Dead Man Walking: An Empirical Reassessment of the Deterrent Effect of Capital Punishment Using the Bounds Testing Approach to Cointegration

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Abstract

This paper empirically estimates a murder supply equation for the United States from 1965 to 2001 within a cointegration and error correction framework. Our findings suggest that any support for the deterrence hypothesis is sensitive to the inclusion of variables for the effect of guns and other crimes. In the long-run we find that real income and the conditional probability of receiving the death sentence are the main factors explaining variations in the homicide rate. In the short-run the aggravated assault rate and robbery rate are the most important determinants of the homicide rate.

JEL: C32, K4

KEYWORDS: Capital Punishment, Cointegration, Deterrent Effect

I. INTRODUCTION

Since Ehrlich's (1975) seminal research, several studies have examined the deterrent effect of capital punishment within an economic framework. Ehrlich's (1975) finding that each execution in the United States between 1935 and 1969 deterred seven or eight murders immediately evoked a flurry of critical comment focusing primarily on the econometric aspects of the study (see eg Baldus and Cole 1975, Bowers and Pierce 1975, Passell and Taylor 1977, Blumstein *et al* 1978). These criticisms were met with a series of spirited defences (see eg Ehrlich 1975a, Ehrlich 1977, Ehrlich and Gibbons 1977, Ehrlich and Randall 1977). However, subsequent studies using data for the United States have reached mixed conclusions on the deterrent effect.

Some studies have found evidence that capital punishment exhibits a deterrent effect (see eg Ehrlich 1977a, Chressanthis 1989, Layson 1985, Brumm and Cloninger, 1996, Ehrlich and Liu 1999, Lott and Landes 2000, Cloninger and Marchesini, 2001 Dezhbakhsh *et al*. 2003, Mocan and Gittings, 2003, Zimmerman, 2004, 2004a, Shepherd 2004, Liu 2004 Dezhbakhsh and Shepherd, 2004). In one recent study Dezhbakhsh *et al*. (2003) concluded that, on average, the execution of each offender saves the lives of 18 potential victims. There are other studies, though, that have found no evidence to support the view that capital punishment has a deterrent effect or have found that the deterrent effect is sensitive to the choice of empirical specification (see eg Forst 1977, Cover and Thistle 1988, Grogger 1990, Yunker 2001, Katz *et al* 2003). Katz *et al* (2003) find that poor conditions in prison have a strong deterrent effect, but find that the deterrent effect of capital punishment is sensitive to the choice of specification and takes on a positive sign as frequently as a negative sign.

This paper tests the deterrent effect of capital punishment in the United States using the bounds testing procedure to cointegration, within an autoregressive distributive lag (ARDL) framework, developed by Pesaran and others (Pesaran and Pesaran 1997, Pesaran and Shin 1999, Pesaran *et al* 2001). The study employs aggregate time series data for the period 1965 to 2001. The contribution of this study to the existing literature on the economics of capital punishment is to employ the cointegration and error correction framework, which has not been used in the capital punishment literature before. The cointegration framework has the advantage that we can estimate the short-run and long-run elasticities for the murder supply equation.

The results of most existing time series studies on this topic are potentially spurious because they do not take account of the stationarity properties of the data. This is true *inter alia* of Ehrlich (1975), Passell and Taylor (1977), Layson (1985) and Yunker (2001), as well as Wolpin's (1978) study for the United Kingdom and the Avio (1979) and Layson (1983) studies for Canada. Cover and Thistle (1988) explicitly test for unit roots and find that the homicide rate is non-stationary. They address this issue through estimating the murder supply function in first differences. The problem with differencing, however, is that it eliminates the trend component. Hence, this approach can only allow examination of the short-term, not long-run, trends in the time series.

The bounds testing approach to cointegration has three major advantages. The first is that it can be applied irrespective of whether the underlying regressors are purely $I(0)$, purely $I(1)$ or mutually cointegrated. We tested the stationarity of the variables using the Augmented Dickey-Fuller test and the small sample unit root tests proposed by Elliot *et al* (1996). To save space the results are not reported, but they suggest that two of the key variables, the robbery and unemployment rates, are $I(0)$, while the other variables are $I(1)$.[1] Using the bounds test is appropriate under these circumstances. The second advantage of using the bounds testing approach to cointegration is that Monte Carlo studies suggest that it performs better than the Engle and Granger (1987), Johansen and Juselieus (1990) and Phillips and Hansen (1990) cointegration test in small samples (see eg. Pesaran and Shin 1999, Haug 2002).

For this reason the bounds test is becoming a popular method to test for cointegration and there are now several published studies which employ it. However, most previous studies which have employed the bounds testing approach have used the critical bounds reported in Pesaran and Pesaran (1997) which are calculated for a sample size of 500 based on 20,000 replications of a stochastic stimulation or Pesaran *et al* (2001), which are calculated for a sample size of 1000 based on 40,000 replications of a stochastic stimulation. With small samples such as these and those employed in the current study the critical value bounds can deviate substantially from those reported in Pesaran and Pesaran (1997) and Pesaran *et al* (2001). To address this issue, in this paper we calculate the exact critical value bounds tailored to our sample size.

A third advantage of using the bounds testing approach to cointegration within the ARDL framework is that it addresses the potential endogeneity problem of the law enforcement variables in the murder supply equation. Most previous estimates of the United States homicide function have used two stages least squares (see eg Ehrlich 1975, Hoenack and Weiler 1980). Layson (1985) argues that because the United States has a uniform crime code and law enforcement authority, it is less likely that law enforcement behavior will be endogenous compared with Canada and thus the econometric justification for using two stage least squares is weak. Layson (1985) performs a Hausman test and is unable to reject the null hypothesis that the criminal justice variables are exogenous. The Hausman test is inapplicable within the ARDL framework. However, Pesaran and Shin (1999, p. 16) contend that "appropriate modification of the orders of the ARDL model is sufficient to simultaneously correct for residual serial correlation and the problem of endogenous regressors".

The remainder of the paper is set out as follows. The next section sets out the generic murder supply equation to be tested and discusses the expected signs on the variables. Section III outlines the econometric methodology in more detail. The results are presented in section IV for various specifications. Foreshadowing the main findings, there is at best mixed support for the deterrence hypothesis and what support exists is sensitive to the inclusion of additional explanatory variables. In the long-run real income and the conditional probability of receiving the death sentence are the main factors explaining variations in the homicide rate. In the short-run the aggravated assault rate and robbery rate are the most important determinants of variations in the homicide rate across all empirical specifications. Section V reports tests for the stability of the coefficients and the final section contains some concluding comments.

