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Structural Intervention Time Series Analysis of Crime Rates: The Impact of Sentence Reform in Virginia

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Abstract

We adopt a structural time series analysis to investigate the impact of parole abolition and sentence reform in Virginia 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 change in legislation on reported crime rates from 1995 onwards, we perform an intervention time series analysis based on structural time series models. We empirically find that the change in legislation has significantly reduced the burglary rates and to a lesser extent the murder rates in Virginia. For other violent crimes such as rape and aggravated assault the evidence of a significant reduction in crime rates is less evident or is not found. This empirical study for Virginia also provides an illustration of how an effective intervention time series analysis can be carried out in crime studies.

Keywords: Intervention time series analysis; Crime rates; Structural time series models; Unobserved components time series models.

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1 Introduction

The contributions of Levitt (2001) and Cantor and Land (2001) have prompted an interesting debate on effective intervention time series analysis. These discussions have become more imminent given the increasing interest in the effects of policy changes by governments and crime-prevention programs. Different approaches to intervention time series analysis have been adopted 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., 1980; McDowall et al., 1995). The standard approach to time series analysis in this framework aims at discriminating between the behaviour of the time series prior to the intervention and after the intervention (McCleary and Hay, 1980; Orwin, 1997). The typical research question is: "Given a known intervention, is there evidence that change in the series of the kind expected actually occurred, and, if so, what can be said of the nature and magnitude of the change?" (Box and Tiao, 1975). From the policy perspective it is important to assess whether a known intervention (policy change) has the intended effect. For example, it is important to know whether an increased reliance on prisons, an increased number of police, tougher gun control laws, and innovative criminal justice programs and policies reduces crime rates and deters potential criminals from committing crimes.

Structural time series models may provide an effective approach to the modelling of interventions. The structural approach to time series analysis was popularized by Harvey (1989) and has been applied in various policy and intervention analysis applications. For example, Harvey and Durbin (1986) investigate the effects of the introduction of the seat belt law in 1983 in Great Britain on the number of car drivers killed and seriously injured. Harvey (1996) analyses the effects of the same British seat belt legislation using a multivariate structural time series framework with control groups. Balkin and Keith Ord (2001) investigate the relationship between speed limit increases and traffic-related fatalities in the US. However, the structural time series approach has not been used extensively in crime analysis.[1]

In this paper we adopt the structural time series framework to investigate the impact of parole[2] abolition and sentence reform in Virginia on reported crime rates. The Commonwealth of Virginia abolished parole and reformed sentencing for all felony[3] offences committed on or

[1]To our knowledge, the structural time series methodology applied to crime data is carried out by Harvey and Fernandes (1989) and Atkinson et al. (1997), who look at the number of outliers and breaks in the monthly number of purse (handbag) snatches in Hyde Park in Chicago. Koopman et al. (2008) model recidivism behaviour of juveniles from a Dutch judicial juvenile institution, using a non-Gaussian structural time series model.

[2]Parole is the releasing of a prisoner either temporarily or before his/her period in prison is finished, with the agreement that he/she behaves well; it is also referred to as "good-time" credit or "earned sentence" credit.

[3]Felony is (an example of) a serious crime which can be punished by one or more years in prison.

after January 1, 1995. This law was passed in a special legislative session in the autumn of 1994. Parole abolition was accompanied with substantially enhanced sentences for violent offenders.[4] To examine the impact of Virginia's abolition of parole on reported crime rates, we consider different empirical approaches to the intervention analysis. First we adopt a univariate structural time series approach to the intervention analysis of time series data, which are serially correlated, often non-stationary, and with strong seasonal and/or cyclical effects. The crime rate series examined in this paper are burglary, larceny, motor vehicle theft, robbery, aggravated assault, murder, and rape.

The focus of this paper is on the impact of the new legislation on reported crime rates. Policy changes that increase the expected punishment per crime can lead to both greater deterrence and greater incapacitation (Kessler and Levitt, 1999). By focussing on changes in crime rates immediately after the introduction of a sentence reform in Virginia, we hope to isolate a pure deterrent effect of the new legislation that is not contaminated by the effect of incapacitation. Hence, to the extent that severity of punishment serves as a deterrent to committing crimes in the short run, we would expect the reported crimes to drop especially for the violent offences: aggravated assault, murder, and rape. Given the change in the legislation of Virginia, we test for the significance and magnitude of a decline in the just mentioned crime rate series, if any.

Our sample includes the 1990 to 1999 period when considerable social and economic changes occurred in the United States. There were declines in crime trends throughout the US during this decade. Furthermore, the second half of the 1990s was an economically prosperous period for the US. For example, unemployment rates declined sharply through most of this period. It was also a period in which a number of innovative criminal justice programs and policies were enacted both at the state level and at the local communities level. Favourable changes in patterns of drug use and access to guns were put in place. These factors could serve as alternative explanations for the decline in crime throughout the US in general, and Virginia in particular. Disentangling the impact of parole abolition on crime rates in Virginia from these other factors poses a considerable methodological challenge. We endeavour to tackle this problem of confounding variables by applying the approach of Harvey (1996) and estimating multivariate structural time series models with control groups.

The paper is organised as follows. In Section 2 we discuss the criminal justice situation in Virginia and its recent changes and developments in the parole and sentence systems in more detail. The data are presented in Section 3. The structural time series models for intervention analysis used in this paper are discussed in Section 4. The empirical results of the investigation of the effects of parole abolition and sentence reform on the crime rates in Virginia are presented in Section 5. In Section 6 we discuss the results and conclude.

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

2 Changes in criminal justice system of Virginia

The abolition of parole in Virginia was proposed during the 1993 campaign of George Allen running 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 a 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."[5]

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. This initiative abolished parole, established a guidelines-based truth-in-sentencing system, and increased sentence length for violent offenders. For a more extensive overview of the changes in the sentencing reform introduced in Virginia after January 1, 1995, we refer to Vujić (2009).

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).

The new sentence reform incorporates guidelines with significant increases in recommended prison sentences for all violent offenders. As can be seen from Table 1, increases in time-served were especially high after the implementation of the legislation for robbery, aggravated assault, murder, and rape.

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

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

[7]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.

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)

Offence	Released FY93[6] Median time	Sentenced FY01 Median expected time			
		No prior	Category II Prior < 40	Category I 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**

Source: The Virginia Criminal Sentencing Commission annual report, 1995

Another example of the time served under the new truth-in-sentencing system and old parole system is presented in Figure 1.[8] In Figure 1, prison time served under the parole system is compared to time served under truth-in-sentencing for offenders convicted of first degree murder, forcible rape, and robbery with firearm. Parole system time served is based on time served by inmates released from prison from 1988 to 1992. Truth-in-sentencing time served is estimated based on sentence length for cases sentenced in 1998. All sentence lengths shown are median values.

The upper part of Figure 1 shows that under the previous parole system, offenders convicted of first degree murder with no prior violent record served 12.4 years in prison, whereas under the truth-in-sentencing system, offenders convicted of this offence would now serve more than 37 years in prison. Offenders with a Category II record who were serving about 14 years in prison will now serve 51 years. Offenders with more serious Category I records who were serving about 15 years will now serve more than 95 years in prison. Analogous interpretations apply to rape and murder convictions. Offenders convicted of forcible rape and armed robbery will receive much longer sentences as a results of the new reform. Similar increases have occurred in time served for offenders convicted of other violent offences, as well as for other property and drug offenders with violent prior records.

