A Bayesian Exploration of the Relationship Between Crime and Unemployment in New Zealand for the Time Period: 1986-2002

Jonathon C Bannatyne[1,2] and Howard P Edwards[2]

Massey University

ABSTRACT

Traditionally, crime-unemployment studies focus on providing inference towards demonstrating causality. However, a definitive model of the complex crime unemployment nexus which can explain the relationship for any given geographical domain, social grouping or economic jurisdiction in any time period has not yet been constructed. Rather than attempting to explain the crime/unemployment relationship by conducting statistical tests, this study uses a Bayesian approach to scenario analysis based on New Zealand crime data reported by year and police district. Using only three years of data, it is shown that a Bayesian hierarchical model can achieve similar results to those of an earlier study based on 12 years of data, and has the potential to provide useful district-specific models. The implications for a longitudinal study over a longer time period are discussed.

[1] Principal Author
[2] Institute of Information and Mathematical Sciences, Massey University at Albany, Private Bag 102-904, North Shore Mail Centre, Auckland, New Zealand

INTRODUCTION

Investigations centred on the relationship between crime and unemployment have historically been numerous and varied. Most studies have focused on the existence of a relationship between crime and unemployment, although some have focused on affirming the direction of causality of the relationship. A theoretical econometric basis for the existence of a relationship and direction of causality from unemployment to crime was posited by Becker (1968) and extended by Ehrlich (1973).

Investigations of the relationship between crime and unemployment in New Zealand have been made by Small and Lewis (1996) and Papps and Winkelmann (2000). The latter study, which covered the time period 1984 to 1996, used two-way fixed effect (police district and time period) Ehrlich-type regression models of log natural crime rate on several predictor variables (including log unemployment rate) for seven crime categories plus total crime. The results of the study were that at a ten percent level of significance, linear models for four crime categories were found to possess a significant unemployment elasticity of crime rate. For the crime rate models estimated, all but one of the unemployment elasticities for crime rate were positive, in common with most studies of other countries.

This study extends the work of Papps and Winkelmann by analysing a much smaller but more recent data set and using two sets of hierarchical Bayesian models for eight different crime rates. The first set of models (which correspond to Papps and Winkelmann's approach) use common values for the predictor variable coefficients (elasticities) but different constants for the twelve police districts; whereas the second set of models use different values for both the elasticities and the constants. The aims are three-fold:

1) To see whether comparable results (in level and precision) are obtained using a smaller data set and employing Bayesian methodology;
2) To examine the potential of district-specific models for explaining regional effects; and
3) To examine the implications for a larger study involving a larger data set.

THE MODELS

Ehrlich suggested a mean (group) supply-of-offence equation

$$(Q/N)_i \quad = \quad P_i^{\,a} F_i^{\,b} Y_i^{c} Y_l^{d} U_l^{\,e} V^{f} Z_i \qquad (1)$$

where $(Q/N)_i$ is the number of offences in crime category i committed by the average person in the community (i.e. the crime rate), V is a vector of environmental variables, P_i relates to the (average subjective) probability of criminal apprehension and hence reduction in the returns to crime, U_l is the probability of being unemployed in (legal) activity, Z_i summarises the effect of psychic and other non-quantifiable variables on the crime rate, and F_i, Y_i, and Y_l are arithmetic means of the monetary components of f_{ij}, w_{ij} and w_{lj} (Ehrlich, 1973). Note that i (also) refers to illegal activities and l refers to legal activities.

The latter three variables relate to an individual j and are defined respectively as:

$$f_{ij} \ = \ d(F_{ij})/d(t_{ij}) \qquad w_{ij} \ = \ d(W_{ij})/d(t_{ij}) \qquad w_{lj} \ = \ d(W_{lj})/d(t_{lj}) \qquad (2)$$

Where F_{ij} relates to the value of the penalty (perhaps loss of illegally acquired assets) if an individual is apprehended and punished, and W_{ij} and W_{lj} relate to the return from illegal activity and legal activity respectively.

A stochastic additive version of (1) is given by

$$ln(Q/N)_i \ = \ K + a\ lnP_i + b\ lnF_i \ + c\ lnY_i + d\ lnY_l + e\ lnU_l \ + f\ lnV \ + m \qquad (3)$$

where K is a constant and m represents unexplained error (Ehrlich (1973)).