II. MODEL SPECIFICATION

Becker (1968) and Ehrlich (1973) develop a supply of offences function where the rational individual will allocate his/her time between legitimate and illegitimate earning activities so as to maximize utility. Ehrlich (1975) extends the supply of offences function to murder, which he argues are a by-product of hate, jealousy or other interpersonal conflict involving pecuniary or non-pecuniary motives or are a by-product of other crimes. According to the economic model of crime, potential offenders will change their behavior at the margin in response to an increase or decrease in the incentives to engage in legitimate or illegitimate earning opportunities. The generic empirical specification employed in this study is a variant of the Ehrlich (1975) murder supply equation, where the murder rate is specified as a function of criminal justice variables, economic variables and demographic variables.

$$\begin{aligned} ln\,M_t &= \alpha_0 + \alpha_1\, ln\,AGE_t + \alpha_2\, ln\,Y_t + \alpha_3\, ln\,PA_t + \alpha_4\, ln\,PS_t + \alpha_5\, ln\,PE_t \\ &+ \alpha_6\, ln\,U_t + \alpha_7\, ln\,L_t + \alpha_8\, ln\,NW_t + \alpha_9\, ln\,FA_t + \alpha_{10}\, ln\,D_t + \alpha_{11}\, ln\,AA_t \\ &+ \alpha_{12}\, ln\,R_t + \varepsilon_t \end{aligned} \tag{1}$$

Each of the variables in Equation (1) are as defined in table 1 and the sources for each of the variables are described in appendix 1. We begin with the dependent variable, which is the log of the number of murders and non-negligent manslaughters per 100,000 population. Glaser (1977) claims that homicides carried out in the heat of the moment are "crimes of passion", which are nondeterrable and should be subtracted out. However, Dezhbakhsh *et al* (2003, pp. 355-356) show that any inference about the deterrent effect is unaffected by the inclusion of nondeterrable murders in the murder rate. The explanatory variables are discussed in more detail below.

Insert Table 1

We use a log linear specification. Bowers and Pierce (1975), Passell and Taylor (1977) and Klein *et al* (1978) suggest that Ehrlich's (1975) findings with a log linear specification are sensitive to functional form. However, Ehrlich (1977a) and Layson (1983, 1985) argue on theoretical and empirical grounds that the log linear form is superior to the linear form.[2] Both Cameron (1994) and Ehrlich (1996) suggest that a log-linear form is more likely to find evidence of a deterrent effect than a linear form. This makes our results more favourable to the deterrence hypothesis.

Criminal Justice Variables

There are three criminal justice variables. $ln\, PA$ is the log of the arrest clearance rate; $lnPS$ is the log of the probability of receiving the death sentence conditional on being apprehended and $ln\, PE$ is the log of the probability of execution, conditional on being sentenced to death. We use sentencing data because the Bureau of Justice statistics no longer collects information on convictions for murder. Cameron (1994, p. 210) suggests that death sentencing should be used more in deterrence studies and Dezhbakhsh *et al* (2003), who also use the conditional probability of being sentenced to death, argue that sentencing data is a viable alternative to using data on convictions.

The economic model suggests that the probability of apprehension, conditional probability of receiving the death sentence and the conditional probability of execution should have a negative effect on the murder rate. Moreover, the economic model suggests a ranking of the magnitude of the coefficients corresponding to the range of possible harms that result from a given risk. The absolute value of the coefficient on the probability of apprehension should be greater than the absolute value of the coefficient on the conditional probability of receiving the death sentence. This, in turn should be greater than the absolute value on the coefficient of the conditional probability of being executed (Ehrlich 1975, Ehrlich 1982).

For probability of sentencing given arrest we use a two-year lag displacement, which follows the approach in Dezhbakhsh *et al* (2003). Thus the conditional sentencing probability is the number of death sentences at *t* divided by the number of arrests for murder at *t*-2. For the probability of execution given the death sentence we use two different lag displacements which reflect the average length of time spent on death row before execution for the pre-moratorium and post-moratorium periods. Prior to the moratorium the average length of time from being sentenced to death to being executed was three years. After the moratorium the average length of time from being sentenced to death to being executed has been nine years (United States Department of Justice, various). Thus, for the period 1965 to 1976, the conditional probability of execution is measured as the number of executions in period t divided by the number of death sentences in t-3. For the period 1977 to 2001, the conditional probability of execution is measured as the number of executions in period t divided by the number of death sentences in t-9. Because we use a log specification, in order to avoid the zeros problem we use two alternative approaches. First, we follow Ehrlich (1975) and Wolpin (1978) and arbitrarily assume that there was one execution in those years where there were no executions. Second, we follow Layson (1983, 1985) and use a Bayesian approach for determining the conditional probability of execution from 1968 to 1976 which allows potential criminals to revise their subjective probabilities of being executed in light of new information (see Layson 1985, p. 74 for details).

As a check on the robustness of our findings we also reran the regressions using an averaging rule to measure the sentencing and execution variables (see Layson 1985). In these regressions we employed a two-year moving average to measure the conditional sentencing variable. To measure the conditional probability of execution given the death sentence for 1965 to 1976 we used a three-year moving average and for 1977 to 2001 we used a nine-year moving average. The results in each case were the same as those reported in terms of the sign and significance of the variables.

Economic variables:

The model contains three economic variables, which measure the returns to legitimate and illegitimate earning activities. These are $ln Y$, which is the log of real per capita personal disposable income; $ln U$, which is the log of the unemployment rate, and $ln L$, which is the log of the labor force participation rate. These variables are included for two reasons. First, as Ehrlich (1975) stresses, some murders are committed as a byproduct of property crime. Thus, variables which influence property crime may also influence the murder rate. Second, income variables may directly affect the demand for malevolent action (Ehrlich 1975, p. 402). The unemployment rate is expected to have a positive sign and the labor force participation rate is expected to have a negative sign. The sign on real income is ambiguous. To the extent that real income reflects the opportunity cost of committing crime we expect it to have a negative sign, but if it is measuring changes in the level of "plunderable wealth" or "victim stock", the expected sign will be positive.

Demographic variables:

$ln AGE$ is the log of the percentage of the resident population aged between 18-24. This is included to control for the differential treatment of young offenders under the law (Ehrlich 1975, p. 402). Ehrlich (1975) uses the percentage of resident population aged between 14-24, but Passell and Taylor (1977) argue this is too broad and use the 18-24 year old age group instead. The expected sign is positive. $ln NW$ is the log of the percentage of resident population that is non-white. The incarceration rate for African-American males is much higher than that for white males. This has been explained in terms of African Americans having more limited labor market opportunities (Freeman 1996). Thus, the non-white variable is included on the grounds that legitimate earning opportunities for non-whites, and in particular African

American males, is not as good as whites. The expected sign is positive. $\ln D$ is the log of the divorce rate. Ehrlich (1975) was criticized for not taking account of the decline in family values on the level of property crime and because homicide is viewed as a by-product of property crime, by extension the homicide rate. Later studies such as Layson (1985) and Cover and Thistle (1988) address this issue through using variables such as the proportion of families where both husband and wife are present. The expected sign on the divorce rate is positive.

