Unemployment and crime: New evidence for an old question

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This paper uses panel data techniques to examine the relationship between unemployment and a range of categories of crime in New Zealand. The data cover sixteen regions over the period 1984 to 1996. Random and fixed effects models are estimated to investigate the possibility of a causal relationship between unemployment and crime. Hypothesis tests show that two-way fixed effects models should be used. The main result of the paper is that there is some evidence of significant effects of unemployment on crime, both for total crime and for some subcategories of crime.

We are grateful to Rachel Bambery, New Zealand Police National Headquarters, for her assistance in obtaining crime and population statistics. The staff of the University of Canterbury Library also gave invaluable help in unraveling the complexities of New Zealand unemployment and income data. The paper has benefited from useful comments by two anonymous referees, Simon Kemp, Jacques Poot and participants of the CEPR conference on “Metropolitan Economic Performance”, Lisbon, October 1998.

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1. Introduction

It is a common observation for many countries that unemployment rates and crime rates are positively associated. A more contentious issue is whether this association means that unemployment causes crime, crime causes unemployment or third factors cause both. Only the first of the three possibilities would imply that the effects of unemployment on crime deserve to be counted among the “non-pecuniary” costs of unemployment that should be taken into account in a cost-benefit analysis of potential unemployment-reducing policies.

The theoretical underpinning of the causality notion was developed some thirty years ago by Becker (1968), Stigler (1970) and Ehrlich (1973), among others. In Ehrlich’s model, individuals divide their time between legal activities and risky illegal activities. If legal income opportunities become scarce relative to potential gains from crime, the model predicts that crime will become more frequent. Increased unemployment could be one such factor.

Numerous subsequent empirical papers have attempted to test the predictions of the Becker-Ehrlich model and to find out whether the magnitude of the unemployment effect is quantitatively important. The hallmark of this literature is its failure to reach consensus as to whether higher levels of unemployment lead to a greater incidence of crime. In a survey of the literature, Box (1987) reports 35 reliable studies on the topic, 20 of which find a positive relationship between unemployment and crime, with the remainder unable to find any such relationship. In the context of New Zealand, a previous econometric study by Small and Lewis (1996), based on time-series techniques and Granger causality tests, lends “strong support to the idea that crime and unemployment are linked in some way” and that unemployment causes crime more often than vice versa.

The objective of this paper is to revisit the issue of whether unemployment has a causal effect on various categories of economic and anti-social crime. For this purpose, we analyse New Zealand regional panel data, regressing crime rates on unemployment rates using fixed and random effects models. Our approach solves several of the problems that have been characteristic of previous empirical papers. In particular, we cannot reject the hypothesis that unobservable period specific effects are correlated with the unemployment rate. This finding suggests that time series regressions will likely be affected by omitted variable bias. Still, we find some evidence that unemployment matters even after time, region, deterrence, and income effects are accounted for.
The paper is structured as follows. Section 2 commences with an eclectic review of some
previous empirical studies. Section 3 gives a discussion of some general data issues as well as a
description of the data that were actually used in this study. The results from the various models
are presented in Section 4. Section 5 concludes with commentary on the implications of these
findings and possible improvements that could be made to the analysis.

2. Previous Studies

As mentioned in the introduction, a consensus as to whether higher levels of unemployment
lead to a greater incidence of crime has not yet been reached. Differences in the results may be
related to a variety of factors: differences in the type of data used and differences in the definition
of crime being two of them.

The empirical literature on the topic of crime and unemployment typically is based on one of
four types of data: aggregate (national) time series data, aggregate cross-section data, regional
panel data or individual level data (cross-sections or panel). Studies of the first two types often
and Brenner (1978) are some early examples. While these studies to varying degrees attempt to
test other factors, they still are likely to be affected by omitted variable bias. The
availability of regional panel data can ameliorate this problem and, indeed, when such data are
used, the evidence is much less supportive of a causal relationship. For example, Entorf and
Spengler (1998) conducted a regional panel study for Germany and found unemployment to have
“small, often insignificant and ambiguous signs”.