During the 1990s, Virginia law makers have enacted various laws to respond to the rising

[8]Adapted from "Crime in the Commonwealth, 1988-1998", web address: `http://www.dcjs.state.va.us`

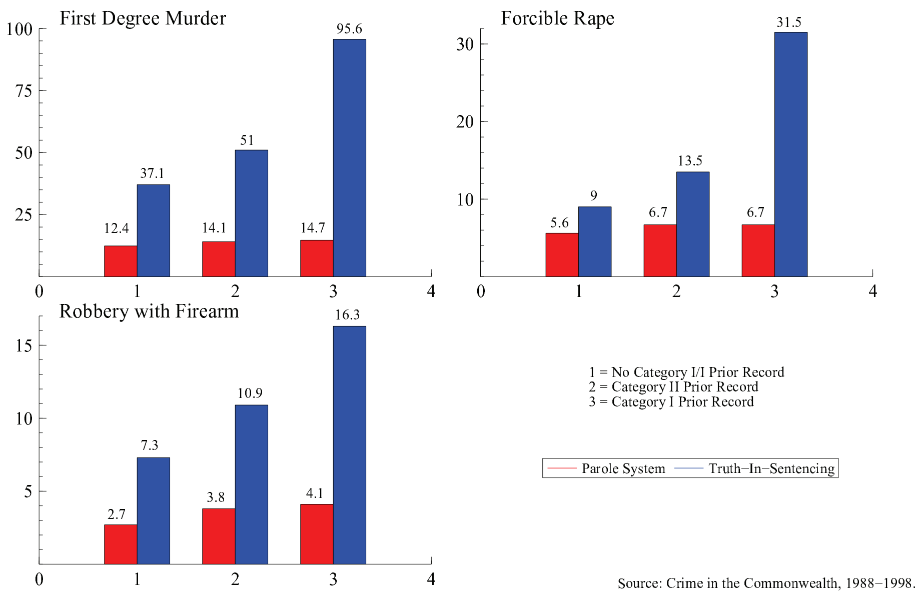

Figure 1: Time served in prison under parole system and truth-in-sentencing system

crime in Virginia. Table 2 summarizes some of the main initiatives passed during this period. In our opinion, only Virginia firearms transaction programme in 1989, one handgun per 30-day purchase limit in 1993, and parole abolition and truth-in-sentencing in 1994 could have served as a deterrent to potential criminals.

To the extent that severity of punishment serves as a deterrent to committing crimes, we would expect the anti-crime initiatives in Virginia to reduce the reported crime rates, especially for violent offences. Figures 2 and 3 in Section 3 show a sharp decline in the analysed crime series during the 1990s, suggesting that these anti-crime initiatives might have had the intended effect. However, it should be noted that sharp declines in violent crime rates have also occurred nationwide and severity of punishment is only one explanation for a drop in crime. A number of alternative explanations can also be used to explain a drop in crime. Blumstein and Wallman (2000a) compile a variety of explanations for the reductions in crime in the US in the 1990s. For example, alternative explanations for drops in crime include: changes in drug use patterns (Johnson et al., 2000), policing and community policing (Eck and Maguire, 2000), growth in prison expansion (Spelman, 2000), reductions in the use of handguns (Blumstein and Wallman, 2000b), expanding economy (Grogger, 2000), and changing demographics (Fox, 2000). According to Levitt and Dubner (2005), the most important crime-drop explanations are increased reliance on prisons, increasing the number of police officers per capita, the crash of the crack market, and the legalisation of abortion.

Despite the complexities inherent in understanding the factors associated with declining crime rates, Virginia's experience with abolition of parole and sentence reform remains of

Table 2: Major Criminal Justice Initiatives in Virginia, 1988-1998

Year	Initiative	Description
1989	**Virginia firearms transaction programme**	A criminal history records check to be conducted on persons purchasing a firearm from a licensed dealer.
1990	DNA analysis & data bank	Persons convicted of a felony must provide a blood sample to produce a DNA profile for storage in the DNA data bank.
1993	**One handgun per 30-day purchase limit**	Limits to one the number of handguns that may be purchased in any 30-day period.
	Serious or habitual offender comprehensive action programme (SHCOAP)	City and county governments can establish multi-agency SHOACPs to share information about serious juvenile offenders.
	Juvenile criminal history records	Police records should maintain fingerprints & case disposition information for juveniles age 13 and older charged with a felony.
1994	Sex offender registry	Police should maintain a registry of persons convicted for sex offences against minors.
	Parole abolition and truth-in-sentencing	Policy intervention which effect we want to empirically test.
	Community-based correction system for state-responsible offenders	Community-based alternative sanctions for state-responsible-offenders.
	Community correction act for local responsible offenders	Community-based corrections programmes as sentencing alternatives.
	Pre-trial services act	Localities can operate pre-trial services programmes to assist judicial officers in bail-related duties.
1995	Virginia juvenile community crime control act	Community-based system of progressively intensive sanctions and services corresponding to the severity of offence, treatment needs and crime trends in the localities.
	Crime victim and witness rights act	Provides crime victims and witnesses with certain legal rights.
1996	Juvenile justice reform	In juvenile proceedings, the welfare of the child and family, community safety, and victims' rights are of paramount concern.

Source: Crime in the Commonwealth, 1988-1998 interest for a number of 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 resulted in steeper declines in crime as compared to expected patterns based on historical data.

3 Data description

We have obtained a data set of monthly time series from the Uniform Crime Reports (UCR) collected by the Virginia State Police in the period from 1984 to, and including, 2010. The pre-intervention period corresponds to the period from January 1984 to December 1994. The post-intervention period corresponds to the period from January 1995 to December 2010. We aim to analyze seven crime variables: burglary, larceny, motor vehicle theft, robbery, aggravated assault, murder, and rape. Next, we shall give a brief overview of the Virginia crime reporting practices.

The UCR is related to a Federal law enforcement programme or a particular city, county or state within the United States (US). It provides a standardized, nationwide view of crime based on data submitted by law enforcement agencies in the US. Hence, we have constructed the data recorded according to the UCR approach, because it enables comparisons of crime statistics across the US. The UCR includes a data summary with counts of aggregated offences known to police and arrests. We consider the number of criminal acts that are reported to the police. The offence rate is, therefore, an indicator of criminal victimization. The number of arrests is taken as a measure of police activity because it relates to crime, see the discussion in Roberts (2005).

UCR summary offences are classified into two groups: Category I and Category II. Category I offences are any prior conviction or juvenile adjudication for a violent crime with a statutory maximum penalty of 40 years or more. Category I offences include: criminal homicide, forcible rape, robbery, aggravated assault, burglary, larceny, motor vehicle theft, and arson. Category II offences are any prior conviction or juvenile adjudication for a violent crime with a statutory maximum penalty less than 40 years. Category II offences include: other assaults, forgery and counterfeiting, false pretences/swindle/confidence games, embezzlement, stolen property offences, destruction/damage/vandalism of property, weapon law violations, prostitution and commercialized vice, sex offences (except rape and prostitution), narcotic drug laws, gambling, offences against the family, driving under the influence, liquor law violations, public drunkenness, disorderly conduct, all other offences (except traffic), curfew/loitering, runaway, and juvenile. Category II offences are recorded in the UCR system only if an arrest occurred. In this paper we shall analyse Category I offences (except arson), because they are the most serious and/or the most frequently reported offences and the best indicators of crime.

The UCR approach is called a “summary” approach because it reports only the most serious offence in a criminal incident, following the Hierarchy Rule. According to the Hierarchy Rule, the most-to-least serious offences are: criminal homicide, forcible rape, robbery, aggravated assault, burglary, larceny, and motor vehicle theft (arson is not subject to this rule). Starting from 2000, Virginia also reported crime data in incident-based format (IBR), where all offences associated with a criminal incident are reported. For example, a homicide that occurs during a robbery with a firearm would be counted as a homicide under the UCR system (one criminal offence), while under the IBR system all three offences would be captured (homicide, robbery, and weapon law violation). Although the IBR approach to recording crime gives a much more detailed picture of crime than the summary system, there are only six states in the US that report crime using the IBR system. Further, the total number of IBR offences is no more than 3.61% higher than the total number for the same offences counted in the UCR system. For the purposes of this paper, we shall therefore use the data in the UCR format in order to ensure consistency of the data in the pre- and post-intervention periods. For more details on UCR versus IBR crime reporting in Virginia, see Roberts (2005).