The two sets of models employed for the New Zealand study are

Set 1:

$$meanCR_{ij} = beta.constanta_i + beta.un*un_{ij} + beta.det*det_{ij} + beta.inc*inc_{ij} + beta.gst*gst_{ij} + beta.nzsei*nzsei_{ij} + beta.pop*pop_{ij} + error_{ij}$$

Set 2:

$$meanCR_{ij} = beta.constanta_i + beta.un_i*un_{ij} + beta.det_i*det_{ij} + beta.inc_i*inc_{ij} + beta.gst_i*gst_{ij} + beta.nzsei_i*nzsei_{ij} + beta.pop_i*pop_{ij} + error_{ij}$$

where

$meanCR_{ij}$ is the mean natural log crime rate;

un_{ij} is the natural log unemployment;

det_{ij} is the natural log 'deterrence rate';

inc_{ij} is the natural log of personal average weekly income;

gst_{ij} is the natural log of the "CPI for all groups" corrected tertiary sector GST sales (in millions of dollars);

$nzsei_{ij}$ is the natural log of the average New Zealand Socio-Economic Index score by occupation major group;

pop_{ij} is the natural log of the usually resident population estimated by Statistics New Zealand;

$error_{ij}$ is assumed random normal error with mean zero and constant variance;

in each case, for the ith police district (i = 1, …, 12) and jth year (j = 1,2,3, starting in 2000). There are eight types of model in each set, corresponding to the seven crime categories used by the New Zealand police (violent, drug and antisocial, dishonesty, property damage, property abuse, sexual, administrative) together with total crime.

The constants $beta.constanta_i$ and coefficients or elasticities *beta.un*, $beta.un_i$ etc are the model parameters. In Set 1 models the constant varies across police districts but the elasticities are the same (in common with Papps and Winkelmann's study), however in Set 2 models both the constant and elasticities vary across districts. See Bannatyne (2003) for a fuller description of the predictor variables including discussion of their "proxy" status for the underlying traits of Ehrlich's model.

BAYESIAN ANALYSIS

“Standard” hierarchical Bayes models are used for each model set. In Set 1, each elasticity is given a diffuse normal prior and the constant terms an exchangeable normal prior with diffuse hyperpriors for the mean (normal) and precision (gamma). In Set 2, each set of elasticities and the constant terms are each given an exchangeable normal prior with diffuse hyperpriors for the mean (normal) and precision (gamma). In other words, exchangeability across police districts is assumed. Appropriate thinning of chains and centring of variables to reduce autocorrelation was employed. See Bannatyne (2003) for details.

Figure 1: WinBUGS doodle for Set 1 model.

