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Author
Grogger, Jeffrey T.

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Grogger, Jeffrey Thomas, Ph.D.

University of California, San Diego, 1987

U·M·I
300 N. Zeeb Rd.
Ann Arbor, MI 48106

UNIVERSITY OF CALIFORNIA

San Diego

Efficient Criminal Justice Policy and the Deterrent Effect of Capital Punishment

A dissertation submitted in partial satisfaction of the requirements for the degree Doctor of Philosophy in Economics

by

Jeffrey Thomas Grogger

Committee in charge:

Professor Halbert White, Chairman
Professor C.W.J. Granger
Professor Richard Carson
Professor David P. Phillips
Professor John Mendeloff

1987

The dissertation of Jeffrey Thomas Grogger is approved, and it is acceptable in quality and form for publication on microfilm:

Chairperson

University of California, San Diego

1987

To my parents

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VITA

August 22, 1959 — Born — Hartford, Connecticut

1981 —	B.A., Economics, University of Kansas
1983 —	M.A., Economics, University of California, San Diego
1987 —	Doctor of Philosophy, University of California, San Diego

FIELDS OF STUDY

Major Field: Econometrics

Studies in Econometrics

Professors Halbert White, Robert F. Engle, Clive W.J. Granger

Studies in Industrial Organization

Professors Dennis Smallwood, Luis Guasch

Studies in Energy Markets and Regulation

Professor Dennis Smallwood

ABSTRACT OF THE DISSERTATION

Efficient Criminal Justice Policy and the Deterrent Effect

of Capital Punishment

by

Jeffrey Thomas Grogger

Doctor of Philosophy in Economics

University of California, San Diego, 1987

Professor Halbert White, Chairman

The deterrent effect of capital punishment has been debated in scholarly and policy circles for at least two centuries. Much more recently, considerable efforts have been expended to characterize efficient operation of the entire criminal justice system, including its penal function.

In the first chapter, data on daily U.S. homicides are analyzed to test whether severe punishments act as a deterrent to murder. Previous linear regression analyses are discussed, after which the Poission regression model is argued, then demonstrated, to provide a superior fit to the data. A specification test for the mean-variance equality implied by the Poisson model is derived, and negative binomial models utilized when these tests

reject the Poisson. Both parametric and non-parametric methods are used to test the deterrence hypothesis: previous findings of a deterrent effect are shown to be quite fragile.

In the second paper, similar techniques are used to analyze a superior set of daily data from California over the period 1960-67. Specification tests for the negative binomial model are developed and a technique is employed to account for the stochastic dependence among the estimated regression coefficients, thereby providing sharper tests of the deterrence hypothesis.

In the third paper, the efficiency of criminal sanctioning policy is addversed. An illustrative model is posited, and optimality conditions derived and interpreted. Data from California counties are used to estimate standard economic models of crime for several categories of homicide and to test for efficiency in sanctioning.

CHAPTER I.

Life or Death: The Deterrent Effect of Severe Punishments on Homicides in the United States

1. Introduction

The question of whether capital punishment deters homicide has concerned legal scholars and practitioners, social scientists and the general public for decades. Over a century ago, learned thought on the matter followed the lines expressed by James Fitzjames Stephen (1864), who stated that "[n]o other punishment deters men so effectually from committing crimes as the punishment of death." He went on to say "This is one of those propositions which it is difficult to prove, simply because they are in themselves more obvious than any proof can make them...". A more recent assertion by Charles Black (1974) displays a much different attitude, although still quite extreme in its own right: "we do not know, and for systematic and visible reasons cannot know what the truth about this deterrent effect may be...A 'scientific'-- that is to say, a soundly based-- conclusion is simply impossible, and no methodological path out of this tangle suggests itself."

In the years since these declarations were made, much effort nevertheless has been given to determine empirically whether capital punishment deters homicide. Different data sources have been used, both cross-sections and time-series, and the various studies have employed different techniques to control for confounding influences in the data in attempt to isolate the effect of executions. These techniques range from the so-called matching technique, whereby data from adjacent jurisdictions with different capital punishment statutes are placed together and simply eyeballed for discernible differences, to multiple regression analysis and econometric simultaneous-equations methods.

Generally, more recent studies have used better data and employed more sophisticated analytical techniques. This study continues that trend, reanalyzing the excellent data collected by Phillips and Hensley (1984), and employing a statistical model which accounts for the non-negative integer nature of the dependent variable. This model provides a fit superior to the simple linear regression model. Also, hypotheses concerning the deterrent effect of capital punishment are tested using both classical and non-parametric techniques. Results are also presented on some questions of secondary interest, notably on the effect of unemployment on homicides in the United States.

2. A Review Of The Literature

Early work by Sellin (1967) employed a matching technique, whereby homicide data from neighboring states is examined for visible deterrent effects. At least one of the states in a cohort would have a capital punishment statute, while the others would not. By using adjacent states, Sellin hoped to control for various socio-economic and political influences which could also affect the murder rate. Sellin's conclusion was that retentionist states had murder rates no lower than their abolitionist neighbors, indeed in many cases homicides were actually greater in the retentionist states. Sellin (1980) later used the same technique to examine murders of police officers and a larger set of homicide data, and came to the same conclusion.

Bailey (1976) employed similar techniques on data collected from individual state prison authorities. In addition to geographical proximity, he also matched states on the basis of socio-economic variables such as per capita income. His findings were much the same as Sellin's earlier work.

Savitz (1958) and Graves (1967) used a similar technique to examine longitudinal data, that is, data collected from one geographical jurisdiction over a period spanning a death sentence or an actual execution. Savitz tabulated capital homicides in Philadelphia for eight weeks before and after the imposition of a death penalty, and found no evidence for deterrence among the four cases he examined. Graves compared homicide rates in California for weeks preceding and following an execution, and also found no definite deterrent effect.

Phillips (1980) appears to have been the first to employ formal statistical tests in a longitudinal matching study. He examined twenty-two well publicized executions in England from 1858 - 1921, tabulating the number of homicides in the weeks before and after the executions. Applying a nonparametric test to the post-execution changes in homicides, he concluded that these highly publicized executions did indeed have a deterrent effect at the time.

Two major shortcomings of all these studies are the imperfection of the control techniques employed, and the small samples used for analysis. These considerations led to a desire among researchers to employ more sophisticated statistical machinery, allowing larger sets of data to be analyzed and greatly improving their ability to isolate the effect of capital punishment from other influences.

In the early 1970's, economist Isaac Ehrlich (1976) generated much controversy and criticism with his econometric analysis of annual U.S. homicide data. As both Ehrlich's work and that of his critics have been the subject of at least two detailed reviews (Friedman (1976), Zeisel (1976)), they will be but briefly covered here.

Three studies (Passell and Taylor (1976), Bowers and Pierce (1976), and Klein, Forst, and Filatov (1978)), attempted with varying degrees of success to replicate Ehrlich's results. Two of the studies (Passell and Taylor, Bowers and Pierce) criticized the data as incomplete and inconsistently collected over the sample period. All three found that the apparent deterrent effect vanished when the model was estimated in a linear rather than log-linear functional form, and when a small number of observations was dropped from the sample. Passell, Taylor and Fisher, and Franklin and Nagin (1978) criticized the model as unidentified, and Klein *et al.* noted that the construction of the threat-of-execution measure negatively biased its coefficient.

Passell (1975) analyzed a cross-sectional data set for 1950 and 1960 using constructs similar to Ehrlich's to measure the perceived threat of execution. He estimated his model by ordinary and two-stage least squares, and under several transformations of the data. He found that, while greater probability of apprehension and more severe prison terms both exerted a deterrent effect, the threat of capital punishment accounted for no independent deterrence.

Ehrlich (1977) then performed another study, using state data from 1940 and 1950. Using Box-Cox (1964) transformations, he reported the log-linear functional form as optimal, rejecting the linear form. Again, his results indicated a strong deterrent effect.

More recently, McManus (1985), using state data from 1950 and a Bayesian estimation methodology, demonstrated the importance of the researcher's priors on empirical deterrence results. His priors ranged from the viewpoint that "only the threat of execution could deter homicides" to the view that only economic and social variables caused fluctuations in murders. Depending on the prior beliefs, posterior parameter estimates indicated that the threat of execution could have a negative, zero, or positive effect on the homicide rate.

McManus found that the inclusion of a binary variable indicating whether a state conducted executions was particularly important: with the indicator included, three of his five prior belief schemes yielded a deterrent effect, while none of the priors indicated a firm deterrent effect when the indicator was treated as a "doubtful variable". This observation could help shed some light on the reasons for the differing conclusions of Passell and Ehrlich (1977): Ehrlich used such an indicator, while Passell omitted it.

Recent research by Phillips and Hensley (1984) has employed a data set quite different from those used earlier. For their analysis, Phillips and Hensley have compiled daily national homicide counts from computerized death certificates. They employed multiple regression analysis, including as regressors a single lagged dependent variable, binary variables for each day of the week, month, and year in the sample, as well as six national holidays. They are interested in both "rewards" and punishments for violence, and include the current value and four lags of those indicator variables of interest: their REWARD variable, equal to one on the day of a publicized heavyweight prize fight, and zero otherwise; the variable NEUTRAL, equal to one for days of a publicized acquittal of a suspected murderer; and PUNISH, set to unity on the day of a publicized life sentence, death sentence, or execution.

They base their conclusion, that "homicides...decrease significantly after stories about murder trials and executions..." on the following test. In their reported regression equation, the standard t-statistic of the fourth lag of PUNISH is -2.43. From the standard normal tables, implicitly drawing on asymptotic normality of the estimated parameters, they find that the probability of observing a (single) t-ratio of such magnitude under the null hypothesis is .0076. Further drawing on the large sample normality result, they conclude that the lack of correlation among the coefficients of the PUNISH variables implies their statistical independence. This independence result then is the basis for a binomial test, from which they conclude that "the probability of finding one or more significance levels of .0076 in 5 independent trials is .0374", or in the critical range for the null of no deterrence.

While the data employed in this analysis are of greatly improved quantity and quality than those previously used to study the deterrence question, the stated significance level of the test employed may be quite far from the actual significance for a number of reasons.

First, it seems curious to us that Phillips and Hensley would use the asymptotic normality of the regression parameters as a basis for the binomial test, rather than calculate significance levels directly from a five-variate normal distribution. This latter procedure is discussed in more detail and employed below.

Further, our specification testing of a model nearly identical to Phillips and Hensley's led us to reject the null hypothesis of correct specification. The standard errors generated by standard regression packages may then be biased, resulting in a test of actual size even greater than ten percent.

Another criticism of their model can be made that its functional form fails to account for the non-negative integer nature of the dependent variable. A linear model may generate predicted values either positive or negative, while the number of daily homicides can take on only positive values. As such, a linear specification could not possibly represent the true data generation process; rather than draw inferences from such a potentially inconsistent model, it may be preferable instead to estimate and test a model which generates only non-negative predictions.

Finally, we believe the most interesting hypothesis to test is whether the total number, or sum, of homicides falls in some given period after a severe punishment, not just on some arbitrary single day in that period.[1] One of the primary arguments for using daily data to is to investigate short-term punishment effects. If the effect of severe punishments were to merely delay, rather than deter homicides, fallacious conclusions could be reached by simply testing the PUNISH coefficients individually rather than in sum.

In order to overcome these potential obstacles, we have implemented a methodology designed to be robust to the types of problems just discussed. After discussing the data below, we describe the technique employed, and present results.

3. The Data

The data on daily U.S. homicides of white victims were provided to us by David P. Phillips. They were constructed from computerized death certificates, distributed by the Inter-University Consortium for Political Science Research and generated by the National Center for Health Statistics. Phillips and Hensley provide precise definitions of the categories of deaths included, and of the data on publicized life sentences and capital punishments, which they also provided. The unemployment rate used is total unemployment from the Bureau of Labor Statistics. The sample period is 1973-1979, providing 2556 observations for analysis. Summary statistics are presented in Appendix Table A1.

4. Methods And Results

The analysis proceeded in two phases. In the first phase, we concentrated on the specification of the conditional mean of daily homicides under the null hypothesis of no deterrence. That is, we identified variables which enter the equation to be estimated, and the functional form in which they enter. We thereby controlled for all identifiable influences on the number of daily homicides, *excluding* the effect of the PUNISH variables. The goal of this step was to generate a series of white noise prediction errors, free of any systematic influence, except (under the alternative hypothesis) that of the punishment variable. These residuals, then, were used to conduct nonparametric tests of the deterrence hypothesis in the second phase of the research. The nonparametric tests were then compared with more familiar test procedures.

In the first phase, we proceeded as follows. We first reproduced as closely as possible the earlier work of Phillips and Hensley. The results of this exercise are given in Table 1A, and are shown to be very close to theirs which are presented in Table 1B. Although the NEUTRAL variable used by them was not available to us, we are reasonably confident that any differences in the estimates can be attributed to this omission, differences in the holiday variables, and to the use of different software.

The results are generally similar, except for the holiday dummies. Homicides are shown to have significant seasonal effects, being high in the summer, falling somewhat in the fall, then increasing in November and December before falling through the remainder of the winter and spring. The day-of-week effect is also strong, with homicides high on the weekend, then falling till the middle of the week before rising again. Yearly effects were significant, without, however, any steadily increasing trend over the sample period.

We next dropped the judicial variables from the model, and tested for the inclusion of longer lags of the dependent variable. Twenty lags were included initially, after which all lags having coefficients with t-statistics less than one were dropped. The test statistic for the joint null hypothesis that the remaining six coefficients are equal to zero is 17.063, greater than the critical value of 12.59 for a χ^2_6 random variable at five per cent significance. The other coefficients in the model change only slightly with changes in the lag structure.

In addition to the seasonal indicators we tested for the inclusion of several economic variables, including total unemployment, male unemployment, unemployment of males 20- 24, overall labor force participation rate, male participation, and personal income. All possible combinations of these variables were tested; to our surprise, the overall unemployment rate was the only one to enter significantly and with plausible sign. Again, no significant changes to other parameters resulted from inclusion of various groupings of economic variables, so all but total unemployment were dropped from the analysis.

Finally, the binary variable MOON, which has the value one on days when the moon is full and zero otherwise, was generated to test, for homicide at least, the popular notion that criminal activity increases when the moon is full (Riddle, Lieber).

The results of least squares estimation on the benchmark variable set are presented in Table 2. One notes the overall similarity of this extended model to Phillips and Hensley's. Generally only imprecisely estimated coefficients differ between the models, while coefficients with relatively high t-ratios differ little. The effect of the full moon, as measured by the coefficient of MOON, is seen to be very insignificant. The effect of unemployment on the contrary is seen to be quite strong, with each percentage point increase in the unemployment rate leading to one additional homicide per day in the United States.

A test by White (1980) for heteroskedasticity (or more generally, for model misspecification) was conducted on this linear model, and significantly rejected the null hypothesis of no misspecification. When standard remedies for heteroskedasticity[2] were employed, and yet the transformed model performed even worse on the heteroskedasticity/misspecification test, it was concluded that the model suffered from some more serious form of misspecification.

We next estimated a log-linear model, in which the dependent variable is the logarithm of the number of homicides. The results of this estimation are given in Table 3. One will note that the parameter estimates are identical to the linear model in terms of signs and relative magnitude.

This model was subjected to the same specification tests as the linear model. Its performance was very similar, again suggesting some rather opaque form of misspecification, possibly related to the inadequacy of the functional form of the model.

The next model to be estimated was a Poisson regression model, discussed in detail by Hausman, Hall and Griliches (1984), and Gourieroux, Monfort, and Trognon (1984) (hereafter GMT). This model can be written as:

$$pr(y_t) = \frac{\lambda_t^{y_t}\exp(\lambda_t)}{y_t!}$$

$$\lambda_t = exp(X_t\beta)$$

Where y_t is the dependent variable homicides on day t, X_t is the vector of regressors, and β is a vector of parameters to be estimated.

This model was estimated by the method of maximum likelihood. The likelihood function for one observation can be written:

$$l_t() = y_t X_t \beta - exp(X_t\beta) - \ln y_t!$$

with first derivatives

$$\frac{\partial l_t}{\partial \beta_i} = X_t(y_t - X_t\beta) \quad i=l, \cdots k$$

This model has many favorable properties for the task at hand. First, the Poisson is a discrete distribution, defined only for non-negative integer values of y_t. It thus explicitly accounts for the nature of our dependent variable, something which the linear and log-linear models fail to do. Next, the log likelihood function is globally concave, ensuring a unique maximum. Finally, the appropriateness of the specification is easy to check. One property of the Poisson specification is that the conditional mean, $\exp(X_t\hat{\beta})=\hat{\lambda}_t$, should equal the conditional variance. Employing the information matrix testing framework (White (1982), Lancaster (1984)), a straightforward test for this condition is relatively easy to calculate.[3]

The results of this estimation are presented in Table 4. Of particular note is the robustness of the parameter estimates to the specification of the functional form of the model. The conditional Poisson estimates are very similar to the log-linear model in magnitudes and signs and to the linear model in signs and relative magnitudes. The log-likelihood shows an improvement in fit over the simple linear model.

The results of the test for the appropriateness of the Poisson specification are reported in Table 5. The test statistic is nR^2, where n = number of observations and R^2=*the* R^2 from the artificial regression used to calculate the test statistic (see note 2 above), corrected for the absence of a constant term. This statistic has a chi-square sampling distribution with one degree of freedom; its value of 29.01 is greater than the critical value of 3.84 for a $\chi^2{}_1$ test at the 5% significance level.

This rejection of the Poisson model led us to estimate a negative binomial regression model. The relationship between the Poisson and negative binomial probability models is well known (Greenwood and Yule (1920), Hausman *et al.* (1984), Gourieroux, et al. (1984)), and is obtained by assuming the Poisson parameter to have the gamma distribution with mean μ and variance $\frac{1}{\alpha}$. The resulting compound distribution for y_t is then negative binomial with mean μ and precision parameter α. As seen more clearly below, one can essentially think of the negative binomial model as allowing one to estimate a model more consistent with count data displaying conditional "over dispersion", while retaining essentially the same specification of the conditional mean as with the Poisson model.

The negative binomial model can be written as:

$$pr(y_t|\, X_t,\beta,\alpha) = \frac{\Gamma(\frac{1}{\alpha+y_t})}{\Gamma(\frac{1}{\alpha})\Gamma(y_t+1)}\,[\alpha\mu]^{y_t}\,[1+\alpha\mu]^{(y_t+\frac{1}{\alpha})}$$

where $\Gamma()$ is the gamma function, and

$$\mu_t = \exp(X_t\beta)$$

This model was also estimated by maximizing the likelihood, which is given as:

$$l_t = \ln\Gamma(y_t+\frac{1}{\alpha})-\ln\Gamma(\frac{1}{\alpha})-\ln\Gamma(y_t+1)+y_t\ln\alpha$$

$$+y_tX_t\beta-(y_t+\frac{1}{\alpha})\ln[1+\alpha exp(X_t\beta)]$$

with first derivatives:

$$\frac{\partial l_t}{\partial\beta_i} = X_{ti}\frac{y_t-exp(X_t\beta)}{1+\alpha exp(X_t\beta)} \quad i=1,\ldots,k$$

$$\frac{\partial l_t}{\partial\alpha} = [\psi(\frac{1}{\alpha})-\psi(\frac{y_t+1}{\alpha})]\alpha^{-2} + \frac{y_t}{\alpha} + \frac{1}{\alpha^2}ln[1+\alpha\exp(X_t\beta)] - \frac{(y_t+\frac{1}{\alpha})\exp(X_t\beta)}{1+\alpha exp(X_t\beta)}$$

where $\psi(\cdot)$ is the digamma function.

The conditional expectation of this model is $E(y_t|X_t)=exp(X_t\hat{\beta})$, and its conditional variance is $var(y_t|X_t) = exp(X_t\hat{\beta})[1+\alpha\exp(X_t\beta)]$. One can thus see that $var(y_t|X_t) > E(y_t|X_t)$, as is true in the data, and how the nuisance parameter α parameterizes the variance.

The negative binomial estimation results are contained in Table 6. The parameter estimates are essentially the same as the Poisson estimates, while the standard errors are generally larger. This is exactly what one would expect: the conditional mean is essentially the same for both models, while imposition of the mean-variance equality on over-dispersed data leads to spuriously small estimated standard errors (see, e.g., Cameron and Trivedi (1985)). The log likelihood is somewhat higher for this model. The nuisance parameter α is estimated very precisely, and implies an average variance-to-mean ratio of roughly 1.2.

Results from GMT (1984b) can be used to construct an interesting test of the specification of the negative binomial model. Their work indicates that the failure of the random disturbance term in the conditional mean to be gamma distributed may result in the inconsistency of the negative binomial estimator. They propose the quasi-generalized pseudo maximum likelihood estimator to obtain consistent estimates in this case. Essentially, the QGPML estimator is a two-step procedure in which one first consistently estimates the nuisance parameter, then inserts the value thus obtained into the pseudo-likelihood function:

$$y_t X_t \beta - (y_t + \frac{1}{\hat{\alpha}}) ln[1 + \hat{\alpha} exp(X_t \beta)]$$

where $\hat{\alpha}$ is the nuisance parameter estimate from the first step. A strongly consistent estimate for α can be obtained from regressing $[y_t - \exp(X_t\beta)]$ on $\exp(2X_t)$; estimation of the vector β proceeds by maximizing the above objective function.

The test of the specification of the negative binomial model can be conducted by comparing the estimate of α from the negative binomial model with the known consistent estimate obtained from the above regression. A significant divergence of the estimates indicates that the gamma distribution for the disturbance term is invalid, hence that the negative binomial estimator may be inconsistent. The value of $\hat{\alpha}$ from the QGPML estimator is .00502, while the value from the negative binomial model is .00606. The value of the t-statistic for the test of equality of these estimates is 1.0, failing to reject the appropriateness of the negative binomial specification.

Misspecification Tests

Several static and dynamic information matrix tests (White [1982,1985]) were performed on this model. A test for twentieth-order serial correlation of the prediction errors failed to reject the null hypothesis of no correlation. Other tests are discussed and results presented in the Appendix.

5. Testing The Deterrence Hypothesis

In this section, two sets of hypotheses are tested. First, tests for deterrent effects on each of twenty-one days following a severe punishment are conducted using non-parametric techniques. These results are then compared to procedures employing more familiar asymptotic t-tests. This comparison shows the tests to be quite similar. For both the nonparametric and the classical procedures, care is taken to determine the size of the individual tests necessary to achieve a test of a desired overall size. Next, t-tests are used to test for longer-term deterrence, that is to test whether the *sums* of effects over periods of several days are different from zero.

A. Testing for Deterrent Effects on Individual Days Following a Severe Punishment

To test for a deterrent effect on the i^{th} day following a severe punishment, the set of prediction errors $\{ \hat{u}_t = y_t - exp(X_t)\}$ was partitioned into a treatment sample of size M (= number of punishments) and a control sample of size N on the basis of the i^{th} lag of the variable PUNISH. That is, the i^{th} treatment subsample consists of all values of $\hat{u}_t$ such that $PUNISH_{t-i}$ is equal to one, while the i^{th} control subsample includes the rest of the prediction errors. Denote the treatment subsamples as $\Omega_i = \{\omega_{i1}, \ldots, \omega_{iM}\}$ and the control samples as $E_i = \{e_{i1}, \ldots, e_{iM}\}$ where $\Omega_i \bigcup E_i = \{\hat{u}_t\}$, i=0,...,20.

For each partitioning then, a rank-sum statistic was calculated to test

$$H_{0i}^{'}\colon \Psi_i(\Omega_i) = \Phi_i(E_i)$$

where Ψ_i and Φ_i are the distribution functions of Ω_i and E_i. The alternative hypothesis is that Φ_i stochastically dominates Ψ_i.

To conduct the tests, the statistics

$$Z_i = \frac{U_i - \frac{1}{2}MN}{\sqrt{\frac{1}{12}MN(M+N+1)}}$$

were calculated, where

U_i is the Mann-Whitney U statistic.

The statistic Z_i has been shown to have a limiting normal distribution, and to be very nearly normally distributed for sample sizes as small as M=N=8 (Mann and Whitney, 1947).

Some care must be taken in determining the size of the individual tests. To emphasize this point, consider a test of twenty independent test statistics. If the size of each test α_i is set to the customary .05 level, one finds that the probability of observing at least one test statistic in the critical range is .66 , vastly greater than intended.

The solution to the problem is straightforward, however, and will be described in terms of the problem at hand. We first note that, since the $\{\hat{u}_t\}$ and $\{PUNISH_t\}$ are each independent sequences, the $\{Z_i\}$ are independent. To correct for the problem above, then, we propose to test the null hypothesis

$$H_{0i}\text{: } \min_i \{ \Delta_i \} = 0$$

against

$$H_{1i}\text{: } \min_i \{ \Delta_i \} < 0$$

where Δ_i is the difference in location between Ψ_i and Φ_i.

Since min { Δ_i } necessarily corresponds to $\min\{Z_i\}$, H_{0i} is simple to test. To find the appropriate critical values, we solve for c the equation

$$\alpha = P[\min\{Z_i\} < c_\alpha] = 1 - P[Z_0 \geqslant c, Z_1 \geqslant c, \ldots, Z_{20} \geqslant c] \tag{1}$$

$$= 1 - P(Z_0)P(Z_1) \cdots P(Z_{20})$$

$$= 1 - P(Z_0)^{21}$$

where α is the desired overall size and c_α is the critical value corresponding to α. Invoking the asymptotic normality of Z_i, we find $c \approx -2.8$ for the case illustrated.

The results from the tests for individual lag effects are displayed in Table 8. One observes that, at overall size of 5 per cent, none of the twenty-one test statistics is significant. From equation (1), one notes though that the individual test size depends on the number of individual tests. If one restricts attention to the first five days after a punishment, then the test statistic of -2.397 just exceeds the critical value of -2.32. On the basis of this test, then, the result from Phillips and Hensley, that homicides decrease significantly on the fourth day following a publicized punishment, would be confirmed.

B. Comparison with Tests Based on T-Statistics

Presented in Table 9 are the parameter estimates and t-ratios from estimation of a negative binomial model in which the first twenty-one lags of PUNISH were included in the conditional mean along with the other variables in the model reported in Table 6 (other parameter estimates changed only slightly with the inclusion of these variables). Given the asymptotic normality of the parameter estimates and virtual diagonality of the relevant portion of the covariance matrix (covariances among the PUNISH variables are all roughly $3*10^{-5}$), the discussion of individual test sizes in the previous section is directly applicable to tests based on the asymptotic t-ratios. As before, none of the individual coefficients is significant for a 5 per cent test of twenty-one parameters. In this case, however, the fourth lag of PUNISH is insignificant also for a test of only the first five lags.[4] Given the disagreement of the results of the two test procedures, as well as the relative weakness of the rejection of the nonparametric test, a weakening of the conclusions regarding the reduction in homicides on the fourth day following a severe punishment seems to be in order.

C. Tests for a Net Deterrent Effect

Inspection of Tables 8 and 9, as well as Table 4 in Phillips and Hensley, reveals a strong increase in homicides on the sixteenth day following a publicized punishment. It would therefore be worthwhile to test whether the sum, or net effect of a punishment over the three week period examined is significantly different from zero.

To conduct this test, we employ asymptotic t-tests of sums of subsets of the parameters reported in Table 9. The test with the most power to reject the null hypothesis of no net deterrence is one which includes only the most significant coefficients. The most significant estimates are those corresponding to the fourth and sixteenth lags of

PUNISH. The test statistic for

$$H_0 : \beta_{PUNISH4} + \beta_{PUNISH16} = 0$$

is -.165, clearly inside the acceptance range. The only other coefficient to approach individual significance is that of the nineteenth lag of PUNISH. The test statistic for

$$H_1 : \beta_{PUNISH4} + \beta_{PUNISH16} + \beta_{PUNISH19} = 0$$

is -1.186, again clearly within the acceptance region.

These tests suggest that, whether or not the effect on the fourth day is significantly negative, the net effect after three weeks is insignificantly different from zero.

Before concluding that the effect of the punishments was merely to delay, rather than deter homicides, an analysis of the residuals associated with the fourth and sixteenth lags of the non-null elements of the PUNISH variable was conducted. The analysis was carried out to ensure that conclusions regarding the delay hypothesis drawn from the formal testing procedures reflected systematic effects of the punishments, rather than data anomalies or factors unaccounted for by the regression models. Specifically, it seems reasonable to require a finding that large negative changes in homicides on the fourth day following a particular punishment event be followed by large positive changes on the sixteenth day following that event, in order to establish the existence of a delay effect.

Table 10 contains the values of the predicition errors fron the model reported in Table 9 associated with the fourth and sixteenth lags of each of the twenty punishments used to construct the PUNISH variable. One notes that in only five cases is a negative residual at the fourth lag associated with a positive residual at the sixteenth. Further, these five cases include neither any of the largest negative fourth lag effects nor any of the largest positive sixteenth lag effects. Finally, the simple correlation coefficient of the two series is in fact positive (ρ=0.228), further weakening any evidence of a delay effect. In short, the evidence in favor of the delay hypothesis appears to be quite weak.

6. Summary And Conclusions

The main results of the paper can be summarized in the following way. First, following earlier work, daily data on U. S. homicides were used to specify a regression model in which daily homicide counts were explained by a set of daily, monthly, and annual binary variables and the monthly unemployment rate. Extending this previous work, the dynamic structure of the model was enhanced, and careful attention paid to choose a statistical model that was more consistent with the data than the linear specification previously utilized. Specification tests were developed to test the appropriateness of the models proposed: the negative binomial regression model was shown to provide a substantially better representation of the data, based on both the results of the specification test and on the improvement in the log-likelihood.

The objective of this portion of the exercise was to develop a suitably specified model of daily homicides, from which inferences could be drawn regarding the deterrent effect of severe punishments. Tests based on the improved model have a sounder basis than previous tests, which had utilized inconsistent standard errors generated by an evidently misspecified linear regression model.

Two deterrence hypotheses were tested, one regarding any single-day decline in homicides in a period following a severe punishment, the other pertaining to a decrease in the sum of homicides over the period examined. Two sets of tests were performed to examine the former hypothesis: one based on non-parametric procedures, the other on regression t-statistics based on asymptotically consistent standard errors.

The results from the tests for single-day effects were mixed. If one restricted attention to the first four days following a punishment, the non-parametric test rejected the null hypothesis of no deterrent effect. This result was not robust, however: the test based on t-statistics failed to reject in this case, and both tests failed to reject when longer periods following a punishment were considered.

The tests of the second hypothesis pertaining to a decrase in the sum of homicides over the three weeks following a severe punishment were also somewhat ambiguous. Formal tests based on the regression parameters and their standard errors failed to reject the null hypothesis of no decrease in the total number of homicides. However, an ancillary data analysis revealed little evidence of a delay effect, rendering the interpretation of the formal test results rather difficult.

In summary, the results of our analysis indicate that the finding of a deterrent effect associated with the type of punishments examined lacks robustness. Changes in the assumptions regarding the stochastic process underlying the data, and differences in testing techniques lead to conflicting conclusions. In the near future, data from the more recent past, during which the use of such severe punishments has markedly increased, will become available. Tests of the deterrence hypothesis based on these new data should therefore have greater power than those conducted here. Until new evidence is provided, however, the sensitivity of the deterrence results indicate that previous conclusions purporting the efficacy of severe punishments in deterring homicides should be regarded as tentative and subject to further corroboration.

Footnotes

1. Phillips and Hensley perform a test for significance of the "impact of a punishment on the entire [following] 21-day period" by summing the variables PUNISH through PUNISH20, then including that sum variable in their regression equation. This is equivalent to imposing that all coefficients be equal, then testing whether that one coefficient is significantly different from zero. As such, it is really a *joint* test for equality of the parameters *and* their difference from zero. From inspection of the coefficients in their Table 4, here reproduced as Table N1, it is perhaps unsurprising that the test would reject this joint null.

2. The residuals from the initial OLS regression were squared, then regressed on the explanatory variables and their squares and cross-products. Each observation was then divided through by the square root of the predicted squared residuals, and the model thus transformed estimated by OLS.

3. Using the notation of White (1985), one finds that the diagonal element associated with the constant in the indicator matrix, $m_t = \nabla^2 \ln f_{t|t-1} + \nabla \ln f_{t|t-1} \nabla \ln f_{t|t-1}$ is given by

$$m_{t\,const,const} = \hat{u}_t^2 - \hat{\lambda}_t$$

where

$$\hat{u}_t = y_t - exp(X_t\hat{\beta})$$

$$\hat{\lambda}_t = exp(X_t\hat{\beta})$$

The first term thus gives an estimate of the conditional variance of the model, while the second is the estimate of the conditional mean. Following Lancaster (1984), the test is computed by regressing a vector of units on the score of the model, $\nabla \ln f_{t|t-1}$, and on $m_{tconst.,const.}$. The number of observations times R^2 from this regression will be distributed as chi-square with one degree of freedom.

