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ABSTRACT

Rapidly growing prison population in the US has led to an upsurge of interest in discerning the impact of this costly increase on crime rates. Estimates of impact vary. We obtain new estimates of the impact of prisons using different data, specification and estimation technique than previous work. We find that both higher levels of imprisonment and increases in labor force participation of women are related to significantly higher crime rate. The impact of female labor force participation is much larger than the impact of imprisonment.

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I. INTRODUCTION

Rapidly growing prison population in the US has led to an upsurge of interest in discerning the impact of this costly increase on crime rates. Estimates of impact vary. Recent work has used state-level panel data on crime rates from the FBI's Uniform Crime Reports (UCR) (e.g., Marvell and Moody, 1994; Levitt, 1996). The specification of these models has been the standard one used since Becker's path breaking article (Becker, 1968).

In this paper, our focus remains on the impact of imprisonment on crime rates. We seek to discern the degree to which existing estimates of the effect of imprisonment on crime rates are robust to changes in data, estimation technique and specification. Specifically, we use aggregate time series data to estimate our model rather than data for smaller sub-national units. Our reasons for doing this relate to measurement error. The UCR relies on voluntary reporting of crime statistics by individual police departments. At the level of the individual police department, both administrative and political changes can lead to abnormalities in reported data or to failures to report any data (see Donohue and Siegelman, 1994 or Boggess and Bound, 1993). In such a setting, aggregate data may more faithfully reflect underlying trends than more disaggregated data. In the process of aggregation, many individual oddities are averaged out and outliers are greatly reduced.

In terms of estimation technique, we use modern time-series methods that are specifically designed to deal with such difficult issues as stationarity, cointegration and direction of causation. To date these techniques have been little used to explore the nature of crime rates, criminal justice system variables or macro socio-demographic variables related to them.

In terms of specification, we add a potentially important explanatory variable, the labor force participation of women. We see this variable as a proxy for the myriad of economic and social changes that have affected the US family and US communities over the last three decades. Recently, a number of authors have suggested that changing family structures and changes in neighbourhood caused by these altered structures are an important and relatively overlooked cause of crime. See, for example, Donohue and Siegelman (1998), Greenwood (1998), Wilson (1998) and Witte (1996,1997). As these authors point out, the influx of women into the labor market with no concomitant decrease in male labor force participation has increased the opportunity for crime and the supply of potential criminals.

To be more specific, we use time-series econometric techniques developed in macroeconomics to analyse the relationship between the crime rate, the level of imprisonment and one important socio-demographic indicator, the labor force participation rate for women. The work provides a check for the robustness of estimates of the effects of increases in imprisonment on the crime rate and begins to explore the potential impact of increased female labor force participation potential impact of increased female labor force participation and the socio-economic changes associated with this increase on crime rates.

To briefly summarise our results, we obtain estimates of the short-run elasticity of the crime rate with respect to imprisonment that are quite similar to Levitt's (1996) and substantially larger than Marvell and Moody's (1994). Our estimation technique also allows us to estimate the long-rung elasticity of imprisonment with respect to the crime rate. We find that the long-run elasticity is slightly larger than the short-run elasticity, -0.309 vs. -0.287. The estimated error correction coefficient, -0.167, indicates a slow speed of convergence of crime rates towards their long-run equilibrium level.

We find significant long-run and short-run effects of female labor supply on crime. To be specific, we find that the long-run effect of a one percentage point rise in the female labor force participation rate increases the crime rate by just over 5 percent. The short-run effect of the crime rate with respect to the labor force participation rate for women is greater than the long-run effect.

The plan of the paper is as follows. The next section describes the statistical techniques that we use. The section that follows contains a discussion of the data used in estimation and the subsequent section provides the empirical results. The final section offers some conclusions.

II. Statistical Methods

The crime rate is a macro indicator and like many macroeconomic variables, such as the unemployment rate or interest rates, raises difficult theoretical and empirical issues. To date most studies of the crime rate try to estimate structural models (e.g., Tauchen, Witte and Griesinger, 1994, Levitt, 1996, 1997). This approach is similar to the approach used by macroeconomists during the 1970s.

