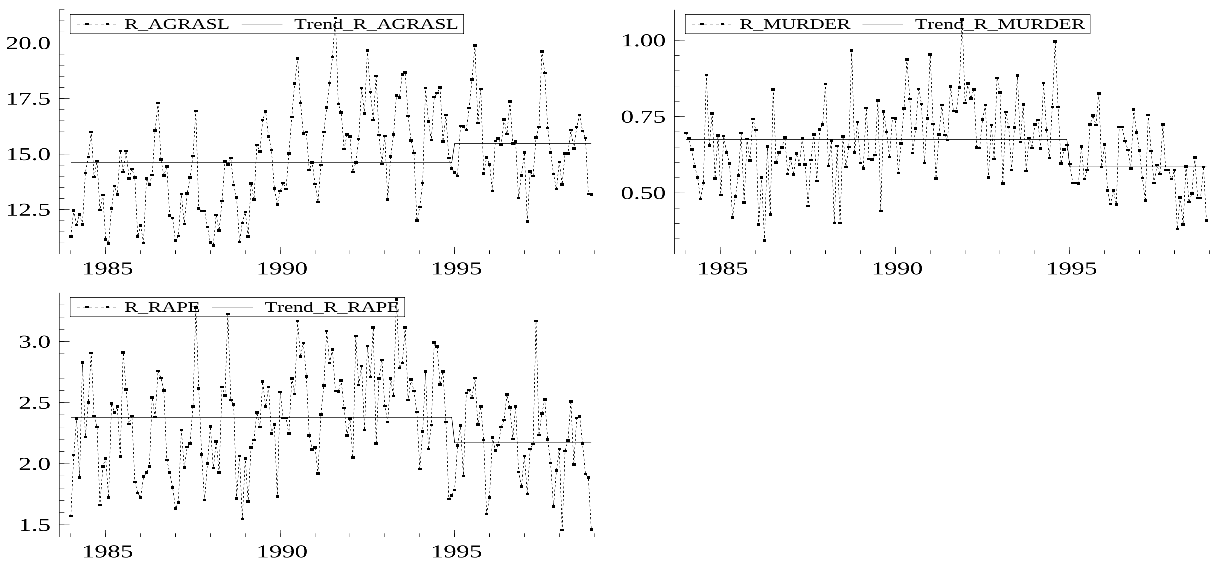

Figure 5: Mean Change in Violent Crime Rates

In most cases significant intervention effects are reported, but the diagnostic test statistics, and in particular the Q statistics and the goodness-of-fit R_s^2 measures, are not satisfactory. The former specifically indicates that the regression errors are serially correlated and therefore the regression effects are not reliable. By presenting these results we emphasize that intervention analysis based on simple regressions are not appropriate for seasonal time series such as for crime rates. This also applies to basic descriptive statistics for mean changes before and after an intervention.

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[11], we may consider autoregressive moving average (ARMA) processes for the explicit modeling of the serial dependence. The regression model with ARMA disturbances is given by

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

mination 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).

[11] In the time series econometrics literature this is known as trend-stationarity.