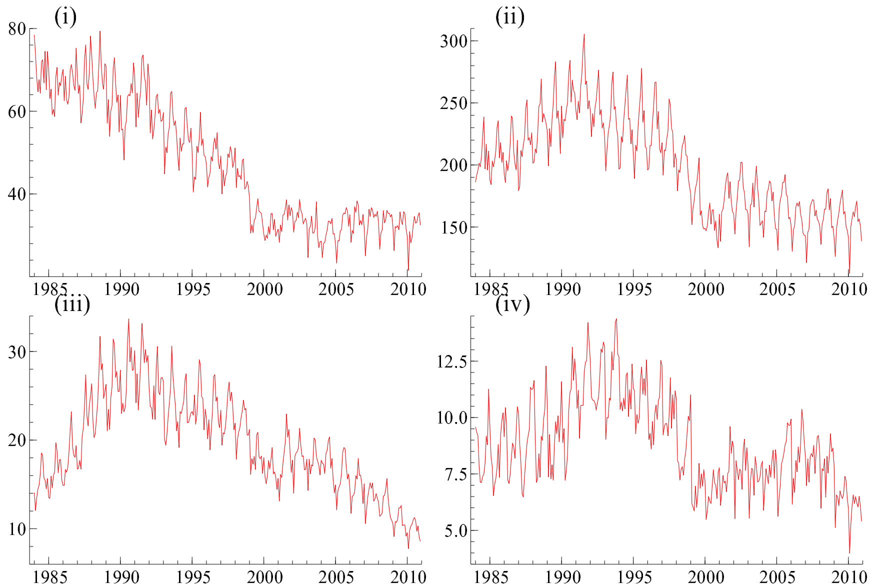

Figure 2: Property crime rates: burglary (i), larceny (ii), motor vehicle theft (iii), and robbery (iv).

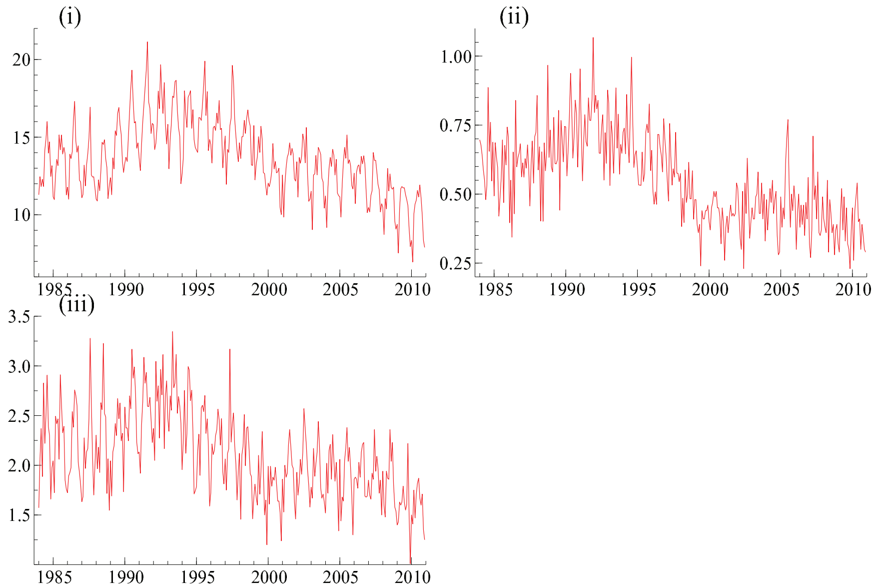

Figure 3: Violent crimes rates: aggravated assault (i), murder (i), and rape (iii).

Figures 2 and 3 present the reported crimes rates per 100,000 population, for property and violent crimes respectively.[9] It can be observed from Figures 2 and 3 that most of the crime series are declining from about the same time that Virginia enacted major legislative initiatives to reduce violent crime. Research to date is unable to determine if these reductions in crime rates are due to specific anti-crime initiatives.[10] Reductions have occurred in the types of crimes that were targeted by these initiatives, indicating that they may have had their intended effect. Declines in violent crime rates in Virginia coincided with declines in violent crime rates nationwide. There is still a lively debate among criminologists and policy makers as to which factors contributed to the crime-drop in the US: the legalisation of abortion 20 years earlier, the expanding economy, community policing, changes in crack and other drug markets, and/or higher arrest and incarceration rates. This paper aims to contribute to a better understanding of the statistical relationship between anti-crime efforts and crime reductions over time.

Policy changes that increase the expected punishment per crime can lead to both greater deterrence and greater incapacitation. The empirical evidence which links increased punishment with lower crime rates is consistent.[11] According to Levitt and Dubner (2005), increases in prison population account for roughly one-third of the drop in crime in the US. However, most empirical tests on deterrence do not separate the effect of deterrence from the effect of incapacitation. Short-run declines in crime are likely to be attributable to deterrence, whereas

[9]Following the UCR categorization scheme, robberies were included together with the property crimes.
[10]Crime in the Commonwealth, 1988-1998.
[11]See for example Ehrlich (1973), Grogger (1991), Kessler and Levitt (1999), Levitt (1997), and Marvell and Moody (1994, 1996).

the incapacitation effect of sentence enhancements will occur only in the long-run (Kessler and Levitt, 1999). In the case of Virginia, the 1994 legislation abolishing parole and establishing a truth-in-sentencing system was a single, most significant factor affecting the size of prison population. Although it took time for the longer prison sentences imposed under the 1994 sentencing reform to have a significant growth effect on Virginia's prison population, decrease in the parole grant rate had an almost immediate effect on the size of the prison population.[12] By looking at changes in crime immediately after the introduction of a sentence reform in Virginia, we hope to isolate a pure deterrent effect of the new legislation that is not contaminated by the effect of incapacitation. Hence, to the extent that severity of punishment serves as a deterrent to committing crimes in the short run, we would expect the reported crimes to drop especially for the violent offences.

4 Methodology

We adopt the structural time series analysis framework to investigate the impact of parole abolition and sentence reform in Virginia on reported crime rates. Structural time series models are formulated in terms of components of interest, for example, trend, seasonal, and irregular components, which have a direct interpretation. Other time-varying components and effects can be included in the model as well as regression and intervention variables. The components are formulated as stochastic dynamic processes. The estimation of parameters and regression coefficients are carried out by state space methods based on the Kalman filter.