Much recent work designed to understand macroeconomic variables has taken a somewhat different approach. In this literature, time series observations are seen as a particular realisation of an underlying stochastic process. Specialised statistical techniques are used to uncover the underlying process. As far as we are aware, these techniques have seen very limited use to study crime rates, other macro indicators for the criminal justice system (e.g., imprisonment statistics) and macro socio-demographic variables related to them.

In modern time-series econometrics, the first question of interest is whether or not the time series being considered are stationary. Broadly speaking, a stochastic process is said to be stationary if its mean and variance are constant over time and the value of the covariance between any two periods depends only on the distance between the two time periods and not on the actual time at which the covariance is computed (Hamilton, 1994, 45-46). Figure 1 illustrates that the behaviour of the time series that we propose to study appears non-stationary, meaning that the series are not mean-reverting. This result suggests that the use of modern time series techniques may be fruitful.

Modern time series techniques allow us to formally test for the stationarity of the time series. They also allow us to estimate the long-run elasticity of crime with respect to the number of prisoners, which has not been possible with the methods currently used for studies of the crime rate.

Much of the literature that has sought to explain changes in crime has analysed only first differenced data, that is, year-to-year growth rates of crime (e.g., Levitt, 1996). The objective for differencing is generally not discussed. From the perspective of modern time-series econometrics, first differencing of the data may transform a non-stationary time series into a stationary allowing use of standard estimating techniques such as OLS. However, a major drawback with differencing is that it eliminates the trend component. Hence, such work can allow examination only of short-term not long-run trends in the time series.

In this paper we apply cointegration analysis to the modelling of crime, thereby accounting for the potential non-stationarity of the data and simultaneously avoiding the loss of valuable long-run information which would result from taking first differences. We employ two procedures. First, the two-step procedure of Engle and Granger (1987), where an estimate of the cointegrating relationship is obtained by an ordinary least squares (OLS) regression of the contemporaneous values of the variables. However, the estimates from the static regression of Engle and Granger may be seriously biased in small samples (e.g., see Hargreaves, 1994). Second, we apply the systems approach of Johansen (1988, 1991). This approach estimates long-run or cointegrating relationships between non-stationary variables using a maximum likelihood procedure which tests for the number of cointegrating relationships and estimates the parameters of these cointegrating relationships. Defining the (3x1) vector $\mathbf{x}_t$ = [log $crim_t$, log $pris_t$, $female_t$]′, we can represent the data in VAR form as

$$\Delta\mathbf{x}_t - \Gamma_1\Delta\mathbf{x}_{t-1} - \Gamma_2\Delta\mathbf{x}_{t-2} - \ldots - \Gamma_{q-1}\Delta\mathbf{x}_{t-q+1} - \Pi\mathbf{x}_{t-q} = \mathbf{b}_0 + \mathbf{B}_1\mathbf{d}_t + \mathbf{u}_t$$

where $\mathbf{\Gamma}_1$ is a (3x3) matrix for I = 1,..,t-q+1, $\mathbf{\Pi}$ is a (3x3) matrix, $\mathbf{b}_0$ is a (3x1) vector of constants, $\mathbf{d}_t$ is a (mx1) vector that contains m stationary variables, $\mathbf{B}_1$ is a conformable (3xm) matrix, and $\mathbf{u}_t$ is a (3x1) vector containing white noise error terms. The Johansen technique estimates the parameters of the VAR and focuses on the long-run parameter vector $\mathbf{\Pi}$ which can be decomposed as $\mathbf{\Pi} = \mathbf{AB}'$ with **A** and **B** both (3xr) matrices and r is the number of cointegrating vectors. **B** are the parameters in the cointegrating relationships and **A** measures the strength of the cointegrating vectors in the Error Correction Models (ECMs). The value of r is obtained using sequential likelihood ratio tests.

III. DATA

The empirical work for this paper employs United States annual time-series data from 1960 to 1996. Although the sample period is shorter than we would like, it is the longest currently available. The FBI provides information on the UCR Crime Index (per 100,000 of the population) going back to 1960[1].