4. Two other models were estimated to perform this test: one identical to the Model presented in Table 1A, but with the negative binomial likelihood, and one identical to the model in Table 7, but with the first five lags (including the contemporaneous value) of *PUNISH* included as well. The t-ratios corresponding to the *PUNISH*4 variable were -2.286 and -2.216, respectively.

Appendix

Several general specification tests of the model reported in Table 6 were performed. Among these were dynamic information matrix tests for twentieth-order serial correlation of the prediction errors, and a more general test for the appropriateness of the dynamic specification of the model. Several static information matrix tests were also conducted.

For the dynamic tests, the vector of indicators can be written:

$$m_{t|t-\lambda} = \frac{u_t u_{t-\lambda} X_t' X_{t-\lambda}}{d_t d_{t-\lambda}}.$$

where

$$d_{t-\lambda} = 1 + \alpha exp(X_{t-\lambda}\beta)$$

and

$$u_t = y_t - exp(X_t\hat{\beta})$$

Tests in various directions can be performed by selecting various portions of the $X_t' X_{t-\lambda}$ matrix. For the serial correlation test, the indicators used were

$$s_{1t} = \left[\frac{u_t u_{t-1}}{d_t d_{t-1}}, \ldots, \frac{u_t u_{t-20}}{d_t d_{t-20}}\right].$$

A more gene¬al test of the dynamic specification was conducted using the indicators:

$$s_{2t} = \left[\frac{u_t u_{t-1}}{d_t d_{t-1}}\, y_{t-1}y_{t-2}\,, \ldots, \frac{u_t u_{t-1}}{d_t d_{t-1}}\, y_{t-11}y_{t-12}\right].$$

For all tests, the test statistic was computed by regressing a unit vector on the scores from the model and the respective indicators. Test results are given in Tables A1 and A2, respectively. The test statistic is nR^2 from the auxiliary regression; as can be seen from the tables, neither test rejects the null of no misspecification.

The static information matrix indicators take the general form

$$m_{0t} = vech\ X_t'X_t\, \frac{u_t^2 - exp(X_t\beta)[1 + 2\alpha exp(X_t\beta)]}{[1 + \alpha exp(X_t\beta)]^2}$$

$$= vech\ X_t'X_t\ d_{0t}$$

where $vech$ denotes the "vec half" operator.

It may be of interest to note that the term $[1 + \alpha exp(X_t\beta)]$ is the ratio of the conditional variance of the model to the conditional mean, while $[1 + 2\alpha exp(X_t\beta)]$ is the ratio of the conditional third central moment to the conditional variance.

The subsets of the $X_t'X_t$ matrix chosen for testing included the diagonal elements corresponding to the constant term, the lagged dependent variables, the day, month, and year indicators, and UNTOT. Results are presented on Tables A3 to A8, respectively. One notes that the only test for which the null hypothesis of no misspecification is not rejected is that corresponding to the variable UNTOT.

There are several reasons for which the model may have failed these tests, including misspecification of the conditional mean and misspecification of higher-order moments. Given the robustness of the parameter estimates to changes in functional form and to inclusion/exclusion of the punishment variables, it seems likely that the failure of higher-order moment restrictions implied by the negative binomial likelihood is the cause of the failures in this case.

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Table 1A

LINEAR REGRESSION OF HOMICIDE MODEL
Dependent variable is HOM

Mean of dependent variable	29.33	R^2	0.45
Standard error of regression	5.97	Adjusted R^2	0.44
Number of observations	2552	Log-likelihood	-8159.49

Variable	Coefficient	T-statistic
INTERCEP	35.2818	35.33
HOM1	0.0357	1.82
MON	-7.4059	-16.24
TUE	-7.6434	-15.37
WED	-8.4908	-16.95
THU	-7.1631	-14.02
FRI	-4.4758	-9.00
SAT	4.1596	8.73
FEB	0.8236	1.38
MAR	-0.4836	-0.83
APR	-0.4304	-0.74
MAY	-0.7118	-1.21
JUN	0.5050	0.86
JUL	2.8343	4.83
AUG	2.4584	4.23
SEP	1.8383	3.11
OCT	1.6563	2.85
NOV	2.5206	4.26
DEC	4.0288	6.85
Y73	-6.4905	-14.02
Y74	-4.5086	-9.98
Y75	-3.7006	-8.25
Y76	-5.9457	-12.99
Y77	-4.1959	-9.32
Y78	-2.9202	-6.55
NYR	24.5257	9.90
MEM	-0.0342	-0.01
IND	4.5259	1.97
LAB	6.1914	2.66
THX	0.0351	0.01
CHR	2.3891	1.03
PUNISH	0.3369	0.25
PUNISH1	1.0599	0.79
PUNISH2	-0.3322	-0.25
PUNISH3	-1.2959	-0.96
PUNISH4	-3.0272	-2.24
FIGHT	1.2761	0.99
FIGHT1	1.0081	0.78
FIGHT2	0.4267	0.33
FIGHT3	3.5027	2.71
FIGHT4	0.8573	0.66

Table 1B

PHILLIPS AND HENSLEY'S LINEAR REGRESSION MODEL
Dependent variable is HOM

R^2	0.438	Adjusted R^2	0.428
Number of observations	2555		

Variable	Coefficient	T-statistic
INTERCEP	39.06	37.14
HOM1	0.03	1.52
MON	-7.23	-15.82
TUE	-7.52	-14.94
WED	-8.38	-16.56
THU	-7.04	-13.68
FRI	-4.35	-8.63
SAT	4.12	8.55
JAN	-3.41	-5.75
FEB	-2.80	-4.64
MAR	-4.11	-6.92
APR	-4.08	-6.83
MAY	-4.31	-7.05
JUN	-3.12	-5.24
JUL	-0.80	-1.35
AUG	-1.20	-2.02
SEP	-1.78	-2.93
OCT	-1.95	-3.30
NOV	-0.94	-1.52
Y73	-6.55	-12.05
Y74	-4.55	-9.96
Y75	-3.75	-8.28
Y76	-6.03	-13.04
Y77	-4.34	-9.53
Y78	-3.08	-6.83
NYR	12.96	6.97
MEM	-0.45	-0.33
IND	2.91	1.68
LAB	2.68	1.94
THX	-1.05	-0.86
CHR	5.32	3.06
PUNISH	0.24	0.17
PUNISH1	0.85	0.62
PUNISH2	-0.58	-0.42
PUNISH3	-1.54	-1.12
PUNISH4	-3.32	-2.43
REWARD	1.08	0.83
REWARD1	0.91	0.70
REWARD2	0.59	0.45
REWARD3	3.54	2.72
REWARD4	0.71	0.55
NEUTRAL	-3.45	-1.71
NEUTRAL1	0.79	0.39
NEUTRAL2	1.88	0.93
NEUTRAL3	0.30	0.15
NEUTRAL4	-0.34	-0.17

Table 2

LINEAR REGRESSION OF HOMICIDE MODEL
Dependent variable is HOM

Mean of dependent variable	29.34	R^2	0.45
Standard error of regression	5.95	Adjusted R^2	0.44
Number of observations	2545	Log-likelihood	-8132.81

Variable	Coefficient	T-statistic
INTERCEP	24.5093	9.26
HOM1	0.0306	1.56
HOM6	0.0370	1.89
HOM7	0.0334	1.71
HOM8	0.0391	1.99
HOM10	-0.0217	-1.11
HOM11	0.0391	2.00
MON	-6.8906	-14.27
TUE	-6.7921	-11.20
WED	-8.0262	-12.56
THU	-6.8304	-11.25
FRI	-4.3351	-7.28
SAT	4.0776	7.66
FEB	1.0829	1.80
MAR	-0.0706	-0.12
APR	-0.0693	-0.12
MAY	-0.2285	-0.38
JUN	0.8860	1.49
JUL	2.8622	4.82
AUG	2.4336	4.14
SEP	1.9632	3.29
OCT	1.9139	3.27
NOV	2.4781	4.15
DEC	3.8627	6.50
Y73	-4.7143	-7.53
Y74	-3.7458	-7.66
Y75	-6.1510	-5.19
Y76	-7.0764	-7.95
Y77	-5.0319	-7.20
Y78	-2.7575	-5.82
NYR	24.4531	9.84
MEM	-0.5007	-0.22
IND	5.1278	2.24
LAB	5.9266	2.56
THX	-0.0312	-0.01
CHR	2.3852	1.04
MOON	1.0785	2.76
UNTOT	0.3294	0.50

Table 3

LOG-LINEAR REGRESSION OF HOMICIDE MODEL
Dependent variable is LOGHOM

Mean of dependent variable	3.34	R^2	0.41
Standard error of regression	0.21	Adjusted R^2	0.40
Number of observations	2545		

Variable	Coefficient	T-statistic
INTERCEP	3.1565	33.60
HOM1	0.0011	1.56
HOM6	0.0008	1.17
HOM7	0.0011	1.57
HOM8	0.0014	2.02
HOM10	-0.0007	-1.05
HOM11	0.0015	2.23
MON	-0.2340	-13.66
TUE	-0.2339	-10.87
WED	-0.2816	-12.42
THU	-0.2300	-10.68
FRI	-0.1324	-6.27
SAT	0.1226	6.49
FEB	0.0357	1.68
MAR	-0.0089	-0.42
APR	-0.0032	-0.15
MAY	-0.0178	-0.84
JUN	0.0260	1.24
JUL	0.0992	4.71
AUG	0.0873	4.19
SEP	0.0635	3.00
OCT	0.0552	2.65
NOV	0.0779	3.68
DEC	0.1235	5.86
Y73	-0.1602	-7.21
Y74	-0.1183	-6.82
Y75	-0.2131	-5.07
Y76	-0.2434	-7.70
Y77	-0.1710	-6.90
Y78	-0.0892	-5.31
NYR	0.6440	7.30
MEM	-0.0235	-0.29
IND	0.1726	2.12
LAB	0.2105	2.56
THX	0.0288	0.35
CHR	0.0961	1.18
MOON	0.0414	2.99
UNTOT	0.0015	0.07

Table 4

CONSTRAINED POISSON REGRESSION MODEL
Dependent Variable is HOM
LOG LIKELIHOOD: -8113.929

Variable	Coefficient	T-statistic
HOM1	0.0010	1.684
HOM6	0.0011	1.872
HOM7	0.0010	1.638
HOM8	0.0013	2.103
HOM10	-0.0006	-0.965
HOM11	0.0015	2.406
MON	-0.2304	-15.494
TUE	-0.2313	-12.302
WED	-0.2783	-13.981
THU	-0.2295	-12.223
FRI	-0.1364	-7.528
SAT	0.1156	7.483
FEB	0.0377	1.995
MAR	-0.0039	-0.207
APR	-0.0040	-0.208
MAY	-0.0101	-0.526
JUN	0.0306	1.632
JUL	0.0972	5.278
AUG	0.0834	4.558
SEP	0.0671	3.608
OCT	0.0653	3.557
NOV	0.0842	4.540
DEC	0.1278	6.986
Y73	-0.1576	-8.164
Y74	-0.1206	-8.172
Y75	-0.1971	-5.454
Y76	-0.2331	-8.533
Y77	-0.1622	-7.649
Y78	-0.0860	-6.084
NYR	0.6174	10.587
MEM	-0.0281	-0.357
IND	0.1695	2.567
LAB	0.1998	2.948
THX	0.0049	0.066
CHR	0.0814	1.225
MOON	0.0104	0.513
UNTOT	0.0357	2.989
CONSTANT	3.2047	39.436

Table 5

TEST FOR SPECIFICATION OF CONSTRAINED POISSON MODEL
Dependent variable is CONST

Value of nR^2 Test Statistic is 29.02

Variable	Coefficient	T-statistic
CONSTU	-0.0280	-0.39
HOMU1	-0.0001	-0.13
HOMU6	-0.0002	-0.33
HOMU7	-0.0001	-0.26
HOMU8	0.0000	-0.08
HOMU10	0.0000	-0.02
HOMU11	0.0000	-0.07
MONU	0.0061	0.44
TUEU	0.0011	0.06
WEDU	0.0031	0.17
THUU	0.0016	0.09
FRIU	0.0036	0.22
SATU	0.0077	0.54
FEBU	-0.0034	-0.19
MARU	-0.0039	-0.22
APRU	-0.0045	-0.24
MAYU	-0.0026	-0.14
JUNU	-0.0053	-0.30
JULU	-0.0010	-0.06
AUGU	-0.0012	-0.06
SEPU	0.0010	0.06
OCTU	-0.0080	-0.48
NOVU	-0.0046	-0.28
DECU	-0.0020	-0.12
Y73U	0.0010	0.06
Y74U	0.0008	0.06
Y75U	-0.0217	-0.66
Y76U	-0.0172	-0.68
Y77U	-0.0070	-0.36
Y78U	-0.0014	-0.11
NYRU	0.0030	0.04
MEMU	-0.0113	-0.17
INDU	0.0063	0.08
LABU	-0.0121	-0.19
THXU	0.0006	0.00
CHRU	0.0000	0.00
MOONU	0.0069	0.63
M11	0.0021	5.38

Table 6

CONSTRAINED NEGATIVE BINOMIAL MODEL
Dependent Variable is HOM
LOG LIKELIHOOD: -8095.229

Variable	Coefficient	T-statistic
HOM1	0.0010	1.563
HOM6	0.0011	1.652
HOM7	0.0010	1.492
HOM8	0.0013	1.939
HOM10	-0.0006	-0.942
HOM11	0.0015	2.240
MON	-0.2302	-14.369
TUE	-0.2314	-11.423
WED	-0.2782	-12.981
THU	-0.2294	-11.333
FRI	-0.1359	-6.943
SAT	0.1161	6.914
FEB	0.0370	1.818
MAR	-0.0048	-0.236
APR	-0.0047	-0.232
MAY	-0.0113	-0.551
JUN	0.0299	1.480
JUL	0.0971	4.896
AUG	0.0832	4.223
SEP	0.0664	3.313
OCT	0.0637	3.225
NOV	0.0836	4.184
DEC	0.1274	6.462
Y73	-0.1572	-7.554
Y74	-0.1203	-7.534
Y75	-0.1991	-5.100
Y76	-0.2348	-7.963
Y77	-0.1633	-7.124
Y78	-0.0863	-5.634
NYR	0.6212	9.442
MEM	-0.0273	-0.327
IND	0.1685	2.345
LAB	0.2004	2.727
THX	0.0050	0.063
CHR	0.0840	1.165
MOON	0.0366	2.837
UNTOT	0.0102	0.464
CONSTANT	3.2029	36.542
ALPHA	0.0061	5.819

Table 7

UNCONSTRAINED NEGATIVE BINOMIAL MODEL
Dependent Variable is HOM
LOG LIKELIHOOD: -8054.598

Variable	Coefficient	T-statistic
HOM1	0.0009	1.425
HOM6	0.0010	1.593
HOM7	0.0010	1.519
HOM8	0.0012	1.902
HOM10	-0.0008	-1.193
HOM11	0.0014	2.211
MON	-0.2270	-14.071
TUE	-0.2290	-11.257
WED	-0.2774	-12.897
THU	-0.2313	-11.396
FRI	-0.1365	-6.936
SAT	0.1165	6.904
FEB	0.0289	1.407
MAR	-0.0161	-0.783
APR	-0.0162	-0.779
MAY	-0.0225	-1.081
JUN	0.0214	1.049
JUL	0.0910	4.553
AUG	0.0789	3.971
SEP	0.0628	3.106
OCT	0.0567	2.847
NOV	0.0805	3.998
DEC	0.1181	5.925
Y73	-0.1558	-7.473
Y74	-0.1243	-7.761
Y75	-0.2050	-5.260
Y76	-0.2402	-8.146
Y77	-0.1658	-7.241
Y78	-0.0881	-5.772
NYR	0.6133	9.297
MEM	-0.0219	-0.262
IND	0.1754	2.433
LAB	0.2070	2.807
THX	0.0028	0.035
CHR	0.0986	1.366
MOON	0.0369	2.865
UNTOT	0.0116	0.527
CONSTANT	3.2231	36.665
PUNISH	0.0112	0.244
PUNISH1	0.0465	1.067
PUNISH2	-0.0076	-0.173
PUNISH3	-0.0510	-1.130
PUNISH4	-0.1047	-2.276
PUNISH5	-0.0592	-1.314
PUNISH6	0.0461	1.037
PUNISH7	-0.0266	-0.572
PUNISH8	-0.0331	-0.738
PUNISH9	-0.0479	-1.066
PUNISH10	0.0209	0.478
PUNISH11	-0.0029	-0.066
PUNISH12	-0.0724	-1.593
PUNISH13	-0.0469	-1.017
PUNISH14	-0.0384	-0.822
PUNISH15	-0.0144	-0.324
PUNISH16	0.0943	2.230
PUNISH17	-0.0362	-0.813
PUNISH18	-0.0103	-0.234
PUNISH19	-0.0830	-1.820
PUNISH20	-0.0472	-1.016
ALPHA	0.0057	5.423

Table 8

TEST STATISTICS FOR RANK-SUM TESTS

Grouping Variable	Z-Score
PUNISH	0.242
PUNISH1	0.730
PUNISH2	-0.590
PUNISH3	-1.036
PUNISH4	-2.397
PUNISH5	-1.229
PUNISH6	0.276
PUNISH7	-0.559
PUNISH8	-0.596
PUNISH9	-0.663
PUNISH10	-0.549
PUNISH11	0.155
PUNISH12	-1.302
PUNISH13	-1.020
PUNISH14	-0.471
PUNISH15	-0.286
PUNISH16	2.332
PUNISH17	-0.605
PUNISH18	-0.008
PUNISH19	-1.437
PUNISH20	-0.569

Table 9

PARAMETER ESTIMATES AND ASYMPTOTIC T-STATISTICS FROM NEGATIVE BINOMIAL MODEL WITH 21 LAGS OF *PUNISH*

Variable	Parameter	T-Ratio
PUNISH	0.011	0.24
PUNISH1	0.046	1.07
PUNISH2	-0.008	-0.17
PUNISH3	-0.051	-1.13
PUNISH4	-0.105	-2.28
PUNISH5	-0.059	-1.31
PUNISH6	0.046	1.03
PUNISH7	-0.266	-0.06
PUNISH8	-0.033	-0.74
PUNISH9	-0.048	-1.07
PUNISH10	0.021	0.48
PUNISH11	-0.003	-0.07
PUNISH12	-0.072	-1.59
PUNISH13	-0.047	-1.01
PUNISH14	-0.038	-0.82
PUNISH15	-0.014	-0.32
PUNISH16	0.094	2.23
PUNISH17	-0.036	-0.81
PUNISH18	-0.010	-0.23
PUNISH19	-0.083	-1.82
PUNISH20	-0.047	-1.02

Table 10

RESIDUALS FROM HOMICIDE MODEL

Punishment	Residual (-4)	Residual (-16)
1	-2.5	-4.4
2	-2.7	-2.9
3	-6.2	0.0
4	-5.3	0.6
5	1.6	6.6
6	-1.6	0.4
7	7.1	-3.7
8	0.9	-3.0
9	11.7	3.7
10	1.5	-3.3
11	-2.8	7.9
12	8.0	11.1
13	-8.9	-2.5
14	-2.0	-8.2
15	3.8	-2.4
16	-0.8	6.8
17	3.4	-3.1
18	0.4	-7.4
19	-1.1	7.0
20	-5.1	-2.6

Table A1
LM TEST FOR SERIAL CORRELATION
Dependent variable is CONST
Value of nR^2 Test Statistic is 13.39

Variable	Coefficient	T-statistic
GRES	0.0993	0.58
HOMU1	-0.0020	-0.69
HOMU6	0.0012	0.55
HOMU7	-0.0020	-0.65
HOMU8	-0.0022	-0.80
HOMU10	0.0006	0.16
HOMU11	0.0030	1.05
MONU	-0.0371	-1.19
TUEU	-0.0814	-1.24
WEDU	-0.1124	-1.71
THUU	-0.1024	-1.82
FRIU	-0.0799	-1.52
SATU	-0.0405	-0.96
FEBU	-0.0092	-0.40
MARU	-0.0108	-0.48
APRU	-0.0096	-0.39
MAYU	-0.0108	-0.45
JUNU	-0.0076	-0.34
JULU	-0.0029	-0.13
AUGU	-0.0054	-0.23
SEPU	-0.0048	-0.21
OCTU	-0.0024	-0.11
NOVU	-0.0056	-0.26
DECU	-0.0016	-0.06
Y73U	-0.0045	-0.13
Y74U	-0.0061	-0.21
Y75U	-0.0155	-0.28
Y76U	-0.0143	-0.27
Y77U	-0.0107	-0.28
Y78U	-0.0046	-0.20
NYRU	0.0026	0.03
MEMU	0.0016	0.02
INDU	-0.0062	-0.07
LABU	-0.0014	-0.02
THXU	-0.0010	-0.01
CHRU	0.0144	-0.23
UNTOTU	0.0012	0.06
MOONU	0.0033	0.22
DALPHA	-0.0004	-0.31
U1	0.0023	0.65
U2	0.0009	1.17
U3	0.0009	1.04
U4	0.0007	0.79
U5	0.0011	1.33
U6	-0.0016	-0.59
U7	0.0026	0.73
U8	0.0029	0.86
U9	0.0004	0.45
U10	-0.0007	-0.16
U11	-0.0038	-1.13
U12	-0.0007	-0.86
U13	-0.0010	-1.16
U14	-0.0004	-0.41
U15	0.0005	0.51
U16	-0.0005	-0.55
U17	-0.0005	-0.60
U18	-0.0002	-0.23
U19	0.0005	0.62
U20	0.0006	0.71

Table A2

DYNAMIC IM SPECIFICATION TESTS
Dependent variable is CONST

Value of nR^2 Test Statistic is 10.43

Variable	Coefficient	T-statistic
GRES	0.0625	0.60
HOMU1	-0.0018	-0.89
HOMU6	0.0000	-0.06
HOMU7	0.0001	0.13
HOMU8	-0.0001	-0.10
HOMU10	0.0000	0.01
HOMU11	-0.0001	-0.18
MONU	-0.0050	-0.29
TUEU	-0.0201	-0.70
WEDU	-0.0214	-0.71
THUU	-0.0228	-0.75
FRIU	-0.0216	-0.75
SATU	-0.0152	-0.64
FEBU	0.0030	0.14
MARU	-0.0023	-0.11
APRU	-0.0036	-0.16
MAYU	-0.0005	-0.02
JUNU	0.0014	0.07
JULU	0.0069	0.32
AUGU	0.0041	0.19
SEPU	0.0046	0.22
OCTU	0.0031	0.15
NOVU	0.0027	0.13
DECU	0.0096	0.47
Y73U	-0.0096	-0.42
Y74U	-0.0070	-0.38
Y75U	-0.0146	-0.34
Y76U	-0.0153	-0.44
Y77U	-0.0111	-0.43
Y78U	-0.0051	-0.30
NYRU	-0.0008	-0.01
MEMU	-0.0026	-0.04
INDU	0.0033	0.04
LABU	-0.0015	-0.02
THXU	-0.0015	-0.01
CHRU	0.0142	0.23
UNTOTU	-0.0010	-0.05
MOONU	0.0028	0.21
DALPHA	-0.0002	-0.22
INDL1	0.0000	-1.12
INDL2	0.0000	-1.91
INDL3	0.0000	1.41
INDL4	0.0000	0.25
INDL5	0.0000	-0.58
INDL6	0.0000	2.27

Table A3

IM SPECIFICATION TESTS
Dependent variable is CONST

Value of nR^2 Test Statistic is 2073.21

Variable	Coefficient	T-statistic
GRES	0.1916	5.17
HOMU1	0.0007	2.29
HOMU6	0.0007	2.47
HOMU7	-0.0001	-0.42
HOMU8	-0.0001	-0.42
HOMU10	-0.0004	-1.25
HOMU11	0.0008	2.58
MONU	-0.0125	-1.76
TUEU	-0.0215	-2.44
WEDU	-0.0244	-2.63
THUU	-0.0147	-1.67
FRIU	-0.0177	-2.04
SATU	-0.0260	-3.47
FEBU	-0.0055	-0.61
MARU	0.0020	0.22
APRU	-0.0043	-0.45
MAYU	-0.0035	-0.39
JUNU	-0.0021	-0.24
JULU	0.0002	0.03
AUGU	-0.0129	-1.40
SEPU	-0.0140	-1.54
OCTU	0.0169	1.97
NOVU	0.0335	3.92
DECU	0.0232	2.75
Y73U	0.0314	3.57
Y74U	0.0101	1.42
Y75U	0.0142	0.84
Y76U	0.0259	1.99
Y77U	0.0098	0.98
Y78U	0.0138	2.02
NYRU	0.0610	1.52
MEMU	-0.0076	-0.24
INDU	-0.0483	-1.22
LABU	-0.0012	-0.04
THXU	-0.0864	-1.24
CHRU	-0.0033	-0.12
UNTOTU	0.0067	0.75
MOONU	0.0020	0.36
DALPHA	0.4381	104.13
INDC	-0.2161	104.81

Table A4

IM SPECIFICATION TESTS
Dependent variable is CONST

Value of nR^2 Test Statistic is 410.42

Variable	Coefficient	T-statistic
GRES	-0.0230	-0.29
HOMU1	0.0005	0.81
HOMU6	0.0011	1.88
HOMU7	0.0019	3.03
HOMU8	0.0006	1.03
HOMU10	0.0004	0.57
HOMU11	0.0009	1.48
MONU	-0.0177	-1.16
TUEU	-0.0072	-0.38
WEDU	-0.0141	-0.71
THUU	-0.0136	-0.73
FRIU	-0.0189	-1.02
SATU	-0.0296	-1.83
FEBU	0.0297	1.52
MARU	-0.0061	-0.32
APRU	0.0021	0.11
MAYU	0.0088	0.46
JUNU	0.0005	0.03
JULU	-0.0188	-0.99
AUGU	-0.0036	-0.18
SEPU	-0.0130	-0.67
OCTU	0.0120	0.65
NOVU	-0.0029	-0.16
DECU	0.0026	0.14
Y73U	-0.0155	-0.83
Y74U	-0.0063	-0.41
Y75U	0.0455	1.24
Y76U	0.0119	0.42
Y77U	0.0152	0.71
Y78U	0.0034	0.23
NYRU	0.0110	0.13
MEMU	-0.0034	-0.05
INDU	0.0079	0.09
LABU	0.0356	0.50
THXU	-0.0032	-0.02
CHRU	0.0160	0.28
UNTOTU	0.0084	0.44
MOONU	-0.0139	-1.15
DALPHA	0.0771	20.74
INDL1	0.0000	-2.24
INDL6	0.0000	-6.95
INDL7	0.0000	-6.78
INDL8	0.0000	-6.01
INDL10	0.0000	-9.15
INDL11	0.0000	-7.07

Table A5

IM SPECIFICATION TESTS
Dependent variable is CONST

Value of nR^2 Test Statistic is 111.26

Variable	Coefficient	T-statistic
GRES	0.0107	0.13
HOMU1	-0.0003	-0.39
HOMU6	-0.0006	-0.89
HOMU7	-0.0005	-0.69
HOMU8	-0.0002	-0.36
HOMU10	0.0000	-0.07
HOMU11	-0.0003	-0.41
MONU	0.0271	1.66
TUEU	0.0286	1.39
WEDU	0.0283	1.32
THUU	0.0312	1.53
FRIU	0.0369	1.83
SATU	0.0364	2.09
FEBU	-0.0046	-0.22
MARU	-0.0154	-0.77
APRU	-0.0128	-0.59
MAYU	-0.0123	-0.60
JUNU	-0.0105	-0.52
JULU	-0.0003	-0.02
AUGU	-0.0041	-0.19
SEPU	-0.0054	-0.26
OCTU	-0.0282	-1.43
NOVU	0.0080	0.40
DECU	-0.0030	-0.16
Y73U	0.0094	0.47
Y74U	0.0005	0.03
Y75U	-0.0184	-0.48
Y76U	-0.0253	-0.85
Y77U	-0.0070	-0.31
Y78U	0.0014	0.09
NYRU	0.0137	0.15
MEMU	0.0159	0.22
INDU	0.0015	0.02
LABU	0.0076	0.10
THXU	-0.0237	-0.15
CHRU	0.0390	0.64
UNTOTU	0.0079	0.39
MOONU	0.0059	0.46
DALPHA	0.0213	9.06
INDD1	-0.0122	-6.33
INDD2	-0.0131	-6.21
INDD3	-0.0121	-5.83
INDD4	-0.0126	-6.80
INDD5	-0.0125	-6.96
INDD6	-0.0167	-9.46

Table A6

IM SPECIFICATION TESTS
Dependent variable is CONST

Value of nR^2 Test Statistic is 383.17

Variable	Coefficient	T-statistic
GRES	-0.0457	-0.57
HOMU1	-0.0007	-1.18
HOMU6	0.0002	0.39
HOMU7	0.0003	0.44
HOMU8	-0.0002	-0.31
HOMU10	0.0003	0.42
HOMU11	-0.0003	-0.51
MONU	-0.0172	-1.11
TUEU	-0.0178	-0.93
WEDU	-0.0210	-1.04
THUU	-0.0249	-1.28
FRIU	-0.0254	-1.34
SATU	-0.0255	-1.55
FEBU	0.0033	0.16
MARU	-0.0002	-0.01
APRU	0.0093	0.45
MAYU	-0.0021	-0.11
JUNU	0.0023	0.12
JULU	0.0086	0.45
AUGU	0.0100	0.50
SEPU	0.0003	0.02
OCTU	0.0002	0.01
NOVU	0.0087	0.47
DECU	0.0067	0.37
Y73U	0.0307	1.61
Y74U	0.0022	0.14
Y75U	-0.0668	-1.80
Y76U	-0.0296	-1.04
Y77U	-0.0063	-0.29
Y78U	0.0058	0.39
NYRU	-0.0097	-0.11
MEMU	0.0147	0.21
INDU	-0.0246	-0.29
LABU	0.0166	0.23
THXU	-0.0086	-0.06
CHRU	-0.0032	-0.06
UNTOTU	-0.0139	-0.72
MOONU	0.0205	1.68
DALPHA	0.0781	19.39
INDM1	-0.0407	-14.97
INDM2	-0.0402	-14.53
INDM3	-0.0461	-15.84
INDM4	-0.0414	-14.48
INDM5	-0.0405	-14.79
INDM6	-0.0434	-16.03
INDM7	-0.0479	-16.51
INDM8	-0.0442	-15.16
INDM9	-0.0378	-15.90
INDM10	-0.0383	-16.05
INDM11	-0.0385	-15.82

Table A7

IM SPECIFICATION TESTS
Dependent variable is CONST

Value of nR^2 Test Statistic is 130.36

Variable	Coefficient	T-statistic
GRES	0.0418	0.50
HOMU1	0.0000	-0.03
HOMU6	0.0005	0.74
HOMU7	-0.0004	-0.58
HOMU8	0.0002	0.24
HOMU10	0.0001	0.15
HOMU11	-0.0001	-0.08
MONU	0.0033	0.21
TUEU	0.0016	0.08
WEDU	0.0062	0.29
THUU	0.0100	0.50
FRIU	0.0052	0.26
SATU	0.0029	0.17
FEBU	0.0055	0.27
MARU	0.0007	0.04
APRU	0.0146	0.68
MAYU	0.0004	0.02
JUNU	0.0059	0.29
JULU	0.0056	0.28
AUGU	-0.0041	-0.20
SEPU	0.0049	0.24
OCTU	0.0039	0.20
NOVU	-0.0039	-0.20
DECU	0.0116	0.60
Y73U	0.0149	0.73
Y74U	0.0280	1.72
Y75U	0.0584	1.50
Y76U	0.0550	1.84
Y77U	0.0405	1.76
Y78U	0.0301	1.92
NYRU	-0.0043	-0.05
MEMU	0.0224	0.31
INDU	0.0038	0.04
LABU	0.0161	0.21
THXU	-0.0269	-0.17
CHRU	-0.0308	-0.50
UNTOTU	-0.0032	-0.16
MOONU	-0.0115	-0.90
DALPHA	0.0279	10.10
INDY1	-0.0131	-6.92
INDY2	-0.0198	-9.19
INDY3	-0.0144	-7.57
INDY4	-0.0172	-9.09
INDY5	-0.0174	-8.44
INDY6	-0.0167	-8.52

Table A8

IM SPECIFICATION TESTS
Dependent variable is CONST

Value of nR^2 Test Statistic is 0.00

Variable	Coefficient	T-statistic
GRES	-0.0010	-0.01
HOMU1	0.0000	-0.01
HOMU6	0.0000	-0.01
HOMU7	0.0000	0.00
HOMU8	0.0000	0.01
HOMU10	0.0000	0.00
HOMU11	0.0000	0.02
MONU	0.0000	0.00
TUEU	-0.0002	-0.01
WEDU	-0.0002	-0.01
THUU	0.0000	0.00
FRIU	0.0002	0.01
SATU	0.0000	0.00
FEBU	0.0002	0.01
MARU	0.0003	0.01
APRU	0.0002	0.01
MAYU	0.0001	0.00
JUNU	0.0003	0.01
JULU	0.0000	0.00
AUGU	0.0002	0.01
SEPU	-0.0001	0.00
OCTU	0.0001	0.01
NOVU	0.0003	0.01
DECU	0.0001	0.01
Y73U	0.0002	0.01
Y74U	0.0001	0.00
Y75U	-0.0001	0.00
Y76U	-0.0001	0.00
Y77U	0.0000	0.00
Y78U	0.0001	0.01
NYRU	0.0001	0.00
MEMU	-0.0001	0.00
INDU	0.0002	0.00
LABU	0.0001	0.00
THXU	0.0013	0.01
CHRU	0.0003	0.00
UNTOTU	0.0003	0.01
MOONU	0.0001	0.01
DALPHA	0.0000	0.03
INDUN	0.0006	0.21

Table N1

Phillips and Hensley's Table 4

Variable	Parameter	T-statistic
PUNISH	0.17	0.13
PUNISH1	0.83	0.61
PUNISH2	-.065	-0.47
PUNISH3	-1.64	-1.19
PUNISH4	-3.44	-2.52
PUNISH5	-1.79	-1.31
PUNISH6	1.45	1.06
PUNISH7	-0.86	-0.63
PUNISH8	-1.19	-0.87
PUNISH9	-1.59	-1.16
PUNISH10	0.04	0.03
PUNISH11	0.51	0.38
PUNISH12	-2.81	-2.06
PUNISH13	-1.31	-0.96
PUNISH14	-1.11	-0.81
PUNISH15	-0.56	-0.41
PUNISH16	2.95	2.17
PUNISH17	-0.88	-0.64
PUNISH18	-0.11	-0.08
PUNISH19	-2.58	-1.89
PUNISH20	-1.75	-1.28

CHAPTER II.