With individual level data, one observes the labour market status of a particular offender at
the time of committing a crime. Studies include Myers (1983), Schmidt and Witte (1984),
Trumball (1989), Tauchen et al. (1994), and Grogger (1991). There are several advantages of
such data: the number of observations is large, these datasets usually provide a large number of
controls and it becomes possible to focus on particular sub-populations, such as the socially less-
advantaged, where an effect might be more likely to occur. With individual level panel data, one
can solve the most common omitted variable problems by comparing the crime propensities of
the same individuals in different employment states. Unfortunately, such individual level panel
data are rarely available and, in their absence, the use of regional panel data is arguably the
“second-best” methodological option.

An independent issue is the definition of crime, with the distinction between economic and
anti-social crime. Economic crimes are those where the motivation is pecuniary gain, while anti-
social crimes are committed for some other reason. Most economic studies have focused on the link between unemployment and economic crimes since such a relation is supported by economic theory, which predicts that potential offenders compare the costs and benefits associated with crime. Nevertheless, the notion that increases in unemployment lead to increases in anti-social crime has been proposed by sociologists and others. As a consequence, the total costs of unemployment may be higher than some studies predict.

Finally, the issue of whether reported crime accurately reflects the actual number of committed crimes arises. Using reported crime might be a misleading indicator of the total amount of crime in society as not all crimes committed are reported to the police. Hence, this measure is dependent on the public’s proclivity to report crimes to the police. This would be of minor empirical importance unless the likelihood that crimes are reported has changed significantly over time. There is some evidence, however, that this was the case. For instance, surveys conducted by Market Research Limited (M.R.L.) in 1993 and 1995 found that the proportion of victims who had reported the most recent crime to the police increased from 67% to 77% between these years. The use of regional panel data will give estimates that are unaffected by this measurement issue as long as the reporting propensity changes in different regions at the same rate over time.¹

3. Data

Annual data on the level of crime were obtained from the New Zealand Police for the period 1984-1996 for 16 police districts. This included the number of offences reported to police in each police district for seven offence groups and the total number of crimes, which they collectively comprise. Numbers are transformed into crime rates by division with the regional population size (in thousands). The reported crime rate for each category is denoted by o₁ to o₇, respectively, while the overall crime rate is represented by o (for “offence”).

The groups used by the New Zealand Police are: violent offences; drug and anti-social offences; dishonesty offences; property damage offences; property abuse offences; sexual offences; administrative offences. One should thus notice that the overall crime rate aggregates very different types of crimes. Even within each category, there is a substantial amount of heterogeneity (see Appendix). While it would be desirable to consider more homogeneous groups, such data were not available to us. The heterogeneity means that any unemployment effect needs to be interpreted as an average effect that may differ from the effect of

¹ This is an assumption we have to make and that we cannot verify given the available data.
unemployment on any component crime. The heterogeneity is moreover likely to drive up the residual variation, and thereby the standard errors, of the estimates.

There are a variety of measures of unemployment in New Zealand. The official measure is derived from the Household Labour Force Survey (HLFS), a quarterly survey by Statistics New Zealand. The HLFS provides estimates which are internationally comparable and are not subject to changes in the definition of “being unemployed”. Unfortunately, the series only includes sub-national estimates since 1990. The quinquennial Census of Population and Dwellings provides the most complete survey of unemployment in New Zealand. However, drawbacks are the infrequent observations provided and the fact that different definitions of unemployment have been used over time.

Because of these shortcomings, the measure of unemployment selected for this study was the number of people registered as unemployed with the Department of Labour, hereinafter denoted by $UN$. Annual averages of this series were obtained for each of 21 employment districts for the same period from Statistics New Zealand’s INFOS and were then matched to the 16 police districts. Unemployment rates were obtained by division with a population estimate and were denoted by $un$. We acknowledge that this is a less than perfect measure of legal employment opportunities. Part of unemployment is related to job search, the length of which depends on many factors apart from job availability, including benefit levels and eligibility. Ideally, we would have liked to include a measure of long-term unemployment but such a statistic was not available for the full time period and the required regions.