At the local level, the UCR data are influenced both by victims' willingness to report crime, by police recording practices and procedures and by police departments willingness to report their statistics to the FBI (see Boggess and Bound, 1993). The UCR crime rate for the US aggregates the information reported by the local police departments and the FBI attempts to adjust national estimates for failures to report and other known biases. See U.S. Department of Justice (1997) for details.

The National Criminal Victimization Survey (NCS) provides an alternative source of data on crime, but was only begun in 1973. At this time, the time series is too short to allow meaningful examination of the time series properties of the data.

Prison population is defined as the number of prisoners serving sentences of at least one year in Federal and State Institutions. These data are compiled as end of year populations. This variable is expressed as a rate per 1,000 of the population[2]. Female labor force participation rates are from the Economic Report of the President, February 1998, Table B-39, 327.

Finally, note that the crime and prison variables used for this study are the logs of the crime rate and logs of the prisoner population per capita. We use the log of the crime rate since this is the functional form generally used in studies of the crime rate. Given the logarithmic nature of these variables, differencing the variables yields growth rates and makes comparison with previous results much easier.

IV. EMPIRICAL RESULTS

Table 1 presents unit root test results using the augmented Dickey-Fuller (ADF) *t*-statistics. The null hypothesis is that the time series are non-stationary (i.e. the series have a unit root). Since all variables in our analysis are trended, we specify the ADF regressions to include a drift term and a deterministic time trend[3].

From Table 1, and noting that the relevant 5 per cent critical value of the ADF test is -3.54, then it is clear that we cannot reject the null that the series are non-stationary, i.e., that the series have unit roots.

Having determined that our series are non-stationary, we next wish to know if they share common trends. In the terminology of time-series econometrics, we wish to know if our series are cointegrated. To determine whether our series are cointegrated, we first apply the single-equation residual based test for the null of no cointegration (see Engle and Granger, 1987 and Phillips and Ouliaris, 1990). This entails being agnostic about the direction of causation and running all possible regressions: (log crim on log pris and female), (log pris on log crim and female) and (female, log crim and log pris) and testing whether the residuals are stationary. Table 2 summarises the test results[4].

From Table 2, we find that the null of no cointegration can be rejected when the ADF is order 1 in the case of regression of log crim on log pris and female and in the case of log pris on log crim and female.

Given we have a model of three variables, each integrated of the same order, then there can be up to two cointegrating vectors. Before applying the method proposed by Johansen (1988, 1991) to study cointegration among the three series, we select the order of the system by estimating vector autogressions (VARs) of different lag lengths.

Since we have a very short time-series (only 37 years) we select 2 for the order of the VAR and use a dummy variable for 1974[5,6]. This lag length left the residuals approximately independently identically normally distributed for all equations. An inspection of the regression results for the individual equations in the VAR(1) model suggest evidence of residual serial correlation in the log crime equation.

In carrying out the cointegration tests we assume the presence of deterministic trends in the levels of the series and therefore include a constant in our model. Table 3 presents the value of the test statistics and their 5 per cent critical value. The trace statistic, shown in the second column, supports rejection of the null hypothesis that $r = 0$ (no cointegration) and indicates the existence of one cointegrating relationship (or two common trends).

The estimated cointegrating relation normalising the coefficient of log crim to 1 is:

$$\log crim = -0.31 \log pris + 0.05 female$$

The results show that the long-run elasticity of prison population with respect to crime is negative as expected. Furthermore, its size, estimated at -0.31, suggests that in the long run a 10 percent increase in prison population leads to roughly a 3 percent decrease in crime. The interpretation of the female labor force coefficient 0.05 is that a one percentage point rise in female labor force participation increases crime by just over 5 percent. These results suggest that changes in family functioning may have much larger effects on crime than imprisonment. The results supports the shift in policy recommendations by a number of researchers (e.g., Greenwood, 1998; Donohue and Siegelman, 1998; Wilson, 1998 and Witte, 1996, 1997) who now emphasise the importance of intensive early childhood programs to prevent crime.