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

$$y_t = \mu_t + \gamma_t + \varepsilon_t, \qquad \varepsilon_t \sim \text{NID}(0, \sigma_\varepsilon^2) \qquad t = 1, \ldots, n, \tag{1}$$

also known as the classical decomposition or basic structural model (BSM). In model (1), y_t is a one-dimensional observation, μ_t is a slowly changing component (often referred to as the trend), γ_t is a periodic component (or the seasonal component), and ε_t is the irregular component. The irregular ε_t is assumed to be normally, independently distributed (NID) with mean zero and variance σ_ε^2. In a structural time series model, also known as an unobserved components model, the right-hand side components of (1) are modelled explicitly as stochastic processes. For example, the trend may evolve stochastically over time as a random walk process

[12]For example, between 1990 and 1993, Virginia's annual parole grant rate averaged about 41% (i.e., about four out of ten prisoners eligible for parole were granted parole). The parole grant rate began to decline in 1993, and by the end of 1994 it dropped to about 14%. After the parole system was abolished in 1994, the grant rate remained below 20% (Crime in the Commonwealth, 1988-1998). Further, sentencing reform applied to virtually all felony convictions, while repeated violent offenders had to spend from two to more than five times longer in prison than under the parole system.

with a fixed drift, that is $\mu_t = \mu_{t-1} + \beta + \eta_t$ with $\eta_t \sim \text{NID}(0, \sigma_\eta^2)$ and with β treated as an unknown coefficient, for $t = 1, \ldots, n$. The disturbance η_t and the irregular ε_s are independent of each other for all time periods $t, s = 1, \ldots, n$. This trend specification with $\beta = 0$ is referred to as the local level component. A more general trend is obtained when β is replaced by an independent time-varying process. When it is replaced by another random walk process, we refer to μ_t as the local linear trend component. The seasonal component can be composed of seasonal dummy variables that may also evolve stochastically over time under appropriate restrictions, so that the component can treat the dynamic properties of the series y_t at the seasonal frequencies effectively and that it does not confound with the trend and irregular components. A more detailed discussion of structural time series models is given by Harvey (1989) and Commandeur and Koopman (2007).

The basic structural time series model (1) can be extended by incorporating fixed explanatory and intervention variables. For example, in the case of the inclusion of one intervention variable w_t, the BSM equation becomes $y_t = \mu_t + \gamma_t + \lambda w_t + \varepsilon_t$, where λ is an unknown regression coefficient. As far as the intervention variable w_t is concerned, in this paper we consider three types of intervention effects which are presented graphically in Figure 4. The first graph illustrates a *pulse intervention* which is used to capture a single special event in a month such as a special holiday or a strike. Such events may cause outlying observations within the time series and the pulse intervention variable can take such observations outside the general model. The pulse intervention variable at time τ is defined by

$$I_t = \begin{cases} 0, & t < \tau, \quad t > \tau, \\ 1, & t = \tau. \end{cases} \tag{2}$$

The second graph in Figure 4 shows what is called a *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 step intervention variable at time τ is defined by

$$B_t = \begin{cases} 0, & t < \tau, \\ 1, & t \geq \tau. \end{cases} \tag{3}$$

A policy change may not be felt instantaneously, but can also effect a gradual change whose full impact is only reached after some time. We do not want to rule out such interventions and therefore also consider the *smooth break intervention* as given by

$$S_t = \begin{cases} 0, & t \leq \tau_1, \\ (t - \tau_1) \;/\; (\tau_2 - \tau_1), & \tau_1 < t \leq \tau_2, \\ 1, & t > \tau_2. \end{cases} \tag{4}$$

It is apparent from the third graph in Figure 4 that the smooth break intervention, defined in equation (4), starts to take effect from time point τ_1 onwards but that it only reaches its full impact after a time period of length $\tau_2 - \tau_1$.

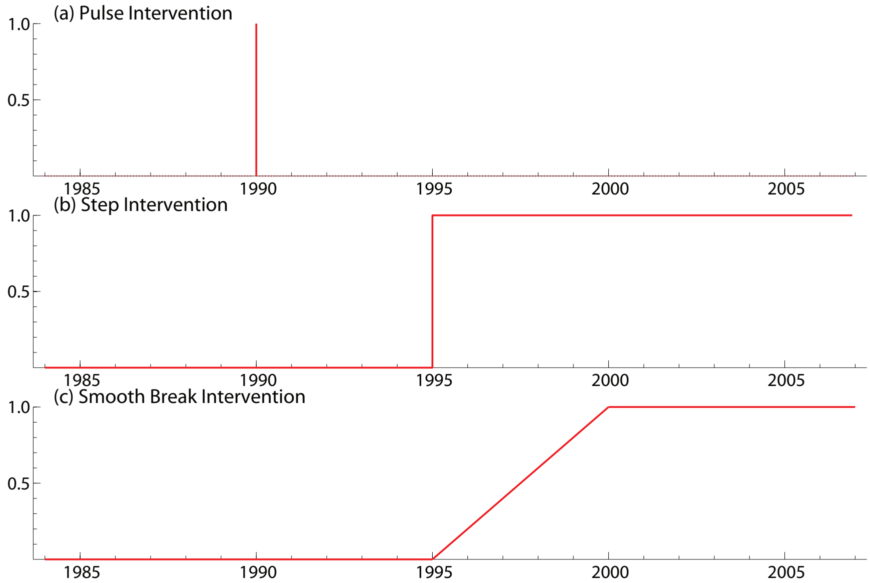

Figure 4: Intervention effects: (a) pulse intervention, modelled as an additive outlier; (b) step intervention, modelled as a level break; (c) smooth break intervention, modelled as a gradual level break.

Although it has taken some time for the longer prison sentences imposed under the 1994 sentencing reform to have a significant growth effect on Virginia's prison population,[13] decreases in the parole grant rate had an almost immediate effect on the size of the prison population.[14] In order to capture the possible instantaneous effects of parole abolition and sentence reform on recorded crime rates in Virginia starting in January 1995 we will therefore first model the effect as a step intervention, defined in equation (3), in Section 5.1.2.

[13]The longer prison sentences imposed under the 1994 sentencing reform could have had a significant growth effect on Virginia's prison population only from about year 2000 and after.

[14]At the beginning of 1995, the inmates confined for offences committed before January 1, 1995 were still admitted under the old parole system. However, in early 1996, only about 25% of its new inmates admitted to the prison came in under the old parole system (by the end of 2000, this number was about 1%).

Before we investigate in Section 5 the dynamic properties of the time series and the intervention effects on the basis of structural time series models, we first analyse the mean changes of the entire pre-intervention period (1984-1994) compared to the post-intervention period (1995-2010). In Figure 5 the sample means are presented for the burglary and the larceny crime series, before and after the intervention. It appears from these two graphs that both burglary and the larceny crime rates are affected by the new legislation; large decreases in these two crimes series are clearly visible after January 1995.

These results may provide a misleading picture of the change because no information on possible trends are incorporated in the calculations. When fixed trends are considered together with a step intervention (3) for January 1995, for the burglary and the larceny crime series we obtain the results shown in Figure 6. Although the drops after January 1995 in burglary and larceny crime rates are still visible after correction for the trends in the series, they are clearly much less pronounced than when the series are analysed in levels, as in Figure 5.

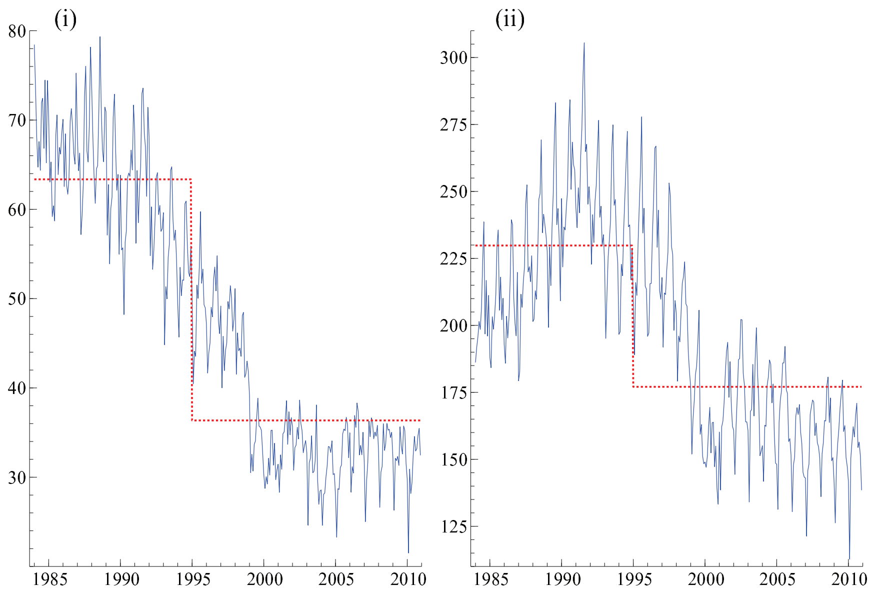

Figure 5: Level change in property crime rates: burglary (left) and larceny (right).