$\ln FA$ is the log of the proportion of fatalities, which involve firearms. Klein *et al* (1978) and Kleck (1979) criticize Ehrlich (1975) for not including a gun variable. Kleck (1979) found that when a gun variable is included the conditional probability of execution becomes statistically insignificant. The effect of gun ownership on crime rates is controversial. Cook *et al* (1995) and Kellerman *et al* (1995) suggest that an increase in gun ownership results in higher crime rates. Lott and Mustard (1997) find that the passage of concealed handgun laws by a state results in a substantial reduction in the number of property and violent crimes. This result is attributed to a deterrent effect where, as criminals become more aware that victims might be armed, they commit less crime. Dezhbakhsh and Rubin (1998) use Lott and Mustard's (1997) data set and correct for econometric problems in the original study. Dezhbakhsh and Rubin (1998) find that the effect of the passage of concealed handgun laws on crime rates is ambiguous with some crimes increasing and others decreasing.

Dezhbakhsh *et al* (2003) use National Rifle Association (NRA) membership to proxy the effect of gun ownership on crime rates. NRA membership might be a good proxy to capture victims' error. However, a potential problem with using NRA membership is that much violent crime is committed with illegally owned guns, in particular among those involved with the drug trade and/or involved in street gang activities (Blumstein 1995, Donohoe and Levitt 1998). Therefore, we believe that the proportion of fatalities which involve firearms is a better proxy than NRA membership to take account of the effect of gun ownership on the murder rate.

Other Crimes

Murder is often the byproduct of violent crime. For example, Zimring (1977) has shown that increasing proportions of homicides are the outcome of robbery. Ehrlich (1975) does not include violent crime as a potential explanatory variable, but Klein *et al* (1978) and McKee and Sesnowitz (1977) find that the conditional probability of execution becomes statistically insignificant when other crimes are added to the murder supply equation. This is attributed to a shift in the propensity to commit crime which shifts the supply function. In contrast, Dezhbakhsh *et al* (2003) find that all of the deterrence variables continue to be statistically significant with the expected sign when violent crimes are added to the murder supply equation. Following Dezhbakhsh *et al* (2003) we include two violent crimes in the murder supply function. These are $ln\,AA$, the log of the aggravated assault rate, and $ln\,R$, the log of the robbery rate.

III. ECONOMETRIC METHODOLOGY

The bounds testing procedure to cointegration is developed within an autoregressive distributed lag framework and can be carried out in two stages. In the first stage, the existence of a long-run relationship among the variables predicted by theory is tested. With prior information about the expected direction of the long-run relationship among the variables, we treat the murder rate as the dependent variable. Here we present a brief outline of the procedure involved. Let us define a vector of variables z_t where $z_t = (y_t, x_t')'$, y_t is the dependent variable and x_t is a vector of regressors. The data generating process of z_t is a *p*-order vector autoregression. For cointegration analysis it is essential that Δy_t be modeled as a conditional ECM:

$$\Delta y_t = \beta_0 + \pi_{yy} y_{t-1} + \pi_{yx.x} x_{t-1} + \sum_{i=1}^{p} \vartheta_i \Delta y_{t-i} + \sum_{j=0}^{q} \phi_j' \Delta x_{t-j} + \theta w_t + \mu_t \qquad (2)$$

Here, π_{yy} and π_{yx} are long-run multipliers. β_0 is the drift and w_t is a vector of exogenous components e.g. dummy variables. Lagged values of Δy_t and current and lagged values of Δx_t model the short-run dynamic structure. The bounds testing procedure tests for the absence of any level relationship between y_t and x_t through exclusion of the lagged levels variables y_{t-1} and x_{t-1} in equation (2). It follows then that our test for the absence of a conditional level relationship between y_t and x_t have the following null and alternative hypotheses:

$$H_0 : \pi_{yy} = 0,\ \pi_{yx.x} = 0', \qquad (3)$$

$$H_1 : \pi_{yy} \neq 0,\ \pi_{yx.x} \neq 0' \text{ or } \pi_{yy} \neq 0,\ \pi_{yx.x} = 0' \text{ or } \pi_{yy} = 0,\ \pi_{yx.x} \neq 0'. \qquad (4)$$

These hypotheses can be examined using the standard *F* statistic. The *F* test has a non-standard distribution which depends upon: (i) whether variables included in the ARDL model are $I(1)$ or $I(0)$, (ii) the number of regressors and (iii) whether the ARDL model contains an intercept and/or a trend. Pesaran *et al* (2001) report two sets of critical values based on 40,000 replications of a stochastic stimulation, which provide critical value bounds for all classifications of the regressors into purely $I(1)$, purely $I(0)$ or mutually cointegrated for a sample size of 1000 observations.

However, in this study, we have a relatively small sample size of 37 observations. With small sample sizes the relevant critical values potentially deviate substantially from the critical values reported in Pesaran *et al* (2001). Therefore, we calculate exact critical value bounds tailored to our sample size. We calculate exact critical value bounds using stochastic simulations for $T = 37$ with eight or nine regressors, based on 40,000 replications for the F-statistic. We employ a model with an intercept, but no trend, which is case II in Pesaran *et al*'s (2001) terminology (see Pesaran *et al* 2001 for details). If the computed F statistics falls outside the critical bounds, a conclusive decision can be made regarding cointegration without knowing the order of integration of the regressors. If the estimated F statistic is higher than the upper bound of the critical values then the null hypothesis of no cointegration is rejected. If the estimated F statistic is lower than the lower bound of critical values, the null hypothesis of no cointegration cannot be rejected. Assuming that a long-run relationship is ascertained in stage one, stage two involves the estimation of the parameters of the long-run relationship and the associated short-run dynamic error correction models (ECM). First the orders of the lags in the ARDL model are selected using a lag selection criterion such as the Schwartz Bayesian Criterion (SBC) and in the second step the selected model is estimated by ordinary least squares.

IV. RESULTS

In the first step of the ARDL analysis we tested for the presence of long-run relationships using four variations of equation (1). In models (1)-(4) we arbitrarily assume that there was one execution per year between 1968 and 1976 and in models (5)-(8) we rerun the same regressions using the Bayesian probabilities of execution between 1968 and 1976. As we use annual data, the maximum number of lags in the

ARDL was set equal to 2. The calculated F-statistics for models (1)-(4) are reported in Table 2 and the calculated F-statistics for models (5)-(8) are reported in Table 3.

$F_M(.)$ is higher than the upper bound critical value in each case, with the exception of model (1), where the calculated F statistic of 3.062 is slightly less than the upper bound critical value of 3.317 at the 10 per cent level. However, given that the unemployment variable is an $I(0)$ process, it is likely that there is a cointegration relationship among the variables in model (1), so we proceed on this basis. In models (2), (3), (4), (6), (7) and (8) the calculated F-statistics are greater than the upper bound critical value at 5 per cent. In model (5) the calculated F statistic is greater than the upper bound critical value at 1 per cent. Thus, we conclude that there is a long-run cointegrating relationship amongst the variables in each model.