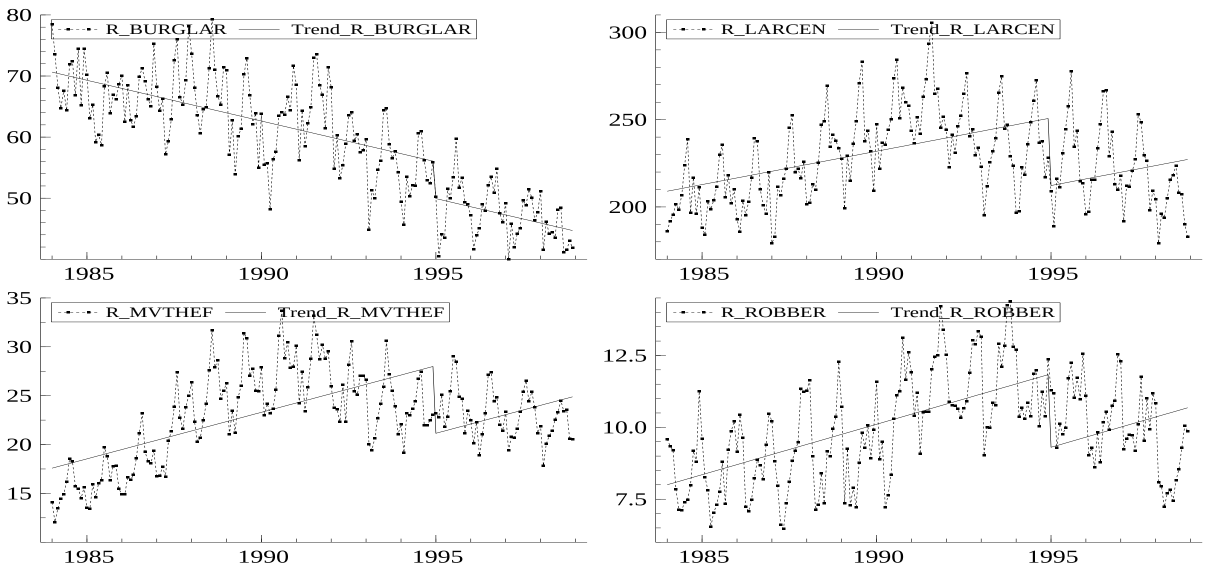

Figure 6: Trend Change in Property Crime Rates

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

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

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. The choice of p and q is usually done on a trial and error basis , following the three-stage iterative procedure of *model selection* as defined by Box and Jenkins (1976). In the first stage, *identification*, a preliminary model is selected on the base of the appearance of the autocorrelation function (ACF) and the partial autocorrelation function (PACF)[12]. Given p and q, the parameters are then estimated by the maximum likelihood (ML) method. As a result of the *estimation* stage, residuals are computed and used as the basis for *diagnostic checking*. A direct plot of the residuals can be a preliminary test for departures from randomness. A statistically valid check is based on testing if sample autocorrelations are not statistically different from zero. To check this, portmanteau Ljung-Box-Pierce $Q(p)$ test statistic is used (Harvey, 1993) and tested against an appropriate significance value from the χ^2_{P-p-q} distribution[13]. A significant departure from randomness indicates that the model is inadequate. In this case, a return to the identification stage is necessary and the complete three-stage process is repeated until a suitable formulation of the model is found.

[12]Identification is based on the ACF and PACF which are estimated from the pre-intervention series. The pre-intervention series is examined, because the intervention can change the form of the time series.

[13]P should be chosen in such a way so as to be reasonably large compared to $p+q$. A rule of thumb is to set P equal to $\sqrt{T}$.

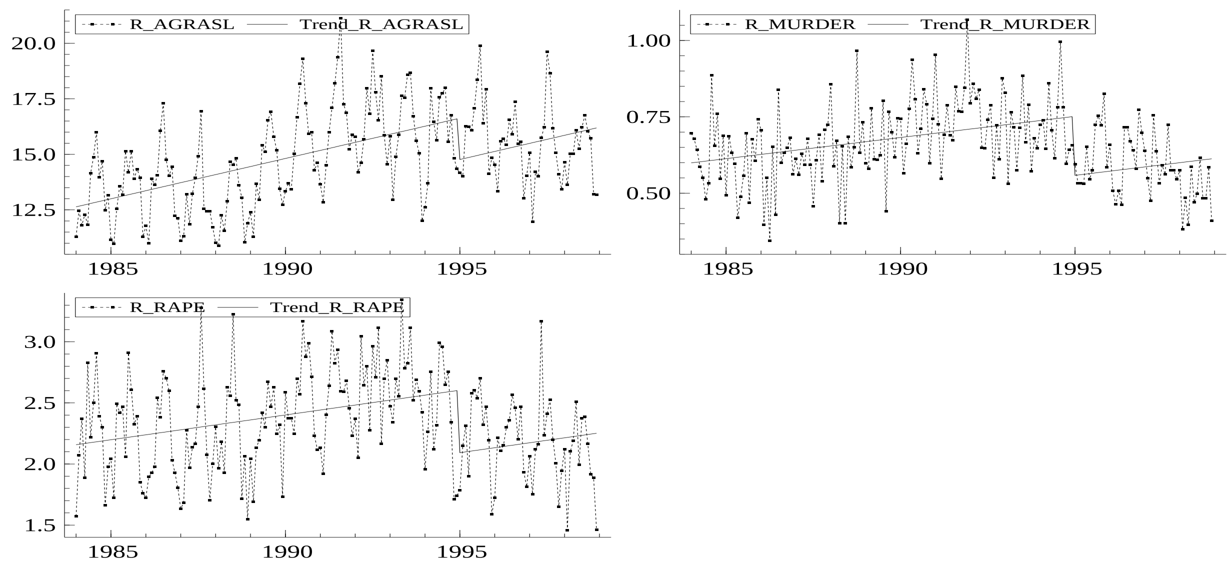

Figure 7: Trend Change in Violent Crime Rates

The model with the best fit and with satisfactory diagnostic statistics for normality, serial independence and homoskedasticity is chosen as the optimal model.