The Deterrent Effect of Capital Punishment in California: An Analysis of Daily Homicide Counts

1. Introduction

In the last several decades, researchers from several disciplines have studied the question of whether capital punishment deters homicide. A number of specific hypotheses have been tested, and data from widely differing sources have been analyzed using various techniques, from the simple to the highly sophisticated (See Grogger [1986] for a survey of a large body of this work).

In this paper, techniques first advanced by Phillips [1983] and Phillips and Hensley [1983], and extended by Grogger [1986] are utilized to analyze daily homicide counts from California over the period 1960-67. We are able to conduct more powerful tests of the deterrence hypothesis than carried out in those studies, however, for a number of reasons. First, we use data from one legal jurisdiction, California, and are able to disaggregate the total homicide count by victim's race, sex, and type of weapon used, and analyze these categories separately. Next, the independent variables used to conduct the tests of the deterrence hypothesis are based on thiry executions. Phillips and Hensley [1984] and Grogger [1986] utilized a punsihment variable comprised of twenty executions, death sentences, of publicized life sentences. Finally, we employ improved statistical techniques for hypothesis testing.

The data used in this study allow for much sharper and conceptually tighter tests of the deterrent effect of capital punishment than those reported by Phillips and Hensley [1984] or Grogger [1986]. First, the use of data from one legal jurisdiction, California, obviates problems of aggregation bias that may result in spurious findings when the data to be analyzed are aggregated over several jurisdictions with differing capital punishment statutes.[1] Next, to the extent that any deterrent effect present in the data is likely to be small in magnitude, the analysis of finer subcategories of homicides helps to ensure that effects too small to be detected in the aggregate statistics are nonetheless revealed. By analyzing distinct subcategories of homicides, one can test whether executions more effectively deter the murders of victims of a particular ethnic group or gender, or murder carried out using a particular type of weapon, such as firearms. Further, the occurrence of thirty executions in California over the period examined allows for tests of the deterrence hypothesis which are at the same time conceptually clearer and statistically more powerful than those based on a smaller number of composite punishments. Finally, the current study utilizes improved techniques for hypothesis testing, which allow one to drop the unlikely assumption, implicit in the earlier studies, that any changes in the number of homicides on a given day following an execution are independent of such responses on other days. More powerful tests of the deterrence hypothesis can therefore be constructed.

In addition to the tests of the deterrence hypothesis, the paper sheds further light on the short-run effect of the unemployment rate on daily homicides. Several seasonal patterns and holiday effects revealed in the data are also discussed.

In the next section, the sources and characteristics of the homicide and execution data are discussed. The methodology used is described in Section III, followed by a discussion of the estimation in Section IV. Results are presented in Section V; the final section then summarizes the results, and draws conclusions from them.

2. The Data

The data on daily homicide counts in California were compiled from computerized death certificates provided by the California Department of Health Statistics, and include all deaths from causes E980-E983 in the Seventh Revision of the International Classification of Diseases. These include deaths from non-accidental poisonings, from assault by firearms and explosives, by cutting and piercing instruments, and by all other means, respectively, for the years 1960-1967. Unemployment data are from the California

Department of Labor.

The detailed information provided in the death certificates allowed the total homicide count to be broken down into several categories pertaining to the race and sex of the victim and type of weapon employed. In Table 1, definitions of these categories are given, and in Table 2 are presented summary statistics of the nineteen classes of homicides originally considered. There were 6458 homicides in California over the sample period, or an average of 2.2 per day. Of these, 4313, or 67 per cent of the victims were white, while the remaining 2145 victims were non-white. It is perhaps worth noting that the large maximum values reported for several categories occurred during the Watts riots in Los Angeles in August 1965.

The execution data are summarized at the bottom of Table 2, and were obtained from the appendix of Bowers [1974]. One notes that over one-half of the executions occurred on Wednesdays; this includes one triple execution which occurred on August 8, 1962. A double execution was carried out on Friday, January 8, 1960. There were nine executions in 1960, eight in 1961, and eleven in 1962. One occurred in 1963; the last execution carried out in California was in 1967.

These execution data thus suggest a policy change during the sample period which, if not accounted for, might lead to a misspecification of the regression models estimated, resulting in flawed inferences. This problem was treated by conducting separate analyses of the data from the full sample period and from the 1960-63 period of more frequent executions. Summary statistics of the homicide data analyzed for this earlier period are presented in Table 2B.

3. Methodology

The statistical analysis was conducted in two stages. A model specification phase was first conducted, during which various statistical models were implemented and tested until, for each homicide category and estimation period, a suitable model was found. Linear models were first fitted, after which models were estimated which are more appropriate for dependent variables which are non-negative whole numbers. Regressors were identical for all models, and included seasonal indicators to control for day-of-week, month, year, and holiday effects, the unemployment rate, and twenty-one lags of the number of executions (NX-NX20).[2] The full-sample models also contained the binary variable *WATTS*, equal to one on the days of the Watts riots in August 1965. The objective of the specification phase was to find a model as close to the "true model" of the data as possible, since the validity of statistical inferences can be undermined if based on a grossly misspecified model.

After suitable specifications were found, attention was turned to the testing of the deterrent effect. Two deterrence hypotheses were considered. The first pertains to the possibility that deterrence may be evidenced by a decrease in homicides on any one day over some period following an execution, while the second is concerned with a possible decrease in the total number of homicides over the entire period.

The first test was conducted as a test of significance of the largest negative t-ratio among the contemporaneous and lagged values of *NX* included in the regression models. The second is carried out as a test for the sum of these coefficients.

A technical discussion of these estimation and testing procedures follows. At this point, the reader interested more in the substantive results and less in the technical methodology may, without loss of continuity, proceed to Section V, in which results are presented.

Model selection was made by the standard econometric practice of model specification, estimation, testing, and re-specification and re-estimation. Information criteria, tests based on the consistency of quasi-generalized pseudo-maximum likelihood (QGPML) estimators, and tests derived from the information matrix testing framework of White (1985) were used to discriminate between the various non-nested probability models considered. For each dependent variable, the estimation/specification testing/re-estimation process went as follows:

1) A linear model was fitted by ordinary least squares. At this point, several categories of homicides were dropped from the analysis due to the marginal significance of the overall regression or extremely high standard errors of the variables of interest. Further discussion is provided in the next section.

2) A Poisson regression model was fitted. This model can be written as:

$$pr(y_t) = \frac{\lambda_t^{y_t}\exp(\lambda_t)}{y_t!}$$

$$\lambda_t = exp(X_t\beta)$$

Where y_t is the dependent variable, X_t is the vector of regressors, and β is a vector of parameters to be estimated.

The Poisson regression model is preferred over the usual linear regression model for a number of reasons. First, the Poisson probability model is a discrete distribution, defined only for non-negative integers, and thus explicitly accounts for this feature of the homicide counts. It further restricts predicted values to be non-negative, again consistent with the data. The usual normal probability model, on the other hand, for which ordinary least squares is the (quasi-)

maximum likelihood estimator, admits of fractional- as well as integral-valued data, and may generate predictions both positive and negative. For these reasons, the Poisson model should provide more efficient estimates.

This model was estimated by the method of maximum likelihood. The likelihood function for one observation can be written:

$$l_t = y_t X_t \beta - exp(X_t \beta) - \ln y_t!$$

3) If the likelihood was higher than for the linear model, a test for the equality of the conditional mean and variance implied by the Poisson specification was employed. This test is based on the (1,1) element of the matrix of indicators from the information matrix testing framework (see White, 1982), and has been discussed elsewhere (Grogger [1986]).

4) If the Poisson model was rejected, a negative binomial model was fitted. Another discrete distribution, this model was chosen for its greater flexibility in allowing the variance to exceed the mean, as occurs in many applications. The negative binomial model can be written as:

$$pr(y_t | X_t, \beta, \alpha) = \frac{\Gamma(\frac{1}{\alpha + y_t})}{\Gamma(\frac{1}{\alpha})\Gamma(y_t + 1)} [\alpha\mu]^{y_t} [1 + \alpha\mu]^{(y_t + \frac{1}{\alpha})}$$

where $\Gamma()$ is the gamma function, and

$$\mu_t = \exp(X_t \beta)$$

This model was also estimated by maximizing the likelihood, which is given as:

$$l_t = \ln\Gamma(y_t+\frac{1}{\alpha})-\ln\Gamma(\frac{1}{\alpha})-\ln\Gamma(y_t+1)+y_t\ln\alpha$$

$$+y_tX_t\beta-(y_t+\frac{1}{\alpha})\ln[1+\alpha exp(X_t\beta)]$$

5) A test for the negative binomial specification was performed. The test is is of the general form presented by Hausman [1978], and based on the consistency of the so-called quasi-generalized pseudo maximum likelihood (QGPML) estimator of Gourieroux, Monfort, and Trognon (GMT). Define $\hat{\gamma} = (\hat{\beta},\hat{\alpha})$ to be the maximum likelihood estimates of the negative binomial model, and $\tilde{\gamma} = (\tilde{\beta},\tilde{\alpha})$ to be the QGPML estimates. The negative binomial model is often motivated by positing that, while y_t is distributed as Poisson with mean $\lambda_t = exp(X_t\beta)$, that λ_t itself varies over the sample period according to a gamma distribution with mean λ_t and nuisance parameter $\alpha > 0$. The resulting compound distribution for y_t is the negative binomial, with mean λ_t and variance $\lambda_t\ (1 + \alpha\lambda_t) > \lambda_t$.

Assuming the correctness of the specification of the conditional mean, GMT demonstrate that both $\hat{\lambda}_t = \exp(X_t\hat{\beta})$ and $\tilde{\lambda}_t = \exp(X_t\tilde{\beta})$ are consistent for λ_0, the true parameter values, provided that λ_t is truly a gamma random variable. If the λ_t follow some other distribution, however, only $\tilde{\gamma}$ remains consistent for γ_0; the method of maximum likelihood applied to the presumed negative binomial model of y_t may produce inconsistent estimates. The importance of a test for this condition is therefore evident.

Under the null of no misspecification, both $\hat{\gamma}$ and $\tilde{\gamma}$ are consistent. From standard maximum likelihood theory, we know that the maximum likelihood estimator attains the Cramer-Rao lower bound, while the QGPML estimator is inefficient. Under these conditions, letting $V(\psi)$ represent the estimate of the covariance matrix of ψ, the Hausman test statistic, defined as

$$H = (\tilde{\gamma} - \hat{\gamma})'[V(\tilde{\gamma}) - V(\hat{\gamma})]^{-1}(\tilde{\gamma} - \hat{\gamma})$$

is distributed as χ^2, with degrees of freedom equal to the dimensionality of $\tilde{\gamma}$. A one degree-of freedom test which essentially compares just the values of $\hat{\alpha}$ and $\tilde{\alpha}$, and requires the computation of only $\hat{\gamma}$ and $\tilde{\alpha}$ can be constructed by restricting attention to the relevant portion of the above quadratic form. White [1985] has proposed a technique for calculating this test which greatly simplifies computation. This method was used to calculate the test statistics presented below.

6) Models which failed the above test were then estimated by QGPML to ensure consistency. The QGPML model based on the negative binomial family was estimated by maximizing the negative binomial likelihood above w.r.t β, but where α is replaced by $\tilde{\alpha}$, which is strongly consistent for α.

7) Finally, the selected model was subjected to various static and dynamic information matrix tests as a last check on the specification. These can be thought of as joint directional tests for the specification of conditional higher-order moments as well as the conditional mean and variance.

All nonlinear models were estimated by Newton-Raphson; t-statistics are based on standard errors of White(1985). We now turn to discussion of the procedures used in testing the deterrence hypothesis.

The tests of the first deterrence hypothesis, that the number of homicides may fall on some single day folowing an execution, was conducted as a test of significance of the algebraic minimum of the twenty-one NX coefficients included in the regression models. Formally, the hypothesis tested for each model is:

$$H_0\text{: min } \{ \beta_{NX}, \beta_{NX1}, \ldots, \beta_{NX20} \} = 0.$$

vs.

$$H_1\text{: min} \{ \beta_{NX}, \beta_{NX1}, \ldots, \beta_{NX20} \} < 0.$$

The critical value for a test of size α is that value c such that the probability that none of the coefficients is less than c is $1 - \alpha$, or algebraically,

$$P(\beta_{NX} > c, \ldots, \beta_{NX20} > c) = 1 - \alpha$$

Clearly, the critical value depends on the stochastic dependence among the estimated parameters.

If the coefficients $\beta_{NX}, \ldots, \beta_{NX20}$ were independent, the test would be performed simply by comparing the asymptotic t-ratios of the (algebraically) smallest coefficient with the $\frac{\alpha}{21}$- per cent critical value from the asymptotic normal distribution. Ideally, intermediate cases would be handled by directly evaluating the multivariate distribution function. This is currently technically impossible, however, for a normal distribution with more than three of four variates.

While the NX coefficients are nearly uncorrelated (hence asymptotically, independent) in all the models, they are not exactly so. Therefore, if one were to base the tests on the assumption of independence, the resulting acceptance region would be too large, leading ine to accept a false null hypothesis with greater probability than that implied by the nominal test size. Rather than accept this undesirable state of affairs, Kwerel's [1975] most stringent bounds were employed to conduct the tests with greater precision.

Kwerel provides bounds on the minimum and maximum probability of the occurrence of at least one of m dependent events. That is, he gives values for p_L, p_U where

$$p_L \leqslant P[\bigcup_{i=1}^{m} X_i] \leqslant p_U$$

by utilizing the identity

$$P(\bigcup X) = S_1 - S_2 + \cdots$$

where

$$S_1 = \sum P(X_i)$$

$$S_2 = \sum P(X_i \bigcap X_j)$$

and so forth. He gives, under certain regularity conditions,

$$p_L = [2S_1/(j+1)]\,[1 - C/j]$$

$$p_U = S_1[1 - \frac{2C}{m}]$$

where

$C = S_2/S_1$

j is the integer part of $2C + 1$.

To conduct the test, then, the value of the smallest t-ratio from a given model is needed. Using the result that asymptotically joint normal variates have asymptotically normal (joint) marginal distributions, one then uses the estimated covariance matrix to calculate S_1 and S_2. If $p_U < \alpha$, where α is the desired overall size of the test, one rejects the null hypothesis, while if $p_L > \alpha$, the null is not rejected. If $p_U < \alpha < p_L$, the test is inconclusive.

4. Estimation

Tables 3A - 3LL contain the least squares regression results for each of the nineteen dependent variables originally considered. Regressors were identical for each model, including seasonal variables, the monthly state unemployment rate, and the contemporaneous and twenty lagged values of NX. The full sample models also contain the binary variable *WATTS*, equal to unity during the Los Angeles race riots in August, 1965, and zero otherwise.

As indicated above, several models were dropped from the analysis at this stage. Models for the black population were dropped in favor of the very similar yet broader models of all non-whites. Most weapons categories were deleted due to insignificance of many parameters, both the seasonal and the execution variables. Due to the independent interest in crimes involving firearms of many in the criminal justice field, however, the models for firearm murders of whites and non-whites were retained. The race/sex categories were also dropped, for males due to their similarity with the respective race models, for females due to the low significance of the regressions. The models for white males were retained, however, due to the potentially significant deterrent effect found there.

In summary, then, the dependent variables analyzed further were: NH, NHW, NHNW, NHWG, NHNWG, and NHWM. These six categories were examined further, both over the full 1960-1967 sample period and the 1960-1963 subsample.

Poisson regression models for these categories are contained in Tables 5A - 5L. Judging from the values of the log-likelihoods presented in Table 4, the movement from the linear to the Poisson specification greatly improves the fit of the models to the data. This was to be expected, since the Poisson distribution accounts for the non-negative integer nature of the dependent variables, while the linear models do not.

Examination of Tables 5A - 5L shows that the Poisson models, while fitting the data better, nonetheless are qualitatively quite similar to the linear models.[4]

The specification test described above for the appropriateness of the Poisson distribution was applied to all twelve of these models. Results are reported in Table 6. The

Poisson specification was rejected for all models estimated over the full sample period, and for the NH and NHWG models estimated over 1960-1963.[5] Reexamination of Table 2 indicates that these models have relatively high unconditional variance-to-mean ratios. It is likely then that a conditional variance-to-mean ratio greater than unity underlies the rejection of the Poisson specification.

Conditional negative binomial models were then estimated for models which failed the Poisson specification test. These results are presented in Tables 7A - 7G. Parameter estimates are very similar to the Poisson models for all categories. From Table 4 one notes that the log-likelihoods increase little for these models over the Poisson values. The preference for the negative binomial specification must therefore stem from the rejection of the Poisson specification, rather than any information criteria.

The QGPML test for the negative binomial specification described above was applied to these estimates, and the results are presented in Table 8. The negative binomial specification is rejected for the NH, NHNW, and NHNWG models, but is not rejected for the others. Examination of Table 2 reveals that these dependent variables contain considerable outliers, and have particularly high estimated kurtosis coefficients. The heavy tails of these distributions then seem the likely causes for the rejection of these models.

These three models were then estimated by the two-step method of GMT. Results are presented in Tables 9A - 9C, and are seen to be very similar to the negative binomial and Poisson estimates.

5. Misspecification Tests

Several static and dynamic information matrix tests were performed on the final specifications. These tests generally indicated the appropriateness of the dynamic specification of the models. The tests are discussed and results presented in the Appendix.

6. Results

The results of the study fall into two categories: general results of primarily secondary interest, and those concerning the tests of the deterrence hypotheses. These are discussed in turn below.

A. General results

Examining the results for the model of the total number of homicides from Table 9A, one sees a strong day-of-week effect, with fewest murders occurring on Mondays , increasing steadily to Saturday when the largest number occurs. Homicides are more likely to occur in the latter half of the year, with October, August, and December being the highest three months. The number of homicides was trending steadily upward over the sample period, with roughly 1.5 more murders occurring daily on average in 1967 than in 1960. Unemployment is seen to have a marginally significant positive impact on the number of daily murders. New Year's and Labor Day exhibit strong increases in homicides, but no other holidays. No negative coefficients of the NX variables approach significance.

Examining the models for murders of whites and non-whites, given in Tables 7B and 9B, one notes their overall similarity with the NH model, with a few exceptions. The model for murders of white males, given in Table 7F, is seen to be quite similar to the models of all whites. The eleventh lag of NX in the model for white males has the largest negative t-ratio of all the models; more attention will be paid to this below.

The models of firearm killings of both racial groups, given in Tables 7D and 7E, seem lacking in overall significance, with many seasonal variables and NX coefficients insignificant. One sees that the fewest homicides of this type occur on Tuesdays, and that the unemployment effect is fairly strong. No negative NX coefficients approach significance, however.

The regressions from the 1960-1963 data, reported in Tables 5G to 5L, are very much like those from the full sample, except that seasonal effects are less precisely estimated, particularly for the white subpopulation. The negative eleventh lag of NX in the white male regression is stronger, and apparently strong enough so that the eleventh lag of NX in the NHW model also approaches significance. Again, this will be discussed in detail below.

B. Tests for Deterrence

Tests of the deterrence hypotheses are based on parameter estimates from the final model specification for each category of homicide. A summary of these specifications is given in Table 10.

The first set of results presented pertains to the test for a decrease in homicides on any single day in the three-week period following an execution. Given the somewhat unusual problem of testing for the (algebraic) minimum of twenty-one estimated coefficients, it may be useful to establish benchmark magnitudes for the critical values. At one extreme would be stochastic independence of the coefficients. In this case, utilizing the asymptotic normal distribution of the estimated t-ratios, the critical value for the test of the minimum coefficient at a level of 5 per cent is obtained by finding $c_{\frac{.05}{21}} = c_{.0024} = -2.82$. At the other extreme of exact dependence, the critical value would be the usual $c_{.05} = -1.645$. The effect of increasing the dependence among the parameters is to reduce the size of the acceptance region corresponding to a test of a given overall size. To provide some intuition for the magnitude of this reduction we note that any coefficient with $t \leqslant -2.82$ would be significant regardless of the dependence among the parameter estimates, while any coefficient with $t > -1.645$ would be always insignificant. The size of the acceptance region thus varies by 75 per cent between the two extremes.

The problem for tests based on regression coefficients which fall between the two extremes is to find a computationally tractable method by which one may improve on tests conducted under the assumption of independence, which is sometimes referred to as the Bonferoni procedure. By "improvement" is meant reducing the size of the acceptance region in accord with the estimated dependence of the coefficients.

Kwerel's technique, described above, provides such a method. For the benefit of readers who turned directly to the results, it is repeated here that Kwerel's method essentially involves using the estimated regression coefficients and covariance matrix to calculate upper and lower bounds, p_U and p_L, for the rejection probability for a test of the significance of the negative NX coefficient with the largest t-statistic (in absolute value). For a test of size α, one rejects the null hypothesis of no single-day deterrent effect if $p_U < \alpha$, while failing to reject if $p_L > \alpha$. If $p_U \ \alpha \ p_L$, the test would be inconclusive. Results from these tests are presented in Table 11. In the table are identified the most significant of the *NX* variables from each category of homicide. Also given are the estimated coefficients of those variables, their asymptotic t-ratios, and the values of p_L and p_U.

Perhaps the most striking feature of the table is the pronounced weakness with which any deterrent effects are evidenced. In five of the twelve models presented, the upper bound on the probability that the difference from zero of the strongest measured deterrent effect is solely a chance occurrence is equal to unity. For the remaider of the models, this upper bound averages .56, and in only one case is lower than 35 per cent. The lower bounds are equally poor, averaging .49, with only three values below 35 per cent, and only one below 25 per cent. The model for white males, estimated over the 1960-63 period, comes nearest to rejecting the null hypothesis, on the eleventh day following an execution. The value of $p_U = .147$, however, is still well above any customary significance level. Evidence of a deterrent effect by which homicides fall on any one day following an execution is thus seen to be very weak, and almost non-existent.

We turn now to the tests for decreases in the total number of homicides over the entire three-week period following an execution. First, drawing on the logic underlying many non-parametric procedures, that negative effects should be evidenced by many negative changes relative to positive ones, the numbers of positive and negative coefficients from the *NX* lag structure from each model are presented in Table 12. The signs are divided about as evenly as possible, with no more than eleven of the twenty-one coefficients negative in any of the models. From this table, evidence of deterrent effects of this type would seem little stronger than that of the first type presented above.

Of course, more powerful tests are provided by parametric techniques. Table 13 contains the sums of the twenty-one *NX* coefficients from each model, and their asymptotic t-ratios. Most of these coefficient sums are seen to be rather small, and eight of the twelve are associated with t-statistics of less than one. Considerably larger negative coefficient sums are reported for the models of homicides of white males, and of non-whites killed by firearms, over both sample periods. Again, however, the asymptotic t-values fall well below the critical value for a one-sided test at five per cent. Thus, while evidence for this type of deterrent effect appears stronger than for the first type, it is still statistically insignificant. Not one of the many tests conducted leads one to reject the null hypothesis of no deterrent effect of either type.

7. Summary and Conclusions

This paper has presented considerable evidence against the hypothesis that executions exhibit a short-term deterrent effect on homicides. These conclusions are based on the largest set of the most disaggregated data yet brought to bear on the issue; on a statistical methodology employed to account for several important features of that data; and on a statistical testing technique designed to provide the most powerful tests available, given current computing techniques.

In many ways, these results are even stronger, though, than the formal statistical machinery would suggest. At least two aspects of the initial set-up of the study should have had the effect of making rejection more likely. The total homicide count was disaggregated by victim's race, sex, and type of weapon used, to ensure that deterrent effects too small to be discerned in the aggregate counts or specific to certain types of murders would nonetheless be detected. The sample was then divided into two periods, to ensure that any deterrent effects present in the earlier period of relatively frequent executions would not be masked by the data from the later period in which only one execution occurred. Despite these features of the initial study design, and the considerable statistical technology applied, though, none of the twenty-four tests applied could reject the null hypothesis, that executions do not deter murder.

Legal scholars and criminologists generally posit three motivations for the punishment of criminals, and for capital punishment in particular. They are retribution, incapacitation, and deterrence. Clearly, the retributive and incapacitative effects of capital punishment cannot be argued. Until better data or statistical methods provide convincing evidence to the contrary, however, neither policy makers nor the public they serve can presume its efficacy as a deterrent.

Footnotes

1. Baldus and Cole [1975] state this problem simply and concisely:

> To illustrate this problem, consider the simplified example of a nation composed of three states, two retentionist (R1 and R2) and one abolitionist (A). Assume that execution risk decreases in R1 and remains constant in the other states, and that the murder rate increases in one state, not necessarily R1, and remains constant in the other two. No matter which of the three states experiences the increase in murders, the nation as a whole would show an aggregate increase in murder rate and decrease in execution risk; analyzing these aggregate figures would suggest a deterrent effect. This inference would be justified only if the increase in the murder rate occurred in R1, where execution risk had decreased. If instead the murder rate increased in state A or R2, the aggregate correlation would be misleading, because the increase in the murder rate in one jurisdiction could not be attributed to lower execution risk in another. The actual behavior of the murder rate and execution risk in different jurisdictions is, of course, far more complicated than in this example. But the point remains that ... use of national data obscures the relationships between murder and execution rates and may yield results which seem consistent with a deterrent effect where no such effect actually exists.

2. Longer lag structures were also examined. In no case were any significant effects present beyond the twenty-first lag.

3. For the 1960-63 estimation period, the variable IND had to be dropped from the NHWG model. For this model, the dependent variable was zero for all observations such that IND=1. As such, one of the likelihood equations was

$$\sum_{t=IND} -exp(\ X_t\beta\ ) = 0.$$

The algorithm attempted to satisfy this by setting $\beta_{IND}=-\infty$, preventing convergence.

4. A rather anomalous situation arose with regard to the NH model for the 1960-63 sample period. Although the Poisson specification was rejected, the maximum likelihood estimate of $\hat{\alpha}$, the negative binomial nuisance parameter, was negative. This is not permissible for a proper distribution; as such, the Poisson estimates were used for inference.

Appendix

The final specification of each model was subjected to several dynamic and static information matrix tests for general misspecification. The tests were performed by regressing a unit vector on the scores of the model plus various elements of the relevant indicator matrix. The test statistic is nR^2 from this auxiliary regression, and is distributed χ^2_m, where m= the number of indicators included.

For the dynamic tests, the indicator matrix takes the form

$$m_{t|t-\lambda} = g_t g_{t-\lambda}$$

where

$$g_{t-\lambda} = X_{t-\lambda}(\, y_{t-\lambda} - \exp(X_{t-\lambda}\beta)) \quad \text{for } \textit{Poisson models},$$

$$= X_{t-\lambda}\frac{(\, y_t - \exp(X_{t-\lambda}\beta))}{1 + \alpha exp(X_{t-\lambda}\beta)} \quad \text{for } \textit{n.b.} \text{ and } \textit{QGPML models}$$

In the negative binomial case, the ML estimate of α is used to conduct the tests, while the QGPML estimate is used for those models.

For the static tests, the indicator matrix takes the form

$$m_{0t} = vech X_t' X_t(u_t^2 - \lambda_t) \quad \text{for } \textit{the Poisson specification},$$

$$= vech\ X_t' X_t\ \frac{[u_t^2 - exp(X_t\beta)][1 + 2\alpha exp(X_t\beta)]}{[1 + \alpha exp(X_t\beta)]^2}$$

for the n.b. and QGPML specifications, where *vech* denotes the "vec half" operator, and

$$u_t = y_t - \exp(X_t\beta).$$

Dynamic tests were performed for $\lambda = 1$ and diagonal elements of $m_{t|t-1}$ corresponding to the month and year variables. These results are presented in Table A1, where on notes the null of no misspecification is not rejected.

Static tests were performed for diagonal elements corresponding to the constant term, the day, month, and year indicators, UNEMP and WATTS. Results presented in Table A2 indicate the failure of many of these tests, primarily of the negative binomial and QGPML models. There are several reasons for which the model may have failed these tests, including misspecification of the conditional mean and misspecification of higher-order moments. In particular, one sees by examining Table 2 that the tests seem sensitive to outliers in the dependent variable, failing for cases where the kurtosis measure is large, but not when it is small. Given the robustness of the parameter estimates to changes in functional form, it seems likely that the failure of higher-order moment restrictions implied by the Poisson and negative binomial likelihoods is the cause of the failures in this case.

Fortunately, the model with the most nearly significant deterrence variable, NHWM for the 1960-63 period, was not rejected by the misspecification tests.