Insert Tables 2 & 3

Once we established that a long-run cointegration relationship existed, model (1) was estimated using the following ARDL (m,n,p,q,r,s,t,u,v) specification:

$$\begin{aligned} ln M_t &= \alpha_0 + \sum_{i=1}^{m}\alpha_1 ln M_{t-i} + \sum_{i=0}^{n}\alpha_2 ln AGE_{t-i} + \sum_{i=0}^{p}\alpha_3 ln Y_{t-i} \\ &+ \sum_{i=0}^{q}\alpha_4 ln PA_{t-i} + \sum_{i=0}^{r}\alpha_5 ln PE_{t-i} + \sum_{i=0}^{s}\alpha_6 ln PS_{t-i} + \sum_{i=0}^{t}\alpha_7 ln U_{t-i} \\ &+ \sum_{i=0}^{u}\alpha_8 ln L_{t-i} + \sum_{i=0}^{v}\alpha_9 ln NW_{t-i} + \varepsilon_t \end{aligned} \quad \textbf{(5)}$$

Similar ARDL specifications were estimated for models (2)-(8). In estimating the ARDL specifications a maximum of 2 lags was used (i_{max}=2). The estimated models are based on minimizing the SBC. The long-run results for models (1) to (4) are reported in table 2 and the long-run results for models (5) to (8) are reported in table

3. The short-run results for models (1) to (4) are reported in table 4 and the short-run results for models (5) to (8) are reported in table 5, in each case together with diagnostic tests. The error correction term in the short-run models is statistically significant at 1 per cent with a negative sign in models (2)-(4) and (6)-(8), at 5 per cent in model (5) and at the 20 per cent level for model (1). This confirms that a long-run equilibrium relationship exists between the variables. Apart from the RESET test in model (7), all the short-run models pass the diagnostic tests for autocorrelation, functional form and heteroskedasticity and the fit of the models is good.

Insert Tables 4 & 5

Deterrence Variables

The results provide at best mixed support for the deterrence hypothesis. In the long-run the three criminal justice variables have the expected sign in most cases, but are generally not statistically significant. The conditional probability of receiving the death sentence is statistically significant in models (2) to (4) and (6) to (8); however the probability of apprehension is only statistically significant in models (3) and (7) and the conditional probability of execution is statistically insignificant in all models. The ranking property of the magnitude of the coefficients which Ehrlich (1982, p. 9) describes as “a key theoretical proposition” does not hold in most models.[3]

In the short-run the probability of apprehension is statistically significant with the expected sign in model (1), but is statistically insignificant in the other models. In the short-run in model (7) the conditional probability of apprehension with a one period lag is statistically significant with a positive sign. One reason for this result might be a moral hazard problem where potential victims of crime react to an increase in public sector deterrence in period t-1, through spending less on private sector deterrence, such as home security, in period t (see Cameron 1988). The conditional probability of being sentenced to death is statistically insignificant in model (1), but is statistically significant with the expected sign in models (2) to (8). The conditional probability of execution is statistically significant with the expected sign in model (1). However, consistent with studies such as Klein *et al* (1978), McKee and Sesnowitz (1977) and Kleck (1979) it becomes statistically insignificant in models (2)- (4) when other crimes and/or the firearm proxy are added to the murder supply equation. It is statistically insignificant in models (5)-(8) which uses the Bayesian probabilities of execution for 1968-1976. Overall, the mild influence of the changes in the schemes discovered here could be a reflection of the literature which shows that criminals are uninformed about punishment schemes (see Cameron, 1988 for a review).

Economic Variables

With the exception of model (5) real income has a negative sign and is significant in most cases in the short-run and long-run. The negative sign is consistent with real income reflecting the opportunity cost of committing property crime. The positive sign in model (5) is consistent with income proxying victim stock. Labor force participation is only entered in models (1) and (5), where it is statistically insignificant in the short-run and long-run. In the long-run results unemployment is statistically significant with a positive sign in models (2) and (6), but is statistically insignificant in the other models. In the short-run in most instances unemployment and unemployment with a one period lag have a negative sign. In the short-run unemployment is statistically significant in models (4), (7) and (8) and lagged unemployment is statistically significant in models (2)-(4) and (6)-(8).

Other studies which have found unemployment to have a statistically significant negative effect on crime rates include Good *et al* (1986) and Britt (1994). This finding is inconsistent with the motivational perspective emphasised in the economics literature, but is consistent with the opportunity perspective stressed in the criminology literature. The opportunity perspective sees crime as a function of the supply of suitable targets for victimization. This perspective suggests that crimes will fall during times of high unemployment. The reason for this is that in times of economic downturn the circulation of people and the level of spending on new property is reduced. As the unemployment rate rises more people will remain in their homes or close neighborhood providing more protection for their property, reducing the incidence of property crime, and curtailing the level of violent crime, most of which occurs outside the home (Cohen 1981, Cohen and Land 1987, Britt 1994).

Demographic Variables and Other Crimes

The proportion of the population aged 18 to 24 generally has the expected positive sign in both the short-run and long-run. In the long-run it is statistically significant in model (3) and in the short-run it is statistically significant in models (2)-(4) and (6)-(8). In the long-run the variable measuring the proportion of the population that is non-white is statistically significant with an unexpected negative sign in model (5), but is otherwise insignificant. In the short-run it is statistically insignificant in models (1) and (5), but is statistically significant with the expected sign in models (4) and (8). The divorce rate is statistically insignificant in both the short-run and the long-run.

The proportion of fatalities that involve firearms is statistically insignificant in the long-run, but is statistically significant in the current period and with a one period lag in the short-run. The robbery rate is consistently statistically significant with the expected positive sign in models (2)-(4) and (6)-(8) in the long-run and short-run. With the exception of models (3) and (7) in the long-run, aggravated assault is also statistically significant with the predicted positive sign in the short-run and long-run and aggravated assault with a one period lag is statistically significant in the short-run.

V. PARAMETER STABILITY

In this section we test the stability of the estimated coefficients for the homicide function, which is important given the small sample size and the debate in the existing literature over the stability of the homicide function. Bowers and Pierce (1975), Passell and Taylor (1977) and Klein *et al* (1977) argue that the murder supply equation becomes unstable in the 1960s and that omitting the post-1960 data from the sample seriously weakens Ehrlich's (1975) conclusion that capital punishment has a deterrent effect. In more recent research Layson (1985) claims that the homicide function is stable, at least up until 1977. To test for parameter stability we use the Pesaran and Pesaran (1997) test. According to Pesaran and Pesaran (1997), the short-run dynamics are essential in testing for the stability of the long-run coefficients. For model (1), the Pesaran and Pesaran (1997) involves estimating the following ECM:

$$\begin{aligned}\Delta lnM_t &= \alpha_0 + \sum_{i=1}^{m}\alpha_1 \Delta lnM_{t-i} + \sum_{i=0}^{n}\alpha_2 \Delta ln\,AGE_{t-i} + \sum_{i=0}^{p}\alpha_3 \Delta lnY_{t-i} \\ &+ \sum_{i=0}^{q}\alpha_4 \Delta ln\,PA_{t-i} + \sum_{i=0}^{r}\alpha_5 \Delta ln\,PE_{t-i} + \sum_{i=0}^{s}\alpha_6 \Delta ln\,PS_{t-i} + \sum_{i=0}^{t}\alpha_7 \Delta lnU_{t-i} \\ &+ \sum_{i=0}^{u}\alpha_8 \Delta ln\,L_{t-i} + \sum_{i=0}^{v}\alpha_9 \Delta ln\,NW_{t-i} + \theta ECM_{t-1} + \varepsilon_t\end{aligned} \qquad \textbf{(6)}$$