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 with little statistical significance. Strong negative effects of the legislation are only found for murder and rape. No statistically significant effects are found for the property crimes and aggravated assault. The diagnostics for these regression results are more satisfactory compared with the earlier regression results. We therefore regard the results reported in Table 3 as more reliable.

Results are also reported for models that include the explanatory variable unemployment and the dummy outlier variable for December 1989 that has shown to be significant in many series. The series with 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 are complex, these results are of interest. On the other hand, the interventions for parole legislation do not change significantly whether explanatory variables are included or not. Although for the series where unemployment is significant, the effect of the legislation becomes less pronounced except for robbery. In order to assess to what extent these preliminary results are reliable, we conduct a more rigorous time series study bases on two model-based methodologies: the Box-Jenkins analysis and the structural time series analysis.

4 Box-Jenkins ARIMA model approach

Most social and economic time series encountered in practice are non-stationary. The ARIMA methodology, developed by Box and Jenkins, is based on the idea that series can be made stationary by operations such as differencing. In the case that the time series is difference stationary, it can be transformed to stationarity by taking first or second differences (or when needed, even higher order differences), possibly in combination with seasonal differencing. Formally we define first and second differences by

$$\Delta y_t = y_t - y_{t-1}, \qquad \Delta^2 y_t = \Delta y_t - \Delta y_{t-1} = y_t - 2y_{t-1} + y_{t-2},$$

respectively, and seasonal differences by

$$\Delta_s = y_t - y_{t-s},$$

where s is the seasonal length (for example, $s = 12$ for a monthly time series). After taking the appropriate differences, the resulting time series will exhibit features of a stationary time series so that the appropriate ARMA(p, q) process can be used to model the remaining serial correlation in the series.

There are different ways in which one can decide on the appropriate degree of differencing (Harvey, 1993). The preliminary approach is to plot the data in levels and differences in order to make a judgement of which plots show trending movements. In the next step, an examination of the correlogram is necessary. For a stationary process, the main feature of the correlogram is that the autocorrelations tend toward zero as the lag increases. Finally, unit root tests provide a more formal approach to determining the degree of differencing. More on unit root testing procedures can be found in Hamilton (1994).

Once the observations have been differenced, estimation and diagnostic checking may proceed as for an ARMA model. The proposed model

$$(1 - \phi_1 B - \ldots - \phi_p B^p)\Delta^d u_t = (1 + \theta_1 B + \ldots + \theta_q B^q)\varepsilon_t. \tag{4}$$

is called an *autoregressive-integrated-moving average process* of order (p, d, q) and denoted as ARIMA(p, d, q). In the above expression, B is the back shift or lag operator such that $B^k u_t = u_{t-k}$ and p and q are fixed integers. The difference function is in the back shift operator contains unit root coefficients, that is $\Delta^d = (1 - B)^d$. The disturbance ε_t is a white noise term (serially uncorrelated across time) and will be assumed normally distributed.

The resulting impact assessment model can be represented as

$$y_t = \delta I_t + u_t, \tag{5}$$

where u_t is given by the ARIMA(p, d, q) model. The use of ARIMA models for analysing time series intervention effects is due to the work of Box and Tiao (1975).

An extension of the ARIMA(p, d, q) model (4) is required to analyse time series with an evolving seasonal process. This can be handled by the use of seasonal differences. The first step is to generalise (4) to:

$$\phi(B)\,\Phi(B^s)\,\Delta^d\Delta_s^D u_t = \theta(B)\,\Theta(B^s)\,\varepsilon_t, \tag{6}$$

for $t = d + sD + 1, \ldots, T$ and where D is the degree of seasonal differencing; we have $\Delta = 1 - B$ and $\Delta_s = 1 - B^s$. The lag polynomial functions are given by

$$\phi(B) = (1 - \phi_1 B - \ldots - \phi_p B^p), \qquad \Phi(B^s) = 1 - \Phi_1 B^s - \cdots - \Phi_P B^{P_s}, \tag{7}$$

$$\theta(B) = (1 + \theta_1 B + \ldots + \theta_q B^q), \qquad \Theta(B^s) = 1 + \Theta_1 B^s + \cdots + \Theta_Q B^{Q_s}, \tag{8}$$

$$\tag{9}$$

This model is known as a *multiplicative seasonal* ARIMA model of order $(p, d, q) \times (P, D, Q)_s$.

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

$$(1 - B)(1 - B^s)u_t = (1 - \theta B)(1 - \Theta B^s)\varepsilon_t,$$

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 effects generally well.