Finally, we obtain the error correction form of the relations in the cointegrating VAR model. The OLS estimates for the unrestricted reduced form error correction model (ECM) for log crime of order one in differences is reported in Table 4 along with the associated standard errors. A broad range of diagnostics (see bottom of Table 4) suggest that the ECM is well specified. All the estimated coefficients are statistically significant at the 5% level or better using two-tailed tests. The estimated elasticity for prison population -

0.287 is dimensionally close to the short-run IV estimates for property crime of -0.321 and -0.261 reported by Levitt (1996) and substantially larger than results reported by Marvel and Moody (1994). The implicit long-run point estimate reported above for a change in prison population on crime is of comparable magnitude and, on the basis of a t-ratio, is not statistically different from the short-run effect. Somewhat surprisingly, the short-run impact of women working on crime is larger than the long-run response. Our estimated speed of adjustment, -0.167, suggests that departures from the steady state equilibrium take many years to be fully corrected[7].

V. CONCLUSIONS

In this paper we have used modern time series techniques to explore the nature of the stochastic process generating crime, imprisonment and the labor force participation of women in the US. The estimates presented in this paper are obtained by use of cointegration analysis, in particular the unrestricted VAR approach of Johansen (1988, 1991). Our work serves as a check on the robustness of the results obtained by other researchers. Our results for the impact of imprisonment on the crime rate are similar to Levitt's (1996) and substantially larger than previous estimates (e.g., Marvell and Moody, 1994). This is surprising given the quite different data (state-level panel versus macro time-series) estimation technique (panel data versus. time-series techniques) and specification (e.g., addition of a highly significant explanatory variable, the labor force participation rate for women) used. Our results indicate that the long-run as well as the short-run impact of crime on imprisonment is substantial although not of overwhelming large magnitude.

To be more specific, we estimate that the short-run elasticity of the crime rate with respect to the prison population is -0.29 and the long-run elasticity is -.31. Our results indicate that any shocks to the long-run steady state relationship will be eliminated quite slowly. Our results suggest that it will take approximately 10 years for the crime rate, once disturbed, to return to its long-run equilibrium level. This implies that the large increase in imprisonment rates that occurred in the 1980s are only now having their full impact on the crime rate.

We find significant short-run and long-run effects of female labor supply on crime. To be specific, we find that the long-run effect of a one percentage point rise in the female labor force participation rate increases the crime rate by just over 5 percent. The short-run effect of the crime rate with respect to the labor force participation rate for women is greater relative to the long-run effect. There are a number of potential explanations for the strong relationship between female labor force participation and the crime rate. First, female labor force participation may only be a proxy for the myriad changes that have occurred in the US family since 1960 (e.g., the rise of single parent households, the re-emergence of gangs). Second, increased labor force participation of women when combined with a only slight decline in the labor force participation of men may have two crime increasing effects: (1) probabilities of apprehension in residential neighborhoods are likely to be lower today than they were in the 1960s since these neighborhoods are much less populated during the day than they were in the 1960s, (2) children, particularly teenagers, are subject to much less supervision than they were in the 1960s.

The fact that the long-run effect of crime with respect to the labor force participation of women is smaller than the short run effect suggests other potential explanations for the observed effect. The short-run effect of increased labor force participation may be particularly high because institutions other than the family (e.g., schools, child care providers, employers) require time to find ways of substituting for the supervision and nurturing provided by mothers who stay at home.

Endnotes:

1. U.S. Federal Bureau of Investigation, *Crime in the United States*, annual.
2. Prison population data for 1960-1970 is contained in 1945-1970 *Historical Statistics, Colonial Times to Present*. 1970-1996 from the *Statistical Abstract of the United States 1997*. Population data is obtained exclusively from *Economic Report of the President*, February 1998, Table B-34, 321.
3. We estimate the following regressions: Dickey-Fuller $\Delta X_t = a_0 + a_1 t + \alpha X_{t-1} + u_t$: first-order ADF regression $\Delta X_t = b_0 + b_1 t + \beta X_{t-1} + \delta \Delta X_{t-1} + v_t$: where X is the variable being tested and t is a time trend. The figures reported in Table 1 are the t-ratios of the estimated coefficients α and β.
4. The residual-based ADF tests are based on the following regressions: ADF(0) $\Delta e_t = \rho_1 e_{t-1} + \mu_t$, ADF(1) $\Delta e_t = \rho_2 e_{t-1} + \Phi_1 \Delta e_{t-1} + \eta_t$ and ADF(2) $\Delta e_t = \rho_3 e_{t-1} + \Phi_2 \Delta e_{t-1} + \Phi_3 \Delta e_{t-2} + \varepsilon_t$ where e are the residuals of the OLS regressions. The ADF statistics reported in Table 2 are computed as the t-ratios of the estimated ρ coefficients.
5. The Akaike information criterion and the Schwarz Bayesian criterion select the orders 3 and 2, respectively. However, the log-likelihood ratio statistic (adjusted for small sample) rejects order 1, but does not reject a VAR of order 2. In the light of these we choose the VAR(2) model.
6. In 1974 the UCR crime index rose by 17% on the previous year. This observation could be regarded as an outlier for the purposes of identification of the long-run relations. Consequently, we include a dummy variable which takes the value of 1 in 1974 and zero elsewhere to control for this outlier. The test statistic of the deletion of this dummy (a χ^2 statistic with 3 degrees of freedom in this case) is 17.72, which rejects the restriction at the usual significance levels in each equation of the VAR.
7. The estimate suggests that over 15% of any deviation from the long-run relationship is eliminated each year. Thus,

disequilibria appear long-lived and most is eliminated within 10 years.

Table 1: Unit root test results for crime, prison population and female labor force participation

ADF order	log crim	log pris	Female
0	-0.89	-3.33	-0.45
1	-1.42	-3.01	-1.35

Table 2: Residual-based ADF statistics for tests of no cointegration between crime, prison population and female labor force participation in the US (1963-1996)*

Based on regressions with trends			
ADF order	(log crim|log pris, female)	(log pris|log crim, female)	(female|log crim, log pris)
0	-2.64	-2.70	-1.75
1	-4.92	-5.00	-2.59
2	-3.05	-3.19	-2.15

* The relevant 5 per cent critical value is -4.48

Table 3: Cointegration results

Null hypothesis	Test statistic	Critical value
r = 0	43.06	31.54
r ≤ 1	15.86	17.86
r ≤ 2	0.81	8.07

Table 4: ECM for crime estimated by OLS based on cointegrating VAR(2)

	Δlog crim
Δlog $crim_{-1}$	0.325** (0.093)
Δlog $pris_{-1}$	-0.287* (0.136)
$\Delta female_{-1}$	0.059** (0.012)
Z_{-1}	-0.167** (0.043)
Dummy 1974	0.114** (0.026)
Constant	1.004** (0.254)
R^2 (adjusted)	0.803
σ	0.025
N (1962-96)	35
LMSC(1)	1.548 (prob-value = 0.213)
ARCH(1)	1.073 (prob-value = 0.300)
FF(1)	0.167 (prob-value = 0.683)
N(2)	1.796 (prob-value = 0.407)
H(1)	0.627 (prob-value = 0.429)

** and * denote statistical significance at the 1% and 5% levels respectively. Standard errors are in parentheses. Z_{-1} = log $crim_{-1}$ + 0.31log $pris_{-1}$ - $0.05female_{-1}$ is the error correction term. LMSC(1) is a test for up to 1st order serial correlation and is asymptotically distributed as $\chi^2(1)$, ARCH(1) is a test for up to 1st order autoregressive conditional heteroscedasticity and is asymptotically distribibuted as $\chi^2(1)$ and FF(1) is the RESET test and is asymptotically distributed as $\chi^2(1)$. N(2) is the Jarque-Bera test for normality and is asymptotically distributed as $\chi^2(2)$, and H(1) is a test for heteroscedasticity and is asymptotically distributed as $\chi^2(1)$.

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Figure 1: US Crime, Prison and Female Labor Force Participation (1960-96)