More generally, when we carry out an intervention analysis to investigate a possible break at some point in time in the crime series, the estimated break may be confounded with other features in the series such as

- the general trend;
- the seasonal pattern;
- changes in intervention and regression effects – other than the intervention of interest – also affecting the crime rates.

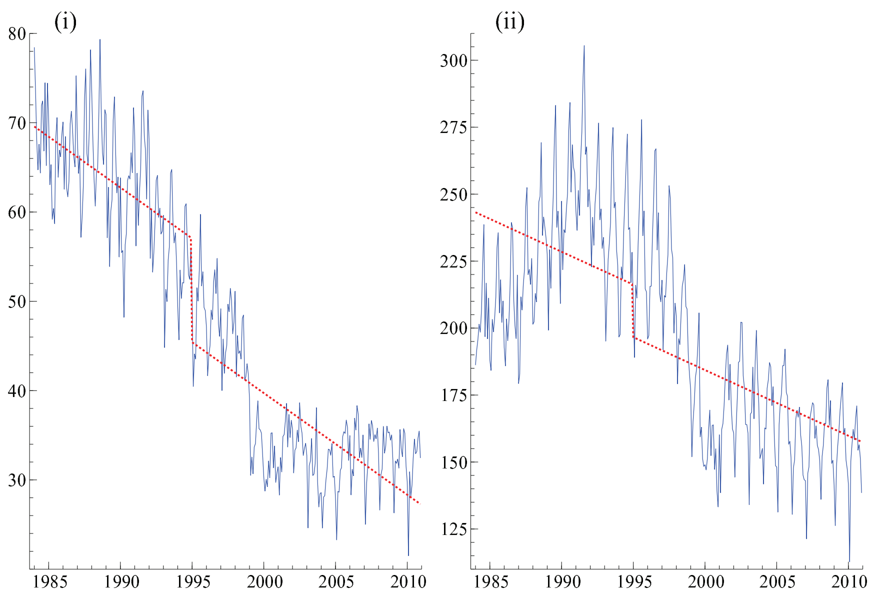

Figure 6: Trend change in property crime rates: burglary (left) and larceny (right).

By adopting the basic structural time series model (1) with a local linear trend specification for μ_t and a step or smooth break intervention for January 1995, the possible confounding effects of a general trend and a seasonal are adequately handled.

However, even when our models for the crime series allow for different factors, including the intervention for January 1995, omitted factors may still affect the crime series. In a bivariate analysis, the omitted factors may also affect a related time series that is not subject to the intervention of interest. We therefore also consider bivariate structural time series models with a treatment and a control time series as in Harvey (1996). In this multivariate approach the model is designed to simultaneously analyse a series representing an eligible crime, that is, a crime that is expected to be affected by the intervention, together with a series representing a non-eligible crime, that is, a crime which is not expected to be affected by the intervention. The former series is often referred to as the treatment series, while the latter series can be referred to as the control or reference series.

The two series are analysed simultaneously using the basic structural time series model (1). In particular, we denote the treatment series as $y_t^{(1)}$ and the reference series as $y_t^{(2)}$ with their model equations given by

$$\begin{aligned} y_t^{(1)} &= \mu_t^{(1)} + \gamma_t^{(1)} + \lambda w_t + \varepsilon_t^{(1)}, \\ y_t^{(2)} &= \mu_t^{(2)} + \gamma_t^{(2)} + \varepsilon_t^{(2)}, \end{aligned} \qquad (5)$$

for $t = 1, \ldots, n$, where the intervention variable w_t is only applied to the treatment series $y_t^{(1)}$. Apart from the intervention variable, the structure of the two model equations in (5) is the same. The stochastic components for trend $\mu_t^{(j)}$, seasonal $\gamma_t^{(j)}$ and irregular $\varepsilon_t^{(j)}$ are mutually independent, for $j = 1, 2$. However, the trend components in both equations are correlated with each other. Also the two seasonal components and the two irregulars can be correlated with their counterparts in the two equations. When a correlation is equal to one, the stochastic evolution over time of the corresponding component is common to both equations. When a correlation is equal to zero, both components still evolve stochastically over time but independently of each other. The multivariate extension of structural time series models is discussed at more length by Harvey (1989) and Commandeur and Koopman (2007).

The empirical results presented in the next section are based on different specifications of the BSM models (univariate and bivariate, with and without intervention variables) and are computed by the time series package STAMP, version 8, of Koopman et al. (2007). It is able to carry out all computations related to the estimation of parameters by the method of maximum likelihood, estimation of the trend, seasonal and irregular components using filtering and smoothing methods, residual statistics and graphics for diagnostic checking, and forecasting. The computations are based on the Kalman filter and related methods which are extensively discussed in Durbin and Koopman (2001).

5 Results

5.1 Univariate structural time series analysis results

5.1.1 Salient features of the crime series

The graphs in Figures 7 and 8 present the estimated trend, seasonal and irregular components. Those for the property crime series are given in Figure 7 while those for the violent crime series are shown in Figure 8. For all series the estimated trends display downward patterns. The crime rates before 2000 are overall higher than those after 2000, and in some cases even substantially higher. The analysed monthly crime series are clearly affected by seasonal variations as we learn from the middle columns in Figures 7 and 8. The seasonal effects are significant for all crime series while many seasonal effects change over time. In the case of burglary we observe summer and Christmas peaks although after 1995 the end of year peak becomes less pronounced. In 2010, the last year of the series, July has the greatest peak in burglary within the year. Larceny and motor vehicle theft only peak in the summer months throughout the analysed period. Both offences have the highest frequency of occurrences in August. Robbery is the lowest in March and April (it shifts to February by the end of the series) and it shows peaks in the second half of the year. In 2010, October has the largest number of reported robberies. The estimated seasonal components in Figure 8 indicate that aggravated assault peaks in the summer months, with July and August having the largest number of reported offences. Rape is highest during spring and the summer months, from May to September, July and August having the highest occurrence of rape incidents. Up to about 2000, murder is highest in the months of July through January, first with a dip in November, later with a dip in October and November. From 2000 onwards the peaks in murder rates shift towards the months of April up to August.

Hird and Ruparel (2007) analysed the seasonality of monthly recorded crime data in England and Wales, and found that the violent assault offences and sexual offences peak in the summer months and through in the winter months, whereas the opposite is true for property crimes. In comparison with their findings, we find that burglary (at least after 1995), and larceny, motor vehicle theft, aggravated assault, and rape all peak in the summer months. Robbery, on the other hand, peaks in the second half of the year, and murder peaks from July through January. From 2000 onwards the peak in murder rates shift to the months of April through August.