Table 4 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 $(1, 0, 0) \times (0, 1, 1)_{12}$ 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 interventions are detected. No statistically significant effects at all were found for the property crimes (except for burglary) and aggravated assault. The results in Table 4 do illustrate the sensitivity of the results with respect to the choice of differencing parameters d and D as part of a Box-Jenkins ARIMA analysis.

5 Structural time series models

Structural time series models are formulated directly in terms of components of interest, that is, trend, seasonal, and error components, plus other relevant terms. This approach is strongly opposed to the philosophy of ARIMA models, where the series are differenced prior to any type of analysis, in order to remove trend and seasonal. Hence, time series modelling is often more straightforward in a STS framework as compared to ARIMA approach. In this part, we shall present the structural time series models.

5.1 The basic structural time series model

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

$$y_t = \mu_t + \gamma_t + \varepsilon_t, \qquad t = 1, ..., n, \tag{10}$$

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 (10) 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*[14] as given by

$$\begin{aligned} y_t &= \mu_t + \varepsilon_t, \qquad \varepsilon_t \sim N\left(0, \sigma_\varepsilon^2\right), \\ \mu_{t+1} &= \mu_t + \eta_t, \qquad \eta_t \sim N\left(0, \sigma_\eta^2\right), \end{aligned} \tag{11}$$

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*:

$$\begin{aligned} y_t &= \mu_t + \varepsilon_t, \qquad \varepsilon_t \sim N\left(0, \sigma_\varepsilon^2\right), \\ \mu_{t+1} &= \mu_t + \nu_t + \xi_t, \qquad \xi_t \sim N\left(0, \sigma_\xi^2\right), \\ \nu_{t+1} &= \nu_t + \zeta_t, \qquad \zeta_t \sim N\left(0, \sigma_\zeta^2\right). \end{aligned} \tag{12}$$

[14] 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.

The local linear trend model contains two state equations: one for modelling the level, and one for modelling the slope. If $\xi_t = \zeta_t = 0$, then $\nu_{t+1} = \nu_t = \nu$, and $\mu_{t+1} = \mu_t + \nu$ so that the trend is exactly linear and (12) reduces to the deterministic linear trend plus noise model. The form (12) with $\sigma^2_\xi > 0$ and $\sigma^2_\zeta > 0$ 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. In the case of a monthly time series the stochastic specification of the trigonometric seasonal component is given by

$$\gamma_t = \gamma_{1t} + \ldots + \gamma_{6t}, \tag{13}$$

where

$$\begin{pmatrix} \gamma_{j,t+1} \\ \gamma^*_{j,t+1} \end{pmatrix} = \begin{bmatrix} \cos\lambda_j & \sin\lambda_j \\ -\sin\lambda_j & \cos\lambda_j \end{bmatrix} \begin{pmatrix} \gamma_{jt} \\ \gamma^*_{jt} \end{pmatrix} + \begin{pmatrix} \omega_{jt} \\ \omega^*_{jt} \end{pmatrix},$$

with frequency $\lambda_j = \pi j/6$, for $j = 1, \ldots, 6$. The disturbances are serially and mutually uncorrelated and they are normally distributed with mean zero and variance matrix

$$\mathrm{Var}\begin{pmatrix} \omega_{jt} \\ \omega^*_{jt} \end{pmatrix} = \begin{bmatrix} \sigma^2_\omega & 0 \\ 0 & \sigma^2_\omega \end{bmatrix}.$$

For γ_{6t} we have $\lambda_6 = \pi$, $\cos\lambda_6 = -1$ and $\sin\lambda_6 = 0$ so that γ^*_{6t} does not have an influence on γ_{6t} and it can therefore be excluded from the model. The ω_{jt}'s and ω^*_{jt}'s are restricted to have a common variance σ^2_ω but this restriction can be relaxed so that they have different variances for $j = 1, \ldots, 6$. More details for the basic structural time series model and its dynamic properties are given by, for example, Harvey (1989) and Durbin and Koopman (2001).

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 (10) and we obtain

$$y_t = \mu_t + \gamma_t \lambda I_t + \varepsilon_t, \qquad t = 1, ..., n, \tag{14}$$

where I_t is defined as in (1) and λ is a fixed but unknown coefficient. It follows that λ measures the change in the level of the series at a known time τ. The resulting model can be put into the state space form.

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 on 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 a bit further in the next section.

5.2 Inclusion of unemployment as explanatory variable

Explanatory variables can also be incorporated in the structural time series model framework. Suppose we have k regressors $x_{1t}, ..., x_{kt}$ with unknown regression coefficients $\beta_1, ..., \beta_k$ which are constant over time. By adding the regression effects into model (14) we obtain

$$y_t = \mu_t + \gamma_t + \sum_{j=1}^{k} \beta_{jt} x_{jt} + \lambda I_t + \varepsilon_t, \qquad t = 1, ..., n, \tag{15}$$

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). For the case of motor vehicle theft it can be seen from the trend without explanatory varaibles 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 does not provide much support for statistically significant impacts of the legislation on reported crime rates generally.