As will be explained later, possible determinants of the crime level other than unemployment are also investigated in the study. Firstly, the clearance rate for each offence group was obtained from the New Zealand Police. This is given by the ratio of the number of crimes cleared by police to the total number of crimes reported for each region and crime sub-category. The overall clearance rate is denoted $p$ while the clearance rates for each offence group are denoted $p1$-$p7$, where the index matches the crime sub-category number.

Secondly, information on the average level of income for each region was obtained. Since there is no annual sub-national data for income in New Zealand, information from the 1986, 1991

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2 This is also the series Small and Lewis (1996) used in their study on the subject. Registered unemployed are those who have chosen, as one of their methods of job search, to enrol with the New Zealand Employment Service and who are available for employment.

3 Details on the matching protocol are available from the authors.

4 An estimate of the population of each region was used since the only adequate data were derived from the Census and, hence, involved interpolation. Since the labour force participation rate fluctuates over the business cycle, it was not appropriate to calculate a labour force estimate in this manner.
Figure 1
New Zealand Unemployment Rate and Crimes per 1000 Residents

![Figure 1](image)

Source: New Zealand Police (o), Statistics New Zealand (un)

and 1996 Censuses on mean personal income for each police district was used. To obtain a complete panel, the income of each district relative to the national average was calculated, using a linear time trend to extrapolate the missing observations. An annual index of real GDP per capita for all New Zealand was derived from the New Zealand National System of Accounts for 1984-1996, based on 1984 = 1000. The income series used in this study, denoted y, was the product of this series and the estimate of the relative income of each region for the appropriate year.

4. Results and Analysis

Figure 1 plots the national unemployment rate and the total crime rate between 1978 and 1996. There is visual evidence that the two series move closely together over time, and the correlation coefficient, r, can be calculated as 0.41. However, as mentioned in the introduction, this is by no means an indication of causality from unemployment to crime. While the hypothesis of reverse causation (from crime to unemployment) seems implausible a priori (although there may be such a feedback process in individual cases), third variables are likely to affect both crime and unemployment.

Information for the years 1978 to 1983 is available at the aggregate level. However, it could not be used in the econometric analysis, as changes in the definition of police districts made a comparable disaggregation impossible.
In order to evaluate and control for the potential influence of third factors, we employ regression analysis. Our general strategy is to start with a very simple model and successively generalize. Following Entorf and Spengler (1998), we use a log-log specification of the unemployment-crime relation in all cases. This gives rise to an estimated coefficient that has the interpretation of an elasticity. A log-log model is also consistent with Ehrlich (1973), who suggested a multiplicative form for the supply-of-offences function when variables are in levels.

One extreme possibility is that unemployment is the sole determinant of the crime rate and that the parameters of the model are identical, regardless of what region or year an observation is drawn from. This implies that a pooled regression can be applied to the data as follows:

\[ \ln o_{it} = \alpha + \beta \ln u_{it} + \varepsilon_{it}. \] (1)

Here the subscript \( i \) indicates the region of the observation and \( t \) the year of the observation. \( \varepsilon_{it} \) denotes the residual associated with observation \( it \). The error term, \( \varepsilon_{it} \), is assumed to have mean zero. Moreover,

\[ E(\varepsilon_{it}, \varepsilon_{js}) = \begin{cases} \sigma_i^2 & \text{for } i = j \text{ and } t = s \\ 0 & \text{else} \end{cases}. \]

Therefore, the model allows for region-specific heteroskedasticity that is accounted for in the computation of the variance-covariance matrix of the OLS estimator for \( \beta \).

The first column of Table 1 reports the parameter estimates, \( \hat{\beta} \), obtained from pooled regressions of the logarithmic crime rates on the logarithmic unemployment rates. These are based on a total of eight separate regressions (one for each type of crime, plus the total). The first row of Table 1 gives the value for the total crime rate. \( \hat{\beta} \) is positive and statistically different from zero. The value of 0.144 indicates that a 10% increase in the unemployment rate is associated with an increase in the crime rate of about 1.4%.
### Table 1
OLS Regression Results: Estimated Unemployment Elasticities