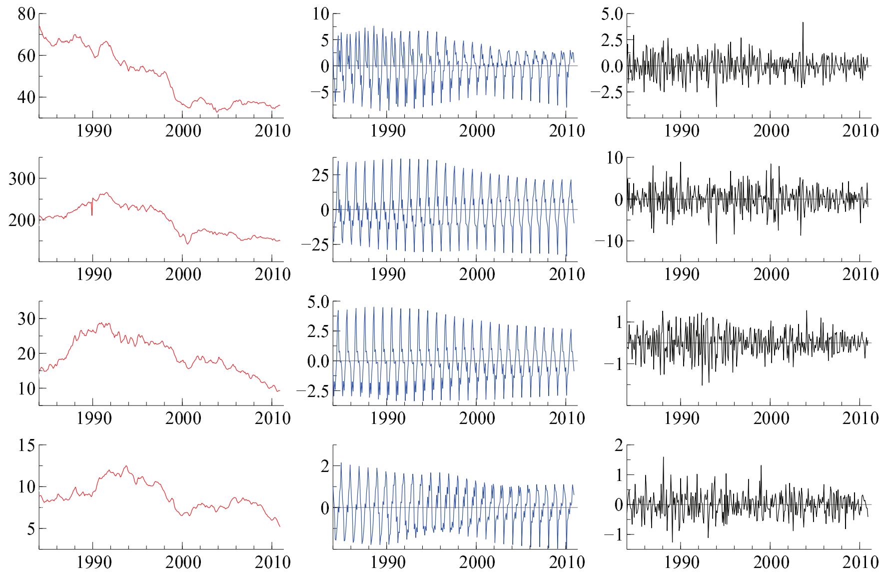

Figure 7: Trend (left), seasonal (middle), and irregular (right) components in property crime rates: burglary (first row); larceny (second row); motor vehicle theft (third row); robbery (fourth row).

These salient features of the crime series can be interpreted from the perspective of economic models of criminality, see, for example, the studies in Becker (1968) and Ehrlich (1973) where criminals are treated as rational agents. In such a framework, the frequency of criminal events tends to increase when the perceived gains from engagement in crime increase, ceteris paribus. It suggests that individual criminals may exhibit a considerable amount of mobility over time, as they seek those situations where perceived gains are greatest and/or the subjective probability of detection and arrest are the smallest. For example, rape incidents occur most often in the summer months, when social interaction is at its highest and climatic conditions make victims more available. On the other hand, an economic crime such as robbery peaks in the winter months, due to the increase in the cost of living and the facilitating environmental conditions during these months. Since a variety of motives exists for murder, this crime is much less dependent on climatic conditions. For a discussion on the seasonality of violent crimes, we refer to Landau and Fridman (1993).

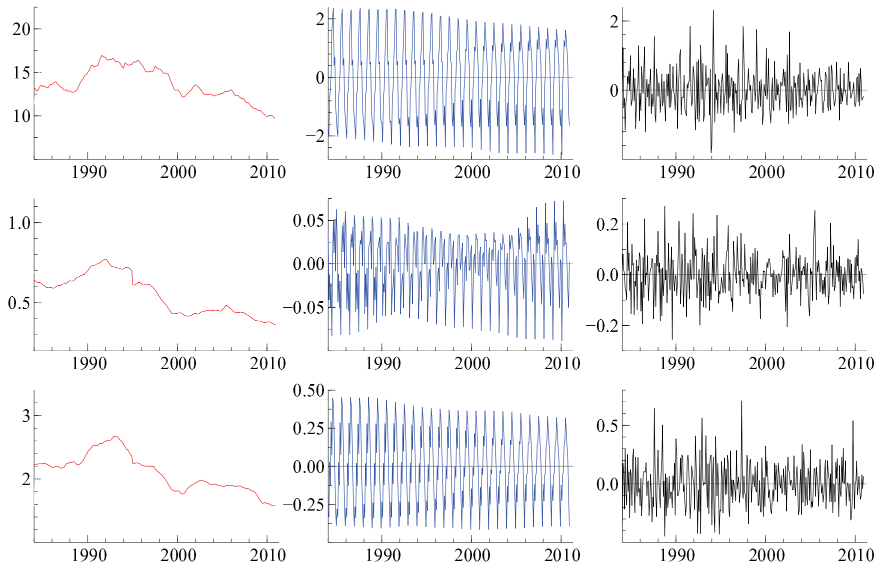

Figure 8: Trend (left), seasonal (middle), and irregular (right) components in violent crime rates: aggravated assault (first row); murder (second row); rape (third row).

5.1.2 Step intervention analysis results

For all seven crime rate series in Figures 2 and 3, we adopt the basic structural time series model as defined in (1) with the trend component as a random walk with fixed drift, together with a step intervention variable (3) for January 1995. For the burglary and larceny series we also controlled for an outlier with a pulse intervention variable (2) for December 1989.

The estimation results are presented in Table 3, while the smooth estimated trend and seasonal components are displayed in Figures 7 and 8 for the property and violent crimes, respectively. The estimated regression coefficients of the step intervention variable for January 1995 are negative for burglary, larceny, murder, and rape. However, a statistically significant effect of the new legislation is only found for burglary and murder. The values of the regression coefficients of the step intervention variable for January 1995 are positive for motor vehicle theft, robbery, and aggravated assault, but these are not significantly different from zero. From these analyses we conclude that the new legislation only resulted in a drop for the burglary and murder offences, but not for the other crime categories.

5.1.3 Smooth break intervention analysis results

The results of the univariate structural time series analysis with a step intervention variable (3) indicate a deterrent impact of the new legislation for burglary and murder. This evidence is based on the intervention variable B_t for which the impact starts in January 1995. In order to investigate the robustness of this result and whether the impact was instantaneous or more gradual, we repeat the empirical analyses of the previous section on the basis of a smooth break intervention S_t instead of a step intervention B_t. Our smooth break intervention S_t is defined in (4); we let the break start in January 1995 and we let it end in different years. Table 4 contains the absolute values of the t-statistics of the estimated intervention effects based on B_t and S_t (for different lengths of the gradual break).

The results provide some evidence that a gradual break (S_t) has been more likely than an abrupt break (B_t) in 1995. In particular, the gradual break that ends in 2000 shows a significant effect for larceny and murder. The estimated regression coefficients associated with this gradual break S_t are found to be negative for all crime series.

The more gradual breaks also lead to less precise interpretations of the break. A smooth break affects the overall trend in the period 1995–2000 and therefore cannot be exclusively associated with an event in, say, January 1995. However, in our empirical study the longer prison sentences imposed under the 1994 sentencing reform are likely to have had gradual effect on Virginia's prison population. For example, when we consider the inmates confined for offences committed in early 1996, about 25% of this new inmate population admitted to the prison came in under the old parole system, before 1995, while at the end of 2000 this number was about 1%. This provides some justification that the gradual intervention S_t should also be considered in our intervention analysis.

5.2 Bivariate intervention analysis results

In our bivariate analyses we consider burglary and murder as 'eligible' crimes. The new legislation also targeted robbery and rape offences, hence we consider these crimes to be 'eligible' as well. Larceny, motor vehicle theft, and aggravated assaults are considered as 'non-eligible' crimes. We analyse sets of two time series simultaneously using the bivariate structural time series model as discussed in Section 4 with one variable treated as a treatment group (burglary, robbery, murder, rape) and one variable treated as a control group (larceny, motor vehicle theft, aggravated assaults). We have twelve combinations of two variables and therefore present the estimation results for twelve bivariate models.