In a similar way error correction models are developed for models (2)-(8). Once the ECMs have been estimated, Pesaran and Pesaran (1997) suggest applying the cumulative sum of recursive residuals (CUSUM) and the CUSUM square (CUSUMSQ) tests proposed by Brown *et al* (1975) to assess the parameter constancy. The ECMs were estimated by ordinary least squares and the residuals were subjected to the CUSUM and CUSUMSQ test. Figure 1 plots the CUSUM and CUSUMSQ statistics for models (1)-(4) and figure 2 plots the CUSUM and CUSUMSQ statistics for models (5)-(8). The results clearly indicate that the parameters are stable since the plot of the CUSUM and CUSUMSQ statistics are confined within the 5 per cent critical bounds of parameter stability for each of the eight models.

Insert Figures 1& 2

VI. CONCLUSION

The debate over whether capital punishment exerts a deterrent effect on the murder rate has raged for decades and is unlikely to subside. The contribution of this paper to the debate is to use a cointegration and error correction framework. Thus, for the first time we provide estimates of the long-run and short-run elasticities of the murder supply equation. We find, at best, mixed support for the deterrent effect. Our findings suggest that support for the deterrence hypothesis is sensitive to the inclusion of variables for the effect of guns and other crimes. Overall, we find that in the long-run real income and the conditional probability of receiving the death sentence are the main factors explaining variations in the homicide rate. Meanwhile, in the short-run the aggravated assault rate and robbery rate are the most important determinants of variations in the homicide rate across all empirical specifications.

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Table 1. *Definition of variables*

Variable	Definition
lnM_t	Log of murders and non-negligent manslaughters per 100,000 population.
$ln\,AGE_t$	Log of the percentage of resident population aged 18-24.
$ln\,Y_t$	Log of real per capita personal disposable income.
$ln\,PA_t$	Log of the arrest clearance rate.
$ln\,PE_t$	Log of the probability of execution, conditional on receiving the death sentence.
$ln\,PS_t$	Log of the probability of receiving the death sentence, conditional on being apprehended.
$ln\,U_t$	Log of the unemployment rate.
$ln\,L_t$	Log of the labor force participation rate.
$ln\,NW_t$	Log of the percentage of resident population that is non-white.
$ln\,FA_t$	Log of the proportion of fatalities that involve firearms.
$ln\,D_t$	Log of the divorce rate.
$ln\,AA_t$	Log of the aggravated assault rate.
$ln\,R_t$	Log of the robbery rate.

Table 2. *Long-run results assuming there was one execution 1968-76*

Regressors	Model 1	Model 2	Model 3	Model 4
$\ln AGE_t$	1.3176	0.0491	0.3438*	0.0781
	(0.7307)	(0.1358)	(1.8799)	(0.6057)
$\ln Y_t$	-2.0112	-0.7144**	-0.7555***	-0.8664***
	(-0.6631)	(-2.1975)	(-4.2582)	(-4.9044)
$\ln PA_t$	-7.0066	0.1810	-1.9552***	0.0145
	(-1.3921)	(0.6231)	(-3.5176)	(0.0788)
$\ln PE_t$	-0.2961	-0.0044	-0.0012	-0.0101
	(-1.6609)	(-0.2697)	(-0.1512)	(-1.0295)
$\ln PS_t$	-0.0650	-0.2366***	-0.1589***	-0.1642***
	(-0.3306)	(-5.0962)	(-2.8411)	(-4.8197)
$\ln U_t$	-0.8882	0.2424**	0.0950	0.0978
	(-0.8278)	(2.4163)	(1.0801)	(1.3881)
$\ln L_t$	4.6412	-	-	-
	(0.7463)			
$\ln NW_t$	-3.3512	-	-	0.4000
	(-0.9922)			(1.4155)
$\ln FA_t$	-	-	0.2043	-
			(0.7765)	
$\ln D_t$	-	-0.0798	-	-
		(-0.2464)		
$\ln AA_t$	-	0.7385***	0.0161	0.4489**
		(3.0296)	(0.0960)	(2.1077)
$\ln R_t$	-	0.3178**	0.5259***	0.5202***
		(2.0406)	(5.7520)	(3.3833)
$Constant$	37.9348	0.6532	12.1078***	2.6376
	(1.0028)	(0.1852)	(3.0297)	(1.4645)
F-test				
$F_M(.)$	3.0624	4.5083	4.0303	5.0981

Critical values

k	90%		95%		99%	
	$I(0)$	$I(1)$	$I(0)$	$I(1)$	$I(0)$	$I(1)$
8	2.126	3.327	2.523	3.853	3.450	5.141
9	2.085	3.317	2.464	3.833	3.359	5.106

Notes: **(***) indicates statistical significance at the 5% and 1% levels respectively. Critical values are calculated using stochastic simulations specific to the sample size based on 40,000 replications. k is the number of regressors.

Table 3. *Long-run results assuming Bayesian probabilities of execution 1968-76*

Regressors	Model 5	Model 6	Model 7	Model 8
$ln\,AGE_t$	-1.7169	0.0589	0.2481	0.0930
	(-1.4324)	(0.1791)	(0.7531)	(0.7613)
$ln\,Y_t$	4.7948*	-0.7049**	-0.4356	-0.8827***
	(1.7466)	(-2.3521)	(-1.0747)	(-5.1633)
$ln\,PA_t$	-2.5534	0.1485	-2.7623**	0.0149
	(-1.1067)	(0.5474)	(-2.5289)	(0.0824)
$ln\,PE_t$	-0.0988	-0.0088	0.0103	-0.0086
	(-1.2868)	(-0.6621)	(0.6967)	(-1.0098)
$ln\,PS_t$	-0.0468	-0.2245***	-0.1631**	-0.1688***
	(-0.3265)	(-4.9626)	(-2.0939)	(-5.2407)
$ln\,U_t$	0.2308	0.2292**	0.1339	0.0954
	(0.5537)	(2.4632)	(0.9728)	(1.3809)
$ln\,L_t$	-6.5755	-	-	0.0954
	(-1.2052)			(1.3809)
$ln\,NW_t$	-8.3620**	-	-	0.3107
	(-2.0198)			(1.0723)
$ln\,FA_t$	-	-	0.1405	-
			(0.3627)	
$ln\,D_t$	-	-0.0995	-	-
		(-0.3260)		
$ln\,AA_t$	-	0.7107***	-0.4312	0.4962**
		(3.1340)	(-0.9054)	(2.4203)
$ln\,R_t$	-	0.3350**	0.7663***	0.4927***
		(2.2694)	(3.0083)	(3.2153)
$Constant$	21.2845	0.8401	14.2607**	2.8648
	(0.9288)	(0.2558)	(2.4768)	(1.5812)
F test				
$F_M(.)$	5.4861	3.9582	4.1466	4.4263

Critical values						
k	90%		95%		99%	
	$I(0)$	$I(1)$	$I(0)$	$I(1)$	$I(0)$	$I(1)$
8	2.126	3.327	2.523	3.853	3.450	5.141
9	2.085	3.317	2.464	3.833	3.359	5.106

Notes: **(***) indicates statistical significance at the 5% and 1% levels respectively. Critical values are calculated using stochastic simulations specific to the sample size based on 40,000 replications. k is the number of regressors.