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<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
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<td><strong>Total offences</strong></td>
<td>0.144*</td>
<td>0.038</td>
<td>0.163*</td>
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<td>(0.023</td>
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<td>0.364*</td>
<td>0.065</td>
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<td>(0.042</td>
<td>(0.068</td>
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<td>-0.043</td>
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<td></td>
<td>(0.041</td>
<td>(0.080</td>
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<td>0.350*</td>
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<td>(0.036</td>
<td>(0.068</td>
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<td><strong>Property damage offences</strong></td>
<td>0.096*</td>
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<td>(0.030</td>
<td>(0.060</td>
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<td><strong>Property abuse offences</strong></td>
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<td>(0.039</td>
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<td>(0.042</td>
<td>(0.091</td>
<td>(0.029</td>
<td>(0.107</td>
</tr>
<tr>
<td><strong>Administrative offences</strong></td>
<td>0.805*</td>
<td>0.393*</td>
<td>0.881*</td>
<td>0.569*</td>
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<td></td>
<td>(0.064</td>
<td>(0.121</td>
<td>(0.058</td>
<td>(0.148</td>
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</table>

**Time effects (13)**
- no
- yes

**Region effects (16)**
- no
- no
- yes
- yes

**Notes:**
The number of observations is 208.
Reported coefficients comprise $\beta$ in Model (1).
Estimated standard errors are in parentheses (covariance matrix estimator with regional heteroskedasticity).
An asterisk indicates statistical significance at the 10% significance level.

Browsing through the remaining coefficients of the first column reveals that for most (five out of seven) subclasses of crime, the estimated elasticity is substantially larger than in total. In the case of administrative offences, the elasticity reaches almost unity. The elasticity is significantly different from zero in six out of seven subclasses of crime. Thus, there appears to be evidence for a substantial effect of unemployment on crime.

Of course, this conclusion is conditional on the validity of the model. We next investigate how appropriate such a regression is in the first place, given the data used in this study. Figures 2a and 2b provide a first indication. Figure 2a is a scatter plot of the average crime rate over the
sample period for each region, $o_i$, against the time-averaged unemployment rate, $un_i$. Figure 2b is a scatter plot of annual observations of the national value of the crime rate, $o_t$, against annual observations of the national value of the unemployment rate, $un_t$.\(^6\)

There is evidence that the model is incorrectly specified. The graphs reveal no strong relationship between $o_i$ and $un_i$ (if anything, this relation is negative) but indicate that $o_t$ and $un_t$ are positively correlated. Either there are region-specific factors present which inhibit the ability to report a positive relation in Figure 2a or there are time-specific factors which create the appearance of a link between unemployment and crime over time or a mixture of both situations exists.

Potential misspecifications of this kind can be addressed by the inclusion of region- or time-specific fixed effects (or both) in the regression. Formally, let

$$\ln o_{it} = \alpha + \mu_i + \lambda_t + \beta \ln un_{it} + \epsilon_{it},$$  \hspace{1cm} (2)

\(^6\)National observations can be considered weighted averages of the regional observations, thus giving convenient estimates of $o$ and $un$ that have a time dimension only.
where $\mu_i$ is a region-specific fixed effect and $\lambda_t$ is a time-specific effect, while $\varepsilon_{it}$ is a white noise error term as before. This is an identical specification to the pooling case, only that now $\mu_i$ and $\lambda_t$ are considered to be parameters to be estimated, whereas before they were part of the error term. A possible factor that might feature in $\mu_i$ is the degree of urbanisation. Figure 2a shows that major metropolitan centres like Auckland, Wellington and Christchurch tend to have low values of $un_i$ and high values of $o_i$. It is quite possible that more densely populated regions offer more employment opportunities but also support higher levels of criminal activity. The age and ethnic structure of the various regions may also impact on $\mu_i$.

The period specific effects $\lambda_t$ capture, for instance, any change in macroeconomic conditions, such as inflation or oil-price shocks that might be expected to lead to higher levels of crime (assuming that they affect all regions equally). In addition, these effects account for changes in the propensity to report crimes over time as long as these are uniform across regions.