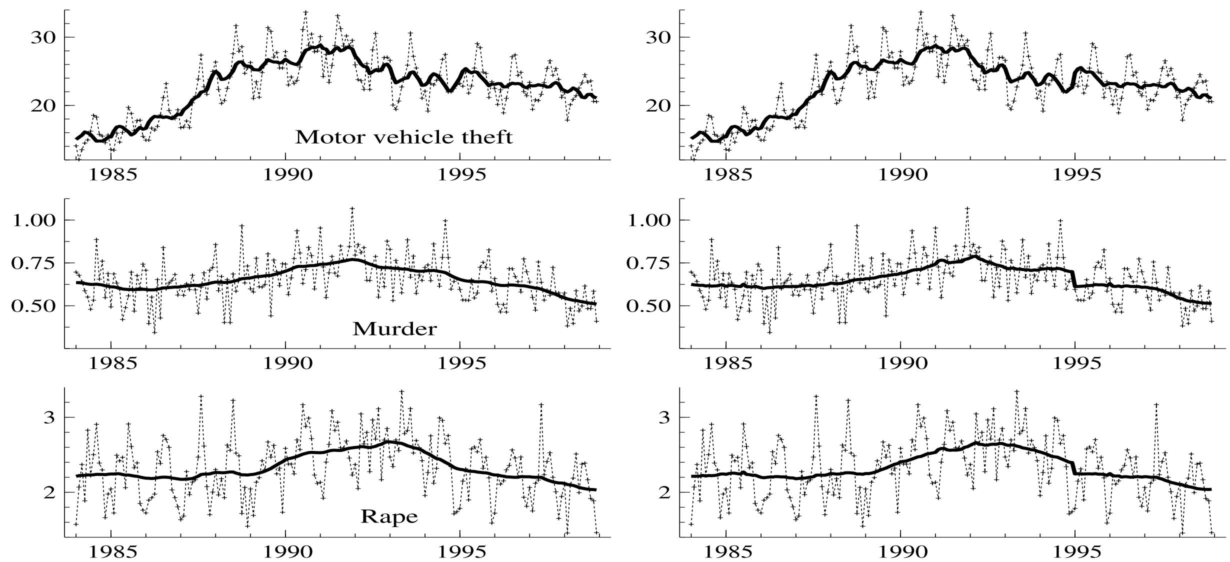

Figure 8: Data and estimated trends for Motor vehicle theft, Murder and Rape using structural time series models without explanatory variables (panels on the left) and with parole abolition and unemployment as explanatory variables (panels on the right).

5.3 Multivariate structural time series models

Until now, we have discussed univariate structural time series models, which means that we model 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 (10) 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 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 arguments hold 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 multivariate regression model.

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 convincingly than the results from an univariate state space approach because more time series are involved simultaneously for 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 to be significant. The maximum t-value is obtained for murder and equals 1.47.

6 Discussion and conclusion

Proposed models for analysing the effects of parole abolition and sentence reform in Virginia clearly favour ARIMA or structural time series 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 - there may be three sources of noise that might eliminate the intervention effect. These are 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 include all these effects and are more effective approaches in analysing 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. The possible explanation for the non-significant effect on the aggravated assault would be the very method in which this category is reported. In contrast to other crimes, which are relatively well defined, "aggravated" assault requires discretion on the part of the police taking the report to distinguish it from "simple" assault. This way of reporting leaves room for the exercise of discretion and there is a possibility that the nature of this distinction has been changing over time (Blumstein, 2000). Hence, this might be a reason for the non-significant intervention coefficient of the aggravated assault which is, by definition, a violent offense.

However, after including unemployment rates in the models, there is very limited support for the deterrent impacts of the intervention on any of the offenses. Specifically, we still find the impact of the intervention to be negative on the reported rate 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 wider data-set, future analysis in this direction would necessarily need to encompass these other factors as well.

We stress that this paper is not intended to be a comprehensive evaluation of the impact of parole evaluation. There are multiple criteria to judge the impacts of a complex intervention such as parole abolition and sentence reform. Some of these might include: issues of equity (have gender and race disparities under the new system been reduced?), cost-effectiveness, and ethical criterion (what are the ethics of abolishing parole?). Further, the present paper only examines the deterrent impacts of the new legislation; it is possible that the increases in time-served for the most violent offenses and offenders would result in reductions in crime due to incapacitation effects. However, with only 4 years of post- intervention data we are not in a position to measure the incapacitation effects of this legislation. Our focus has only been on reported crimes. A more comprehensive evaluation does need to focus on multiple outcome measures including arrest rates, changes in conviction patterns, and changes in the mix of offenders flowing through the criminal justice system.