Table 4. *Short-run results assuming there was one execution 1968-76*

Regressors	Model 1	Model 2	Model 3	Model 4
$\Delta ln M_{t-1}$	-	-	-0.1323 (-1.6083)	-
$\Delta ln AGE_t$	0.1738 (0.9433)	0.5283** (2.6634)	0.5379*** (4.6087)	0.3781*** (2.8860)
$\Delta ln AGE_{t-1}$	-	0.7321*** (4.2166)	0.8983*** (6.0166)	0.5893*** (3.9387)
$\Delta ln Y_t$	-0.2653 (-0.8119)	-0.2780* (-1.9070)	-0.3351*** (-4.1306)	-0.42011*** (-4.2074)
$\Delta ln PA_t$	-0.9243** (-2.4868)	0.0704 (0.6239)	-0.0238 (-0.2796)	0.0071 (0.0788)
$\Delta ln PS_t$	-0.0086 (-0.3291)	-0.0748*** (-7.0741)	-0.0563*** (-5.2429)	-0.0678*** (-8.4131)
$\Delta ln PE_t$	-0.0391** (-2.1501)	-0.0017 (-0.2655)	-0.0005 (-0.1503)	-0.0049 (-0.9812)
$\Delta ln U_t$	-0.1172 (-1.4578)	-0.0027 (-0.0906)	-0.0259 (-1.0600)	-0.0472* (-1.7568)
$\Delta ln U_{t-1}$	-	-0.0750** (-2.4635)	-0.0696** (-2.5151)	-0.0692*** (-3.0455)
$\Delta ln FA_t$	-	-	0.5171*** (4.5681)	-
$\Delta ln FA_{t-1}$	-	-	0.4779*** (4.8166)	-
$\Delta ln AA_t$	-	0.6107*** (5.6302)	0.6160*** (8.9917)	0.4795*** (4.9150)
$\Delta ln AA_{t-1}$	-	0.3386*** (4.6076)	0.6813*** (9.0602)	0.3425*** (6.1679)
$\Delta ln R_t$	-	0.4335*** (4.8884)	0.3689*** (6.7558)	0.5208*** (6.4649)
$\Delta ln D_t$	-	-0.0310 (-0.2523)	-	-
$\Delta ln NW_t$	0.2634 (0.5935)	-	-	0.3934*** (2.9433)
$\Delta ln L_t$	0.6123 (0.9106)	-	-	-
ECM_{t-1}	-0.1319^ (-1.5677)	-0.3891*** (-5.5227)	-0.4436*** (-6.7391)	-0.4849*** (-7.2794)
$Constant$	5.0043 (1.2609)	0.2542 (0.1824)	5.3705*** (4.1198)	1.2790 (1.4635)
$\overline{R}^2$	0.9516	0.9693	0.9923	0.9826
$\chi^2_{RESET}(1)$	0.3201	0.8481	0.7850	0.5186
$\chi^2_{AUTO}(2)$	0.0105	4.2337	3.2358	0.1792
$\chi^2_{HETERO}(1)$	1.4382	3.3431	0.0647	0.5124

Notes: ^(*)**(***) indicates statistical significance at the 20%, 10%, 5% and 1% levels respectively. The critical value for $\chi^2(1)$ is 6.63 and for $\chi^2(2)$ is 9.21 at the 1% significance level.

Table 5. *Short-run results assuming Bayesian probabilities of execution 1968-76*

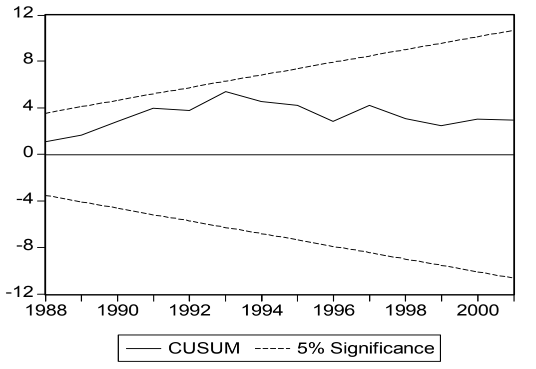
Regressors	Model 5	Model 6	Model 7	Model 8
$\Delta ln M_{t-1}$	0.3541** (2.2209)	-	-0.1301^ (-1.6091)	-
$\Delta ln AGE_t$	-0.3026^ (-1.3983)	0.5303*** (2.7052)	0.4835*** (3.9852)	0.3894*** (2.9965)
$\Delta ln AGE_{t-1}$	-	0.7268*** (4.3005)	0.9699*** (6.3920)	0.6265*** (4.3773)
$\Delta ln Y_t$	0.2884 (0.8867)	-0.2915** (-2.0071)	-0.2746*** (-3.1316)	-0.4359*** (-4.2728)
$\Delta ln PA_t$	-0.4499 (-1.2679)	0.0614 (0.5527)	0.0053 (0.0611)	0.0074 (0.0824)
$\Delta ln PA_{t-1}$	-	-	0.6877*** (4.9116)	-
$\Delta ln PS_t$	-0.0454^ (-1.6959)	-0.0746*** (-7.4056)	-0.0516*** (-4.2141)	-0.0696*** (-9.1451)
$\Delta ln PS_{t-1}$	-	-	-0.0089^ (-1.3113)	-
$\Delta ln PE_t$	-0.0174 (-1.1934)	-0.0036 (-0.6161)	0.0034 (0.8056)	-0.0043 (-0.9446)
$\Delta ln U_t$	0.0407 (0.4849)	-0.0046 (-0.1686)	-0.0311^ (-1.3587)	-0.0505** (-1.9809)
$\Delta ln U_{t-1}$	-	-0.0789** (-2.5531)	-0.0642** (-2.1355)	-0.0706*** (-3.0515)
$\Delta ln FA_t$	-	-	0.5004*** (4.3140)	-
$\Delta ln FA_{t-1}$	-	-	0.5554*** (5.0662)	-
$\Delta ln AA_t$	-	0.6106*** (5.6903)	0.5532*** (7.0342)	0.4901*** (5.0166)
$\Delta ln AA_{t-1}$	-	0.3373*** (4.7227)	0.6978*** (9.3746)	0.3339*** (6.1307)
$\Delta ln R_t$	-	0.4324*** (4.7227)	0.4129*** (7.1073)	0.5209*** (6.4477)
$\Delta ln R_{t-1}$	-	-	-0.1694* (-1.9385)	-
$\Delta ln D_t$	-	-0.0411 (-0.3343)	-	-
$\Delta ln NW_t$	-0.6213^ (-1.4826)	-	-	0.3615*** (2.7546)
$\Delta ln NW_{t-1}$	0.8964*** (3.1042)	-	-	-
$\Delta ln L_t$	0.2938 (0.4010)	-	-	-
$\Delta ln L_{t-1}$	3.0937*** (3.3021)	-	-	-
ECM_{t-1}	-0.1762** (-2.2721)	-0.4135*** (-5.0179)	-0.3304*** (-3.3641)	-0.4938*** (-6.8930)
$Constant$	3.7507 (1.0158)	0.3473 (0.2501)	4.7117*** (3.5088)	1.4147^ (1.5488)