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Table 1

VARIABLE DEFINITIONS

Dependent Variables	Homicide Counts for:
NH	Total Population
NHW	Whites
NHNW	Non-whites
NHB	Blacks
NHWM	White Males
NHNWM	Non-white Males
NHBM	Black Males
NHWF	White Females
NHNWF	Non-white Females
NHBF	Black Females
NHWG	Whites, by Firearms
NHNWG	Non-whites, by Firearms
NHBG	Blacks, by Firearms
NHWK	Whites, by Knives
NHNWK	Non-whites, by Knives
NHBK	Blacks, by Knives
NHWO	Whites, by Other Weapons
NHNWO	Non-whites, by Other Weapons
NHBO	Blacks, by Other Weapons
Independent Variables	
Execution Measure	
NX	Number of Executions
NXJ	j^{th} Lag of NX
Binary Indicators	Equal to 1 on:
MON	Monday
TUE	Tuesday
WED	Wednesday
THU	Thursday
FRI	Friday
SAT	Saturday
FEB	February
MAR	March
APR	April
MAY	May
JUN	June
JUL	July
AUG	August
SEP	September
OCT	October
NOV	November
DEC	December
Y61	1961
Y62	1962
Y63	1963
Y64	1964
Y65	1965
Y66	1966
Y67	1967
NYR	New Year's
MEM	Memorial Day
IND	Independence Day
LAB	Labor Day
THX	Thanksgiving
CHR	Christmas
WATTS	August 13-17, 1965
Unemployment	
UNEMP	

Table 2

SUMMARY STATISTICS OF CALIFORNIA HOMICIDE DATA

Category	Minimum	Maximum	Sum	Mean	Standard Deviation
NH	0	28	6458	2.21	1.76
NHW	0	11	4313	1.47	1.34
NHNW	0	17	2145	0.73	0.97
NHB	0	17	1996	0.68	0.94
NHWM	0	9	2884	0.99	1.07
NHNWM	0	17	1652	0.57	0.86
NHBM	0	17	1540	0.53	0.83
NHWF	0	5	1429	0.48	0.73
NHNWF	0	3	493	0.17	0.43
NHBF	0	3	456	0.16	0.41
NHWG	0	9	2085	0.71	0.93
NHNWG	0	16	1182	0.40	0.74
NHBG	0	16	1120	0.38	0.72
NHWK	0	3	764	0.26	0.55
NHNWK	0	3	580	0.20	0.45
NHBK	0	3	546	0.19	0.44
NHWO	0	7	1464	0.50	0.76
NHNWO	0	4	383	0.13	0.38
NHBO	0	4	330	0.11	0.35

Number of Executions by Day of Week

Monday	Tuesday	Wednesday	Thursday	Friday
2	3	16	3	6

Table 2B

SUMMARY STATISTICS OF CALIFORNIA HOMICIDE DATA, 1960-63

Category	Minimum	Maximum	Sum	Mean	Standard Deviation
NH	0	8	2680	1.86	1.51
NHW	0	7	1812	1.26	1.18
NHNW	0	5	868	0.60	0.83
NHB	0	5	806	0.56	0.80
NHWM	0	7	1177	0.82	0.95
NHNWM	0	5	654	0.45	0.71
NHBM	0	5	605	0.42	0.68
NHWF	0	4	635	0.44	0.68
NHNWF	0	2	214	0.15	0.40
NHBF	0	2	201	0.14	0.37
NHWG	0	4	863	0.60	0.84
NHNWG	0	4	424	0.29	0.57
NHBG	0	4	400	0.28	0.55
NHWK	0	3	298	0.21	0.49
NHNWK	0	2	262	0.18	0.43
NHBK	0	2	247	0.17	0.42
NHWO	0	5	651	0.45	0.68
NHNWO	0	4	182	0.13	0.38
NHBO	0	4	159	0.11	0.36

Table 3A

LINEAR REGRESSIONS ON CALIFORNIA HOMICIDES

Dependent variable is NH

Mean of dependent variable	2.22	R^2	0.14
Standard error of regression	1.65	Adjusted R^2	0.12
Number of observations	2902	Log-likelihood	-5543.75

Variable	Coefficient	T-statistic
INTERCEP	0.2984	0.40
MON	-0.5036	-4.28
TUE	-0.4820	-4.12
WED	-0.4691	-3.97
THU	-0.3593	-3.03
FRI	0.3401	2.91
SAT	0.6379	5.45
FEB	0.1602	1.00
MAR	0.1280	0.82
APR	0.2098	1.11
MAY	0.3818	1.95
JUN	0.2560	1.51
JUL	0.5898	3.21
AUG	0.9354	4.54
SEP	0.6720	2.56
OCT	0.9386	3.49
NOV	0.5918	2.89
DEC	0.8364	4.41
Y61	-0.3396	-2.05
Y62	0.0396	0.32
Y63	-0.0017	-0.01
Y64	0.2661	2.09
Y65	0.7535	5.92
Y66	0.8582	5.32
Y67	1.3013	8.20
NYR	1.6777	2.64
MEM	-0.2406	-0.41
IND	-0.0010	0.00
LAB	1.8386	3.07
THX	0.5063	0.84
CHR	0.4736	0.80
UNEMP	0.2021	1.92
NX	0.4069	1.41
NX1	-0.4431	-1.53
NX2	0.0140	0.05
NX3	-0.0401	-0.14
NX4	0.1874	0.65
NX5	-0.1905	-0.66
NX6	-0.1812	-0.63
NX7	0.2034	0.70
NX8	-0.3807	-1.32
NX9	-0.2129	-0.74
NX10	0.2602	0.90
NX11	-0.2849	-0.99
NX12	0.0516	0.18
NX13	-0.1339	-0.49
NX14	0.2540	0.93
NX15	0.1842	0.67
NX16	0.3884	1.42
NX17	-0.2658	-0.97
NX18	0.3755	1.37
NX19	0.2931	1.07
NX20	0.5955	2.17

Table 3B

LINEAR REGRESSIONS ON CALIFORNIA HOMICIDES

Dependent variable is NHW

Mean of dependent variable	1.48	R^2	0.08
Standard error of regression	1.30	Adjusted R^2	0.07
Number of observations	2902	Log-likelihood	-4843.60

Variable	Coefficient	T-statistic
INTERCEP	0.5736	0.98
MON	-0.3647	-3.94
TUE	-0.3161	-3.44
WED	-0.3103	-3.35
THU	-0.2483	-2.67
FRI	0.0018	0.02
SAT	0.2760	3.01
FEB	0.0348	0.28
MAR	-0.0440	-0.36
APR	0.0652	0.44
MAY	0.1367	0.89
JUN	0.0492	0.37
JUL	0.2627	1.82
AUG	0.4747	2.93
SEP	0.3199	1.55
OCT	0.5013	2.38
NOV	0.2393	1.49
DEC	0.4744	3.18
Y61	-0.2214	-1.70
Y62	0.0522	0.53
Y63	-0.0208	-0.21
Y64	0.2046	2.04
Y65	0.3856	3.86
Y66	0.4894	3.86
Y67	0.8098	6.50
NYR	1.1420	2.29
MEM	-0.2822	-0.60
IND	-0.3043	-0.65
LAB	1.0097	2.15
THX	-0.2447	-0.52
CHR	0.0242	0.05
UNEMP	0.1050	1.27
NX	0.1237	0.54
NX1	-0.2670	-1.17
NX2	0.0261	0.12
NX3	-0.1252	-0.55
NX4	0.0252	0.11
NX5	-0.1867	-0.82
NX6	-0.0951	-0.42
NX7	-0.0172	-0.08
NX8	-0.1757	-0.77
NX9	-0.0142	-0.06
NX10	0.4416	1.95
NX11	-0.2855	-1.26
NX12	0.0135	0.06
NX13	-0.0215	-0.10
NX14	0.3339	1.55
NX15	0.0558	0.26
NX16	0.1384	0.64
NX17	-0.1761	-0.82
NX18	0.2159	1.00
NX19	-0.0427	-0.20
NX20	0.3846	1.78

Table 3C

LINEAR REGRESSIONS ON CALIFORNIA HOMICIDES

Dependent variable is NHNW

Mean of dependent variable	0.74	R^2	0.10
Standard error of regression	0.94	Adjusted R^2	0.08
Number of observations	2902	Log-likelihood	-3896.00

Variable	Coefficient	T-statistic
INTERCEP	-0.2752	-0.65
MON	-0.1390	-2.08
TUE	-0.1659	-2.51
WED	-0.1588	-2.37
THU	-0.1111	-1.65
FRI	0.3383	5.11
SAT	0.3618	5.46
FEB	0.1254	1.38
MAR	0.1721	1.96
APR	0.1447	1.35
MAY	0.2451	2.20
JUN	0.2067	2.15
JUL	0.3271	3.14
AUG	0.4607	3.94
SEP	0.3521	2.36
OCT	0.4373	2.87
NOV	0.3525	3.04
DEC	0.3620	3.37
Y61	-0.1181	-1.26
Y62	-0.0126	-0.18
Y63	0.0191	0.26
Y64	0.0615	0.85
Y65	0.3679	5.10
Y66	0.3688	4.03
Y67	0.4914	5.47
NYR	0.5357	1.49
MEM	0.0416	0.12
IND	0.3033	0.90
LAB	0.8289	2.44
THX	0.7511	2.20
CHR	0.4494	1.34
UNEMP	0.0970	1.62
NX	0.2832	1.73
NX1	-0.1761	-1.07
NX2	-0.0121	-0.07
NX3	0.0851	0.52
NX4	0.1622	0.99
NX5	-0.0038	-0.02
NX6	-0.0861	-0.52
NX7	0.2206	1.35
NX8	-0.2050	-1.25
NX9	-0.1988	-1.21
NX10	-0.1815	-1.11
NX11	0.0006	0.00
NX12	0.0381	0.23
NX13	-0.1123	-0.72
NX14	-0.0799	-0.51
NX15	0.1284	0.83
NX16	0.2501	1.61
NX17	-0.0897	-0.58
NX18	0.1596	1.03
NX19	0.3359	2.16
NX20	0.2109	1.36

Table 3D

LINEAR REGRESSIONS ON CALIFORNIA HOMICIDES
Dependent variable is NHB

Mean of dependent variable	0.69	R^2	0.09
Standard error of regression	0.90	Adjusted R^2	0.08
Number of observations	2902	Log-likelihood	-3788.68

Variable	Coefficient	T-statistic
INTERCEP	-0.2020	-0.50
MON	-0.1432	-2.23
TUE	-0.1818	-2.85
WED	-0.1808	-2.81
THU	-0.1241	-1.92
FRI	0.3001	4.70
SAT	0.3328	5.21
FEB	0.1299	1.48
MAR	0.1657	1.95
APR	0.1044	1.01
MAY	0.2262	2.11
JUN	0.1704	1.84
JUL	0.2761	2.75
AUG	0.4175	3.71
SEP	0.3001	2.09
OCT	0.3866	2.63
NOV	0.2966	2.65
DEC	0.3349	3.23
Y61	-0.1104	-1.22
Y62	-0.0028	-0.04
Y63	0.0212	0.31
Y64	0.0462	0.66
Y65	0.3490	5.02
Y66	0.3509	3.98
Y67	0.4444	5.13
NYR	0.5788	1.67
MEM	-0.0563	-0.17
IND	0.3664	1.13
LAB	0.8724	2.67
THX	0.8155	2.48
CHR	0.3632	1.12
UNEMP	0.0864	1.50
NX	0.2026	1.28
NX1	-0.1965	-1.24
NX2	0.0263	0.17
NX3	0.1002	0.63
NX4	0.0419	0.26
NX5	-0.0092	-0.06
NX6	-0.0514	-0.32
NX7	0.1999	1.26
NX8	-0.1905	-1.21
NX9	-0.2172	-1.37
NX10	-0.1708	-1.08
NX11	-0.0213	-0.14
NX12	0.0395	0.25
NX13	-0.1122	-0.75
NX14	-0.0735	-0.49
NX15	0.1646	1.10
NX16	0.2318	1.55
NX17	-0.0817	-0.55
NX18	0.1286	0.86
NX19	0.1739	1.16
NX20	0.2082	1.39

Table 3E
LINEAR REGRESSIONS ON CALIFORNIA HOMICIDES
Dependent variable is NHWM

Mean of dependent variable	0.99	R^2	0.08
Standard error of regression	1.04	Adjusted R^2	0.06
Number of observations	2902	Log-likelihood	-4196.67

Variable	Coefficient	T-statistic
INTERCEP	0.2706	0.58
MON	-0.2346	-3.17
TUE	-0.2381	-3.24
WED	-0.1807	-2.43
THU	-0.1643	-2.20
FRI	0.0984	1.34
SAT	0.2854	3.88
FEB	-0.0296	-0.29
MAR	-0.0983	-1.01
APR	-0.0312	-0.26
MAY	0.0272	0.22
JUN	-0.0209	-0.20
JUL	0.1191	1.03
AUG	0.3115	2.40
SEP	0.1861	1.13
OCT	0.3135	1.86
NOV	0.1836	1.43
DEC	0.2528	2.12
Y61	-0.2344	-2.25
Y62	-0.0051	-0.06
Y63	0.0059	0.07
Y64	0.1616	2.02
Y65	0.2804	3.50
Y66	0.3348	3.30
Y67	0.5728	5.74
NYR	0.3965	0.99
MEM	-0.1948	-0.52
IND	-0.4255	-1.14
LAB	0.9460	2.51
THX	-0.4646	-1.23
CHR	-0.0070	-0.02
UNEMP	0.0931	1.40
NX	0.1509	0.83
NX1	-0.1308	-0.72
NX2	0.0715	0.39
NX3	-0.1126	-0.62
NX4	0.0683	0.37
NX5	-0.1471	-0.81
NX6	0.0852	0.47
NX7	-0.1352	-0.74
NX8	-0.1602	-0.88
NX9	-0.0553	-0.30
NX10	0.1923	1.06
NX11	-0.3531	-1.94
NX12	0.0015	0.01
NX13	-0.1324	-0.77
NX14	0.0388	0.22
NX15	-0.2565	-1.49
NX16	0.1682	0.98
NX17	-0.0987	-0.57
NX18	0.0604	0.35
NX19	-0.0060	-0.04
NX20	0.3067	1.78

Table 3F
LINEAR REGRESSIONS ON CALIFORNIA HOMICIDES
Dependent variable is NHNWM

Mean of dependent variable	0.57	R^2	0.08
Standard error of regression	0.83	Adjusted R^2	0.07
Number of observations	2902	Log-likelihood	-3563.29

Variable	Coefficient	T-statistic
INTERCEP	-0.1087	-0.29
MON	-0.1144	-1.92
TUE	-0.1169	-1.98
WED	-0.0947	-1.59
THU	-0.0823	-1.37
FRI	0.3225	5.46
SAT	0.3129	5.29
FEB	0.0836	1.03
MAR	0.1397	1.78
APR	0.0972	1.02
MAY	0.1528	1.54
JUN	0.1246	1.45
JUL	0.2206	2.37
AUG	0.3426	3.29
SEP	0.2079	1.57
OCT	0.3361	2.48
NOV	0.2505	2.42
DEC	0.2354	2.46
Y61	-0.0481	-0.57
Y62	0.0351	0.56
Y63	0.0545	0.85
Y64	0.0935	1.45
Y65	0.3550	5.52
Y66	0.3025	3.71
Y67	0.3857	4.81
NYR	0.5378	1.68
MEM	-0.1798	-0.60
IND	0.3586	1.19
LAB	0.6216	2.05
THX	0.3813	1.25
CHR	0.5304	1.77
UNEMP	0.0519	0.97
NX	0.1265	0.87
NX1	-0.0818	-0.56
NX2	0.0603	0.41
NX3	-0.0328	-0.22
NX4	0.0506	0.34
NX5	-0.0218	-0.15
NX6	0.0118	0.08
NX7	0.1568	1.07
NX8	-0.1540	-1.05
NX9	-0.1158	-0.79
NX10	-0.1722	-1.18
NX11	-0.0043	-0.03
NX12	-0.0335	-0.23
NX13	-0.0692	-0.50
NX14	-0.1448	-1.04
NX15	0.1911	1.38
NX16	0.2423	1.75
NX17	-0.0834	-0.60
NX18	0.1833	1.33
NX19	0.1991	1.44
NX20	0.1558	1.12

Table 3G

LINEAR REGRESSIONS ON CALIFORNIA HOMICIDES

Dependent variable is NHBM

Mean of dependent variable	0.53	R^2	0.08
Standard error of regression	0.80	Adjusted R^2	0.07
Number of observations	2902	Log-likelihood	-3460.62

Variable	Coefficient	T-statistic
INTERCEP	-0.0124	-0.03
MON	-0.1285	-2.24
TUE	-0.1420	-2.49
WED	-0.1295	-2.25
THU	-0.1014	-1.75
FRI	0.2731	4.79
SAT	0.2656	4.66
FEB	0.0903	1.15
MAR	0.1336	1.76
APR	0.0718	0.78
MAY	0.1316	1.38
JUN	0.0877	1.06
JUL	0.1847	2.06
AUG	0.3005	2.99
SEP	0.1484	1.16
OCT	0.2856	2.18
NOV	0.1964	1.97
DEC	0.2112	2.28
Y61	-0.0331	-0.41
Y62	0.0469	0.77
Y63	0.0636	1.03
Y64	0.0936	1.50
Y65	0.3404	5.48
Y66	0.2869	3.65
Y67	0.3601	4.66
NYR	0.5691	1.84
MEM	-0.1596	-0.55
IND	0.3984	1.37
LAB	0.6616	2.27
THX	0.4342	1.48
CHR	0.4314	1.49
UNEMP	0.0392	0.76
NX	0.0995	0.70
NX1	-0.1120	-0.79
NX2	0.0927	0.66
NX3	-0.0230	-0.16
NX4	-0.0508	-0.36
NX5	-0.0359	-0.25
NX6	0.0349	0.25
NX7	0.1594	1.13
NX8	-0.1491	-1.05
NX9	-0.1404	-0.99
NX10	-0.1671	-1.19
NX11	-0.0387	-0.27
NX12	-0.0080	-0.06
NX13	-0.0763	-0.57
NX14	-0.1160	-0.87
NX15	0.2198	1.64
NX16	0.2707	2.03
NX17	-0.0803	-0.60
NX18	0.1416	1.06
NX19	0.0328	0.25
NX20	0.1462	1.09

Table 3H
LINEAR REGRESSIONS ON CALIFORNIA HOMICIDES
Dependent variable is NHWF

Mean of dependent variable	0.49	R^2	0.03
Standard error of regression	0.73	Adjusted R^2	0.01
Number of observations	2902	Log-likelihood	-3170.66

Variable	Coefficient	T-statistic
INTERCEP	0.3030	0.93
MON	-0.1300	-2.50
TUE	-0.0779	-1.51
WED	-0.1296	-2.49
THU	-0.0840	-1.61
FRI	-0.0966	-1.87
SAT	-0.0094	-0.18
FEB	0.0644	0.91
MAR	0.0543	0.79
APR	0.0964	1.16
MAY	0.1095	1.26
JUN	0.0702	0.94
JUL	0.1437	1.77
AUG	0.1632	1.79
SEP	0.1338	1.15
OCT	0.1878	1.58
NOV	0.0557	0.62
DEC	0.2216	2.65
Y61	0.0130	0.18
Y62	0.0573	1.04
Y63	-0.0267	-0.48
Y64	0.0430	0.76
Y65	0.1053	1.87
Y66	0.1546	2.17
Y67	0.2371	3.39
NYR	0.7454	2.66
MEM	-0.0874	-0.33
IND	0.1212	0.46
LAB	0.0637	0.24
THX	0.2198	0.83
CHR	0.0312	0.12
UNEMP	0.0119	0.26
NX	-0.0272	-0.21
NX1	-0.1361	-1.06
NX2	-0.0454	-0.35
NX3	-0.0126	-0.10
NX4	-0.0431	-0.34
NX5	-0.0396	-0.31
NX6	-0.1803	-1.41
NX7	0.1180	0.92
NX8	-0.0154	-0.12
NX9	0.0411	0.32
NX10	0.2493	1.96
NX11	0.0676	0.53
NX12	0.0120	0.09
NX13	0.1109	0.92
NX14	0.2951	2.44
NX15	0.3123	2.58
NX16	-0.0299	-0.25
NX17	-0.0774	-0.64
NX18	0.1555	1.29
NX19	-0.0367	-0.30
NX20	0.0779	0.64

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LINEAR REGRESSIONS ON CALIFORNIA HOMICIDES

Dependent variable is NHNWF

Mean of dependent variable	0.17	R^2	0.03
Standard error of regression	0.43	Adjusted R^2	0.01
Number of observations	2902	Log-likelihood	-1646.30

Variable	Coefficient	T-statistic
INTERCEP	-0.1666	-0.86
MON	-0.0246	-0.80
TUE	-0.0490	-1.61
WED	-0.0641	-2.08
THU	-0.0288	-0.93
FRI	0.0159	0.52
SAT	0.0489	1.60
FEB	0.0418	1.00
MAR	0.0324	0.80
APR	0.0475	0.97
MAY	0.0924	1.80
JUN	0.0821	1.85
JUL	0.1065	2.22
AUG	0.1182	2.20
SEP	0.1442	2.10
OCT	0.1012	1.44
NOV	0.1020	1.91
DEC	0.1266	2.56
Y61	-0.0700	-1.62
Y62	-0.0477	-1.46
Y63	-0.0354	-1.07
Y64	-0.0320	-0.96
Y65	0.0129	0.39
Y66	0.0663	1.58
Y67	0.1057	2.55
NYR	-0.0021	-0.01
MEM	0.2214	1.43
IND	-0.0553	-0.36
LAB	0.2073	1.33
THX	0.3697	2.35
CHR	-0.0810	-0.52
UNEMP	0.0452	1.64
NX	0.1567	2.07
NX1	-0.0943	-1.25
NX2	-0.0724	-0.96
NX3	0.1179	1.56
NX4	0.1116	1.47
NX5	0.0181	0.24
NX6	-0.0979	-1.29
NX7	0.0638	0.84
NX8	-0.0510	-0.68
NX9	-0.0830	-1.10
NX10	-0.0092	-0.12
NX11	0.0049	0.06
NX12	0.0716	0.95
NX13	-0.0432	-0.60
NX14	0.0649	0.91
NX15	-0.0628	-0.88
NX16	0.0078	0.11
NX17	-0.0063	-0.09
NX18	-0.0237	-0.33
NX19	0.1368	1.91
NX20	0.0551	0.77

Table 3J

LINEAR REGRESSIONS ON CALIFORNIA HOMICIDES

Dependent variable is NHBF

Mean of dependent variable	0.16	R^2	0.03
Standard error of regression	0.41	Adjusted R^2	0.01
Number of observations	2902	Log-likelihood	-1521.62

Variable	Coefficient	T-statistic
INTERCEP	-0.1897	-1.02
MON	-0.0147	-0.50
TUE	-0.0398	-1.36
WED	-0.0513	-1.74
THU	-0.0228	-0.77
FRI	0.0270	0.92
SAT	0.0672	2.30
FEB	0.0396	0.99
MAR	0.0321	0.83
APR	0.0327	0.69
MAY	0.0946	1.93
JUN	0.0827	1.95
JUL	0.0914	1.99
AUG	0.1171	2.27
SEP	0.1517	2.31
OCT	0.1010	1.50
NOV	0.1002	1.96
DEC	0.1238	2.61
Y61	-0.0774	-1.87
Y62	-0.0497	-1.59
Y63	-0.0425	-1.34
Y64	-0.0474	-1.49
Y65	0.0085	0.27
Y66	0.0639	1.58
Y67	0.0843	2.13
NYR	0.0097	0.06
MEM	0.1033	0.69
IND	-0.0320	-0.22
LAB	0.2108	1.41
THX	0.3813	2.53
CHR	-0.0681	-0.46
UNEMP	0.0472	1.79
NX	0.1031	1.42
NX1	-0.0845	-1.17
NX2	-0.0664	-0.92
NX3	0.1232	1.70
NX4	0.0927	1.28
NX5	0.0267	0.37
NX6	-0.0862	-1.19
NX7	0.0405	0.56
NX8	-0.0414	-0.57
NX9	-0.0768	-1.06
NX10	-0.0037	-0.05
NX11	0.0174	0.24
NX12	0.0475	0.66
NX13	-0.0358	-0.52
NX14	0.0425	0.62
NX15	-0.0553	-0.81
NX16	-0.0390	-0.57
NX17	-0.0014	-0.02
NX18	-0.0130	-0.19
NX19	0.1411	2.06
NX20	0.0619	0.90

Table 3K
LINEAR REGRESSIONS ON CALIFORNIA HOMICIDES
Dependent variable is NHWG

Mean of dependent variable	0.71	R^2	0.05
Standard error of regression	0.92	Adjusted R^2	0.04
Number of observations	2902	Log-likelihood	-3836.60

Variable	Coefficient	T-statistic
INTERCEP	-0.0230	-0.06
MON	-0.1363	-2.09
TUE	-0.1776	-2.74
WED	-0.0685	-1.05
THU	-0.0258	-0.39
FRI	0.1066	1.64
SAT	0.1164	1.79
FEB	-0.0400	-0.45
MAR	-0.0571	-0.66
APR	0.1364	1.30
MAY	0.2292	2.11
JUN	0.0986	1.05
JUL	0.1461	1.43
AUG	0.3074	2.69
SEP	0.2209	1.51
OCT	0.3712	2.49
NOV	0.3141	2.77
DEC	0.3023	2.87
Y61	-0.1921	-2.09
Y62	-0.0842	-1.22
Y63	-0.0879	-1.25
Y64	-0.0112	-0.16
Y65	0.1724	2.44
Y66	0.2336	2.61
Y67	0.4360	4.95
NYR	0.3333	0.94
MEM	0.0677	0.20
IND	-0.1297	-0.39
LAB	0.3226	0.97
THX	-0.1973	-0.59
CHR	0.1793	0.54
UNEMP	0.0910	1.55
NX	0.0179	0.11
NX1	-0.1543	-0.96
NX2	0.0034	0.02
NX3	-0.1240	-0.77
NX4	0.2055	1.28
NX5	-0.0320	-0.20
NX6	-0.0290	-0.18
NX7	0.0812	0.50
NX8	-0.0102	-0.06
NX9	-0.0982	-0.61
NX10	0.3587	2.23
NX11	-0.1576	-0.98
NX12	-0.0106	-0.07
NX13	0.0162	0.11
NX14	0.1969	1.29
NX15	-0.0312	-0.20
NX16	0.0121	0.08
NX17	-0.1216	-0.80
NX18	0.0658	0.43
NX19	-0.0222	-0.15
NX20	0.2425	1.59

Table 3L
LINEAR REGRESSIONS ON CALIFORNIA HOMICIDES
Dependent variable is NHNWG

Mean of dependent variable	0.41	R^2	0.09
Standard error of regression	0.71	Adjusted R^2	0.07
Number of observations	2902	Log-likelihood	-3109.20

Variable	Coefficient	T-statistic
INTERCEP	-0.4442	-1.38
MON	-0.0709	-1.39
TUE	-0.1039	-2.06
WED	-0.0307	-0.60
THU	-0.0205	-0.40
FRI	0.2786	5.52
SAT	0.2275	4.50
FEB	0.0593	0.85
MAR	0.1121	1.67
APR	0.1694	2.08
MAY	0.1644	1.94
JUN	0.1817	2.48
JUL	0.1798	2.26
AUG	0.4160	4.67
SEP	0.2969	2.61
OCT	0.3767	3.24
NOV	0.2384	2.70
DEC	0.2535	3.10
Y61	-0.1169	-1.63
Y62	-0.0046	-0.09
Y63	-0.0319	-0.58
Y64	0.0150	0.27
Y65	0.2708	4.92
Y66	0.3097	4.44
Y67	0.3981	5.81
NYR	0.4120	1.50
MEM	-0.0096	-0.04
IND	0.4545	1.77
LAB	0.2108	0.81
THX	0.5633	2.17
CHR	0.4480	1.75
UNEMP	0.0847	1.86
NX	0.1372	1.10
NX1	-0.1063	-0.85
NX2	-0.1226	-0.98
NX3	0.1920	1.53
NX4	0.0698	0.56
NX5	-0.1177	-0.94
NX6	0.0319	0.25
NX7	0.0300	0.24
NX8	-0.1571	-1.25
NX9	-0.2073	-1.66
NX10	-0.0614	-0.49
NX11	0.0420	0.34
NX12	0.1085	0.87
NX13	-0.1200	-1.01
NX14	-0.1610	-1.36
NX15	0.0740	0.63
NX16	0.1425	1.20
NX17	-0.1379	-1.16
NX18	0.1043	0.88
NX19	0.2919	2.46
NX20	0.1813	1.53

Table 3M

LINEAR REGRESSIONS ON CALIFORNIA HOMICIDES

Dependent variable is NHBG

Mean of dependent variable	0.39	R^2	0.09
Standard error of regression	0.69	Adjusted R^2	0.07
Number of observations	2902	Log-likelihood	-3031.29

Variable	Coefficient	T-statistic
INTERCEP	-0.4386	-1.40
MON	-0.0604	-1.22
TUE	-0.1039	-2.11
WED	-0.0286	-0.57
THU	-0.0228	-0.46
FRI	0.2640	5.37
SAT	0.2195	4.46
FEB	0.0697	1.03
MAR	0.1132	1.73
APR	0.1462	1.84
MAY	0.1640	1.99
JUN	0.1822	2.55
JUL	0.1623	2.10
AUG	0.3864	4.46
SEP	0.2732	2.47
OCT	0.3620	3.20
NOV	0.2228	2.59
DEC	0.2541	3.19
Y61	-0.1185	-1.70
Y62	-0.0082	-0.16
Y63	-0.0366	-0.69
Y64	0.0050	0.09
Y65	0.2717	5.07
Y66	0.2982	4.39
Y67	0.3699	5.54
NYR	0.4235	1.59
MEM	-0.0022	-0.01
IND	0.4793	1.92
LAB	0.2329	0.92
THX	0.5853	2.31
CHR	0.3327	1.33
UNEMP	0.0832	1.88
NX	0.1234	1.01
NX1	-0.0861	-0.71
NX2	-0.1015	-0.83
NX3	0.2152	1.77
NX4	0.0894	0.73
NX5	-0.1059	-0.87
NX6	0.0500	0.41
NX7	0.0154	0.13
NX8	-0.1328	-1.09
NX9	-0.1824	-1.50
NX10	-0.0725	-0.60
NX11	0.0586	0.48
NX12	0.1184	0.97
NX13	-0.1069	-0.93
NX14	-0.1499	-1.30
NX15	0.0867	0.75
NX16	0.1061	0.92
NX17	-0.1258	-1.09
NX18	0.1159	1.01
NX19	0.1885	1.63
NX20	0.1622	1.40

Table 3N

LINEAR REGRESSIONS ON CALIFORNIA HOMICIDES

Dependent variable is NHWK

Mean of dependent variable	0.26	R^2	0.05
Standard error of regression	0.54	Adjusted R^2	0.03
Number of observations	2902	Log-likelihood	-2311.38

Variable	Coefficient	T-statistic
INTERCEP	0.0830	0.34
MON	-0.0511	-1.32
TUE	-0.0383	-1.00
WED	-0.1128	-2.91
THU	-0.0722	-1.86
FRI	0.0534	1.39
SAT	0.1486	3.87
FEB	0.0873	1.65
MAR	0.0755	1.48
APR	0.0292	0.47
MAY	0.0468	0.73
JUN	-0.0028	-0.05
JUL	0.1479	2.45
AUG	0.0790	1.17
SEP	0.1171	1.36
OCT	0.1040	1.18
NOV	0.0396	0.59
DEC	0.1219	1.96
Y61	0.0130	0.24
Y62	0.0656	1.60
Y63	0.0513	1.23
Y64	0.1054	2.52
Y65	0.1253	3.00
Y66	0.1354	2.56
Y67	0.2209	4.24
NYR	0.0712	0.34
MEM	-0.0851	-0.44
IND	-0.1877	-0.96
LAB	0.2366	1.20
THX	-0.1749	-0.88
CHR	-0.1930	-0.99
UNEMP	0.0052	0.15
NX	0.1224	1.29
NX1	0.0092	0.10
NX2	-0.0241	-0.25
NX3	-0.0978	-1.03
NX4	-0.0441	-0.46
NX5	-0.0898	-0.94
NX6	0.0054	0.06
NX7	0.0164	0.17
NX8	-0.0404	-0.43
NX9	-0.0197	-0.21
NX10	-0.0774	-0.82
NX11	-0.0857	-0.90
NX12	0.0752	0.79
NX13	0.0739	0.82
NX14	-0.0656	-0.73
NX15	0.0046	0.05
NX16	-0.0262	-0.29
NX17	-0.0936	-1.04
NX18	0.1079	1.20
NX19	0.0724	0.81
NX20	0.0845	0.94

Table 30
LINEAR REGRESSIONS ON CALIFORNIA HOMICIDES
Dependent variable is NHNWK

Mean of dependent variable	0.20	R^2	0.04
Standard error of regression	0.45	Adjusted R^2	0.02
Number of observations	2902	Log-likelihood	-1751.87