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 favorable) 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. The regression and ARIMA models assume a single parameter working throughout the time period. The structural time series framework provides a broader framework and allows the parameters to change over the time period. This approach based on unobserved (possibly nonstationary) components does not require differencing which can result in messy time series when outlying observations are present. Moreover, the incorporation of explanatory and intervention variables is straightforward. Finally, the structural time series models are flexible and can be generalised to a multivariate setting without much extra effort. From our perspective, the structural time series models 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.

Appendix

Definitions of the analysed crime categories (Levitt, 1996):

1. *Motor Vehicle Theft* - The theft or attempted theft of a motor vehicle.

2. *Burglary* - The unlawful entry of a structure to commit a felony or a theft. Attempted forcible entry is included.

3. *Robbery* - The taking or attempting to take anything of value from the care, custody, or control of a person or persons by force, or threat of force, or violence, and/or by putting the victim in fear.

4. *Larceny* - The unlawful taking of property from possession of another. Examples are thefts of bicycles or automobile accessories, shoplifting, pocket-picking, or the stealing of any property or article which is not taken by force and violence or by fraud. Attempted larcenies are included. Embezzlement, “con” games, forgery, and worthless checks are excluded.

5. *Aggravated Assault* - An unlawful attack by one person upon another for the purpose of inflicting severe or aggravated bodily injury. This type of assault usually is accompanied by the use of a weapon or by means likely to produce death or great bodily harm. Simple assaults are excluded (Levitt, 1996).

6. *Murder* - The unlawful killing of one human by another, especially with premeditated malice. Source: The American Heritage Dictionary of the English Language, 2000, Fourth Edition, Houghton Mifflin Company.

7. *Forcible Rape* - The carnal knowledge of an individual against his or her will. Included are rapes by force and attempts or assaults to rape.

References

Balkin, S. and J. K. Ord (2001), *Assessing the impact of speed-limit increases on fatal interstate crashes*, Journal of Transportation and Statistics : 1-26.

Blumstein, A. (2000), *Disaggregating the Violence Trends.* In Blumstein, A. and Wallman, J. (eds.), The Crime Drop in America, Cambridge University Press, New York, NY, pp. 13-44.

Blumstein, A. and J. Wallman (eds.) (2000), *The Crime Drop in America*, Cambridge University Press, New York, NY.

Blumstein, A. and J. Wallman (2000), *The recent rise and fall of American violence.* In Blumstein, A. and Wallman, J. (eds.), The Crime Drop in America, Cambridge University Press, New York, NY, pp. 1-12.

Box, G. E. P. and G. M. Jenkins (1976), *Time Series Analysis: Forecasting and Control*, revised edition, Holden-Day, San Francisko, CA.

Box, G. E. P. and G. C. Tiao (1975), *Intervention analysis with applications to economic and environmental problems*, Journal of American Statistical Association, pp. 70-79.

Brockwell, P. J. and R. A. Davis (2002), *Introduction to Time Series and Forecasting*, Second Edition, Springer, ITSM2000 time series package.

Cantor, D. and K. C. Land (1985), *Unemployment and crime rates in the post world War II United States: A theoretical and empirical analysis*, American Sociological Review 50:317-332.

Cantor, D. and K. C. Land (2001), *Unemployment and Crime Rate Fluctuations: A comment on Greenberg*, Journal of Quantative Criminology 17:329-342.

Durbin, J. and S. J. Koopman (2001), *Time Series Analysis by State Space methods*, Oxford University Press, Oxford.

Eck, J. and E. Maguire (2000), *Have changes in policing reduced violent crime? An assessment of the evidence.* In Blumstein, A. and Wallman, J. (eds.), The Crime Drop in America, Cambridge University Press, New York, NY, Pp. 207-265.

Fox, J. A. (2000), *Demographics and U.S. homicide.* In Blumstein, A. and Wallman, J. (eds.), The Crime Drop in America, Cambridge University Press, New York, NY, 288-317.

Governor's Commission on Parole Abolition and Sentencing Reform (1994), Final Report, Richmond, VA.

Greenberg, D.F. (2001), *Time Series Analysis of Crime Rates*, Journal of Quantative Criminology 17:291-327.

Grogger, J. (2000), *An economic model of recent trends in violence.* In Blumstein, A. and Wallman, J. (eds.), The Crime Drop in America, Cambridge University Press, New York, NY, Pp. 266-287.