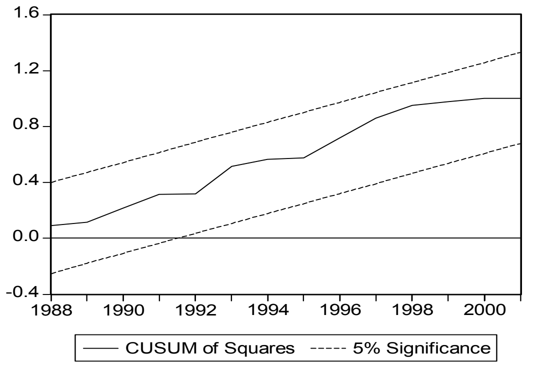
$\overline{R}^2$	0.7476	0.9699	0.9926	0.9825
$\chi^2_{RESET}(1)$	1.7455	0.6086	9.1774	0.1202
$\chi^2_{AUTO}(2)$	3.9560	4.9612	4.7332	0.3533
$\chi^2_{HETERO}(1)$	1.6544	3.5374	0.0199	0.6790

Notes: ^(*)**(***) indicates statistical significance at the 20%, 10%, 5% and 1% levels respectively. The critical value for $\chi^2(1)$ is 6.63 and for $\chi^2(2)$ is 9.21 at the 1% significance level.

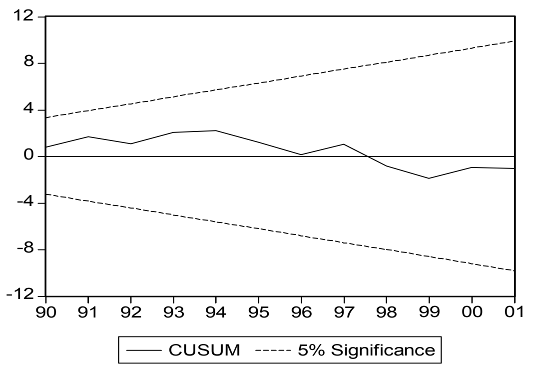
Figure 1.
Plot of the CUSUM and CUSUMSQ test for parameter stability models (1)-(4)

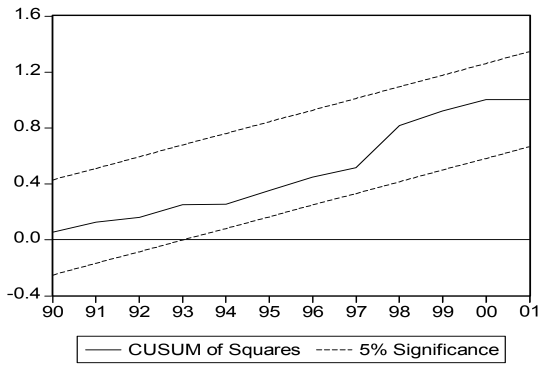
Model 1



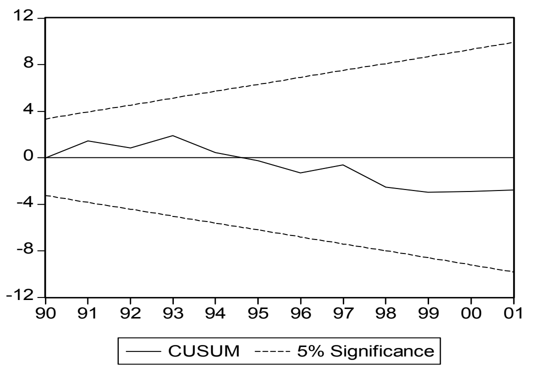


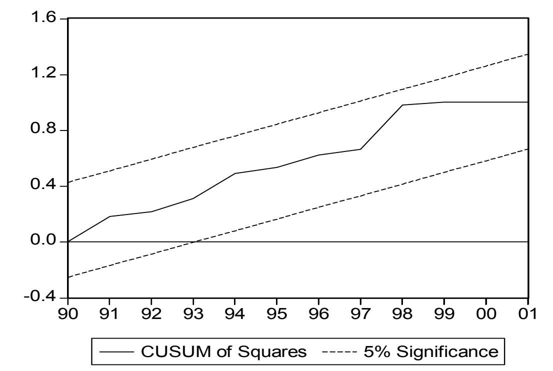
Model 2



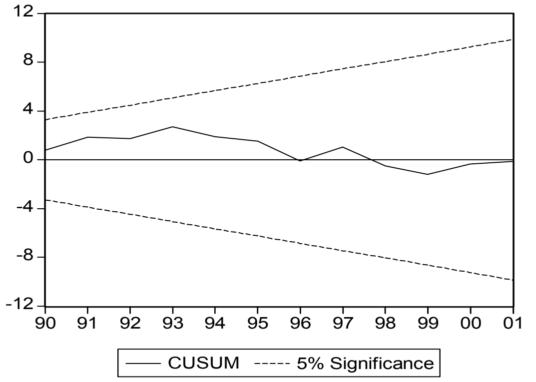


Model 3





Model 4



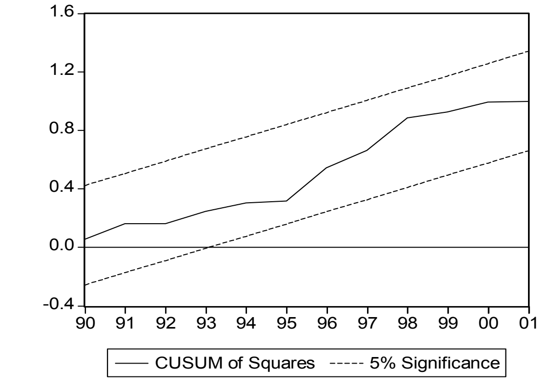
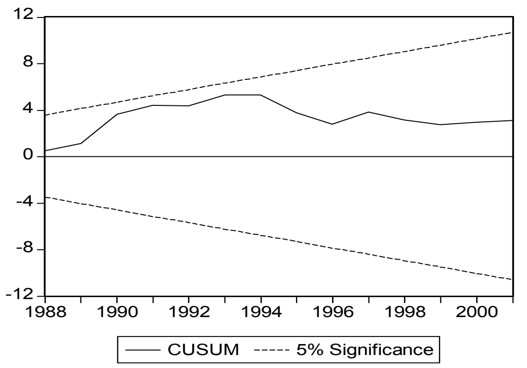
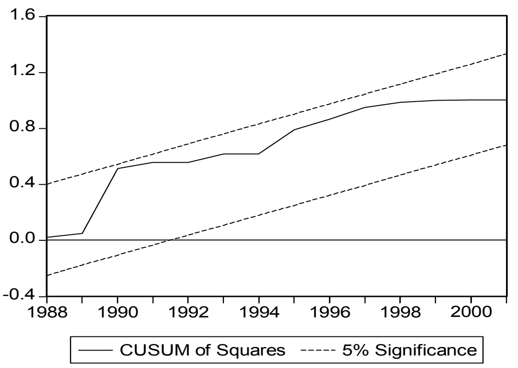