Variable	Coefficient	T-statistic
INTERCEP	0.0626	0.31
MON	-0.0799	-2.51
TUE	-0.0639	-2.02
WED	-0.0951	-2.98
THU	-0.0641	-2.00
FRI	0.0645	2.04
SAT	0.1017	3.21
FEB	0.0196	0.45
MAR	0.0119	0.28
APR	0.0107	0.21
MAY	0.0816	1.54
JUN	0.0075	0.16
JUL	0.0917	1.84
AUG	0.0583	1.04
SEP	0.0594	0.83
OCT	0.0520	0.71
NOV	0.0597	1.08
DEC	0.1106	2.15
Y61	-0.0141	-0.31
Y62	-0.0152	-0.45
Y63	0.0196	0.57
Y64	0.0523	1.52
Y65	0.0481	1.40
Y66	0.0347	0.80
Y67	0.0400	0.93
NYR	0.0972	0.57
MEM	-0.0797	-0.50
IND	0.0237	0.15
LAB	0.1161	0.72
THX	0.0853	0.52
CHR	-0.1354	-0.84
UNEMP	0.0150	0.52
NX	0.0468	0.60
NX1	-0.0992	-1.26
NX2	0.1451	1.85
NX3	-0.1174	-1.50
NX4	0.0782	1.00
NX5	0.0602	0.77
NX6	-0.0499	-0.64
NX7	0.0682	0.87
NX8	-0.0796	-1.01
NX9	0.0205	0.26
NX10	-0.1265	-1.62
NX11	-0.0235	-0.30
NX12	-0.0612	-0.78
NX13	-0.0080	-0.11
NX14	0.0542	0.73
NX15	0.0098	0.13
NX16	0.0919	1.24
NX17	-0.0058	-0.08
NX18	0.0781	1.05
NX19	0.0036	0.05
NX20	-0.0378	-0.51

Table 3P
LINEAR REGRESSIONS ON CALIFORNIA HOMICIDES
Dependent variable is NHBK

Mean of dependent variable	0.19	R^2	0.04
Standard error of regression	0.44	Adjusted R^2	0.02
Number of observations	2902	Log-likelihood	-1677.04

Variable	Coefficient	T-statistic
INTERCEP	0.0920	0.47
MON	-0.0801	-2.58
TUE	-0.0727	-2.36
WED	-0.1124	-3.61
THU	-0.0662	-2.12
FRI	0.0540	1.75
SAT	0.0948	3.07
FEB	0.0141	0.33
MAR	0.0019	0.05
APR	-0.0006	-0.01
MAY	0.0607	1.17
JUN	-0.0208	-0.47
JUL	0.0719	1.48
AUG	0.0425	0.78
SEP	0.0353	0.51
OCT	0.0445	0.63
NOV	0.0306	0.57
DEC	0.0979	1.96
Y61	-0.0099	-0.23
Y62	-0.0050	-0.15
Y63	0.0230	0.69
Y64	0.0498	1.48
Y65	0.0453	1.35
Y66	0.0289	0.68
Y67	0.0374	0.89
NYR	0.1114	0.67
MEM	-0.0665	-0.42
IND	0.0369	0.24
LAB	0.1253	0.79
THX	0.1006	0.63
CHR	-0.1292	-0.82
UNEMP	0.0118	0.43
NX	0.0306	0.40
NX1	-0.0938	-1.23
NX2	0.1516	1.98
NX3	-0.1412	-1.85
NX4	-0.0386	-0.50
NX5	0.0635	0.83
NX6	-0.0442	-0.58
NX7	0.0503	0.66
NX8	-0.0739	-0.97
NX9	0.0268	0.35
NX10	-0.1180	-1.55
NX11	-0.0451	-0.59
NX12	-0.0551	-0.72
NX13	-0.0289	-0.40
NX14	0.0681	0.94
NX15	0.0211	0.29
NX16	0.0978	1.35
NX17	0.0007	0.01
NX18	0.0558	0.77
NX19	-0.0152	-0.21
NX20	-0.0306	-0.42

Table 3Q
LINEAR REGRESSIONS ON CALIFORNIA HOMICIDES
Dependent variable is NHWO

Mean of dependent variable	0.50	R^2	0.03
Standard error of regression	0.75	Adjusted R^2	0.01
Number of observations	2902	Log-likelihood	-3269.86

Variable	Coefficient	T-statistic
INTERCEP	0.5136	1.52
MON	-0.1773	-3.30
TUE	-0.1001	-1.88
WED	-0.1290	-2.39
THU	-0.1502	-2.78
FRI	-0.1582	-2.96
SAT	0.0110	0.21
FEB	-0.0125	-0.17
MAR	-0.0624	-0.88
APR	-0.1004	-1.17
MAY	-0.1394	-1.56
JUN	-0.0465	-0.60
JUL	-0.0312	-0.37
AUG	0.0882	0.94
SEP	-0.0181	-0.15
OCT	0.0262	0.21
NOV	-0.1144	-1.22
DEC	0.0502	0.58
Y61	-0.0424	-0.56
Y62	0.0709	1.24
Y63	0.0157	0.27
Y64	0.1104	1.90
Y65	0.0880	1.51
Y66	0.1204	1.63
Y67	0.1530	2.11
NYR	0.7374	2.54
MEM	-0.2649	-0.98
IND	0.0131	0.05
LAB	0.4505	1.65
THX	0.1275	0.46
CHR	0.0379	0.14
UNEMP	0.0088	0.18
NX	-0.0166	-0.13
NX1	-0.1218	-0.92
NX2	0.0468	0.35
NX3	0.0966	0.73
NX4	-0.1362	-1.03
NX5	-0.0648	-0.49
NX6	-0.0715	-0.54
NX7	-0.1148	-0.87
NX8	-0.1250	-0.94
NX9	0.1037	0.78
NX10	0.1604	1.22
NX11	-0.0422	-0.32
NX12	-0.0511	-0.39
NX13	-0.1116	-0.89
NX14	0.2026	1.62
NX15	0.0824	0.66
NX16	0.1524	1.22
NX17	0.0391	0.31
NX18	0.0423	0.34
NX19	-0.0929	-0.74
NX20	0.0576	0.46

Table 3R
LINEAR REGRESSIONS ON CALIFORNIA HOMICIDES
Dependent variable is NHNWO

Mean of dependent variable	0.13	R^2	0.02
Standard error of regression	0.38	Adjusted R^2	0.00
Number of observations	2902	Log-likelihood	-1244.92

Variable	Coefficient	T-statistic
INTERCEP	0.1064	0.63
MON	0.0118	0.44
TUE	0.0019	0.07
WED	-0.0330	-1.23
THU	-0.0264	-0.98
FRI	-0.0047	-0.18
SAT	0.0326	1.23
FEB	0.0464	1.27
MAR	0.0481	1.36
APR	-0.0354	-0.83
MAY	-0.0008	-0.02
JUN	0.0175	0.45
JUL	0.0555	1.33
AUG	-0.0136	-0.29
SEP	-0.0042	-0.07
OCT	0.0086	0.14
NOV	0.0544	1.17
DEC	-0.0021	-0.05
Y61	0.0128	0.34
Y62	0.0072	0.25
Y63	0.0314	1.09
Y64	-0.0059	-0.20
Y65	0.0489	1.69
Y66	0.0244	0.67
Y67	0.0534	1.48
NYR	0.0265	0.18
MEM	0.1309	0.97
IND	-0.1749	-1.29
LAB	0.5021	3.69
THX	0.1024	0.75
CHR	0.1367	1.01
UNEMP	-0.0026	-0.11
NX	0.0992	1.51
NX1	0.0294	0.45
NX2	-0.0347	-0.53
NX3	0.0105	0.16
NX4	0.0143	0.22
NX5	0.0537	0.81
NX6	-0.0681	-1.03
NX7	0.1224	1.86
NX8	0.0317	0.48
NX9	-0.0120	-0.18
NX10	0.0065	0.10
NX11	-0.0179	-0.27
NX12	-0.0092	-0.14
NX13	0.0157	0.25
NX14	0.0269	0.43
NX15	0.0445	0.71
NX16	0.0156	0.25
NX17	0.0539	0.87
NX18	-0.0228	-0.37
NX19	0.0404	0.65
NX20	0.0674	1.08

Table 3S
LINEAR REGRESSIONS ON CALIFORNIA HOMICIDES
Dependent variable is NHBO

Mean of dependent variable	0.11	R^2	0.02
Standard error of regression	0.35	Adjusted R^2	0.00
Number of observations	2902	Log-likelihood	-1056.42

Variable	Coefficient	T-statistic
INTERCEP	0.1445	0.91
MON	-0.0028	-0.11
TUE	-0.0051	-0.21
WED	-0.0398	-1.59
THU	-0.0352	-1.39
FRI	-0.0179	-0.72
SAT	0.0184	0.74
FEB	0.0460	1.34
MAR	0.0506	1.53
APR	-0.0411	-1.02
MAY	0.0015	0.04
JUN	0.0089	0.25
JUL	0.0419	1.07
AUG	-0.0114	-0.26
SEP	-0.0084	-0.15
OCT	-0.0199	-0.35
NOV	0.0433	0.99
DEC	-0.0170	-0.42
Y61	0.0179	0.51
Y62	0.0105	0.39
Y63	0.0348	1.29
Y64	-0.0086	-0.32
Y65	0.0320	1.18
Y66	0.0238	0.69
Y67	0.0370	1.10
NYR	0.0438	0.32
MEM	0.0125	0.10
IND	-0.1498	-1.18
LAB	0.5142	4.03
THX	0.1296	1.01
CHR	0.1596	1.26
UNEMP	-0.0086	-0.38
NX	0.0487	0.79
NX1	-0.0166	-0.27
NX2	-0.0238	-0.38
NX3	0.0262	0.43
NX4	-0.0089	-0.14
NX5	0.0332	0.54
NX6	-0.0572	-0.93
NX7	0.1343	2.18
NX8	0.0162	0.26
NX9	-0.0616	-1.00
NX10	0.0197	0.32
NX11	-0.0349	-0.57
NX12	-0.0238	-0.39
NX13	0.0236	0.41
NX14	0.0083	0.14
NX15	0.0568	0.97
NX16	0.0279	0.48
NX17	0.0434	0.74
NX18	-0.0432	-0.74
NX19	0.0005	0.01
NX20	0.0765	1.31

Table 3T
LINEAR REGRESSIONS OF CALIFORNIA HOMICIDES
1960-63 Subsample

Dependent variable is NH			
Mean of dependent variable	1.86	R^2	0.10
Standard error of regression	1.45	Adjusted R^2	0.07
Number of observations	1441	Log-likelihood	-2557.18

Variable	Coefficient	T-statistic
INTERCEP	0.8270	1.07
MON	-0.3680	-2.46
TUE	-0.2680	-1.80
WED	-0.4486	-2.96
THU	-0.3759	-2.47
FRI	0.2567	1.73
SAT	0.6621	4.45
FEB	-0.3919	-1.87
MAR	-0.3361	-1.69
APR	-0.2427	-1.05
MAY	0.1112	0.49
JUN	-0.0795	-0.38
JUL	0.2511	1.12
AUG	0.4228	1.71
SEP	0.1804	0.61
OCT	0.3431	1.12
NOV	0.0280	0.12
DEC	0.3207	1.44
Y61	-0.3381	-2.13
Y62	0.0250	0.23
Y63	-0.0320	-0.28
NYR	0.4373	0.51
MEM	0.2377	0.32
IND	-0.4351	-0.59
LAB	1.2710	1.70
THX	0.5483	0.73
CHR	0.8368	1.13
UNEMP	0.1833	1.66
NX	0.4281	1.64
NX1	-0.4331	-1.66
NX2	0.0752	0.29
NX3	-0.0596	-0.23
NX4	0.2282	0.87
NX5	-0.2214	-0.85
NX6	-0.2996	-1.15
NX7	0.1257	0.48
NX8	-0.3986	-1.53
NX9	-0.1146	-0.44
NX10	0.2621	1.01
NX11	-0.4856	-1.86
NX12	-0.0129	-0.05
NX13	-0.2538	-1.03
NX14	0.2487	1.01
NX15	0.1732	0.70
NX16	0.4475	1.81
NX17	-0.2797	-1.13
NX18	0.2781	1.13
NX19	0.2615	1.06
NX20	0.4551	1.84

Table 3U
LINEAR REGRESSIONS OF CALIFORNIA HOMICIDES
1960-63 Subsample

Dependent variable is NHW

Mean of dependent variable	1.26	R^2	0.07
Standard error of regression	1.16	Adjusted R^2	0.04
Number of observations	1441	Log-likelihood	-2235.91

Variable	Coefficient	T-statistic
INTERCEP	1.0422	1.68
MON	-0.3060	-2.56
TUE	-0.1642	-1.38
WED	-0.2957	-2.44
THU	-0.2446	-2.01
FRI	-0.0069	-0.06
SAT	0.3508	2.95
FEB	-0.3490	-2.08
MAR	-0.3483	-2.19
APR	-0.2810	-1.52
MAY	-0.0429	-0.23
JUN	-0.1635	-0.98
JUL	0.1049	0.58
AUG	0.1510	0.76
SEP	0.0447	0.19
OCT	0.1145	0.47
NOV	-0.1408	-0.73
DEC	0.0657	0.37
Y61	-0.1941	-1.53
Y62	0.0474	0.54
Y63	-0.0389	-0.43
NYR	-0.0075	-0.01
MEM	-0.0724	-0.12
IND	-0.4725	-0.80
LAB	0.4104	0.69
THX	-0.2976	-0.49
CHR	0.1992	0.34
UNEMP	0.0703	0.80
NX	0.1758	0.84
NX1	-0.2893	-1.38
NX2	0.0722	0.34
NX3	-0.1488	-0.71
NX4	0.0326	0.16
NX5	-0.2112	-1.01
NX6	-0.1959	-0.94
NX7	-0.0889	-0.43
NX8	-0.1927	-0.92
NX9	0.0451	0.22
NX10	0.4209	2.02
NX11	-0.4486	-2.15
NX12	-0.0348	-0.17
NX13	-0.1182	-0.60
NX14	0.3236	1.64
NX15	0.0411	0.21
NX16	0.1588	0.80
NX17	-0.1923	-0.97
NX18	0.1305	0.66
NX19	-0.0625	-0.32
NX20	0.2894	1.46

Table 3V
LINEAR REGRESSIONS OF CALIFORNIA HOMICIDES
1960-63 Subsample

Dependent variable is NHNW

Mean of dependent variable	0.60	R^2	0.08
Standard error of regression	0.82	Adjusted R^2	0.04
Number of observations	1441	Log-likelihood	-1727.51

Variable	Coefficient	T-statistic
INTERCEP	-0.2151	-0.49
MON	-0.0620	-0.74
TUE	-0.1038	-1.24
WED	-0.1529	-1.79
THU	-0.1313	-1.54
FRI	0.2636	3.15
SAT	0.3113	3.72
FEB	-0.0429	-0.36
MAR	0.0122	0.11
APR	0.0384	0.29
MAY	0.1540	1.20
JUN	0.0840	0.71
JUL	0.1462	1.16
AUG	0.2718	1.96
SEP	0.1358	0.81
OCT	0.2286	1.33
NOV	0.1688	1.24
DEC	0.2550	2.04
Y61	-0.1439	-1.61
Y62	-0.0224	-0.36
Y63	0.0069	0.11
NYR	0.4448	0.92
MEM	0.3102	0.74
IND	0.0374	0.09
LAB	0.8606	2.05
THX	0.8459	2.00
CHR	0.6376	1.53
UNEMP	0.1130	1.82
NX	0.2523	1.72
NX1	-0.1438	-0.98
NX2	0.0030	0.02
NX3	0.0891	0.61
NX4	0.1955	1.33
NX5	-0.0103	-0.07
NX6	-0.1037	-0.71
NX7	0.2146	1.46
NX8	-0.2058	-1.40
NX9	-0.1597	-1.09
NX10	-0.1587	-1.08
NX11	-0.0371	-0.25
NX12	0.0219	0.15
NX13	-0.1356	-0.98
NX14	-0.0749	-0.54
NX15	0.1321	0.95
NX16	0.2887	2.08
NX17	-0.0875	-0.63
NX18	0.1476	1.06
NX19	0.3240	2.34
NX20	0.1657	1.19

Table 3W
LINEAR REGRESSIONS OF CALIFORNIA HOMICIDES
1960-63 Subsample

Dependent variable is NHB

Mean of dependent variable	0.56	R^2	0.08
Standard error of regression	0.78	Adjusted R^2	0.04
Number of observations	1441	Log-likelihood	-1665.31

Variable	Coefficient	T-statistic
INTERCEP	-0.2176	-0.52
MON	-0.0836	-1.04
TUE	-0.1350	-1.69
WED	-0.1821	-2.23
THU	-0.1728	-2.11
FRI	0.2183	2.73
SAT	0.2764	3.45
FEB	-0.0304	-0.27
MAR	0.0185	0.17
APR	0.0032	0.03
MAY	0.1496	1.22
JUN	0.0335	0.30
JUL	0.1231	1.02
AUG	0.2719	2.05
SEP	0.1529	0.95
OCT	0.2201	1.33
NOV	0.1463	1.13
DEC	0.2737	2.28
Y61	-0.1468	-1.72
Y62	-0.0116	-0.20
Y63	0.0071	0.12
NYR	0.5033	1.09
MEM	0.0924	0.23
IND	0.0913	0.23
LAB	0.8635	2.15
THX	0.9036	2.23
CHR	0.3875	0.97
UNEMP	0.1134	1.91
NX	0.1664	1.18
NX1	-0.1608	-1.14
NX2	0.0350	0.25
NX3	0.0982	0.70
NX4	0.0637	0.45
NX5	-0.0172	-0.12
NX6	-0.0669	-0.48
NX7	0.1895	1.35
NX8	-0.1867	-1.33
NX9	-0.1546	-1.10
NX10	-0.1541	-1.10
NX11	-0.0686	-0.49
NX12	0.0196	0.14
NX13	-0.1343	-1.01
NX14	-0.0727	-0.55
NX15	0.1709	1.28
NX16	0.2624	1.98
NX17	-0.0823	-0.62
NX18	0.1081	0.81
NX19	0.1547	1.16
NX20	0.1632	1.23

Table 3W
LINEAR REGRESSIONS OF CALIFORNIA HOMICIDES
1960-63 Subsample

Dependent variable is NHWM

Mean of dependent variable	0.82	R^2	0.06
Standard error of regression	0.93	Adjusted R^2	0.03
Number of observations	1441	Log-likelihood	-1922.11

Variable	Coefficient	T-statistic
INTERCEP	0.5301	1.06
MON	-0.1537	-1.60
TUE	-0.0912	-0.95
WED	-0.1688	-1.73
THU	-0.0940	-0.96
FRI	0.0768	0.80
SAT	0.3705	3.87
FEB	-0.2944	-2.19
MAR	-0.2904	-2.27
APR	-0.1755	-1.18
MAY	-0.0833	-0.57
JUN	-0.1582	-1.18
JUL	-0.0541	-0.38
AUG	0.0326	0.20
SEP	0.0381	0.20
OCT	0.0873	0.44
NOV	-0.0705	-0.45
DEC	-0.0206	-0.14
Y61	-0.2221	-2.17
Y62	-0.0127	-0.18
Y63	-0.0029	-0.04
NYR	0.0748	0.14
MEM	0.0802	0.17
IND	-0.1964	-0.41
LAB	0.5256	1.10
THX	-0.5316	-1.10
CHR	-0.0445	-0.09
UNEMP	0.0731	1.03
NX	0.2000	1.19
NX1	-0.1786	-1.06
NX2	0.1239	0.74
NX3	-0.1158	-0.69
NX4	0.0883	0.52
NX5	-0.1498	-0.89
NX6	0.0572	0.34
NX7	-0.1643	-0.98
NX8	-0.1896	-1.13
NX9	0.0183	0.11
NX10	0.1975	1.18
NX11	-0.4133	-2.46
NX12	-0.0098	-0.06
NX13	-0.1938	-1.22
NX14	0.0721	0.45
NX15	-0.2843	-1.79
NX16	0.2361	1.49
NX17	-0.1103	-0.69
NX18	0.0120	0.08
NX19	-0.0147	-0.09
NX20	0.2417	1.52

Table 3X
LINEAR REGRESSIONS OF CALIFORNIA HOMICIDES
1960-63 Subsample

Dependent variable is NHNWM

Mean of dependent variable	0.45	R^2	0.07
Standard error of regression	0.69	Adjusted R^2	0.04
Number of observations	1441	Log-likelihood	-1489.46

Variable	Coefficient	T-statistic
INTERCEP	0.0278	0.08
MON	-0.0299	-0.42
TUE	-0.0851	-1.20
WED	-0.0943	-1.30
THU	-0.1029	-1.42
FRI	0.2163	3.06
SAT	0.2651	3.74
FEB	-0.0816	-0.82
MAR	-0.0131	-0.14
APR	0.0183	0.17
MAY	0.0393	0.36
JUN	0.0097	0.10
JUL	0.0473	0.44
AUG	0.1481	1.26
SEP	-0.0021	-0.01
OCT	0.1696	1.16
NOV	0.1033	0.90
DEC	0.0943	0.89
Y61	-0.0595	-0.79
Y62	0.0270	0.51
Y63	0.0440	0.82
NYR	0.5897	1.44
MEM	-0.0568	-0.16
IND	-0.0739	-0.21
LAB	0.4733	1.33
THX	0.8841	2.46
CHR	0.8401	2.38
UNEMP	0.0551	1.05
NX	0.0825	0.66
NX1	-0.0736	-0.59
NX2	0.1217	0.98
NX3	-0.0199	-0.16
NX4	0.0618	0.50
NX5	-0.0423	-0.34
NX6	-0.0073	-0.06
NX7	0.1423	1.14
NX8	-0.1665	-1.34
NX9	-0.0904	-0.73
NX10	-0.1626	-1.31
NX11	-0.0477	-0.38
NX12	-0.0628	-0.50
NX13	-0.0891	-0.76
NX14	-0.1374	-1.17
NX15	0.1934	1.64
NX16	0.2867	2.44
NX17	-0.0562	-0.48
NX18	0.1715	1.46
NX19	0.1776	1.51
NX20	0.1041	0.88

Table 3Y

LINEAR REGRESSIONS OF CALIFORNIA HOMICIDES

1960-63 Subsample

Dependent variable is NHBM

Mean of dependent variable	0.42	R^2	0.07
Standard error of regression	0.66	Adjusted R^2	0.04
Number of observations	1441	Log-likelihood	-1423.53

Variable	Coefficient	T-statistic
INTERCEP	0.0748	0.21
MON	-0.0576	-0.85
TUE	-0.1265	-1.87
WED	-0.1358	-1.97
THU	-0.1480	-2.14
FRI	0.1684	2.49
SAT	0.2185	3.23
FEB	-0.0628	-0.66
MAR	-0.0127	-0.14
APR	-0.0047	-0.05
MAY	0.0283	0.27
JUN	-0.0336	-0.35
JUL	0.0190	0.19
AUG	0.1310	1.17
SEP	-0.0042	-0.03
OCT	0.1500	1.08
NOV	0.0814	0.74
DEC	0.1006	0.99
Y61	-0.0512	-0.71
Y62	0.0394	0.79
Y63	0.0526	1.03
NYR	0.6336	1.63
MEM	-0.0262	-0.08
IND	-0.0224	-0.07
LAB	0.4777	1.41
THX	0.9318	2.72
CHR	0.5923	1.76
UNEMP	0.0493	0.98
NX	0.0534	0.45
NX1	-0.0995	-0.84
NX2	0.1477	1.24
NX3	-0.0165	-0.14
NX4	-0.0473	-0.40
NX5	-0.0567	-0.47
NX6	0.0217	0.18
NX7	0.1439	1.21
NX8	-0.1552	-1.31
NX9	-0.0916	-0.77
NX10	-0.1631	-1.38
NX11	-0.0877	-0.74
NX12	-0.0369	-0.31
NX13	-0.0909	-0.81
NX14	-0.1095	-0.97
NX15	0.2265	2.02
NX16	0.3088	2.75
NX17	-0.0594	-0.53
NX18	0.1249	1.11
NX19	0.0059	0.05
NX20	0.0982	0.87

Table 3Z
LINEAR REGRESSIONS OF CALIFORNIA HOMICIDES
1960-63 Subsample

Dependent variable is NHWF			
Mean of dependent variable	0.44	R^2	0.04
Standard error of regression	0.68	Adjusted R^2	0.01
Number of observations	1441	Log-likelihood	-1455.76

Variable	Coefficient	T-statistic
INTERCEP	0.5121	1.42
MON	-0.1523	-2.19
TUE	-0.0730	-1.06
WED	-0.1269	-1.80
THU	-0.1506	-2.13
FRI	-0.0837	-1.21
SAT	-0.0197	-0.28
FEB	-0.0546	-0.56
MAR	-0.0579	-0.63
APR	-0.1056	-0.98
MAY	0.0405	0.38
JUN	-0.0053	-0.05
JUL	0.1590	1.52
AUG	0.1184	1.03
SEP	0.0065	0.05
OCT	0.0272	0.19
NOV	-0.0703	-0.63
DEC	0.0863	0.83
Y61	0.0280	0.38
Y62	0.0602	1.17
Y63	-0.0360	-0.69
NYR	-0.0823	-0.21
MEM	-0.1527	-0.44
IND	-0.2760	-0.80
LAB	-0.1152	-0.33
THX	0.2340	0.67
CHR	0.2438	0.71
UNEMP	-0.0028	-0.05
NX	-0.0242	-0.20
NX1	-0.1107	-0.91
NX2	-0.0517	-0.43
NX3	-0.0329	-0.27
NX4	-0.0557	-0.46
NX5	-0.0613	-0.50
NX6	-0.2531	-2.08
NX7	0.0754	0.62
NX8	-0.0031	-0.03
NX9	0.0268	0.22
NX10	0.2234	1.84
NX11	-0.0352	-0.29
NX12	-0.0250	-0.21
NX13	0.0756	0.66
NX14	0.2515	2.18
NX15	0.3254	2.83
NX16	-0.0773	-0.67
NX17	-0.0819	-0.71
NX18	0.1185	1.03
NX19	-0.0478	-0.42
NX20	0.0477	0.41

Table 3AA
LINEAR REGRESSIONS OF CALIFORNIA HOMICIDES
1960-63 Subsample
Dependent variable is NHNWF

Mean of dependent variable	0.15	R^2	0.05
Standard error of regression	0.40	Adjusted R^2	0.02
Number of observations	1441	Log-likelihood	-693.78

Variable	Coefficient	T-statistic
INTERCEP	-0.2429	-1.14
MON	-0.0321	-0.78
TUE	-0.0187	-0.46
WED	-0.0586	-1.41
THU	-0.0284	-0.68
FRI	0.0473	1.16
SAT	0.0462	1.13
FEB	0.0388	0.68
MAR	0.0253	0.47
APR	0.0201	0.32
MAY	0.1148	1.83
JUN	0.0743	1.30
JUL	0.0989	1.61
AUG	0.1237	1.83
SEP	0.1379	1.68
OCT	0.0590	0.70
NOV	0.0655	0.99
DEC	0.1607	2.63
Y61	-0.0844	-1.94
Y62	-0.0494	-1.64
Y63	-0.0372	-1.21
NYR	-0.1449	-0.62
MEM	0.3670	1.80
IND	0.1113	0.55
LAB	0.3873	1.89
THX	-0.0382	-0.19
CHR	-0.2025	-1.00
UNEMP	0.0579	1.91
NX	0.1697	2.37
NX1	-0.0703	-0.98
NX2	-0.1188	-1.65
NX3	0.1091	1.52
NX4	0.1338	1.86
NX5	0.0320	0.45
NX6	-0.0963	-1.34
NX7	0.0723	1.01
NX8	-0.0393	-0.55
NX9	-0.0692	-0.96
NX10	0.0038	0.05
NX11	0.0106	0.15
NX12	0.0846	1.18
NX13	-0.0465	-0.69
NX14	0.0624	0.92
NX15	-0.0613	-0.90
NX16	0.0021	0.03
NX17	-0.0313	-0.46
NX18	-0.0240	-0.35
NX19	0.1465	2.16
NX20	0.0616	0.91

Table 3BB
LINEAR REGRESSIONS OF CALIFORNIA HOMICIDES
1960-63 Subsample

Dependent variable is NHBF

Mean of dependent variable	0.14	R^2	0.05
Standard error of regression	0.38	Adjusted R^2	0.02
Number of observations	1441	Log-likelihood	-637.17

Variable	Coefficient	T-statistic
INTERCEP	-0.2924	-1.43
MON	-0.0260	-0.66
TUE	-0.0085	-0.22
WED	-0.0463	-1.16
THU	-0.0249	-0.62
FRI	0.0499	1.27
SAT	0.0579	1.47
FEB	0.0324	0.59
MAR	0.0312	0.60
APR	0.0079	0.13
MAY	0.1212	2.01
JUN	0.0671	1.22
JUL	0.1041	1.76
AUG	0.1408	2.16
SEP	0.1571	2.00
OCT	0.0701	0.87
NOV	0.0648	1.02
DEC	0.1731	2.94
Y61	-0.0957	-2.29
Y62	-0.0510	-1.76
Y63	-0.0454	-1.53
NYR	-0.1303	-0.58
MEM	0.1186	0.61
IND	0.1137	0.58
LAB	0.3858	1.96
THX	-0.0282	-0.14
CHR	-0.2048	-1.05
UNEMP	0.0641	2.20
NX	0.1129	1.64
NX1	-0.0613	-0.89
NX2	-0.1127	-1.63
NX3	0.1147	1.67
NX4	0.1110	1.61
NX5	0.0395	0.57
NX6	-0.0886	-1.29
NX7	0.0456	0.66
NX8	-0.0315	-0.46
NX9	-0.0629	-0.91
NX10	0.0089	0.13
NX11	0.0191	0.28
NX12	0.0565	0.82
NX13	-0.0434	-0.67
NX14	0.0368	0.56
NX15	-0.0557	-0.85
NX16	-0.0465	-0.71
NX17	-0.0229	-0.35
NX18	-0.0168	-0.26
NX19	0.1488	2.29
NX20	0.0650	1.00

Table 3CC
LINEAR REGRESSIONS OF CALIFORNIA HOMICIDES
1960-63 Subsample

Dependent variable is NHWG

Mean of dependent variable	0.60	R^2	0.04
Standard error of regression	0.83	Adjusted R^2	0.01
Number of observations	1441	Log-likelihood	-1757.19

Variable	Coefficient	T-statistic
INTERCEP	0.1958	0.44
MON	-0.1120	-1.30
TUE	-0.1250	-1.47
WED	-0.0519	-0.60
THU	0.0197	0.22
FRI	0.1721	2.02
SAT	0.1219	1.43
FEB	-0.1968	-1.64
MAR	-0.2137	-1.87
APR	-0.0715	-0.54
MAY	0.0820	0.63
JUN	-0.1470	-1.23
JUL	-0.0572	-0.44
AUG	0.0945	0.67
SEP	0.0306	0.18
OCT	0.1641	0.93
NOV	0.1343	0.97
DEC	0.0123	0.10
Y61	-0.1918	-2.11
Y62	-0.0913	-1.45
Y63	-0.1010	-1.57
NYR	0.3487	0.71
MEM	0.1752	0.41
IND	-0.4671	-1.10
LAB	0.3157	0.74
THX	-0.2108	-0.49
CHR	0.4557	1.07
UNEMP	0.0823	1.30
NX	0.0412	0.28
NX1	-0.2021	-1.35
NX2	-0.0124	-0.08
NX3	-0.1235	-0.83
NX4	0.2088	1.39
NX5	-0.0338	-0.22
NX6	-0.0644	-0.43
NX7	0.0638	0.43
NX8	-0.0364	-0.24
NX9	-0.0940	-0.63
NX10	0.4021	2.69
NX11	-0.2518	-1.68
NX12	-0.0432	-0.29
NX13	0.0096	0.07
NX14	0.1783	1.26
NX15	-0.0541	-0.38
NX16	0.0162	0.12
NX17	-0.1266	-0.89
NX18	0.0388	0.27
NX19	0.0047	0.03
NX20	0.2263	1.59

Table 3DD
LINEAR REGRESSIONS OF CALIFORNIA HOMICIDES
1960-63 Subsample

Dependent variable is NHNWG

Mean of dependent variable	0.29	R^2	0.07
Standard error of regression	0.56	Adjusted R^2	0.04
Number of observations	1441	Log-likelihood	-1175.01