Hamilton, J. D. (1994), *Time Series Analysis*, Princeton University Press, Princeton, New Jersey.

Harvey, A. C. (1989), *Forecasting, Structural Time Series Models and the Kalman Filter*, Cambridge, Cambridge University Press.

Harvey, A. C. and J. Durbin (1986), *The effect of seat belt legislation on British road casualties: A case study in structural time series modeling*, Journal of Royal Statistical Society B 149:187-227.

Harvey, A. C. (1993), *Time Series Models*, Prentice Hall International.

Harvey, A. C. (1996), *Intervention analysis with control groups*, International Statistical Review 64: 313-328.

Johnson, B., Golub, A., and E. Dunlap (2000), *The rise and decline of hard drugs, drug markets, and violence in inner-city New York*. In Blumstein, A. and Wallman, J. (eds.), The Crime Drop in America, Cambridge University Press, New York, NY, pp. 164-206.

Koopman, S.J. and Harvey, A.C. (1997), *Multivariate structural time series models* In Heij, C., Schumacher, H., Hanzon, B. and Praagman, C. (eds.), Systematic dynamics in economic and financial models, Chichester: Wiley and Sons, pp. 269-298.

Koopman, S. J., Harvey, A. C., Shephard, N. and J. A. Doornik (2000), *Structural Time Series Analysis, Modeling, and Prediction using STAMP*, Timberlake Consultants Press, London.

Levitt, S. D. (1996), *The Effect of Prison Population Size on Crime Rates: Evidence from Prison Overcrowding Litigation*, The Quarterly Journal of Economics, Volume 111, Issue 2, 319-351.

Liu, L. M., Hudak, G. B., Box, G .E. P., Muller, M. E. and Tiao, G. C. (1992). Forecasting and Time Series Analysis Using the SCA Statistical System. SCA Corp: Chicago.

Loftin, C., Heumann, M., and D. McDowall (1983), *Mandatory sentencing and firearms violence: evaluating an alternative to gun control*, Law & Society Review 17: 287-318.

McCleary, R. and R. A. Hay (1980), *Applied Time Series Analysis for the Social Sciences*, Beverly Hills, Sage.

McDowall, D., Lofton, C., and B. Wiersema (1995), *Easing concealed firearm laws: effects on homicide in three states*, Journal of Criminal Law and Criminology, 86: 193-206.

Orwin, R.G.(1997). Twenty-One Yaers Old and Counting: The Interrupted Time Series Comes of Age. In E. Chelimsky and W.R. Shadish (Eds). Evaluation for the 21st Century, pp. 443-465. Thousand Oaks, CA: Sage.

Spelman, W. (2000), *The limited importance of prison expansion.* In Blumstein, A. and Wallman, J. (eds.), The Crime Drop in America, Cambridge University Press, New York, NY, pp. 97-129

SPSS (1999). SPSS Trends 10.0, SPSS, Chicago.

Virginia Criminal Sentencing Commission (1995), Annual Report, Virginia Criminal Sentencing Commission, Richmond, VA.

Virginia Criminal Sentencing Commission (2001). Annual Report, Virginia Criminal Sentencing Commission, Richmond, VA.

Table 2: Estimated interventions for regression models

		coeff	t-test	N	$Q(20)$	p.e.v.	R_s^2
BURGLAR	Level	-16.04	-14.59	1.19	247.43	42.1	-2.72
	trend	-6.02	-4.29	0.88	245.05	28.38	-1.51
	trend + seas	-5.52	-5.47	3.98	209.86	13.61	-0.2
LARCEN	Level	-10.11	-2.39	3.62	510.51	625.45	-6.3
	trend	-38.75	-6.48	1	485.38	514.04	-5
	trend + seas	-36.92	-9.05	19.47	741.05	222.7	-1.6
MVTHEF	Level	0.23	0.3	15.13	734.93	20.39	-7.32
	trend	-6.91	-7.16	0.76	380.02	13.39	-4.46
	trend + seas	-6.66	-8.15	9.06	792.1	8.94	-2.65
ROBBER	Level	0.08	0.25	4.59	429.43	3.16	-2.71
	trend	-2.55	-6.51	2.35	310.34	2.21	-1.6
	trend + seas	-2.44	-8.05	1.72	231.12	1.23	-0.45
AGRASL	level	0.86	2.42	7.21	547.47	4.41	-2.74
	trend	-1.86	-3.82	3.82	575.43	3.4	-1.88
	trend + seas	-1.78	-5.76	0.86	280.57	1.28	-0.08
MURDER	Level	-0.089	-4.31	2.72	53.6	0.015	0.3
	trend	-0.19	-6.29	2.61	24.12	0.0136	0.36
	trend + seas	-0.19	-6.27	1.72	30.5	0.0122	0.43
RAPE	Level	-0.21	-3.13	0.62	313.86	0.15	-0.54
	trend	-0.51	-5.16	0.22	303.32	0.14	-0.41
	trend + seas	-0.51	-7.44	1.9	32.81	0.06	0.37