The estimation results are given in Columns (2)-(4) of Table 1. Column (2) includes time effects but no region effects. Column (3) includes region effects but no time effects. Column (4) includes both time and region effects. As we would expect from Figures 2a and 2b, the estimated
unemployment elasticities are more affected by the inclusion of period fixed effects than by the inclusion of region fixed effects. In all but one case, the magnitude of the unemployment elasticity drops when period effects are included and increases when region effects are included. In the most general model, with both region and time effects, an overall drop in the elasticity is observed, since the time effect dominates the region effect. The elasticity for the total crime rate is about halved in magnitude, relative to the pooled model without fixed effects. In terms of statistical significance, only three of the eight estimated elasticities remain significant (dishonesty, sexual, and administrative offences) once time and region fixed effects are included in the model.

The significance of the two types of fixed effects can be tested by means of various $F$-tests. Table 2 reports the relevant test statistics. In the first column, the two-way fixed effects model is compared to a model with region effects only, i.e., the null hypothesis is that $\lambda_t = 0$ for all $t$. A comparison of the $F$-statistic with the critical value of 1.83 shows that the time effects are jointly

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</tr>
<tr>
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<td>Time</td>
<td>Region effects</td>
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<td>Total offences</td>
<td>4.87</td>
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<td>40.85</td>
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<td>Property damage offences</td>
<td>8.51</td>
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<td>Property abuse offences</td>
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<td>Administrative offences</td>
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<td>6.40</td>
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<td>Model includes time fixed effects</td>
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<td>yes</td>
<td>n.a.</td>
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<tr>
<td>Model includes region fixed effects</td>
<td>yes</td>
<td>n.a.</td>
<td>no</td>
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<th>Distribution under $H_0$</th>
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<th>$F(15,179)$</th>
<th>$\chi^2(1)$</th>
<th>$\chi^2(1)$</th>
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<td>Critical value ($\alpha=0.05$)</td>
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<td>1.67</td>
<td>3.84</td>
<td>3.84</td>
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significant. A similar conclusion may be drawn from the second column of Table 2, with regard to the region effects. From this point of view, the two-way fixed effects model is the superior model.

However, as far as estimation of the unemployment elasticity of crime is concerned, efficiency gains may be realised by excluding some of the fixed effects and modeling them as random effects instead. After all, 27 degrees of freedom are lost in the two-way fixed effects model relative to the simple model. As a consequence, standard errors increase, in the case of the total crime rate by more than 100%. Those degrees of freedom could be preserved if the time and region effects were modeled as random effects. In order to do so, one needs to assume that the unemployment rate is uncorrelated with the time and region effects, respectively. If this assumption is valid, the fixed effects estimator is inefficient and a random effects estimator should be used. Otherwise, the random effects estimator for the unemployment elasticity is biased and inconsistent. In essence, the decision is whether to make inferences conditional on the effects observed in the sample or unconditional (marginal) inferences with respect to the population characteristics.

The validity of the assumption of no correlation can be tested using Hausman’s (1978) test. This test involves comparing the estimated parameter values for the unemployment elasticity under both random and fixed effects specifications. Under the null hypothesis that unemployment is uncorrelated with the random effects, the coefficients estimated by either model are consistent but only the random effects estimator is efficient. However, if the null hypothesis is false, the use of random effects produces an inconsistent estimator whereas the fixed effects estimator remains consistent.

Columns 3-6 of Table 2 report the results of these tests. The first hypothesis is that the time effects are uncorrelated with the unemployment rate. This test can be based either on a model that does not control for region fixed effects (Column 3) or on a model that does include such effects (Column 4), both under the null hypothesis and under the alternative. In the former case, the hypothesis of no correlation, and thus the random effects specification, is always rejected. If region fixed effects are included as well, the evidence is less clear-cut. This may reflect the lower power of the test, stemming from the reduced degrees of freedom of the model. In two cases (violent and drug and antisocial offences), the Hausman test remains significant. The Hausman test results for the region effects are weaker. Based on the model without time effects (Column 5) correlation between unemployment rate and the error component is detected in three out of seven cases. If time fixed effects are included as well, the null hypothesis is always accepted.
Based on these various tests, one can argue whether or not the regional effects should be modeled as random or as fixed. While the regional effects are jointly highly significant (Column 2 of Table 2), the evidence for a correlation with unemployment is not strong. Nevertheless, the two-way fixed effects model seems to be justifiable in order to hedge the results against this type of omitted variable bias for all subclasses of crime.