Variable	Coefficient	T-statistic
INTERCEP	-0.5476	-1.84
MON	-0.0558	-0.97
TUE	-0.0787	-1.38
WED	-0.0265	-0.46
THU	-0.0408	-0.70
FRI	0.1659	2.91
SAT	0.1323	2.32
FEB	-0.1223	-1.52
MAR	-0.0055	-0.07
APR	0.1261	1.42
MAY	0.1367	1.56
JUN	0.0563	0.70
JUL	0.0640	0.74
AUG	0.2773	2.93
SEP	0.1702	1.49
OCT	0.2639	2.25
NOV	0.1500	1.62
DEC	0.2045	2.39
Y61	-0.1652	-2.72
Y62	-0.0134	-0.32
Y63	-0.0452	-1.05
NYR	0.4147	1.26
MEM	0.0519	0.18
IND	0.3697	1.30
LAB	0.3641	1.27
THX	0.8251	2.86
CHR	0.6811	2.40
UNEMP	0.1238	2.93
NX	0.1204	1.21
NX1	-0.0955	-0.95
NX2	-0.1014	-1.01
NX3	0.1968	1.97
NX4	0.0831	0.83
NX5	-0.1270	-1.26
NX6	0.0125	0.12
NX7	0.0043	0.04
NX8	-0.1423	-1.42
NX9	-0.1560	-1.56
NX10	-0.0363	-0.36
NX11	-0.0075	-0.08
NX12	0.1028	1.03
NX13	-0.1439	-1.52
NX14	-0.1633	-1.72
NX15	0.0672	0.71
NX16	0.1707	1.81
NX17	-0.0967	-1.02
NX18	0.1116	1.18
NX19	0.2867	3.03
NX20	0.1583	1.67

Table 3EE

LINEAR REGRESSION OF CALIFORNIA HOMICIDES
1960-63 Subsample
Dependent variable is NHBG

Mean of dependent variable	0.28	R^2	0.07
Standard error of regression	0.54	Adjusted R^2	0.04
Number of observations	1441	Log-likelihood	-1123.13

Variable	Coefficient	T-statistic
INTERCEP	-0.5468	-1.90
MON	-0.0334	-0.60
TUE	-0.0735	-1.34
WED	-0.0222	-0.40
THU	-0.0459	-0.82
FRI	0.1600	2.91
SAT	0.1354	2.46
FEB	-0.1005	-1.30
MAR	0.0053	0.07
APR	0.0973	1.14
MAY	0.1451	1.72
JUN	0.0578	0.75
JUL	0.0544	0.66
AUG	0.2679	2.94
SEP	0.1749	1.59
OCT	0.2585	2.28
NOV	0.1460	1.64
DEC	0.2147	2.61
Y61	-0.1644	-2.80
Y62	-0.0158	-0.39
Y63	-0.0502	-1.21
NYR	0.4219	1.33
MEM	0.0539	0.20
IND	0.3897	1.42
LAB	0.3527	1.28
THX	0.8419	3.02
CHR	0.4319	1.58
UNEMP	0.1208	2.96
NX	0.1045	1.08
NX1	-0.0738	-0.76
NX2	-0.0829	-0.86
NX3	0.2146	2.23
NX4	0.1021	1.05
NX5	-0.1200	-1.24
NX6	0.0290	0.30
NX7	-0.0129	-0.13
NX8	-0.1173	-1.22
NX9	-0.1345	-1.39
NX10	-0.0547	-0.57
NX11	0.0072	0.07
NX12	0.1068	1.11
NX13	-0.1324	-1.45
NX14	-0.1546	-1.69
NX15	0.0787	0.86
NX16	0.1295	1.42
NX17	-0.0911	-1.00
NX18	0.1212	1.33
NX19	0.1760	1.93
NX20	0.1372	1.50

Table 3FF

LINEAR REGRESSION OF CALIFORNIA HOMICIDES
1960-63 Subsample
Dependent variable is NHWK

Mean of dependent variable	0.21	R^2	0.05
Standard error of regression	0.48	Adjusted R^2	0.02
Number of observations	1441	Log-likelihood	-975.01

Variable	Coefficient	T-statistic
INTERCEP	0.2063	0.80
MON	-0.0323	-0.65
TUE	-0.0053	-0.11
WED	-0.1138	-2.25
THU	-0.0410	-0.81
FRI	0.0349	0.70
SAT	0.1808	3.64
FEB	0.0201	0.29
MAR	-0.0002	0.00
APR	0.0004	0.00
MAY	0.0757	0.99
JUN	0.0451	0.65
JUL	0.1718	2.30
AUG	0.0170	0.21
SEP	0.0876	0.88
OCT	0.0423	0.41
NOV	0.0010	0.01
DEC	0.1073	1.44
Y61	0.0331	0.63
Y62	0.0684	1.86
Y63	0.0493	1.32
NYR	-0.1295	-0.45
MEM	-0.1699	-0.69
IND	-0.2656	-1.07
LAB	-0.2337	-0.94
THX	-0.1382	-0.55
CHR	-0.2339	-0.95
UNEMP	-0.0130	-0.35
NX	0.1362	1.57
NX1	0.0009	0.01
NX2	-0.0056	-0.06
NX3	-0.0985	-1.13
NX4	-0.0630	-0.72
NX5	-0.0924	-1.06
NX6	-0.0071	-0.08
NX7	-0.0395	-0.45
NX8	-0.0529	-0.61
NX9	-0.0052	-0.06
NX10	-0.1133	-1.30
NX11	-0.1172	-1.35
NX12	0.0749	0.86
NX13	0.0341	0.41
NX14	-0.0653	-0.79
NX15	-0.0079	-0.10
NX16	-0.0155	-0.19
NX17	-0.0961	-1.16
NX18	0.0849	1.03
NX19	0.0441	0.54
NX20	0.0481	0.58

Table 3GG

LINEAR REGRESSION OF CALIFORNIA HOMICIDES
1960-63 Subsample

Dependent variable is NHNWK

Mean of dependent variable	0.18	R^2	0.05
Standard error of regression	0.43	Adjusted R^2	0.02
Number of observations	1441	Log-likelihood	-792.69

Variable	Coefficient	T-statistic
INTERCEP	0.0073	0.03
MON	-0.0099	-0.23
TUE	-0.0033	-0.08
WED	-0.0512	-1.15
THU	-0.0454	-1.01
FRI	0.1112	2.55
SAT	0.1387	3.17
FEB	-0.0167	-0.27
MAR	-0.0052	-0.09
APR	0.0106	0.16
MAY	0.0624	0.93
JUN	0.0102	0.17
JUL	0.0908	1.38
AUG	0.0634	0.88
SEP	0.0489	0.56
OCT	0.0630	0.70
NOV	0.0505	0.71
DEC	0.1150	1.76
Y61	-0.0182	-0.39
Y62	-0.0156	-0.48
Y63	0.0189	0.57
NYR	-0.1692	-0.67
MEM	-0.1520	-0.70
IND	-0.1967	-0.90
LAB	0.1119	0.51
THX	0.1332	0.60
CHR	-0.2184	-1.00
UNEMP	0.0189	0.58
NX	0.0410	0.53
NX1	-0.0959	-1.25
NX2	0.1269	1.65
NX3	-0.1156	-1.51
NX4	0.1051	1.37
NX5	0.0590	0.77
NX6	-0.0586	-0.76
NX7	0.0662	0.86
NX8	-0.0723	-0.94
NX9	0.0322	0.42
NX10	-0.1224	-1.60
NX11	-0.0069	-0.09
NX12	-0.0707	-0.92
NX13	-0.0102	-0.14
NX14	0.0517	0.71
NX15	0.0192	0.26
NX16	0.1067	1.47
NX17	0.0015	0.02
NX18	0.0691	0.95
NX19	-0.0038	-0.05
NX20	-0.0701	-0.96

Table 3HH

LINEAR REGRESSION OF CALIFORNIA HOMICIDES
1960-63 Subsample
Dependent variable is NHBK

Mean of dependent variable	0.17	R^2	0.05
Standard error of regression	0.42	Adjusted R^2	0.02
Number of observations	1441	Log-likelihood	-753.51

Variable	Coefficient	T-statistic
INTERCEP	0.0033	0.01
MON	-0.0197	-0.46
TUE	-0.0160	-0.38
WED	-0.0770	-1.78
THU	-0.0597	-1.37
FRI	0.0843	1.99
SAT	0.1247	2.93
FEB	-0.0224	-0.37
MAR	-0.0161	-0.28
APR	0.0042	0.06
MAY	0.0391	0.60
JUN	-0.0243	-0.41
JUL	0.0845	1.32
AUG	0.0523	0.74
SEP	0.0531	0.62
OCT	0.0671	0.77
NOV	0.0293	0.42
DEC	0.1151	1.81
Y61	-0.0204	-0.45
Y62	-0.0056	-0.18
Y63	0.0215	0.67
NYR	-0.1409	-0.57
MEM	-0.1310	-0.62
IND	-0.1921	-0.90
LAB	0.1041	0.49
THX	0.1444	0.67
CHR	-0.2229	-1.05
UNEMP	0.0218	0.69
NX	0.0259	0.35
NX1	-0.0874	-1.17
NX2	0.1368	1.83
NX3	-0.1396	-1.87
NX4	-0.0188	-0.25
NX5	0.0631	0.84
NX6	-0.0539	-0.72
NX7	0.0491	0.66
NX8	-0.0637	-0.85
NX9	0.0424	0.57
NX10	-0.1126	-1.51
NX11	-0.0321	-0.43
NX12	-0.0643	-0.86
NX13	-0.0323	-0.46
NX14	0.0681	0.96
NX15	0.0335	0.47
NX16	0.1156	1.64
NX17	0.0091	0.13
NX18	0.0433	0.61
NX19	-0.0230	-0.33
NX20	-0.0634	-0.90

Table 3II

LINEAR REGRESSION OF CALIFORNIA HOMICIDES
1960-63 Subsample
Dependent variable is NHWO

Mean of dependent variable	0.45	R^2	0.05
Standard error of regression	0.68	Adjusted R^2	0.02
Number of observations	1441	Log-likelihood	-1457.88

Variable	Coefficient	T-statistic
INTERCEP	0.6400	1.77
MON	-0.1618	-2.32
TUE	-0.0339	-0.49
WED	-0.1300	-1.84
THU	-0.2232	-3.15
FRI	-0.2139	-3.09
SAT	0.0481	0.69
FEB	-0.1724	-1.77
MAR	-0.1344	-1.45
APR	-0.2099	-1.94
MAY	-0.2005	-1.88
JUN	-0.0616	-0.63
JUL	-0.0097	-0.09
AUG	0.0395	0.34
SEP	-0.0735	-0.53
OCT	-0.0920	-0.64
NOV	-0.2761	-2.45
DEC	-0.0540	-0.52
Y61	-0.0355	-0.48
Y62	0.0703	1.37
Y63	0.0128	0.24
NYR	-0.2267	-0.57
MEM	-0.0777	-0.22
IND	0.2603	0.75
LAB	0.3284	0.94
THX	0.0514	0.15
CHR	-0.0226	-0.06
UNEMP	0.0010	0.02
NX	-0.0015	-0.01
NX1	-0.0881	-0.72
NX2	0.0902	0.74
NX3	0.0733	0.60
NX4	-0.1131	-0.93
NX5	-0.0849	-0.69
NX6	-0.1244	-1.02
NX7	-0.1132	-0.93
NX8	-0.1034	-0.85
NX9	0.1443	1.18
NX10	0.1321	1.09
NX11	-0.0796	-0.65
NX12	-0.0665	-0.55
NX13	-0.1619	-1.41
NX14	0.2106	1.83
NX15	0.1031	0.89
NX16	0.1580	1.37
NX17	0.0305	0.26
NX18	0.0068	0.06
NX19	-0.1113	-0.97
NX20	0.0150	0.13

Table 3JJ

LINEAR REGRESSION OF CALIFORNIA HOMICIDES
1960-63 Subsample
Dependent variable is NHNWO

Mean of dependent variable	0.13	R^2	0.03
Standard error of regression	0.38	Adjusted R^2	0.00
Number of observations	1441	Log-likelihood	-616.43

Variable	Coefficient	T-statistic
INTERCEP	0.3252	1.61
MON	0.0038	0.10
TUE	-0.0218	-0.56
WED	-0.0752	-1.91
THU	-0.0452	-1.14
FRI	-0.0136	-0.35
SAT	0.0404	1.04
FEB	0.0961	1.77
MAR	0.0229	0.44
APR	-0.0984	-1.63
MAY	-0.0450	-0.76
JUN	0.0175	0.32
JUL	-0.0086	-0.15
AUG	-0.0689	-1.07
SEP	-0.0833	-1.07
OCT	-0.0983	-1.23
NOV	-0.0316	-0.50
DEC	-0.0645	-1.11
Y61	0.0395	0.96
Y62	0.0066	0.23
Y63	0.0332	1.13
NYR	0.1993	0.89
MEM	0.4103	2.13
IND	-0.1357	-0.70
LAB	0.3846	1.98
THX	-0.1124	-0.57
CHR	0.1749	0.91
UNEMP	-0.0297	-1.04
NX	0.0909	1.34
NX1	0.0475	0.70
NX2	-0.0225	-0.33
NX3	0.0079	0.12
NX4	0.0074	0.11
NX5	0.0578	0.85
NX6	-0.0575	-0.85
NX7	0.1441	2.12
NX8	0.0088	0.13
NX9	-0.0359	-0.53
NX10	0.0000	0.00
NX11	-0.0227	-0.34
NX12	-0.0102	-0.15
NX13	0.0185	0.29
NX14	0.0366	0.57
NX15	0.0457	0.71
NX16	0.0113	0.18
NX17	0.0077	0.12
NX18	-0.0332	-0.52
NX19	0.0411	0.64
NX20	0.0774	1.20

Table 3KK

LINEAR REGRESSION OF CALIFORNIA HOMICIDES
1960-63 Subsample
Dependent variable is NHBO

Mean of dependent variable	0.11	R^2	0.03
Standard error of regression	0.36	Adjusted R^2	0.00
Number of observations	1441	Log-likelihood	-536.46

Variable	Coefficient	T-statistic
INTERCEP	0.3258	1.71
MON	-0.0305	-0.83
TUE	-0.0455	-1.25
WED	-0.0829	-2.22
THU	-0.0673	-1.80
FRI	-0.0261	-0.71
SAT	0.0163	0.45
FEB	0.0925	1.80
MAR	0.0293	0.60
APR	-0.0983	-1.73
MAY	-0.0346	-0.62
JUN	0.0000	0.00
JUL	-0.0158	-0.29
AUG	-0.0484	-0.80
SEP	-0.0750	-1.02
OCT	-0.1055	-1.40
NOV	-0.0290	-0.49
DEC	-0.0561	-1.02
Y61	0.0379	0.97
Y62	0.0098	0.36
Y63	0.0358	1.29
NYR	0.2224	1.05
MEM	0.1695	0.93
IND	-0.1064	-0.58
LAB	0.4067	2.22
THX	-0.0827	-0.45
CHR	0.1785	0.98
UNEMP	-0.0293	-1.08
NX	0.0360	0.56
NX1	0.0005	0.01
NX2	-0.0188	-0.29
NX3	0.0232	0.36
NX4	-0.0196	-0.30
NX5	0.0398	0.62
NX6	-0.0421	-0.65
NX7	0.1533	2.39
NX8	-0.0057	-0.09
NX9	-0.0625	-0.97
NX10	0.0132	0.21
NX11	-0.0436	-0.68
NX12	-0.0229	-0.36
NX13	0.0305	0.50
NX14	0.0139	0.23
NX15	0.0586	0.96
NX16	0.0173	0.28
NX17	-0.0003	0.00
NX18	-0.0564	-0.93
NX19	0.0017	0.03
NX20	0.0895	1.47

Table 4

LOG-LIKELIHOODS FOR VARIOUS ESTIMATORS

Full Sample

Variable	OLS	Poisson	Negative Binomial
NH	-5544.0	-5158.4	-5146.2
NHW	-4843.9	-4457.5	-4450.7
NHNW	-3896.2	-3216.9	-3212.6
NHWG	-3836.8	-3249.3	-3238.2
NHNWG	-3109.4	-2278.7	-2276.0
NHNWG	-4196.9	-3733.6	-3730.0

1960-63 Subsample

Variable	OLS	Poisson	Negative Binomial
NH	-2557.6	-2416.0	-2416.0
NHW	-2236.3	-2059.8	
NHNW	-1727.9	-1452.4	
NHWG	-1757.6	-1480.4	-1475.5
NHNWG	-1175.4	-941.6	
NHWG	-1922.5	-1693.6	

Table 5A

POISSON REGRESSION MODEL
Dependent Variable is NH
LOG LIKELIHOOD: -5158.409

Variable	Coefficient	T-statistic
MON	-0.241	-4.860
TUE	-0.220	-4.460
WED	-0.214	-4.322
THU	-0.160	-3.254
FRI	0.134	2.998
SAT	0.242	5.514
FEB	0.082	1.209
MAR	0.062	0.926
APR	0.087	1.086
MAY	0.177	2.113
JUN	0.121	1.657
JUL	0.269	3.520
AUG	0.360	4.216
SEP	0.307	2.775
OCT	0.421	3.764
NOV	0.274	3.178
DEC	0.373	4.772
Y61	-0.160	-2.279
Y62	0.020	0.368
Y63	0.004	0.068
Y64	0.136	2.499
Y65	0.310	5.868
Y66	0.391	5.713
Y67	0.553	8.340
NYR	0.586	2.892
MEM	-0.157	-0.558
IND	0.000	0.001
LAB	0.705	3.626
THX	0.224	0.965
CHR	0.164	0.788
UNEMP	0.089	2.015
WATTS	1.236	7.679
NX	0.197	1.693
NX1	-0.304	-1.878
NX2	0.031	0.264
NX3	0.010	0.087
NX4	0.101	0.888
NX5	-0.138	-0.925
NX6	-0.158	-1.024
NX7	0.099	0.789
NX8	-0.246	-1.588
NX9	-0.077	-0.608
NX10	0.124	1.205
NX11	-0.147	-1.073
NX12	0.024	0.181
NX13	-0.114	-0.805
NX14	0.127	1.103
NX15	0.101	0.891
NX16	0.176	1.769
NX17	-0.109	-0.894
NX18	0.172	1.661
NX19	0.144	1.232
NX20	0.275	2.642
CONSTANT	-0.082	-0.259

Table 5B

POISSON REGRESSION MODEL
Dependent Variable is NHW
LOG LIKELIHOOD: -4457.491

Variable	Coefficient	T-statistic
MON	-0.254	-4.235
TUE	-0.211	-3.578
WED	-0.208	-3.503
THU	-0.163	-2.754
FRI	0.000	0.005
SAT	0.158	2.935
FEB	0.028	0.348
MAR	-0.035	-0.429
APR	0.034	0.353
MAY	0.090	0.889
JUN	0.030	0.341
JUL	0.175	1.892
AUG	0.279	2.705
SEP	0.211	1.576
OCT	0.326	2.410
NOV	0.160	1.536
DEC	0.307	3.257
Y61	-0.157	-1.834
Y62	0.039	0.593
Y63	-0.013	-0.186
Y64	0.151	2.298
Y65	0.250	3.855
Y66	0.331	3.972
Y67	0.508	6.300
NYR	0.576	2.368
MEM	-0.265	-0.740
IND	-0.242	-0.716
LAB	0.594	2.416
THX	-0.196	-0.573
CHR	0.008	0.029
UNEMP	0.067	1.239
WATTS	0.825	3.375
NX	0.090	0.601
NX1	-0.263	-1.386
NX2	0.034	0.235
NX3	-0.062	-0.424
NX4	0.034	0.240
NX5	-0.194	-1.050
NX6	-0.108	-0.616
NX7	-0.021	-0.129
NX8	-0.152	-0.874
NX9	0.003	0.022
NX10	0.241	2.107
NX11	-0.230	-1.317
NX12	0.010	0.063
NX13	-0.031	-0.199
NX14	0.225	1.779
NX15	0.048	0.339
NX16	0.104	0.795
NX17	-0.117	-0.780
NX18	0.145	1.150
NX19	-0.053	-0.331
NX20	0.256	2.066
CONSTANT	-0.212	-0.554

Table 5C

POISSON REGRESSION MODEL
Dependent Variable is NHNW
LOG LIKELIHOOD: -3212.607

Variable	Coefficient	T-statistic
MON	-0.217	-2.382
TUE	-0.247	-2.684
WED	-0.235	-2.551
THU	-0.164	-1.793
FRI	0.371	4.636
SAT	0.407	5.141
FEB	0.198	1.575
MAR	0.264	2.149
APR	0.205	1.374
MAY	0.364	2.361
JUN	0.312	2.322
JUL	0.467	3.310
AUG	0.528	3.341
SEP	0.510	2.508
OCT	0.619	3.003
NOV	0.511	3.229
DEC	0.518	3.553
Y61	-0.168	-1.324
Y62	-0.027	-0.271
Y63	0.035	0.345
Y64	0.098	0.984
Y65	0.423	4.477
Y66	0.512	4.118
Y67	0.640	5.299
NYR	0.624	1.645
MEM	0.045	0.097
IND	0.366	0.962
LAB	0.909	2.692
THX	0.787	2.338
CHR	0.454	1.347
UNEMP	0.136	1.687
WATTS	1.663	6.079
NX	0.404	2.187
NX1	-0.392	-1.257
NX2	0.037	0.177
NX3	0.132	0.687
NX4	0.227	1.130
NX5	-0.030	-0.116
NX6	-0.310	-0.955
NX7	0.322	1.616
NX8	-0.512	-1.546
NX9	-0.242	-0.992
NX10	-0.206	-0.877
NX11	-0.006	-0.026
NX12	0.047	0.191
NX13	-0.386	-1.198
NX14	-0.208	-0.754
NX15	0.202	1.025
NX16	0.304	1.890
NX17	-0.088	-0.403
NX18	0.219	1.142
NX19	0.462	2.684
NX20	0.314	1.598
CONSTANT	-1.745	-3.043

Table 5D

POISSON REGRESSION MODEL
Dependent Variable is NHWG
LOG LIKELIHOOD: -3249.286

Variable	Coefficient	T-statistic
MON	-0.200	-2.295
TUE	-0.261	-2.961
WED	-0.087	-1.022
THU	-0.027	-0.317
FRI	0.134	1.678
SAT	0.146	1.844
FEB	-0.051	-0.414
MAR	-0.101	-0.828
APR	0.182	1.314
MAY	0.316	2.199
JUN	0.139	1.092
JUL	0.199	1.471
AUG	0.354	2.370
SEP	0.294	1.519
OCT	0.496	2.552
NOV	0.426	2.874
DEC	0.407	2.996
Y61	-0.267	-2.223
Y62	-0.131	-1.369
Y63	-0.131	-1.344
Y64	-0.009	-0.095
Y65	0.206	2.257
Y66	0.319	2.667
Y67	0.542	4.733
NYR	0.397	1.021
MEM	0.100	0.239
IND	-0.227	-0.449
LAB	0.445	1.136
THX	-0.280	-0.610
CHR	0.195	0.539
UNEMP	0.117	1.520
WATTS	1.323	4.671
NX	0.032	0.144
NX1	-0.306	-1.104
NX2	0.031	0.150
NX3	-0.173	-0.732
NX4	0.275	1.539
NX5	-0.080	-0.318
NX6	-0.089	-0.341
NX7	0.124	0.592
NX8	-0.008	-0.035
NX9	-0.134	-0.569
NX10	0.387	2.525
NX11	-0.309	-1.119
NX12	-0.023	-0.097
NX13	0.010	0.044
NX14	0.266	1.518
NX15	-0.043	-0.197
NX16	0.042	0.215
NX17	-0.184	-0.788
NX18	0.104	0.527
NX19	-0.061	-0.256
NX20	0.335	1.913
CONSTANT	-1.314	-2.402

Table 5E

POISSON REGRESSION MODEL
Dependent Variable is NHNWG
LOG LIKELIHOOD: -2278.674

Variable	Coefficient	T-statistic
MON	-0.206	-1.670
TUE	-0.287	-2.258
WED	-0.049	-0.408
THU	-0.035	-0.287
FRI	0.566	5.473
SAT	0.481	4.597
FEB	0.201	1.175
MAR	0.333	1.997
APR	0.464	2.353
MAY	0.469	2.228
JUN	0.513	2.858
JUL	0.497	2.578
AUG	0.826	3.945
SEP	0.797	2.942
OCT	0.976	3.574
NOV	0.660	3.080
DEC	0.678	3.484
Y61	-0.308	-1.805
Y62	-0.035	-0.255
Y63	-0.108	-0.774
Y64	0.038	0.278
Y65	0.521	4.184
Y66	0.754	4.562
Y67	0.907	5.676
NYR	0.796	1.708
MEM	-0.107	-0.149
IND	0.919	2.175
LAB	0.542	1.046
THX	0.968	2.405
CHR	0.716	1.831
UNEMP	0.216	2.026
WATTS	2.102	8.913
NX	0.359	1.440
NX1	-0.435	-1.003
NX2	-0.244	-0.739
NX3	0.390	1.964
NX4	0.213	0.785
NX5	-0.777	-1.364
NX6	0.027	0.072
NX7	0.067	0.207
NX8	-0.916	-1.602
NX9	-0.568	-1.435
NX10	-0.081	-0.278
NX11	0.111	0.385
NX12	0.303	1.089
NX13	-1.716	-1.726
NX14	-1.260	-1.808
NX15	0.238	0.907
NX16	0.310	1.513
NX17	-0.471	-1.212
NX18	0.269	1.061
NX19	0.648	3.299
NX20	0.487	2.030
CONSTANT	-3.127	-4.083

Table 5F

POISSON REGRESSION MODEL
Dependent Variable is NHWM
LOG LIKELIHOOD: -3733.638

Variable	Coefficient	T-statistic
MON	-0.257	-3.482
TUE	-0.255	-3.470
WED	-0.189	-2.593
THU	-0.173	-2.375
FRI	0.081	1.202
SAT	0.233	3.590
FEB	-0.013	-0.137
MAR	-0.142	-1.495
APR	-0.161	-1.768
MAY	-0.111	-1.248
JUN	-0.108	-1.175
JUL	0.007	0.082
AUG	0.116	1.404
SEP	-0.034	-0.409
OCT	0.079	1.000
NOV	0.040	0.470
DEC	0.123	1.469
Y61	-0.178	-1.946
Y62	-0.022	-0.264
Y63	0.004	0.044
Y64	0.166	2.085
Y65	0.247	3.163
Y66	0.228	3.143
Y67	0.425	6.172
NYR	0.300	0.925
MEM	-0.296	-0.653
IND	-0.624	-1.238
LAB	0.773	2.752
THX	-0.647	-1.273
CHR	-0.018	-0.053
UNEMP	-0.010	-0.683
WATTS	0.916	3.288
NX	0.152	0.859
NX1	-0.209	-0.914
NX2	0.082	0.486
NX3	-0.094	-0.513
NX4	0.075	0.431
NX5	-0.271	-1.107
NX6	0.069	0.358
NX7	-0.235	-0.998
NX8	-0.245	-1.064
NX9	-0.046	-0.248
NX10	0.166	1.133
NX11	-0.570	-2.122
NX12	-0.015	-0.072
NX13	-0.256	-1.105
NX14	0.019	0.105
NX15	-0.416	-1.720
NX16	0.155	1.042
NX17	-0.093	-0.527
NX18	0.058	0.344
NX19	-0.041	-0.210
NX20	0.290	1.929

Table 5G

POISSON REGRESSION MODEL: 1960-63 SUBSAMPLE
Dependent Variable is NH
LOG LIKELIHOOD: -2415.979

Variable	Coefficient	T-statistic
MON	-0.214	-2.731
TUE	-0.150	-1.955
WED	-0.264	-3.291
THU	-0.220	-2.749
FRI	0.124	1.740
SAT	0.299	4.327
FEB	-0.213	-1.991
MAR	-0.189	-1.855
APR	-0.153	-1.280
MAY	0.059	0.521
JUN	-0.045	-0.426
JUL	0.128	1.165
AUG	0.202	1.671
SEP	0.087	0.584
OCT	0.173	1.135
NOV	0.007	0.058
DEC	0.158	1.472
Y61	-0.170	-2.198
Y62	0.017	0.305
Y63	-0.012	-0.216
NYR	0.214	0.553
MEM	0.132	0.341
IND	-0.283	-0.623
LAB	0.611	1.940
THX	0.325	0.880
CHR	0.367	1.189
UNEMP	0.093	1.692
NX	0.224	1.893
NX1	-0.304	-1.812
NX2	0.033	0.276
NX3	-0.029	-0.242
NX4	0.102	0.879
NX5	-0.138	-0.909
NX6	-0.209	-1.309
NX7	0.077	0.587
NX8	-0.259	-1.616
NX9	-0.056	-0.438
NX10	0.092	0.863
NX11	-0.293	-1.911
NX12	-0.002	-0.011
NX13	-0.164	-1.119
NX14	0.133	1.134
NX15	0.090	0.773
NX16	0.177	1.744
NX17	-0.138	-1.108
NX18	0.124	1.144
NX19	0.140	1.184
NX20	0.223	2.056
CONSTANT	0.096	0.245

Table 5H

POISSON REGRESSION MODEL: 1960-63 SUBSAMPLE
Dependent Variable is NHW
LOG LIKELIHOOD: -2059.790

Variable	Coefficient	T-statistic
MON	-0.258	-2.715
TUE	-0.129	-1.421
WED	-0.247	-2.582
THU	-0.200	-2.106
FRI	-0.004	-0.051
SAT	0.234	2.786
FEB	-0.279	-2.142
MAR	-0.287	-2.306
APR	-0.239	-1.650
MAY	-0.027	-0.195
JUN	-0.127	-1.000
JUL	0.079	0.596
AUG	0.103	0.704
SEP	0.035	0.194
OCT	0.087	0.474
NOV	-0.114	-0.773
DEC	0.050	0.385
Y61	-0.148	-1.555
Y62	0.037	0.552
Y63	-0.029	-0.419
NYR	0.004	0.008
MEM	-0.083	-0.164
IND	-0.467	-0.799
LAB	0.325	0.770
THX	-0.323	-0.545
CHR	0.141	0.338
UNEMP	0.052	0.769
NX	0.142	0.945
NX1	-0.291	-1.461
NX2	0.051	0.349
NX3	-0.101	-0.665
NX4	0.024	0.159
NX5	-0.201	-1.054
NX6	-0.184	-0.999
NX7	-0.069	-0.399
NX8	-0.167	-0.931
NX9	0.030	0.202
NX10	0.203	1.721
NX11	-0.423	-2.104
NX12	-0.022	-0.133
NX13	-0.100	-0.608
NX14	0.222	1.716
NX15	0.030	0.206
NX16	0.099	0.748
NX17	-0.140	-0.920
NX18	0.085	0.635
NX19	-0.058	-0.352
NX20	0.200	1.543
CONSTANT	0.073	0.153

Table 5I

POISSON REGRESSION MODEL: 1960-63 SUBSAMPLE
Dependent Variable is NHNW
LOG LIKELIHOOD: -1452.370

Variable	Coefficient	T-statistic
MON	-0.118	-0.855
TUE	-0.197	-1.400
WED	-0.300	-2.041
THU	-0.274	-1.846
FRI	0.375	3.036
SAT	0.438	3.575
FEB	-0.083	-0.438
MAR	0.001	0.008
APR	0.012	0.057
MAY	0.232	1.148
JUN	0.119	0.635
JUL	0.218	1.098
AUG	0.377	1.762
SEP	0.161	0.601
OCT	0.322	1.193
NOV	0.244	1.149
DEC	0.368	1.949
Y61	-0.212	-1.588
Y62	-0.034	-0.345
Y63	0.018	0.188
NYR	0.579	0.965
MEM	0.508	0.856
IND	0.068	0.095
LAB	1.113	2.333
THX	1.113	2.298
CHR	0.734	1.589
UNEMP	0.173	1.823
NX	0.382	1.987
NX1	-0.326	-1.054
NX2	0.007	0.036
NX3	0.107	0.568
NX4	0.257	1.352
NX5	-0.013	-0.053
NX6	-0.279	-0.875
NX7	0.332	1.657
NX8	-0.540	-1.550
NX9	-0.247	-1.000
NX10	-0.231	-0.976
NX11	-0.072	-0.306
NX12	0.038	0.158
NX13	-0.367	-1.157
NX14	-0.169	-0.627
NX15	0.214	1.093
NX16	0.303	1.920
NX17	-0.130	-0.595
NX18	0.204	1.083
NX19	0.439	2.619
NX20	0.278	1.406
CONSTANT	-1.750	-2.589

Table 5J

POISSON REGRESSION MODEL: 1960-63 SUBSAMPLE
Dependent Variable is NHWG
LOG LIKELIHOOD: -1480.390