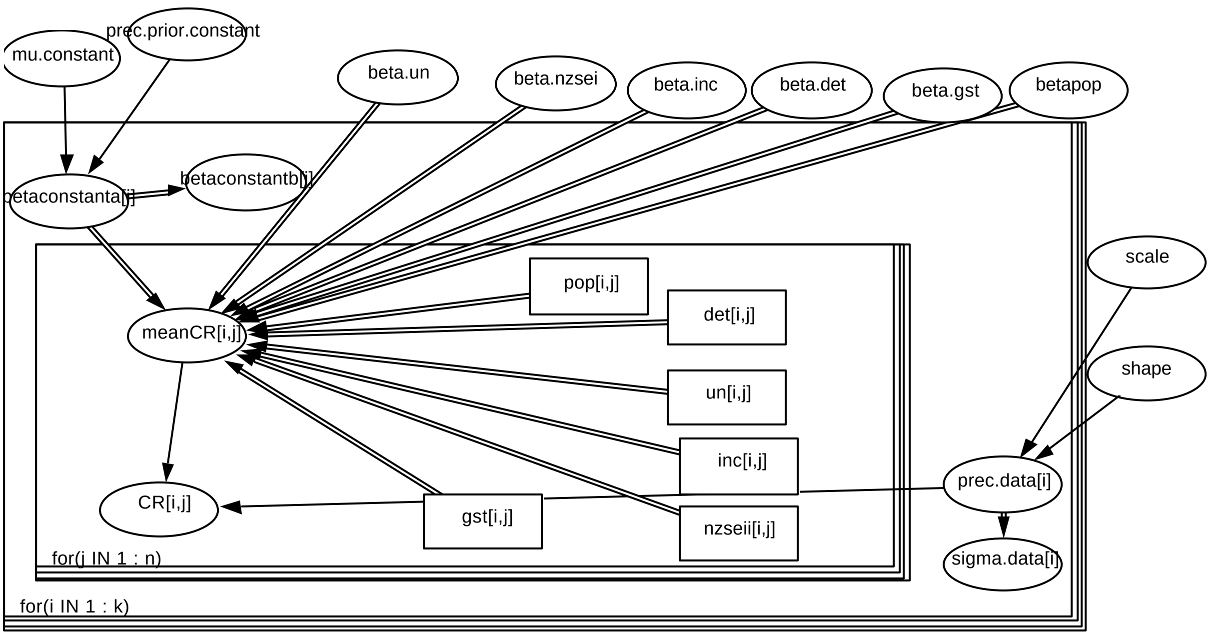
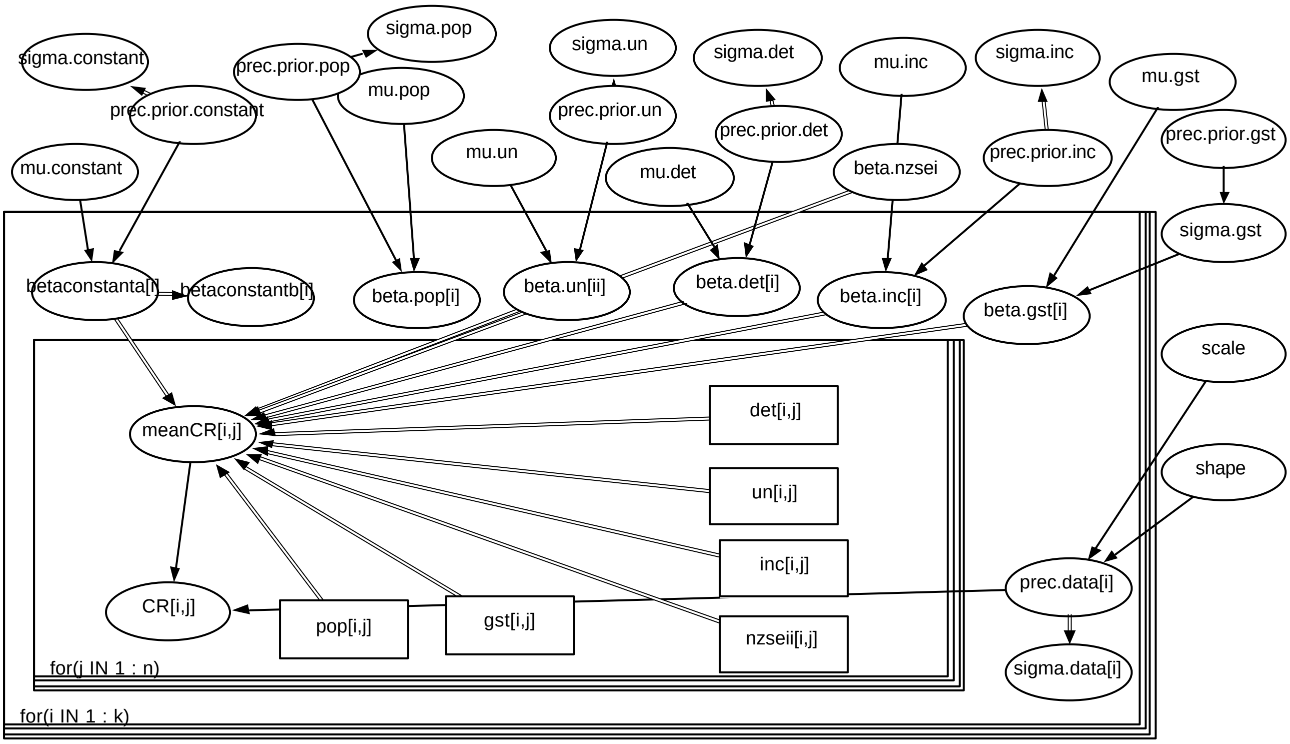


Figure 2: WinBUGS doodle for Set 2 model.



COMPUTATIONAL ASPECTS

A full examination of all the models in Set 1 or Set 2 requires extensive computational time for MCMC simulation of all relevant nodes, as there are 12 police districts × 8 crime categories = 96 models in each set, with six predictor variables in each model. Therefore attention was restricted to (i) models with one predictor variable un_{ij}, and (ii) models with predictor variables un_{ij}, det_{ij} and inc_{ij}. As well as reducing the amount of computation, these models also provide a direct comparison with Papps and Winkelmann's study where the same sets of predictor variables were used.