Table 3: Estimated step interventions for univariate structural time series models

		Burglary	Larceny	MVT	Robbery	AA	Murder	Rape
Interventions								
Structural break		-3.98	-8.00	1.67	0.52	0.20	-0.09	-0.12
(95:01)		(-1.95)	(-1.24)	(1.39)	(0.85)	(0.32)	(-1.83)	(-0.96)
Outlier		-12.57	-36.88					
(89:12)		(-5.84)	(-5.95)					
Variances								
	σ^2_{irr}	2.34	18.49	0.73	0.28	0.48	0.01	0.04
		[1.00]	[1.00]	[1.00]	[1.00]	[1.00]	[1.00]	[1.00]
	σ^2_{lvl}	1.17	15.07	0.50	0.09	0.06	0.0002	0.001
		[0.50]	[0.82]	[0.69]	[0.33]	[0.13]	[0.02]	[0.03]
	σ^2_{seas}	0.01	0.04	0.001	0.001	0.00	0.00	0.00
		[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Diagnostics								
Serial correlation	$r(1)$	0.10	0.04	0.09	0.10	0.06	0.02	-0.01
Portmanteau test	$Q(24)$	33.13	41.27	40.51	27.52	26.60	32.70	10.41
Homoscedasticity	$H(103)$	0.49	0.59	0.39	0.52	0.55	0.62	0.57
Normality	N	2.97	11.63	5.08	4.96	7.81	5.67	3.49
Goodness-of-fit								
	LogL	-324.15	-653.60	-128.87	42.63	7.34	671.04	419.87
	p.e.v.	6.87	57.54	1.91	0.64	0.79	0.01	0.05
	R^2_s	0.31	0.34	0.11	0.23	0.33	0.40	0.42
	AIC	2.03	4.15	0.74	-0.36	-0.14	-4.44	-2.82

In our analysis we consider the BSM with a deterministic slope for the trend component and with intervention effects; the sample size is 324; for intervention effects, we report the t-statistic between round brackets; for the variances, we report the q-ratio in square brackets (it is the ratio of the component variance against the irregular variance); MVT = Motor vehicle theft; AA = Aggravated assault.

Table 4: Estimated step (B_t) and smooth break (S_t) interventions from structural time series models for both property and violent crimes

Offence	break 1995	gradual 1996	gradual 1998	gradual 2000	gradual 2002	gradual 2004	gradual 2006
	B_t	S_t	S_t	S_t	S_t	S_t	S_t
Burglary	1.95	0.48	0.10	1.48	0.60	0.94	0.07
Larceny	1.24	0.35	0.38	2.37	1.39	1.44	1.26
Motor vehicle theft	1.39	0.02	0.06	0.91	0.65	0.62	0.75
Robbery	0.85	0.09	0.37	1.71	0.76	0.89	0.15
Aggravated assault	0.32	0.24	0.16	1.45	0.82	1.21	0.74
Murder (2nd degree)	1.83	0.55	1.34	2.68	1.78	1.09	0.69
Rape (forcible)	0.96	0.55	0.69	1.79	0.78	0.61	0.47

Note: We report t-tests (absolute values) for the step B_t and smooth break S_t interventions, see (3) and (4) respectively. The break for B_t takes place in January 1995. The start of the smooth break S_t is τ_1 and corresponds with January 1995 while τ_2 is the end of the gradual break and is January in the year indicated by the column headings.

The bivariate structural time series model for crime series is also used to assess the effect of parole abolition and of reformed sentencing in Virginia. Since more data is used and since we explicitly model eligible (or treatment) and non-eligible (or control) crime series jointly, we expect an increase of the statistical significance of the intervention from a bivariate analysis in comparison to an univariate analysis. If the treatment variable is affected by the new legislation while the control variable is not, we expect to obtain a strong significant effect of the intervention from our estimation procedure.

The economic interpretation for having treatment and control crime groups can be given as follows. Observed changes in crime around the time of the introduction of the new legislation "may reflect a combination of the true deterrent impact of harsher repeat-offender enhancements and of other factors correlated with but not caused by the law change, such as changes in demographics, in other state policies, and in broad social norms against crime," see Kessler and Levitt (1999).

The estimation results for burglary as a treatment series and three different control series are presented in Table 5. The analogous specifications for robbery, murder, and rape as "treatment" series are presented in Tables 6, 7, and 8, respectively. We find significant negative effects in two out of three of the bivariate structural time series specifications for burglary, with motor vehicle theft and aggravated assault as control groups. The estimated regression coefficient ranges from -3.99 to -5.19, which is in the neighbourhood of the univariate estimate of -3.98. The estimated bivariate models for burglary satisfy all of the diagnostic requirements of residual independence, homoscedasticity, and normality. Inspection of the Akaike information criterion indicates that the fit of the bivariate models (all around 2.02) is about as good as the fit of the univariate model (2.03).

A similar picture is obtained for the bivariate structural time series analyses of the murder series, see Table 7. Negative significant effects of the new legislation are found in all three bivariate structural time series models with control groups. When motor vehicle theft and aggravated assault are treated as non-eligible crimes, the estimated effect of the new legislation on murder is -0.10, which is almost identical to the univariate result of -0.09, see Table 3. The bivariate model residuals for murder also satisfy all of the model assumptions, while the fit of the bivariate models is similar to that of the univariate model (all with an AIC of around -4.45).

When we treat robbery as a treatment series, we do not find significant results in any of the three bivariate model specifications, see Table 6. This finding suggests that although the new legislation targeted robbery as a most violent property crime, we do not find any confirmation that the behaviour of this series has been significantly altered by the new legislation. When we consider the bivariate results in Table 8, where rape is handled as a treatment series, we find a significant negative effect for rape when it is modelled together with aggravated assault as a control group. The estimated effect is -0.24, which is larger in absolute value than the univariate estimate of -0.12. The AIC values of -2.84 for rape in the bivariate model and of -2.82 in the univariate model again indicate that these two models fit the rape crime series about equally well.

In summary, the multivariate estimation results confirm that new legislation significantly affected burglary (-3.99 to -5.19) and murder (-0.10). As far as rape is concerned, we find a significant drop of -0.24 in one of the three bivariate model specifications, which is a larger effect than the (insignificant) univariate estimation result of -0.15. We have also considered the simultaneous treatment of all seven crime series in a unified model but this multivariate analysis has not led to an improvement of the univariate or bivariate specifications presented above. Also, we have not found a common trend in the seven crime variables.

6 Discussion

We have adopted the structural time series framework to investigate the impact of parole abolition and sentence reform in Virginia 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 new legislation on reported crime rates, we considered intervention analysis with both univariate and multivariate structural time series models. The examined crime rate series are monthly data on burglary, larceny, motor vehicle theft, robbery, aggravated assault, murder, and rape in the years 1984-2010.

Virginia's abolition of parole and reform of the sentencing system provides a useful social experiment to study. First, the legislation had a big impact on society and it focussed on all felonies. Second, the legislation was enacted at a time in which there were various, favourable changes in a number of social and economic indicators. Third, the 1990s also witnessed 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. According to the Virginia crime officials, research to date has been unable to determine if the observed reductions in crime rates were due to specific anti-crime initiatives. Hence, we have aimed to contribute to a better understanding of the statistical relationship between anti-crime efforts and crime reductions over time.