Variable	Coefficient	T-statistic
MON	-0.206	-1.464
TUE	-0.232	-1.657
WED	-0.093	-0.669
THU	0.026	0.195
FRI	0.256	2.040
SAT	0.195	1.523
FEB	-0.313	-1.682
MAR	-0.370	-2.034
APR	-0.138	-0.668
MAY	0.120	0.623
JUN	-0.260	-1.379
JUL	-0.134	-0.680
AUG	0.117	0.557
SEP	0.019	0.075
OCT	0.232	0.887
NOV	0.191	0.946
DEC	0.009	0.049
Y61	-0.279	-2.086
Y62	-0.141	-1.467
Y63	-0.155	-1.586
NYR	0.444	0.743
MEM	0.275	0.464
LAB	0.517	0.862
THX	-0.339	-0.466
CHR	0.591	1.148
UNEMP	0.117	1.222
NX	0.086	0.386
NX1	-0.432	-1.405
NX2	-0.009	-0.040
NX3	-0.200	-0.816
NX4	0.267	1.438
NX5	-0.092	-0.350
NX6	-0.133	-0.483
NX7	0.109	0.499
NX8	-0.056	-0.236
NX9	-0.140	-0.593
NX10	0.397	2.574
NX11	-0.633	-1.822
NX12	-0.078	-0.297
NX13	0.020	0.088
NX14	0.231	1.274
NX15	-0.086	-0.385
NX16	0.025	0.128
NX17	-0.206	-0.850
NX18	0.062	0.298
NX19	0.005	0.020
NX20	0.319	1.778
CONSTANT	-1.068	-1.571

Table 5K

POISSON REGRESSION MODEL: 1960-63 SUBSAMPLE
Dependent Variable is NHNWG
LOG LIKELIHOOD: -941.615

Variable	Coefficient	T-statistic
MON	-0.208	-1.023
TUE	-0.312	-1.482
WED	-0.086	-0.424
THU	-0.175	-0.831
FRI	0.490	2.771
SAT	0.403	2.261
FEB	-0.439	-1.541
MAR	-0.048	-0.186
APR	0.339	1.149
MAY	0.419	1.442
JUN	0.141	0.522
JUL	0.133	0.444
AUG	0.717	2.383
SEP	0.385	0.996
OCT	0.722	1.895
NOV	0.410	1.341
DEC	0.539	2.047
Y61	-0.452	-2.433
Y62	-0.027	-0.191
Y63	-0.124	-0.881
NYR	0.937	1.256
MEM	0.141	0.138
IND	1.129	1.530
LAB	1.130	1.506
THX	1.636	2.920
CHR	1.160	2.207
UNEMP	0.356	2.671
NX	0.333	1.273
NX1	-0.417	-0.947
NX2	-0.310	-0.866
NX3	0.368	1.734
NX4	0.225	0.817
NX5	-0.750	-1.313
NX6	0.046	0.123
NX7	0.012	0.034
NX8	-0.809	-1.415
NX9	-0.526	-1.317
NX10	-0.100	-0.324
NX11	-0.031	-0.093
NX12	0.307	1.101
NX13	-1.670	-1.679
NX14	-1.215	-1.744
NX15	0.232	0.841
NX16	0.320	1.515
NX17	-0.382	-0.994
NX18	0.295	1.171
NX19	0.644	3.243
NX20	0.489	2.013
CONSTANT	-3.651	-3.795

Table 5L

POISSON REGRESSION MODEL: 1960-63 SUBSAMPLE
Dependent Variable is NHWM
LOG LIKELIHOOD: -1693.611

Variable	Coefficient	T-statistic
MON	-0.204	-1.711
TUE	-0.113	-0.977
WED	-0.226	-1.863
THU	-0.122	-1.023
FRI	0.092	0.838
SAT	0.378	3.627
FEB	-0.351	-2.204
MAR	-0.359	-2.357
APR	-0.220	-1.257
MAY	-0.094	-0.553
JUN	-0.189	-1.222
JUL	-0.062	-0.376
AUG	0.014	0.075
SEP	0.035	0.158
OCT	0.088	0.392
NOV	-0.089	-0.504
DEC	-0.031	-0.196
Y61	-0.264	-2.216
Y62	-0.021	-0.251
Y63	-0.006	-0.073
NYR	0.092	0.156
MEM	0.090	0.153
IND	-0.333	-0.465
LAB	0.554	1.188
THX	-1.117	-1.103
CHR	-0.057	-0.098
UNEMP	0.078	0.927
NX	0.234	1.309
NX1	-0.279	-1.128
NX2	0.128	0.738
NX3	-0.123	-0.648
NX4	0.101	0.560
NX5	-0.225	-0.911
NX6	0.066	0.338
NX7	-0.272	-1.063
NX8	-0.280	-1.162
NX9	0.029	0.158
NX10	0.147	0.972
NX11	-0.766	-2.454
NX12	-0.009	-0.042
NX13	-0.307	-1.268
NX14	0.085	0.465
NX15	-0.459	-1.816
NX16	0.211	1.403
NX17	-0.109	-0.599
NX18	0.020	0.111
NX19	-0.024	-0.120
NX20	0.256	1.615
CONSTANT	-0.487	-0.822

Table 6

RESULTS OF TEST FOR POISSON SPECIFICATION (*chisq*1)

Full Sample

Variable	Test Statistic
NH	15.38*
NHW	10.16*
NHNW	7.26*
NHWG	19.44*
NHNWG	4.35*
NHWM	6.68*

1960-63 Subsample

Variable	Test Statistic
NH	5.91*
NHW	.86
NHNW	3.60
NHWG	11.10*
NHNWG	.14
NHWM	.576

* significant at 5 per cent

Table 7A

NEGATIVE BINOMIAL REGRESSION MODEL
Dependent Variable is NH
LOG LIKELIHOOD: -5146.208

Variable	Coefficient	T-statistic
MON	-0.242	-4.609
TUE	-0.221	-4.246
WED	-0.218	-4.154
THU	-0.163	-3.131
FRI	0.126	2.631
SAT	0.243	5.172
FEB	0.080	1.121
MAR	0.059	0.842
APR	0.082	0.964
MAY	0.171	1.938
JUN	0.117	1.527
JUL	0.264	3.254
AUG	0.353	3.887
SEP	0.296	2.525
OCT	0.411	3.458
NOV	0.266	2.911
DEC	0.369	4.434
Y61	-0.157	-2.116
Y62	0.021	0.366
Y63	0.005	0.088
Y64	0.137	2.383
Y65	0.311	5.545
Y66	0.389	5.366
Y67	0.550	7.829
NYR	0.599	2.715
MEM	-0.155	-0.530
IND	-0.009	-0.032
LAB	0.701	3.289
THX	0.227	0.917
CHR	0.171	0.765
UNEMP	0.086	1.831
WATTS	1.224	6.046
NX	0.199	1.613
NX1	-0.303	-1.816
NX2	0.036	0.294
NX3	0.001	0.011
NX4	0.100	0.818
NX5	-0.141	-0.903
NX6	-0.162	-1.006
NX7	0.103	0.785
NX8	-0.246	-1.530
NX9	-0.075	-0.567
NX10	0.122	1.084
NX11	-0.156	-1.083
NX12	0.023	0.162
NX13	-0.116	-0.788
NX14	0.129	1.063
NX15	0.097	0.806
NX16	0.184	1.748
NX17	-0.112	-0.862
NX18	0.167	1.489
NX19	0.144	1.171
NX20	0.278	2.520
CONSTANT	-0.055	-0.164

Table 7B

NEGATIVE BINOMIAL REGRESSION MODEL
Dependent Variable is NHW
LOG LIKELIHOOD: -4450.731

Variable	Coefficient	T-statistic
MON	-0.253	-4.045
TUE	-0.210	-3.410
WED	-0.209	-3.367
THU	-0.163	-2.641
FRI	-0.002	-0.031
SAT	0.160	2.828
FEB	0.026	0.309
MAR	-0.037	-0.438
APR	0.030	0.293
MAY	0.087	0.823
JUN	0.028	0.310
JUL	0.173	1.787
AUG	0.273	2.533
SEP	0.205	1.466
OCT	0.321	2.266
NOV	0.155	1.421
DEC	0.304	3.080
Y61	-0.156	-1.746
Y62	0.040	0.573
Y63	-0.012	-0.172
Y64	0.151	2.201
Y65	0.251	3.707
Y66	0.329	3.790
Y67	0.507	6.019
NYR	0.578	2.209
MEM	-0.264	-0.716
IND	-0.249	-0.707
LAB	0.592	2.255
THX	-0.196	-0.553
CHR	0.007	0.026
UNEMP	0.065	1.161
WATTS	0.823	2.989
NX	0.090	0.565
NX1	-0.263	-1.352
NX2	0.038	0.252
NX3	-0.067	-0.434
NX4	0.036	0.243
NX5	-0.195	-1.021
NX6	-0.109	-0.599
NX7	-0.021	-0.122
NX8	-0.154	-0.848
NX9	0.004	0.028
NX10	0.238	1.907
NX11	-0.235	-1.293
NX12	0.010	0.058
NX13	-0.032	-0.197
NX14	0.229	1.728
NX15	0.045	0.306
NX16	0.107	0.789
NX17	-0.118	-0.756
NX18	0.143	1.070
NX19	-0.052	-0.312
NX20	0.260	2.002
CONSTANT	-0.200	-0.500

Table 7C

NEGATIVE BINOMIAL REGRESSION MODEL
Dependent Variable is NHNW
LOG LIKELIHOOD: -3212.607

Variable	Coefficient	T-statistic
MON	-0.217	-2.382
TUE	-0.247	-2.684
WED	-0.235	-2.551
THU	-0.164	-1.793
FRI	0.371	4.636
SAT	0.407	5.141
FEB	0.198	1.575
MAR	0.264	2.149
APR	0.205	1.374
MAY	0.364	2.361
JUN	0.312	2.322
JUL	0.467	3.310
AUG	0.528	3.341
SEP	0.510	2.508
OCT	0.619	3.003
NOV	0.511	3.229
DEC	0.518	3.553
Y61	-0.168	-1.324
Y62	-0.027	-0.271
Y63	0.035	0.345
Y64	0.098	0.984
Y65	0.423	4.477
Y66	0.512	4.118
Y67	0.640	5.299
NYR	0.624	1.645
MEM	0.045	0.097
IND	0.366	0.962
LAB	0.909	2.692
THX	0.787	2.338
CHR	0.454	1.347
UNEMP	0.136	1.687
WATTS	1.663	6.079
NX	0.404	2.187
NX1	-0.392	-1.257
NX2	0.037	0.177
NX3	0.132	0.687
NX4	0.227	1.130
NX5	-0.030	-0.116
NX6	-0.310	-0.955
NX7	0.322	1.016
NX8	-0.512	-1.546
NX9	-0.242	-0.992
NX10	-0.206	-0.877
NX11	-0.006	-0.026
NX12	0.047	0.191
NX13	-0.386	-1.198
NX14	-0.208	-0.754
NX15	0.202	1.025
NX16	0.304	1.890
NX17	-0.088	-0.403
NX18	0.219	1.142
NX19	0.462	2.684
NX20	0.314	1.598
CONSTANT	-1.745	-3.043

Table 7D

NEGATIVE BINOMIAL REGRESSION MODEL
Dependent Variable is NHWG
LOG LIKELIHOOD: -3238.215

Variable	Coefficient	T-statistic
MON	-0.196	-2.127
TUE	-0.260	-2.782
WED	-0.088	-0.971
THU	-0.026	-0.294
FRI	0.128	1.494
SAT	0.147	1.728
FEB	-0.053	-0.411
MAR	-0.102	-0.796
APR	0.177	1.200
MAY	0.312	2.041
JUN	0.135	0.997
JUL	0.193	1.338
AUG	0.343	2.154
SEP	0.289	1.405
OCT	0.486	2.346
NOV	0.421	2.670
DEC	0.400	2.758
Y61	-0.262	-2.057
Y62	-0.131	-1.288
Y63	-0.128	-1.248
Y64	-0.008	-0.077
Y65	0.210	2.163
Y66	0.319	2.517
Y67	0.543	4.448
NYR	0.439	1.075
MEM	0.098	0.222
IND	-0.245	-0.455
LAB	0.447	1.067
THX	-0.283	-0.585
CHR	0.197	0.502
UNEMP	0.115	1.411
WATTS	1.298	3.592
NX	0.029	0.117
NX1	-0.311	-1.075
NX2	0.042	0.196
NX3	-0.181	-0.718
NX4	0.281	1.465
NX5	-0.085	-0.321
NX6	-0.084	-0.303
NX7	0.123	0.548
NX8	-0.012	-0.049
NX9	-0.132	-0.536
NX10	0.372	2.058
NX11	-0.324	-1.110
NX12	-0.026	-0.104
NX13	0.004	0.017
NX14	0.276	1.501
NX15	-0.045	-0.197
NX16	0.046	0.222
NX17	-0.185	-0.750
NX18	0.109	0.519
NX19	-0.058	-0.231
NX20	0.341	1.826
CONSTANT	-1.302	-2.239

Table 7E

NEGATIVE BINOMIAL REGRESSION MODEL
Dependent Variable is NHNWG
LOG LIKELIHOOD: -2275.978

Variable	Coefficient	T-statistic
MON	-0.213	-1.693
TUE	-0.295	-2.280
WED	-0.058	-0.474
THU	-0.044	-0.355
FRI	0.545	5.087
SAT	0.479	4.463
FEB	0.200	1.142
MAR	0.333	1.962
APR	0.465	2.313
MAY	0.464	2.162
JUN	0.509	2.777
JUL	0.491	2.490
AUG	0.824	3.852
SEP	0.789	2.843
OCT	0.967	3.459
NOV	0.653	2.984
DEC	0.673	3.376
Y61	-0.304	-1.743
Y62	-0.031	-0.222
Y63	-0.104	-0.730
Y64	0.042	0.306
Y65	0.522	4.094
Y66	0.754	4.476
Y67	0.904	5.538
NYR	0.824	1.731
MEM	-0.108	-0.149
IND	0.921	2.096
LAB	0.542	1.019
THX	0.986	2.371
CHR	0.739	1.838
UNEMP	0.212	1.942
WATTS	2.055	6.953
NX	0.367	1.462
NX1	-0.439	-0.999
NX2	-0.237	-0.703
NX3	0.377	1.765
NX4	0.205	0.723
NX5	-0.784	-1.363
NX6	0.022	0.059
NX7	0.074	0.227
NX8	-0.916	-1.594
NX9	-0.564	-1.408
NX10	-0.085	-0.287
NX11	0.106	0.358
NX12	0.298	1.040
NX13	-1.719	-1.728
NX14	-1.254	-1.792
NX15	0.240	0.899
NX16	0.327	1.580
NX17	-0.471	-1.202
NX18	0.261	0.982
NX19	0.656	3.253
NX20	0.485	1.962
CONSTANT	-3.095	-3.948

Table 7F

NEGATIVE BINOMIAL REGRESSION MODEL
Dependent Variable is NHWM
LOG LIKELIHOOD: -3729.974

Variable	Coefficient	T-statistic
MON	-0.249	-3.279
TUE	-0.248	-3.273
WED	-0.182	-2.427
THU	-0.165	-2.197
FRI	0.086	1.235
SAT	0.242	3.586
FEB	-0.026	-0.260
MAR	-0.108	-1.079
APR	-0.051	-0.420
MAY	0.015	0.118
JUN	-0.028	-0.256
JUL	0.112	0.970
AUG	0.253	1.966
SEP	0.173	1.030
OCT	0.294	1.733
NOV	0.175	1.357
DEC	0.238	2.026
Y61	-0.261	-2.387
Y62	-0.009	-0.105
Y63	0.012	0.140
Y64	0.174	2.121
Y65	0.264	3.259
Y66	0.335	3.192
Y67	0.532	5.217
NYR	0.321	0.961
MEM	-0.293	-0.635
IND	-0.621	-1.215
LAB	0.773	2.632
THX	-0.652	-1.263
CHR	-0.015	-0.043
UNEMP	0.087	1.279
WATTS	0.911	3.007
NX	0.163	0.889
NX1	-0.198	-0.853
NX2	0.098	0.569
NX3	-0.088	-0.466
NX4	0.091	0.508
NX5	-0.255	-1.026
NX6	0.085	0.426
NX7	-0.219	-0.917
NX8	-0.226	-0.963
NX9	-0.033	-0.173
NX10	0.172	1.102
NX11	-0.550	-2.021
NX12	0.000	0.002
NX13	-0.238	-1.010
NX14	0.041	0.221
NX15	-0.398	-1.620
NX16	0.175	1.147
NX17	-0.082	-0.449
NX18	0.078	0.451
NX19	-0.024	-0.121
NX20	0.314	2.031
CONSTANT	-0.702	-1.455

Table 7G

NEGATIVE BINOMIAL REGRESSION MODEL: 1960-63 SUBSAMPLE
Dependent Variable is NHWG
LOG LIKELIHOOD: -1475.471

Variable	Coefficient	T-statistic
MON	-0.210	-1.407
TUE	-0.229	-1.544
WED	-0.091	-0.622
THU	0.030	0.207
FRI	0.253	1.880
SAT	0.198	1.451
FEB	-0.306	-1.544
MAR	-0.366	-1.894
APR	-0.130	-0.593
MAY	0.125	0.602
JUN	-0.255	-1.270
JUL	-0.136	-0.641
AUG	0.112	0.494
SEP	0.026	0.094
OCT	0.235	0.836
NOV	0.193	0.885
DEC	0.013	0.064
Y61	-0.275	-1.915
Y62	-0.139	-1.351
Y63	-0.153	-1.457
NYR	0.487	0.762
MEM	0.255	0.394
LAB	0.520	0.808
THX	-0.329	-0.435
CHR	0.558	0.958
UNEMP	0.118	1.147
NX	0.076	0.304
NX1	-0.432	-1.355
NX2	0.004	0.018
NX3	-0.209	-0.787
NX4	0.280	1.384
NX5	-0.090	-0.328
NX6	-0.120	-0.412
NX7	0.110	0.467
NX8	-0.054	-0.211
NX9	-0.142	-0.570
NX10	0.375	1.981
NX11	-0.636	-1.762
NX12	-0.075	-0.276
NX13	0.008	0.034
NX14	0.247	1.282
NX15	-0.090	-0.376
NX16	0.019	0.091
NX17	-0.204	-0.794
NX18	0.069	0.308
NX19	0.005	0.022
NX20	0.329	1.699
CONSTANT	-1.078	-1.480

Table 8

HAUSMAN TESTS FOR NEGATIVE BINOMIAL SPECIFICATION

1960-1967 Period

Category	Test Statistic (χ_1^2)
NH	2481.2
NHW	2251.9
NHNW	1149.2
NHWM	1764.4
NHWG	1047.6
NHNWG	2066.2

1960-1963 Period

NHWG	1964.7

Table 9A

QUASI-GENERALIZED PSEUDO-MAXIMUM LIKELIHOOD MODEL
Dependent Variable is NH
LOG LIKELIHOOD: -2757.439

Variable	Coefficient	T-statistic
MON	-0.242	-3.893
TUE	-0.222	-3.588
WED	-0.224	-3.597
THU	-0.168	-2.708
FRI	0.116	1.991
SAT	0.244	4.247
FEB	0.076	0.896
MAR	0.053	0.636
APR	0.070	0.692
MAY	0.159	1.520
JUN	0.110	1.206
JUL	0.252	2.604
AUG	0.335	3.096
SEP	0.270	1.943
OCT	0.386	2.731
NOV	0.247	2.278
DEC	0.357	3.602
Y61	-0.151	-1.713
Y62	0.024	0.348
Y63	0.009	0.128
Y64	0.140	2.052
Y65	0.312	4.667
Y66	0.383	4.465
Y67	0.544	6.504
NYR	0.623	2.185
MEM	-0.150	-0.442
IND	-0.030	-0.095
LAB	0.698	2.558
THX	0.233	0.775
CHR	0.186	0.664
UNEMP	0.079	1.409
WATTS	1.212	3.905
NX	0.205	1.377
NX1	-0.300	-1.604
NX2	0.047	0.314
NX3	-0.017	-0.113
NX4	0.101	0.687
NX5	-0.144	-0.819
NX6	-0.171	-0.945
NX7	0.113	0.731
NX8	-0.247	-1.368
NX9	-0.076	-0.485
NX10	0.117	0.844
NX11	-0.180	-1.074
NX12	0.021	0.131
NX13	-0.119	-0.716
NX14	0.132	0.913
NX15	0.086	0.595
NX16	0.196	1.481
NX17	-0.119	-0.789
NX18	0.158	1.153
NX19	0.148	1.014
NX20	0.287	2.114
CONSTANT	0.004	0.009

Table 9B

QUASI-GENERALIZED PSEUDO-MAXIMUM LIKELIHOOD MODEL
Dependent Variable is NHNW
LOG LIKELIHOOD: -3066.064

Variable	Coefficient	T-statistic
MON	-0.226	-2.167
TUE	-0.259	-2.470
WED	-0.253	-2.403
THU	-0.178	-1.698
FRI	0.350	3.706
SAT	0.402	4.281
FEB	0.200	1.388
MAR	0.261	1.857
APR	0.204	1.197
MAY	0.348	1.969
JUN	0.298	1.939
JUL	0.451	2.768
AUG	0.515	2.823
SEP	0.476	2.033
OCT	0.577	2.432
NOV	0.493	2.710
DEC	0.506	3.017
Y61	-0.163	-1.112
Y62	-0.024	-0.211
Y63	0.041	0.361
Y64	0.106	0.928
Y65	0.419	3.815
Y66	0.505	3.530
Y67	0.619	4.441
NYR	0.700	1.502
MEM	0.061	0.114
IND	0.346	0.747
LAB	0.906	2.131
THX	0.807	1.903
CHR	0.519	1.233
UNEMP	0.123	1.323
WATTS	1.623	3.613
NX	0.469	2.112
NX1	-0.379	-1.124
NX2	0.026	0.108
NX3	0.098	0.425
NX4	0.207	0.880
NX5	-0.047	-0.162
NX6	-0.332	-0.942
NX7	0.360	1.543
NX8	-0.516	-1.439
NX9	-0.259	-0.930
NX10	-0.217	-0.813
NX11	-0.040	-0.152
NX12	0.040	0.145
NX13	-0.399	-1.151
NX14	-0.231	-0.755
NX15	0.182	0.783
NX16	0.322	1.589
NX17	-0.098	-0.392
NX18	0.201	0.887
NX19	0.486	2.303
NX20	0.322	1.400
CONSTANT	-1.643	-2.492

Table 9C

QUASI-GENERALIZED PSEUDO-MAXIMUM LIKELIHOOD MODEL
Dependent Variable is NHNWG
LOG LIKELIHOOD: -2214.715

Variable	Coefficient	T-statistic
MON	-0.227	-1.665
TUE	-0.304	-2.188
WED	-0.071	-0.533
THU	-0.057	-0.425
FRI	0.520	4.391
SAT	0.471	3.961
FEB	0.193	1.020
MAR	0.333	1.815
APR	0.471	2.162
MAY	0.451	1.944
JUN	0.495	2.499
JUL	0.471	2.205
AUG	0.819	3.513
SEP	0.760	2.524
OCT	0.938	3.090
NOV	0.629	2.655
DEC	0.658	3.043
Y61	-0.297	-1.567
Y62	-0.018	-0.121
Y63	-0.088	-0.576
Y64	0.058	0.389
Y65	0.523	3.754
Y66	0.757	4.136
Y67	0.894	5.031
NYR	0.907	1.660
MEM	-0.105	-0.137
IND	0.930	1.824
LAB	0.554	0.939
THX	1.046	2.156
CHR	0.811	1.724
UNEMP	0.201	1.695
WATTS	2.008	4.424
NX	0.398	1.423
NX1	-0.452	-0.980
NX2	-0.226	-0.633
NX3	0.341	1.343
NX4	0.185	0.602
NX5	-0.802	-1.346
NX6	0.007	0.018
NX7	0.094	0.274
NX8	-0.912	-1.548
NX9	-0.561	-1.332
NX10	-0.094	-0.291
NX11	0.088	0.270
NX12	0.288	0.918
NX13	-1.727	-1.718
NX14	-1.241	-1.741
NX15	0.249	0.860
NX16	0.372	1.547
NX17	-0.463	-1.130
NX18	0.238	0.818
NX19	0.690	2.898
NX20	0.480	1.734
CONSTANT	-3.014	-3.545

Table 10

SUMMARY OF FINAL SPECIFICATIONS

Full Sample

Variable	Specification
NH	QGPML
NHW	Negative Binomial
NHNW	QGPML
NHWG	Negative Binomial
NHNWG	QGPML
NHWM	Negative Binomial
1960-63 Subsample	
NH	Poisson*
NHW	Poisson
NHNW	Poisson
NHWG	Negative Binomial
NHNWG	Poisson
NHWM	Poisson

* See Note 2

Table 11

TESTS FOR SINGLE-DAY DETERRENT EFFECTS

Category	Variable	Coefficient	T-statistic	p_L	p_U
		1960-1967 Period			
NH	NX1	-0.300	-1.604	0.544	1.000
NHW	NX1	-0.263	-1.352	0.668	1.000
NHNW	NX8	-0.516	-1.439	0.640	1.000
NHWM	NX11	-0.550	-2.021	0.349	0.444
NHWG	NX11	-0.324	-1.110	0.760	1.000
NHNWG	NX14	-1.241	-1.741	0.489	0.822
		1960-1963 Period			
NH	NX11	-0.293	-1.911	0.408	0.571
NHW	NX11	-0.423	-2.104	0.299	0.364
NHNW	NX8	-0.540	-1.550	0.574	1.000
NHWM	NX11	-0.766	-2.454	0.136	0.147
NHWG	NX11	-0.636	-1.762	0.475	0.786
NHNWG	NX14	-1.215	-1.744	0.479	0.816

Table 12

NUMBERS OF POSITIVE AND NEGATIVE SIGNS AMONG DETERRENCE VARIABLES

Category	Negative Signs	Positive Signs
	1960-1967 Period	
NH	9	12
NHW	10	11
NHNW	10	11
NHWM	11	10
NHWG	11	10
NHNWG	9	12
	1960-1963 Period	
NH	10	11
NHW	11	10
NHNW	10	11
NHWM	11	10
NHWG	10	11
NHNWG	10	11

Table 13

TESTS FOR DECREASES IN TOTAL NUMBER OF HOMICIDES OVER THREE-WEEK PERIOD FOLLOWING EXECUTIONS

Category	Sum of Coefficients	T-statistic
	1960-1967 Period	
NH	0.235	0.298
NHW	-0.047	-0.058
NHNW	0.197	0.144
NHWM	-1.095	-1.066
NHWG	0.183	0.154
NHNWG	-3.046	-1.414
	1960-1963 Period	
NH	-0.177	-0.260
NHW	-0.673	-0.810
NHNW	0.184	0.149
NHWM	-1.576	-1.455
NHWG	-0.530	-0.408
NHNWG	-2.940	-1.392

Table A1

RESULTS OF DYNAMIC INFORMATION MATRIX TESTS
DIAGONAL ELEMENTS: MONTHS

Full Sample

Model	Test Statistic (χ_1^2)
NH	8.7
NHW	13.6
NHNW	14.2
NHWG	17.1
NHNWG	11.6
NHWM	15.7
1960-63 Subsample	
NH	12.5
NHW	14.8
NHNW	9.2
NHWG	24.0*
NHNWG	26.9*
NHWM	21.5*

* significant at 5 per cent

Table A2

RESULTS OF DYNAMIC INFORMATION MATRIX TESTS
DIAGONAL ELEMENTS: YEARS

Full Sample

Model	Test Statistic (χ^2_7)
NH	8.4
NHW	12.5
NHNW	7.3*
NHWG	16.2
NHNWG	13.9
NHWM	11.9

1960-63 Subsample

Model	Test Statistic (χ^2_7)
NH	6.2
NHW	8.5*
NHNW	6.0
NHWG	11.5*
NHNWG	6.2
NHWM	1.4

* significant at 5 per cent

Table A3

RESULTS OF STATIC INFORMATION MATRIX TESTS
DIAGONAL ELEMENTS: CONSTANT

Full Sample

Model	Test Statistic (χ_1^2)
NH	867.1*
NHW	683.1*
NHNW	742.0*
NHWG	898.5*
NHNWG	291.9*
NHWM	721.7*

1960-63 Subsample

Model	Test Statistic (χ_1^2)
NH	5.9
NHW	.86
NHNW	3.6
NHWG	654.6*
NHNWG	.14
NHWM	.6

* significant at 5 per cent

Table A4

RESULTS OF STATIC INFORMATION MATRIX TESTS
DIAGONAL ELEMENTS: DAYS

Full Sample

Model	Test Statistic (χ^2_6)
NH	841.3**
NHW	47.3*
NHNW	663.4*
NHWG	118.7*
NHNWG	197.9*
NHWM	38.3*

1960-63 Subsample

Model	Test Statistic (χ^2_6)
NH	11.0
NHW	7.8
NHNW	13.3*
NHWG	121.6*
NHNWG	14.3*
NHWM	12.5

* significant at 5 per cent

Table A5

RESULTS OF STATIC INFORMATION MATRIX TESTS
DIAGONAL ELEMENTS: MONTHS

Full Sample

Model	Test Statistic (χ^2_{11})
NH	888.0*
NHW	122.8*
NHNW	702.9*
NHWG	337.2*
NHNWG	345.6*
NHWM	87.1*
1960-63 Subsample	
NH	26.0*
NHW	25.4*
NHNW	13.8
NHWG	236.0*
NHNWG	21.0*
NHWM	11.2

* significant at 5 per cent

Table A6

RESULTS OF STATIC INFORMATION MATRIX TESTS
DIAGONAL ELEMENTS: YEARS

Full Sample

Model	Test Statistic (χ^2_7)
NH	735.4*
NHW	41.2*
NHNW	559.2*
NHWG	34.5*
NHNWG	213.0*
NHWM	19.2*

1960-63 Subsample

Model	Test Statistic (χ^2_7)
NH	5.3
NHW	2.3
NHNW	6.9
NHWG	20.6*
NHNWG	2.3
NHWM	9.5

* significant at 5 per cent

Table A7

RESULTS OF STATIC INFORMATION MATRIX TESTS
DIAGONAL ELEMENTS: UNEMP

Full Sample

Model	Test Statistic (χ^2_1)
NH	782.1*
NHW	34.0*
NHNW	588.8*
NHWG	179.3*
NHNWG	219.4*
NHWM	11.3*

1960-63 Subsample

Model	Test Statistic (χ^2_1)
NH	9.1*
NHW	2.0
NHNW	4.8*
NHWG	121.0*
NHNWG	.72
NHWM	1.4

* significant at 5 per cent

Table A8

RESULTS OF STATIC INFORMATION MATRIX TESTS
DIAGONAL ELEMENTS: WATTS

Full Sample

Model	Test Statistic (χ_1^2)
NH	2.6
NHW	3.2
NHNW	2.9
NHWG	0.3
NHNWG	3.2
NHWM	3.8*

* significant at 5 per cent

CHAPTER III.

Efficient Criminal Justice Policy:
Theory and Empirical Evidence

1. Introduction

Beginning with Becker's [1968] seminal work, researchers have developed and tested the so-called economic theory of crime, that explains criminal behavior as a rational response to the relative costs and benefits of legitimate and illegitimate earnings and consumption prospects.

While these efforts are generally viewed as economists' main contribution to the field of criminal justice, other researchers have analyzed the role of plea bargaining, either as an instrument by which the prosecutor may conserve scarce judicial resources (Landes [1971], Rhodes [1976]), or as a method by which to screen guilty suspects, and provide insurance against the conviction of innocent ones (Grossman and Katz [1983]).

One aspect of crime and justice which has yet to receive attention from economists, however, is the efficient use of various sanctions to control several different categories of crime. The problem of efficiently allocating resources to control crimes of differing severity and deterrability is particularly well-suited to the methods of economic analysis, and of increasing policy relevance in an era of secularly increasing crime rates and fiscal restraint. This problem is analyzed in this paper, and tested using data on various categories of homicides committed in California over the period 1976-1984.

In the first section, the basic model is set out, optimality conditions obtained and interpreted, and the tests to be employed described. In Sections II and III, the data and estimation methods are discussed. Tests of the efficiency hypothesis are reported in Section IV, along with other results relating to the fit of the data to the economic model of crime. These results are summarized and conclusions drawn in the final section.