For a full discussion of these and other models used, including convergence and model fitting diagnostics, see Bannatyne (2003).

RESULTS

Estimates of log unemployment elasticities: comparison of Papps and Winkelmann's (PW) models (mean and *SE*) **with Set 1** (posterior mean and *posterior SD*) **and Set 2** (average posterior mean and *posterior SD*) **hierarchical Bayes models with one predictor variable *log unemployment* (un_{ij})**

Crime category	PW	Set 1	68% intervals overlap?	Set 2	68% intervals overlap?
Total	0.08 *0.048*	-0.00578 *0.05175*	Yes	-0.03221 *0.07722*	Yes
Violent	0.109 *0.064*	-0.2192 *0.09471*	No	-0.2814 *0.12670*	No
Drug & Antisocial	-0.043 *0.118*	0.0301 *0.08081*	Yes	0.000382 *0.09544*	Yes
Dishonesty	0.188* *0.093*	0.1264 *0.06829*	Yes	0.1251 *0.08153*	Yes
Property Damage	0.031 *0.047*	-0.1218 *0.09188*	No#	-0.2532 *0.14110*	No
Property Abuse	0.064 *0.083*	-0.241 *0.1085*	No	-0.1469 *0.12620*	No#
Sexual	0.300* *0.107*	-0.2856 *0.2004*	No	-0.6072 *0.29480*	No
Administrative	0.569* *0.148*	-0.468 *0.2612*	No	-0.4401 *0.37840*	No

* Significant at the 10% level
# Not by much

Estimates of log unemployment elasticities: comparison of Papps and Winkelmann's (PW) models (mean and *SE*) **with Set 1** (posterior mean and *posterior SD*) **and Set 2** (average posterior mean and *posterior SD*) **hierarchical Bayes models with three predictor variables *log unemployment* (un_{ij}), *log deterrence rate* (det_{ij}), and *log average weekly income* (inc_{ij}).**

Crime category	PW	Set 1	68% intervals overlap?	Set 2	68% intervals overlap?
Total	0.088* *0.047*	-0.06718 *0.1191*	Yes	-0.06456 *0.1345*	Yes
Violent	0.075 *0.059*	-0.0676 *0.1939*	Yes	-0.1561 *0.2312*	Yes
Drug & Antisocial	-0.037 *0.104*	-0.2064 *0.1641*	Yes	-0.360 *0.1876*	No#
Dishonesty	0.156* *0.091*	0.06502 *0.120*	Yes	0.0852 *0.1363*	Yes
Property Damage	0.037 *0.044*	-0.4713 *0.1878*	No	-0.5578 *0.2333*	No
Property Abuse	0.093 *0.072*	-0.5306 *0.1831*	No	-0.8109 *0.2629*	No
Sexual	0.326* *0.144*	-0.296 *0.2862*	No	-0.6671 *0.4705*	No
Administrative	0.576* *0.148*	-0.7735 *0.471*	No	-0.6619 *0.6508*	No

* Significant at the 10% level
\# Not by much

CONCLUSIONS AND FURTHER WORK

Almost half the parameter estimates obtained using the Bayesian models were consistent with those obtained by Papps and Winkelmann despite using data from a different time period. More importantly, similar precision was obtained from the Bayesian Set 1 models despite having only 3 years of data as opposed to 12 years for Papps and Winkelmann. In other words a hierarchical Bayesian model (assuming exchangeability across police districts) is potentially more efficient and should therefore produce more precise parameter estimates for a longitudinal study, i.e. using data from a larger time period. This is currently being carried out using 12 years of data to 2002.

Secondly, the Set 2 models, although presenting some MCMC convergence issues, have the potential to produce better models by police district (different elasticities). It is intended to extend these to the longitudinal study as well.

REFERENCES

Bannatyne, JC (2003). Crime and unemployment: a Bayesian extension to the New Zealand literature. MApplStat thesis (in preparation), Massey University.

Becker, GS (1968). Crime and punishment: an economic approach. *Journal of Political Economy*, 76, 169-217.

Ehrlich, I. (1973). Participation in illegitimate activities: a theoretical and empirical investigation. *Journal of Political Economy*, 81, 521-565.

Papps, K and Winkelmann, R (2000). Unemployment and crime: new evidence for an old question. *New Zealand Economic Papers,* 34(1), 53-72.

Small, J and Lewis, C (1996). Economic crime in New Zealand: causation or coincidence? University of Auckland Department of Economics working paper #158.