It is shown how a structural intervention time series analysis can be used for the evaluation of the effects of anti-crime laws on reducing crime rates. When we simultaneously correct for confounding variables such as a general trend and a seasonal pattern in crime rates, different types of effects can be considered: temporary effects using pulse intervention variables, breaks or permanent effects using step intervention variables, and gradual and permanent effects using smooth break intervention variables. Corrections for other confounding factors can be estab-

Table 5: Estimated interventions for multivariate STS models - Burglary as a treatment series

	Statistic	Burglary	Larceny	Burglary	MVT	Burglary	AA
Intervention		-2.75		-5.19		-3.99	
(95:01)		(-1.55)		(-2.69)		(-2.00)	
Outlier		-12.47	-38.36	-12.03		-11.92	
(89:12)		(-5.79)	(-5.79)	(-5.73)		(-5.79)	
Variances of disturbances							
	σ^2_{irr}	2.38	16.61	2.35	0.69	2.32	0.43
		[1.00]	[1.00]	[1.00]	[1.00]	[1.00]	[1.00]
	σ^2_{lvl}	1.13	10.30	1.22	0.45	1.18	0.06
		[0.48]	[0.62]	[0.52]	[0.65]	[0.51]	[0.14]
	σ^2_{seas}	0.01	0.01	0	0	0.01	0.00
		[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Diagnostics							
Independence	$Q(24)$	32.65	37.03	33.09	38.00	35.22	24.90
First-order ACF	$r(1)$	0.10	0.03	0.09	0.04	0.10	0.06
Homoscedasticity	$H(.)$	0.48	0.58	0.48	0.38	0.51	0.54
Normality	N	2.93	18.14	3.28	5.06	3.04	7.58
Goodness-of-fit							
	LogL	-935.38		-434.61		-303.26	
	p.e.v.	6.84		6.76		6.87	
		9.72	56.83	1.06	1.76	0.63	0.79
	R^2_s	0.32	0.35	0.33	0.18	0.32	0.33
	AIC	2.02	4.13	2.01	0.65	2.03	-0.16

Note: Sample size is 324; t-statistic in round brackets; q-ratio (ratio of the estimated standard deviations of the state disturbances and estimated standard deviation of the irregular) in square brackets; BSM model fitted to all specifications; MVT = Motor vehicle theft; AA = Aggravated assault.

Table 6: Estimated interventions for multivariate STS models - Robbery as a treatment series

	Statistic	Robbery	Larceny	Robbery	MVT	Robbery	AA
Intervention		0.73		-0.14		0.41	
(95:01)		(1.33)		(-0.27)		(0.72)	
Outlier			-33.57				
(89:12)			(-5.61)				
Variances of disturbances							
	σ^2_{irr}	0.28	18.35	0.27	0.68	0.28	0.45
		[1.00]	[1.00]	[1.00]	[1.00]	[1.00]	[1.00]
	σ^2_{lvl}	0.09	10.34	0.10	0.27	0.09	0.05
		[0.32]	[0.56]	[0.39]	[0.40]	[0.32]	[0.11]
	σ^2_{seas}	0.00	0.03	0.00	0.00	0.00	0.00
		[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Diagnostics							
Independence	$Q(24)$	25.65	41.04	21.94	41.22	26.65	27.29
First-order ACF	$r(1)$	0.09	0.05	0.06	0.09	0.10	0.07
Homoscedasticity	$H(.)$	0.52	0.58	0.46	0.41	0.52	0.54
Normality	N	6.97	16.81	7.78	6.02	5.40	8.47
Goodness-of-fit							
	LogL	-593.87		-65.95		63.57	
	p.e.v.	0.63		0.63		0.64	
		1.95	57.55	0.36	1.90	0.19	0.79
	R^2_s	0.24	0.34	0.24	0.12	0.23	0.33
	AIC	-0.37	4.15	-0.37	0.73	-0.35	-0.15

Note: Sample size is 324; t-statistic in round brackets; q-ratio (ratio of the estimated standard deviations of the state disturbances and estimated standard deviation of the irregular) in square brackets; BSM model fitted to all specifications; MVT = Motor vehicle theft; AA = Aggravated assault.

Table 7: Estimated interventions for multivariate STS models - Murder as a treatment series

	Statistic	Murder	Larceny	Murder	MVT	Murder	AA
Intervention		-0.08		-0.10		-0.10	
(95:01)		(-2.52)		(-2.32)		(-2.55)	
Outlier			-36.57				
(89:12)			(-5.93)				
Variances of disturbances							
	σ^2_{irr}	0.01	18.07	0.01	0.68	0.01	0.47
		[1.00]	[1.00]	[1.00]	[1.00]	[1.00]	[1.00]
	σ^2_{lvl}	0.00	2.43	0.00	0.27	0.00	0.02
		[0.00]	[0.13]	[0.02]	[0.39]	[0.02]	[0.05]
	σ^2_{seas}	0.00	0.00	0.00	0.00	0.00	0.00
		[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Diagnostics							
Independence	$Q(24)$	31.13	44.16	29.16	44.84	29.45	25.45
First-order ACF	$r(1)$	0.01	0.06	0.01	0.09	0.04	0.06
Homoscedasticity	$H(.)$	0.61	0.60	0.59	0.39	0.62	0.54
Normality	N	7.30	13.94	7.45	6.53	4.30	8.75
Goodness-of-fit							
	LogL	25.10		547.51		684.11	
	p.e.v.	0.01		0.01		0.01	
		0.04	57.22	0.01	1.90	0.01	0.79
	R^2_s	0.44	0.34	0.43	0.12	0.42	0.33
	AIC	-4.49	4.14	-4.47	0.73	-4.46	-0.15

Note: Sample size is 324; t-statistic in round brackets; q-ratio (ratio of the estimated standard deviations of the state disturbances and estimated standard deviation of the irregular) in square brackets; BSM model fitted to all specifications; MVT = Motor vehicle theft; AA = Aggravated assault.

Table 8: Estimated interventions for multivariate STS models - Rape as a treatment series

	Statistic	Rape	Larceny	Rape	MVT	Rape	AA
Intervention		-0.14		-0.19		-0.24	
(95:01)		(-1.29)		(-1.67)		(-2.63)	
Outlier			-35.37				
(89:12)			(-5.79)				
Variances of disturbances							
	σ^2_{irr}	0.04	18.20	0.04	0.69	0.04	0.48
		[1.00]	[1.00]	[1.00]	[1.00]	[1.00]	[1.00]
	σ^2_{lvl}	0.00	9.20	0.00	0.33	0.00	0.02
		[0.02]	[0.51]	[0.03]	[0.48]	[0.02]	[0.04]
	σ^2_{seas}	0.00	0.04	0.00	0.00	0.00	0.00
		[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Diagnostics							
Independence	$Q(24)$	10.37	41.18	11.43	41.35	9.10	25.21
First-order ACF	$r(1)$	0.01	0.04	0.00	0.08	0.02	0.07
Homoscedasticity	$H(.)$	0.56	0.59	0.56	0.39	0.59	0.54
Normality	N	3.51	14.23	3.27	5.36	2.41	7.78
Goodness-of-fit							
	LogL	-227.63		296.91		434.44	
	p.e.v.	0.05		0.05		0.05	
		0.33	57.84	0.05	1.92	0.03	0.78
	R^2_s	0.43	0.33	0.43	0.11	0.43	0.33
	AIC	-2.84	4.15	-2.84	0.74	-2.84	-0.16

Note: Sample size is 324; t-statistic in round brackets; q-ratio (ratio of the estimated standard deviations of the state disturbances and estimated standard deviation of the irregular) in square brackets; BSM model fitted to all specifications; MVT = Motor vehicle theft; AA = Aggravated assault.

lished by extending our framework in a multivariate fashion. For this purpose we typically model a treatment ('eligible') series and a control ('non-eligible') series jointly in a bivariate structural time series model.

The empirical results have indicated that the legislation of January 1, 1995 has significantly affected only burglary (-3.99) and murder (-0.09). Significant *gradual* drops in crime rates based on a smooth break intervention variable for the 1995-2000 period have been found for larceny and murder. The bivariate analyses for burglary have yielded two significant drops of -3.99 (with aggravated assault as reference) and -5.19 (with motor vehicle theft as reference). In the case of rape, we found a significant drop of -0.24 in one of the three bivariate model specifications. We have not found an effect of the new legislation for aggravated assault which is also a violent offence. A possible reason for this is the method of reporting. While the other crimes are relatively well defined, aggravated assault requires discretion on the part of the police to distinguish it from "simple" assault. It is a possible that the manner in which descretion is exercised has changed over time (Blumstein, 2000).

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