1. The Model

It is assumed that there are n different types of crimes, the levels of which are given by the vector $c = (c^1, c^2, \ldots, c^n)$. The direct costs imposed on society in terms of lost and damaged property as well as psychic losses are given by the social (dis)utility function $U(c)$. It is assumed that $U_i = \frac{\partial U}{\partial c^i} < 0$, $i=1,\ldots n$. Society, through its law enforcement and judicial functions, has a number of policy measures, or sanctions, available to it to control crime. For the i^{th} crime type, the levels of these sanctions are denoted $s^i = (s_1^i, s_2^i, \ldots, s_m^i)$. These s_j^i are expressed in whatever units are natural for the given sanction. For example, an s_j^i may represent an apprehension or conviction probability, the average fine or prison sentence imposed for the i^{th} crime, or the proportion of capital punishments imposed. Collectively, the m sanctions available to control each type of crime are denoted by $s = (s^1, s^2, \ldots, s^n)$. Each crime is related to the level of sanctions by an aggregate crime function, which, drawing on previous research, can be thought of as the aggregated first-order conditions of potential criminals, who respond to the level of sanctions and to legitimate employment and consumption prospects so as to maximize their expected utility. These reaction functions, which serve as behavioral feasibility constraints to society, are given as $c^i = f^i(s^i, \psi^i)$, where ψ^i is a vector of economic and socio-demographic variables which influence the overall level of crime but are not under the control of the criminal justice authorities. It is assumed that $f_j^i = \frac{\partial f^i}{\partial s_j^i} < 0$ for all i and j. This last assumption is based on empirical evidence rather than theory (see Block and Heineke for a model in which this condition may not hold), but is the only relevant case to consider. Any "sanction" such that $f_j^i > 0$ would optimally be set to zero. Finally, the budget constraint of the criminal justice authorities is given by $C(s) \leqslant \overline{C}$, where $C_j^i = \frac{\partial C}{\partial s_j^i} > 0$.

Noting that efficiency will require the exhaustion of the budget $\overline{C}$, the criminal justice authorities' problem can be written as

$$\min L = U(c) + \sum_{i=1}^{n} \lambda_i [c^i - f^i(s^i, \psi^i)]$$

$$+ \mu[\overline{C} - C(s)]$$

where $\lambda = (\lambda_1, \lambda_2, \ldots, \lambda_n)$ and μ are Lagrange multipliers. From the first-order conditions, one obtains

$$\frac{f_j^i / C_j^i}{f_j^k / C_j^k} = \frac{\lambda_k}{\lambda_i} \qquad i,k=1,\ldots,n,\ j=i,\ldots,m \tag{1}$$

and

$$\frac{f_j^i}{C_j^i} = \frac{f_l^i}{C_l^i} \qquad i=1,\ldots,n,\ j,l=1,\ldots,m \tag{2}$$

Now, λ_i is the shadow value of reducing the level of the i^{th} crime by one unit, valued in social utility units, or the social disutility weight attributed to the i^{th} crime type. More heinous crimes will thus have a larger λ_i. Equation (1) can thus be interpreted as stating that resources expended on a given sanction should be allocated such that the marginal deterrent effect on crime type i from the marginal dollar spent on the sanction, relative to the marginal deterrent effect on crime type k from the marginal dollar expended on that sanction, should be in proportion to the ratio of disutility weights attributed to those crimes by society. Equation (2) states that, for a given crime type, sanction levels should be chosen such that the marginal deterrent effect of each sanction from the last dollar spent on it are equal across sanctions.

Equations (1) and (2) can be combined to yield

$$\lambda_i \frac{f_j^i}{C_j^i} = \lambda_k \frac{f_l^k}{C_l^k} \tag{3}$$

That is, that sanction levels should be chosen such that marginal deterrent effect on crime i achieved by the marginal expenditure on sanction j equals the marginal deterrent effect on crime k achieved by the marginal expenditure on sanction l, when weighted by the respective crimes' social disutility weights. This condition (3) must hold across all crime types and sanctions.

Examination of equation (3) reveals that the relative values of three factors influence the optimal level of a given sanction to control a specific type of crime: the severity of the crime (λ_i), the effectiveness of the sanction in deterring the crime (f_j^i), and the cost of the sanction in controlling the crime (C_j^i). Crimes viewed as more serious by society will generally be sanctioned more severely, while more effective and less costly sanctions will find greater utilization. Barring any sort of principal-agent problems which would cause law enforcement officials' and prosecutors' objective functions to differ from the social welfare function, then, these are the potentially testable implications of the theory. We turn now to a discussion of how these predictions might be tested empirically.

To test the model requires data and an estimation and testing strategy that allows one to isolate these three potentially counteracting influences. One such strategy would be to estimate aggregate crime functions of the type reported by earlier authors across several types of crimes, and base tests on these estimates. Two issues are apparent when considering such a strategy, however: the difficulty in establishing relative social disutility weights for many crime categories (e.g., assault and robbery), and the lack of any *a priori* notion of the relative deterrability of most crimes.

To overcome these obstacles, the empirical analysis in this paper is based on crime functions estimated for several types of homicides. Specifically, data are used on rates of spousal and familial homicides, and on homicides known to have been committed pursuant to a robbery or burglary (hereafter, property crime homicides), as well as the overall homicide rate. Use of such data substantially solves both problems above. First, one may posit that society abhors all killings *per se*; it is likely that societal expressions of greater displeasure with certain types of murders, as evidenced by desires for harsher penalties for certain types of homicides, may already reflect the notion that certain types of homicides are more deterrable than others. Second, intuition and empirical evidence suggests that property crimes fit the economic model of crime reasonably well, and are thus likely to be more deterrable than "crimes of passion" such as the slaying of one's spouse or other family member.

When crime categories are equally disdained by society, equation (1) reduces to

$$\frac{f_j^i}{C_j^i} = \frac{f_j^k}{C_j^k} \tag{4}$$

Assuming that costs of sanction j are roughly equal across categories, equation (4) indicates that efficiency requires greater sanctions against the more deterrable class of homicides. Together with our *a priori* notions of deterrability, then, the model predicts that criminal justice authorities should allocate greater sanctioning resources against property crime homicides than familial or spousal homicides.

We turn now to a description of the data used in the empirical analysis, then to a discussion of the tests employed.

3. The Data

The data employed in the analysis are from California, collected over the period 1976-1984. The county was used as the unit of observation, which is the smallest unit for which data on many of the variables analyzed were available. The observations are of annual magnitudes; the data set is thus a time-series of cross sections.

The criminal justice variables were compiled from various data bases maintained by the California Department of Justice's Bureau of Criminal Statistics (BCS). Homicide counts were taken from the BCS Homicide File. This file includes a great deal of information on each incident of homicide, including (when known) the relationship of the victim to the offender, and the events precipitating the crime. For this study, these data elements were used to tally familial, spousal, and property crime homicides, as well as the total number of homicides committed. These counts were transformed into rates by dividing them by the total county population (in 100,000's), provided by the California Department of Finance. It is important to note that the homicide rates so constructed are rates of deaths by homicide, rather that rates of homicide events. The empirical results presented below should therefore be interpreted accordingly.

Three sanction variables are employed, including measures of the probability of arrest for homicide, of conviction, given arrest, and of receiving a death sentence, given conviction.[1,2]

The unemployment rate used, *UNEMP*, is from the California Department of Labor, and the personal income variable, *PINC* (in 100's), from the federal Department of Commerce's *Local Area Personal Income*. The variable *WHITE* is the percentage of the county population classified as white in the 1980 Census.

Previous studies (Ehrlich [1973,1975,1977], Vandaele [1973],Passell [1975]) have considered the possible endogeneity of the probability of arrest measure, and have used per capita police expenditures in an instrumental variables framework to correct for it. Quite curiously, though, none of these studies considered the possible endogeneity of the other judicial policy variables. For our purposes, several other variables were collected to serve as instruments for the P_{CON} and P_{DS} measures, as well.

Per capita police expenditures, *POLEXP*, serve as an instrument for the arrest probability measure. Similarly, judicial expenditures per capita, JUDEXP, serve as an instrument for conviction probability.[3] The variable *PLBG*, the ratio of pre-trial guilty verdicts to all dispositions in all Superior Court criminal cases, serves as an instrument for both P_{CON} and P_{DS}, as a measure of prosecutors' propensity to seek harsher sentences.[4] Another instrument for P_{DS} is *REPVOT*, the percentage of Republicans among registered voters. This serves as a measure of community preferences for the imposition of capital punishments, as may find expression in the prosecutor's recommendations at sentencing. More conservative communities are thought to favor death sentences.

The variables were collected for all 58 counties for nine years. After some preliminary data analysis, data from the smaller counties were found to be so affected by small sample problems as to be of little use for the analysis.[5] The twenty-five largest counties were therefore chosen for analysis , leaving 225 observations for the estimations reported below.

The names and definitions of all variables used are summarized in Table 1. The data are summarized in Table 2. On notes that property-crime related murders accounted for roughly 13 per cent of the total, while familial and spousal homicides made up sixteen and eight percent, respectively.

4. Estimation Methods

The equations estimated are given as

$$Homicide\ rate_{ij} = \alpha_0 + \alpha_1 P_{ARR_{ij}} + \alpha_2 P_{CON_{ij}} + \alpha_3 P_{DS_{ij}} + \alpha_4 UNEMP_{ij} + \alpha_5 PINC_{ij} + \alpha_6 YD_{ij} + u_{ij} \qquad (5)$$

where the j subscript denotes the category of homicides, i denotes observations within the class, YD_{ij} is a vector of dummy variables for the years 1977-1984, and u_{ij} is a random disturbance term.

Ordinary least squares (OLS) estimates of equation (5) are presented in Table 3. Instrumental variables (IV) estimates are given in Table 4. These IV estimates are obtained by estimating equation (5), with actual values of the policy variables P_{ARR},P_{CON},and P_{DS} replaced by predicted values obtained by regressing each of the variables on their respective instruments and *UNEMP*,*PINC*, and *YD*. One notes that the overall fit of the model, as given by the joint χ^2 or R^2 statistics, varies across categories. Further discussion of this point is deferred to the next section.

5. Results

The results of the study fall into two categories. The first concerns the overall fit of the data to the economic model of crime, and the second pertains to the test of the efficiency results from the model presented in Section I.

A. The Overall Performance of the Economic Model of Crime

We first present a general discussion of the adequacy of the economic model of crime to represent the different homicide rates under study. Examining the OLS estimates in Table 3, one notes that the P_{ARR} and P_{CON} variables have their traditional sign in the overall and property crime models, while only P_{CON} is negative in the familial and spousal models. Further, the capital punishment variable is positive in all models.

There are several possible explanations of this occurrence. First, while positive signs would lead one to necessarily reject Ehrlich's [1975] model, the less restrictive models of Block and Heineke [1975] and Witte [1980] are not necessarily ruled out by such results. However, the magnitude and apparent significance of the P_{DS} coefficients is troubling; without appealing to a very severe form of risk preference, it would appear difficult to explain this result within the model. Another more plausible explanation is that the models are misspecified, due to the endogeneity of the judicial variables, and that the resultant bias in the least-squares estimates is misleading.

Hausman's [1978] test can be used to detect model misspecification arising from simultaneity bias. To conduct the test, one first forms predicted values of the suspected endogenous sanction variables by regressing them on the maintained exogenous variables *UNEMP*, *PINC*, and *YD*, and their respective instruments. The homicide rate variables are then regressed on both actual and predicted values of the sanction variables, and on the exogenous variables. The test is then conducted as a test of the joint significance of the coefficients of the predicted sanction variables.

Parameter estimates, test statistics, and significance levels are reported in Table 5. One sees that the null hypothesis of no simultaneity is rejected most convincingly for the models of property crime homicides and the overall homicide rate, but not for the models of familial or spousal killings. These results suggest that the misspecification of the *HRAT* and *HPRAT* models is likely due to endogeneity of the sanction variables, while the *HRRAT* and *HSRAT* models likely suffer from some other, possibly deeper, form of misspecification.

Instrumental variables techniques were employed to correct for the simultaneity problem. Results from this exercise largely confirm those of the Hausman tests. Examining Table 4, one observes that all judicial variables in the *HRAT* and *HPRAT* equations have traditional signs, and the P_{ARR} and P_{CON} coefficients are significant at the five per cent level in both equations. Furthermore, the signs of the variables *UNEMP* and *PINC* are correct under traditional preference restrictions as well. The coefficient of *PINC* is significant in both equations, as is the *UNEMP* coefficient in the *HPRAT* model. The marginal significance of the *UNEMP* coefficient in the *HRAT* equation may be due to the slight collinearity detected between the *PINC* and *UNEMP* variables.

One notes also that increasing proportions of non-white residents correlate strongly with higher rates of homicide. This result holds for all categories examined, and has been reported by other Finally, the Wald statistics for overall model fit at the bottom of Table 4 are seen to be quite large for both of these homicide categories, strongly affirming the joint significance of the included regressors. researchers, as well.

Turning to a discussion of the familial and spousal homicide rates, it should be noted that the results of the Hausman tests for these categories have two implications. First, as mentioned above, ordinary least squares should provide unbiased, consistent parameter estimates. Table 3 thus serves as the basis for the following discussion. Second, any apparent model failures are likely due to other, possibly deeper, forms of misspecification.

One notes first that the economic model of crime explains quite little of the variance of either familial or spousal homicide rates. Examining the R^2 measures at the bottom of Table 3, one sees that the model explains only 22 and 13 percent of the variance of the respective categories.

More seriously, the P_{ARR} and P_{DS} measures enter both equations with non-traditional sign, as does the unemployment rate. At this point, one must choose between the economic model of crime as an explanation for such offenses on the one hand, and such basic tenets as the assumption of risk aversion on the other. Further, even if one is willing to reject these usual risk preference assumptions, one is left having to explain why an increase in the probability of conviction, given arrest, might deter such murders, but an increase in the arrest probability has the opposite effect. One is tempted to conjecture that explanations would entail truly bizarre preferences over different types of risk.

Finally, given the lack of simultaneity bias for these categories, both OLS and IV should provide consistent parameter estimates. For a properly specified model, then, these estimates should be roughly equal. Comparing the coefficients for these categories from Tables 3 and 4, however, one sees that some of these coefficients change sign, and several differ by orders of magnitude, further eroding ones confidence in the model's ability to serve as an adequate representation of the data.

Further insights into the adequacy of the economic model of crime may be gained from comparing the elasticities of the homicide rates with respect to the explanatory variables, defined as $\epsilon_X = \frac{\partial y}{\partial X}\frac{X}{y}$ for dependent variable y and explanatory variable X. These elasticities, evaluated at the variable means, are given in Table 6 for those coefficients which enter the equations with traditional sign. One sees that the P_{ARR} variable has roughly three times the effect on property crime homicides as on the overall rate, while the conviction threat measure has somewhat less than twice the impact in the latter category as the former. It may be interesting to note that, if one ignores the insignificance of the P_{DS} coefficient, the ranking of the judicial elasticities for both of these categories is that required by Ehrlich's [1975] theoretical model, that $\epsilon_{P_{ARR}} < \epsilon_{P_{CON}} < \epsilon_{P_{DS}} < 0$. Given the statistical insignificance of $\epsilon_{P_{DS}}$ from zero, however, it would be erroneous to interpret this finding as corroborating his results.

The rate of property crime homicides is seen to be almost three times as sensitive to changes in the unemployment rate as homicides overall. These felony murders are also more responsive to changes in personal income. This seems in accord with intuition that suggests that property crimes, of which homicide is a probabilistic outcome, should be particularly responsive to changes in legitimate earnings opportunities.

We also see that the effects of those explanatory variables with traditional signs are much weaker in the models of familial and spousal murders than in the property crime and overall equations. Again, this observation is consistent with the intuition suggested above.

Finally, before presenting the tests of the model presented in Section I, we turn attention to results pertaining to the deterrent effect of capital punishment. In the models of familial and spousal homicide rates, the P_{DS} coefficient has positive sign. There seems to be little of inferential value here, however, given the small t-values of the coefficients and gross misspecification of the model which generated them.

In the *HRAT* and *HPRAT* equations, however, the P_{DS} variable has plausible signs. The t-values are quite low, however: one cannot reject the null hypothesis that increases in the probability of a death sentence have no deterrent effect. We now proceed to discuss the empirical tests of the theoretical predictions derived in Section I.

B. Tests of the Model of Efficient Sanctioning Policy

In this context, the results of the Hausman tests have behavioral as well as technical implications. A finding of endogeneity between a particular homicide rate and the sanction variables indicates that police and prosecutorial efforts respond to changes in the level of homicides of that type, with increases in criminal activity calling forth increases in criminal justice sanctioning. The theoretical predictions and ensuing discussion from Section I suggest that increases in property crime homicides should call forth such a response, while rising spousal or familial homicide rates may not.

Turning again to Table 5, we see that these predictions are confirmed. The test statistics at the bottom of the table strongly suggest that sanctioning levels are responsive to changes in the rates of property crime homicides, and to changes in the overall rate.

Among these categories of homicides, a measure of the relative responsiveness of criminal justice policy can be obtained by comparing the coefficients of the sanction variables from the IV estimates in Table 4 with those from the OLS estimates in Table 3. The ratio of the IV estimate of the P_{ARR} variable to the OLS estimate in the *HRAT* model is 9.2, while the corresponding ratio for the P_{CON} measure is 17.4 . The respective ratios in the *HPRAT* category are 15.9 and 66.1 . This finding appears to strengthen the confirmation of the theory, as it suggests that the criminal justice response is strongest for the category of homicide believed to be most deterrable.

On the other hand, the test statistics at the bottom of Table 5 indicate no response of sanction levels to changes in familial or spousal homicide rates. This again is as predicted by the theory, as such crimes were posited to be less deterrable on *a priori* grounds.

Of course, a more direct test of the theory could be conducted by comparing actual sanctions and law enforcement and prosecutorial expenditure levels for each category of homicide. Such finely detailed data that would be necessitated by this approach were not available to us, however: by and large, the broad predictions of the theory, that the greatest criminal justice resources be expended where they are most effective, is confirmed the the available data.

6. Summary and Conclusions

The main results of the study can be summarized in the following way. First, law enforcement and judicial policy efforts appear to be allocated in a broadly efficient manner, responding to potentially more deterrable types of homicide, but not to those one might characterize as crimes of passion.

Next, the standard economic model of crime appears to offer an adequate explanation for overall homicide rates, and for rates of homicides committed pursuant to crimes of acquisition. As an explanation of familial and spousal murder rates, however, the model is quite poor.

Homicides committed pursuant to crimes of acquisition are more sensitive to changes in both significant sanction variables. Increases in the arrest threat measure are roughly three times as effective in deterring property crime murders as homicides overall, while increased probability of conviction has roughly twice the effect in the property crime as in the overall category. Increases in the unemployment rate are related to increases in both of these categories of homicide: the effect of such increases on property crime murders is roughly three times that on murders overall. The effects of changes in personal income are stronger in the former category, as well. Increased death sentences had no effect on homicide rates in California over the period examined.

It should also be noted that the results indicate considerable responsiveness of homicide rates to changes in unemployment and income. Effective manpower programs are therefore likely to have societal benefits beyond their direct employment and income effects, which should be included in program design and evaluation.

Finally, to the extent that these results may in part be determined by unmeasured influences specific to California, research to corroborate or refute these results, based on data from other jurisdictions, would be invaluable to increasing understanding.

Footnotes

1. The probability of arrest measure used is the ratio of clearances for homicide to the number of homicides. Unfortunately, these clearance data are not reported as line items, but rather only in summary fashion. Thus, the calculation of crime-type-specific arrest probabilities is impossible. The probability of conviction measure is taken as the ratio of convictions for murder to the number of arrest dispositions for murder. The threat of execution measure, P_{DS}, is the ratio of the number of death sentences imposed to the number of murder convictions.

2. No measure of alternative penal sanctions, such as length of imprisonment, was included for several reasons. First, it is difficult to conceive of a useful measure of expected sentence length when the unit of observation is the county, while sentencing statutes apply statewide. The measure typically used is the average length of time served by prisoners released in the current period. When this measure was employed in the current analysis, it entered with traditionally plausible sign, but was highly insignificant. As it caused minimal changes in other parameter values, it was dropped from the analysis. Further, California's determinate sentencing law was enacted in 1978, under which persons convicted of a given offense receive (and serve) a set term. This bears on the analysis in two ways. First, the average sentence of prisoners currently released from prison, who were necessarily sentenced under earlier indeterminate sentencing practices, is likely to be an inadequate measure of expected sentence for individuals currently contemplating a crime. Second, it suggests that the expected sentence should equal the statutory sentence, which is then equal across counties and over time (at least since 1978). The effect of this expected sentence variable is therefore subsumed in the constant term. While the determinate sentencing law then precludes estimation of the effect of alternative sanctions, it

also ensures that the other parameters estimated are not corrupted by omitted variable bias.

3. Both of these measures are from California Department of Finance sources.

4. Data for *PLBG* were obtained from the *Annual Report of the California Judicial Council.*

5. For example, while the mean homicide rates for the more and less populous counties were roughly equal, the variance of the latter was twice that of the former. Further, in tiny Alpine county, population 1100, homicide rates per 100,000 would swing from zero, or roughly one standard deviation below the mean, to 111, or more than *ten* standard deviations above the mean, as the result of one homicide there.

6. Results from the top 20 and top 31 counties, or all those included in a Metropolitan Statistical Area, were very similar.

7. Further specification tests were performed on the reduced forms of the homicide equations, both as a further, general check on the adequacy of the models, and to ensure that rejection of the exogeneity hypothesis was in fact attributable to simultaneity bias, rather than some other form of misspecification detected by the tests. These test results, and the reduced form equations on which they are based, are reported in the Appendix. In general, these tests indicate the overall adequacy of the specification of the models, and suggest that the rejection of the exogeneity tests in the *HRAT* and *HPRAT* equations was due to simultaneity bias.

Appendix

In Table A1 are presented the four reduced form homicide equations implied by the instrumental variables estimation reported in Section III. Table A2 contains several χ^2_{16} test statistics used both to test the general adequacy of the specifications and to determine whether rejection of the exogeneity tests reported in Section IV might be due to some form of misspecification other than simultaneously bias.

The tests were conducted by comparing OLS estimates of the reduced form with weighted or generalized least squares (GLS) estimates, where the weights used were various functions of the instrumental variables. Under the null hypothesis of no model misspecification, OLS and GLS estimates are both consistent, and OLS estimates are efficient, as well. Hausman's method can be used in such circumstances to compute general tests of model specification. The test statistics presented in Table A2 take the general form

$$H = (\hat{\beta}_{GLS} - \hat{\beta}_{OLS})' \, [\hat{V}(\hat{\beta}_{GLS}) - \hat{V}(\hat{\beta}_{OLS})]^{-1} \, (\hat{\beta}_{GLS} - \hat{\beta}_{OLS})$$

The statistic H has an asymptotic χ^2 distribution with degrees of freedom equal to the number of parameters in the model.

Turning to the results of the tests in Table A2, one sees that the null hypothesis of no misspecification is accepted at the 5 per cent level for all tests except one. The rejection of the null when the observations were weighted was largely due to changes in the estimated *REPVOT* and *PINC* coefficients. Taken as a whole, however, the test results appear to indicate the overall adequacy of the specification of these equations, and bolster our confidence that the rejection of the exogeneity tests in the *HRAT* and *HPRAT* models was in fact due to simultaneity bias.

Table 1

VARIABLE DEFINITIONS

Variable	*Definition*
HRAT	Overall Homicide Rate
HPRAT	Rate of homicides known to have been committed pursuant to robberies or burglaries
HRRAT	Rate of homicides in which victim and offender are known to be related.
HSRAT	Rate of homicides in which victim and offender are known to be married.
P_{ARR}	Arrest probability
P_{CON}	Probability of conviction for murder, given conviction
P_{DS}	Probability of receiving a death sentence, given conviction
UNEMP	Unemployment rate
PINC	Real personal income per capita

Table 2

SUMMARY STATISTICS

Variable	Mean	Standard deviation
HRAT	9.32	4.74
HPRAT	1.28	1.12
HRRAT	1.39	0.81
HSRAT	0.69	0.54
P_{ARR}	0.71	0.14
P_{CON}	0.43	0.22
P_{DS}	0.037	0.089
UNEMP	8.52	2.69
PINC	43.41	7.96
POLEXP	67.48	19.07
JUDEXP	0.03	0.005
PLBG	72.41	9.62
REPVOT	34.88	6.05

Table 3

ORDINARY LEAST SQUARES ESTIMATION RESULTS

Variable	Category			
	HRAT	*HPRAT*	*HRRAT*	*HSRAT*
CONSTANT	47.11	6.61	5.10	2.55
	(13.10)	(6.59)	(6.29)	(4.30)
P_{ARR}	-5.15	-1.06	0.72	0.29
	(-3.50)	(-2.63)	(1.83)	(1.06)
P_{CON}	-3.23	-0.14	-0.46	-0.24
	(-3.65)	(-0.48)	(-2.30)	(-1.76)
P_{DS}	8.67	0.79	0.56	0.27
	(5.35)	(1.65)	(1.09)	(0.68)
UNEMP	0.21	0.13	-0.0062	-0.021
	(1.93)	(3.48)	(-0.24)	(-1.17)
PINC	-0.13	0.011	-0.078	-0.015
	(-3.66)	(1.12)	(-3.46)	(-2.60)
WHITE	-0.37	-0.079	-0.034	-0.012
	(-15.90)	(-10.60)	(-5.76)	(-2.89)
Y77	1.11	0.52	0.042	-0.17
	(1.34)	(2.36)	(0.16)	(-0.96)
Y78	1.19	0.44	-0.022	-0.17
	(1.58)	(2.36)	(-0.15)	(-0.94)
Y79	2.37	0.54	0.11	-0.042
	(3.38)	(3.01)	(0.51)	(-0.25)
Y80	2.47	0.64	-0.16	-0.26
	(2.71)	(2.91)	(-0.68)	(-1.51)
Y81	1.58	0.69	0.039	-0.026
	(1.77)	(3.04)	(0.18)	(-0.15)
Y82	-1.06	0.18	-0.19	-0.30
	(-1.49)	(0.84)	(-0.83)	(-1.78)
Y83	-2.16	-0.14	-0.26	-0.37
	(-2.94)	(-0.71)	(-1.30)	(-2.23)
Y84	-1.19	0.077	-0.20	-0.30
	(-1.53)	(0.40)	(-0.92)	(-1.91)
R^2	.60	.49	.22	.13
Adjusted R^2	.58	.45	.17	.07
Standard Error	3.08	0.83	0.74	0.52

t-statistics (in parentheses) based on standard errors of White (1985)

Table 4

INSTRUMENTAL VARIABLES ESTIMATION RESULTS

Variable	Category			
	HRAT	*HPRAT*	*HRRAT*	*HSRAT*
CONSTANT	99.65	23.62	3.00	0.18
	(8.55)	(8.18)	(1.07)	(0.09)
P_{ARR}	-47.23	-16.86	5.28	5.13
	(-3.30)	(-4.76)	(1.53)	(2.14)
P_{CON}	-56.18	-12.05	-7.07	-6.00
	(-3.31)	(-2.87)	(-1.73)	(-2.11)
P_{DS}	-13.70	-7.07	-10.27	-5.32
	(-0.61)	(-1.28)	(-1.90)	(-1.42)
UNEMP	0.26	0.094	0.058	0.042
	(1.28)	(1.90)	(1.22)	(1.26)
PINC	-0.32	-0.059	-0.0087	0.0042
	(-4.65)	(-3.44)	(-0.52)	(0.04)
WHITE	-0.19	-0.024	-0.022	-0.0069
	(-4.29)	(-2.19)	(-2.06)	(-0.93)
Y77	-3.10	-1.01	-0.037	-0.036
	(-2.05)	(-2.70)	(-0.10)	(-0.14)
Y78	-2.13	-0.78	-0.17	-0.12
	(-1.56)	(-2.30)	(-0.52)	(-0.50)
Y79	0.66	-0.31	0.66	0.49
	(0.41)	(-0.79)	(1.69)	(1.82)
Y80	-0.56	-0.64	0.20	0.19
	(-0.34)	(-1.56)	(0.50)	(-0.68)
Y81	-4.91	-0.92	-0.58	-0.54
	(-2.60)	(-1.97)	(-1.28)	(-1.70)
Y82	-11.97	-2.05	-1.58	-1.63
	(-2.86)	(-1.97)	(-1.57)	(-2.33)
Y83	-12.45	-2.68	-0.68	-0.85
	(-4.46)	(-3.87)	(-1.02)	(-1.82)
Y84	-13.30	-3.04	-0.74	-0.82
	(-4.56)	(-4.22)	(-1.05)	(-1.67)
Joint χ^2_{15}	211.31	189.41	53.48	35.09
Standard Error	3.06	0.76	0.74	0.51

t-statistics in parentheses

Table 5

HAUSMAN TESTS FOR ENDOGENEITY

Coefficients	Category			
	HRAT	*HPRAT*	*HRRAT*	*HSRAT*
P_{ARR}	-4.70	-0.89	0.59	0.19
P_{CON}	-2.70	0.032	-0.47	-0.25
P_{DS}	8.66	0.77	0.69	0.34
$\hat{P}_{ARR}$	-36.57	-15.59	5.20	5.23
$\hat{P}_{CON}$	-57.67	-12.52	-6.68	-5.83
$\hat{P}_{DS}$	-32.06	-9.83	-9.57	-5.19
F	11.65	16.48	1.81	2.30
prob $F_{3,206}$	0.00	0.00	0.145	0.075

Table 6

ELASTICITIES OF VARIABLES WITH TRADITIONAL SIGNS*

Elasticity	Category			
	HRAT	*HPRAT*	*HRRAT*	*HSRAT*
$\epsilon_{P_{ARR}}$	-3.61	-9.38	---	---
$\epsilon_{P_{CON}}$	-2.57	-4.00	-0.14	-0.15
$\epsilon_{P_{DS}}$	-0.0055	-0.021	---	---
ϵ_{UNEMP}	0.23	0.63	---	---
ϵ_{PINC}	-1.50	-2.00	-0.87	-0.94

* evaluated at sample means

Table A1

REDUCED FORM ESTIMATES OF THE HOMICIDE EQUATIONS

Variable	Category			
	HRAT	*HPRAT*	*HRRAT*	*HSRAT*
CONSTANT	28.70	1.99	7.13	3.72
	(5.31)	(1.49)	(5.61)	(4.15)
POLEXP	0.10	0.03	-0.004	-0.004
	(5.07)	(6.36)	(-0.80)	(-1.39)
JUDEXP	0.008	-0.21	-0.04	-0.02
	(0.07)	(-0.83)	(-1.80)	(-1.09)
PLBG	-0.02	-0.006	-0.01	-0.004
	(-0.76)	(-0.88)	(-2.13)	(-0.91)
REPVOT	0.07	0.003	0.009	-0.002
	(1.45)	(0.29)	(0.88)	(-0.23)
UNEMP	0.28	0.14	-0.02	-0.03
	(2.08)	(4.29)	(0.76)	(-1.43)
PINC	-0.12	0.006	-0.03	-0.02
	(-3.13)	(0.57)	(-3.03)	(-2.40)
WHITE	-0.28	-0.05	-0.43	-0.02
	(-7.27)	(-4.73)	(-4.76)	(-2.63)
Y77	-0.90	-0.06	0.12	-0.08
	(-0.90)	(-0.25)	(0.52)	(-0.48)
Y78	-1.91	-0.51	0.05	-0.06
	(-1.74)	(-1.88)	(0.20)	(-0.31)
Y79	-0.46	-0.37	0.20	0.09
	(-0.41)	(-1.36)	(0.77)	(0.47)
Y80	0.25	-0.05	-0.09	-0.16
	(0.24)	(-0.21)	(-0.36)	(-0.94)
Y81	0.34	0.18	0.22	0.09
	(0.34)	(0.77)	(0.97)	(0.57)
Y82	-1.38	-0.14	0.10	-0.13
	(-1.41)	(-0.60)	(0.46)	(-0.81)
Y83	-2.95	-0.62	-0.20	-0.21
	(-2.87)	(-2.45)	(-0.08)	(-1.22)
Y84	-2.14	-0.44	0.04	0.13
	(-2.08)	(-1.72)	(0.16)	(-0.75)
R^2	.59	.56	.22	.13
Standard Error	3.13	0.77	0.74	0.52

Table A2

HAUSMAN TESTS FOR GENERAL MISSPECIFICATION

Weights	Category			
Square root of:	*HRAT*	*HPRAT*	*HRRAT*	*HSRAT*
POLEXP	7.53	7.35	2.33	5.81
TOTEXP[a]	7.52	7.35	2.31	5.78
REPVOT	4.85	34.39*	15.90	--

Notes:

a - TOTEXP = POLEXP + JUDEXP

* - Significant at 5 per cent
Dashed cell indicates non-positive definiteness of covariance matrix. Other instruments (JUDEXP, PLBG) were also used as weights, but covariance matrices were not positive definite.

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