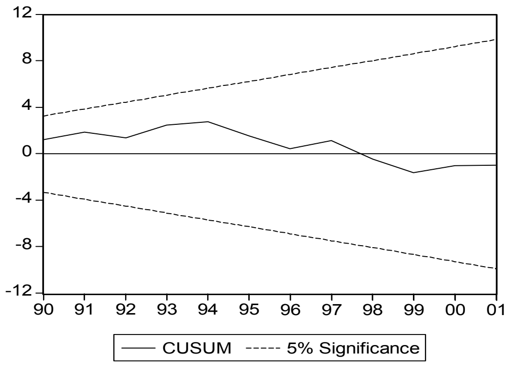
Figure 2.
Plot of the CUSUM and CUSUMSQ test for parameter stability for models (5)-(8)

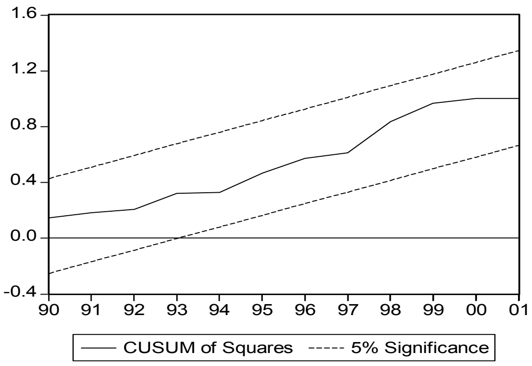
Model 5



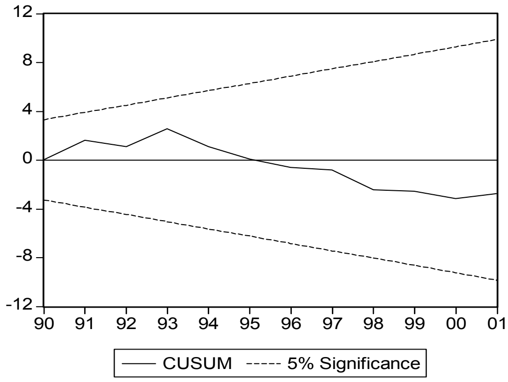


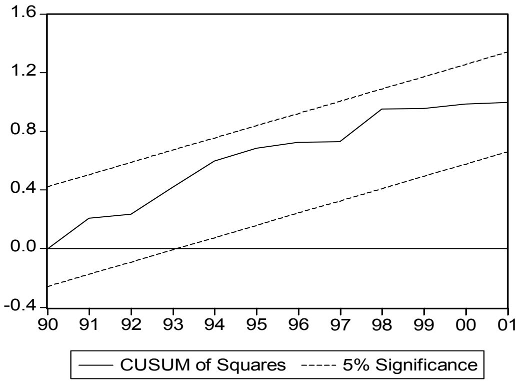
Model 6



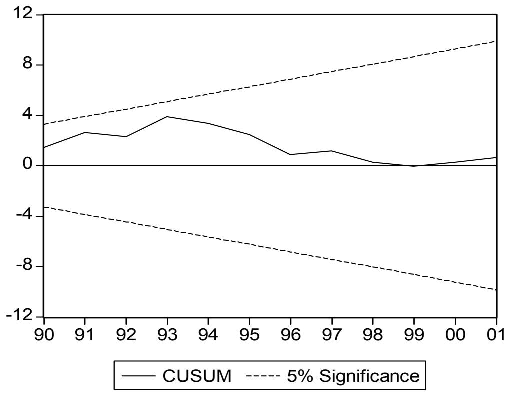


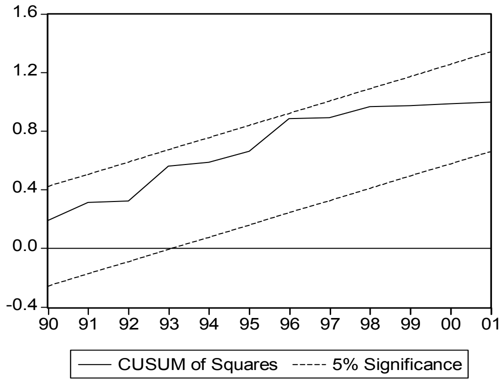
Model 7





Model 8





APPENDIX : SOURCE OF THE VARIABLES

Variable	Source
Murder rate	FBI Uniform Crime Reports (various)
Probability of apprehension	FBI Uniform Crime Reports (various)
Conditional probability of receiving a death sentence	Capital Punishment in the United States (various)
Conditional probability of execution	Capital Punishment in the United States (various)
The proportion of the resident population aged 18-24	Statistical Abstract of the United States (various)
Real income	Kurian (2001), Statistical Abstract of the United States (various)
Unemployment rate	Statistical Abstract of the United States (various)
The proportion of fatalities involving firearms	FBI Uniform Crime Reports (various)
Aggravated assault rate	FBI Uniform Crime Reports (various)
Robbery rate	FBI Uniform Crime Reports (various)
Divorce rate	Statistical Abstract of the United States (various)
Labor force participation	Kurian (2001), Statistical Abstract of the United States (various)
Proportion of the population that is non-white.	Statistical Abstract of the United States (various)
Consumer Price Index	US Department of Labor, Bureau of Labor Statistics (1982-84 = 100)

NOTES

[1] The unit root tests are available from the authors on request.

[2] Ehrlich (1977a) and Layson (1983, 1985) select a log linear form on the basis of a Box-Cox transformation. This method is inapplicable to the model being used here.

[3] We also estimated models with just the deterrence variables as explanatory variables. When we arbitrarily assumed that there was one execution per year between 1968 and 1976 and when we used the Bayesian probabilities of execution between 1968 and 1976, the probability of apprehension and the conditional probability of execution were both significant with a negative sign, but the probability of receiving the death sentence was statistically insignificant. The results are as follows: Assuming one execution per year between 1968 and 1976, lnPA = -1.5698** (-2.4911), lnPE = -0.1919*** (-3.3663), lnPS = -0.0720 (-0.5544), c = 7.9160*** (3.1379), Fm(.) = 5.1414. Assuming the Bayesian probabilities of execution between 1968 and 1976, lnPA = -1.6381**** (-2.996), lnPE = -0.1611*** (-5.2330), lnPS = -0.0121 (-0.1199), c = 8.7506*** (5.6515), Fm(.) = 7.5229.