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

		coeff	t-test	N	$Q(20)$	p.e.v.	R_s^2
BURGLAR	trseas + ar1	-5.37	-3.13	5.09	28.18	8.93	0.21
	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
LARCEN	trseas + ar1	-18.76	-2.28	48.41	43.01	79.47	0.069
	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
MVTHEF	trseas + ar1	-1.11	-0.73	0.84	28.8	2.34	0.042
	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
ROBBER	trseas + ar1	-1.99	-3.59	0.95	16.75	0.72	0.15
	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
AGRASL	trseas + ar1	-1.58	-3.18	0.098	35.97	0.912	0.22
	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
MURDER	trseas + ar1	-0.19	-5.85	0.94	18.47	0.012	0.44
	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
RAPE	trseas + ar1	-0.5	-6.35	3.69	13.96	0.0604	0.39
	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

Table 4: Estimated interventions for ARIMA models

		coeff	t-test	N	$Q(20)$	p.e.v.	R_s^2
	$\text{ARIMA}(1,0,0)\times(0,1,1)_{12}$	-8.42	-3.64	37.59	33.35	12.17	0.02
BURGLAR	Airline model	-4	-1.56	43.04	18.3	10.86	0.09
	$\text{ARIMA}(1,0,0)\times(0,1,1)_{12}$	-12.27	-1.58	194.7	47.54	96.61	0.008
LARCEN	Airline model	-4.39	-0.69	49.69	19.07	74.14	0.09
	$\text{ARIMA}(1,0,0)\times(0,1,1)_{12}$	0.19	0.12	2.21	30.33	2.68	-0.12
MVTHEF	Airline model	2.18	1.64	1.67	25.43	2.5	0.071
	$\text{ARIMA}(1,0,0)\times(0,1,1)_{12}$	-0.78	-1.32	1.46	36.63	0.903	-0.13
ROBBER	Airline model	0.68	1.03	6.51	16.02	0.788	0.1
	$\text{ARIMA}(1,0,0)\times(0,1,1)_{12}$	-0.14	-0.24	0.05	46.25	1.24	0.01
AGRASL	Airline model	0.27	0.41	4.24	14.6	0.881	0.24
	$\text{ARIMA}(1,0,0)\times(0,1,1)_{12}$	-0.12	-3.87	1.86	33.77	0.0155	0.32
MURDER	Airline model	-0.09	-1.6	1.58	14.55	0.0083	0.58
	$\text{ARIMA}(1,0,0)\times(0,1,1)_{12}$	-0.29	-3.77	1.87	33.73	0.0817	0.06
RAPE	Airline model	-0.13	-0.94	1.96	12.48	0.0461	0.69

Table 5: Estimated interventions for structural time series model

		coeff	t-test	N	$Q(20)$	p.e.v.	R_s^2
BURGLAR	level + seas	-4.67	-1.86	18.15	22.92	10.2	0.1
	trend + seas	-3.97	-1.59	18.82	21.94	10.04	0.11
	trend + seas + outl	-3.74	-1.61	0.63	20.63	8.80	0.22
	level + seas + unempl	-3.51	-1.50	0.80	18.17	8.76	0.23
LARCEN	level + seas	-6.58	-1.02	34.64	19.1	68.62	0.2
	trend + seas	-4.24	-0.68	27.92	20.9	68.67	0.2
	trend + seas + outl	-4.11	-0.69	1.81	20.28	55.15	0.36
	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	0.30
	trend + seas	0.27	0.41	4.10	17.90	0.82	0.30
	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	0.060	0.40
	trend + seas	-0.30	-2.99	1.27	14.98	0.061	0.39
	level + seas + unempl	-0.14	-1.12	2.32	11.56	0.057	0.42

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
ROBBER	multi	·	·	4.33	11.74	0.65	0.23
	multi + unempl	·	·	3.28	12.07	0.65	0.24
MURDER	multi	-0.089	-4.31	1.91	8.14	0.0109	0.49
	multi + unempl	-0.081	-3.33	2.01	8.21	0.0109	0.49
RAPE	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

Table 7: Intervention results for different models (without unemployment)

		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)	-0.2 (-4.3)
	fit	0.37	0.39	0.69	0.39	0.45