An augmented model

Of course, even the two-way fixed effects model can suffer from further omitted variable bias with respect to the estimated unemployment elasticity if correlated variables are omitted that are neither constant over time nor constant over regions. It is not difficult to come up with examples. For instance, the proportion of non-married young men is likely to vary both over time and over regions. Elsewhere, this proportion has been shown to be correlated both with unemployment and with criminal activity (e.g., Akerlof, 1998). While we suspect that the variation of such a variable over the 13 year observation period is small relative to its variation over regions, it is clear that subsuming this effect under the region-fixed effect is only an approximation that introduces error and, potentially, bias.

To avoid bias, such variables should then be included as regressors in the model along with the unemployment rate in a multiple regression framework. Unfortunately, lack of data availability imposes serious limitations on our ability to model any additional effects. A rich set of regionally disaggregated data is simply not available for New Zealand. Hence, we restrict our attention to two additional effects, deterrence and income. Both variables are part of the traditional Becker-Ehrlich model of rational crime. It is generally hypothesised that the deterrence rate has a negative effect on the crime rate. As the likelihood of potential criminals being caught increases, the expected penalty resulting from crime increases. This decreases the probability that a rational agent will choose to commit an offence.

The effect of the regional income level is less clear cut. Increases in income can be thought of as reflecting an increase in the benefits derived from legal activities, thus a negative relation may be posited. However, as income increases, the potential gains from economic crimes also increase. This would increase the attractiveness of crime relative to legal work and a positive relation between \( o \) and \( y \) may be observed. Which effect will dominate is unclear. Entorf and

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7 The expected penalty is given by the probability of capture and conviction times the severity of the sentence imposed. Buchanan and Hartley (1996) note that in New Zealand although the severity of prison sentences remained roughly constant for part of the period 1983-1992 the “penalty probability” fell due to decreases in the conviction rate over this period. As long as this fall is uniform across regions, however, it will not affect the results, but, rather, be subsumed into the time fixed effects.
Spengler (1998) believed that the unemployment rate could be interpreted as a measure of legal income opportunities, while the absolute level of income represented illegal income opportunities.\textsuperscript{8}

As described in Section 3, a suitable proxy variables for deterrence is available, namely the clearance rate, $p$, as is an estimate of the regional income level in year $t$, $y$. Table 3 reports the results of two-way fixed effects estimation of the following model:

$$\ln o_{it} = \alpha + \mu_i + \lambda_t + \beta \ln u_{it} + \gamma \ln p_{it} + \delta \ln y_{it} + \epsilon_{it}. \quad (3)$$

Model (3) offers a clear improvement over Model (1), as the $F$-test for joint significance of deterrence and income rejects the restricted model in each case. The results show that the clearance rate has a significant effect on the crime rate for each of the offence groups, except for administrative offences. However, in half of the cases a positive relation is found, contrary to the prior hypothesis. This is puzzling, as the clearance rate is given by the ratio of the number of crimes cleared to the total number of crimes reported and, hence, potentially biased downwards. For instance, an overestimate of the number of crimes due to measurement error leads to an underestimate of the clearance rate, thereby introducing a negative correlation between the error and the clearance rate. Another reason for endogeneity could be that a high crime rate may lead to a higher clearance rate as the police act more aggressively to counter the increase in crime.

In an attempt to overcome either type of endogeneity, we also estimate a model in which the current clearance rate is instrumented by its first lag. The last column of Table 3 shows the results of a Hausman test, where the model reported in Table 3 is tested against the instrumented model.\textsuperscript{9} The test does not reject the null hypothesis, with one exception, and we take this as a confirmation of Model (3) with current clearance rate included, although we admit that this conclusion might be sensitive to the limitations of the instrument (see, for example, Levitt (1997)).

Apart from the mixed effect of deterrence, the estimates appear quite plausible. The level of income has a negative effect for every offence group and the overall crime rate. This suggests that the effect of an increase in legal income opportunities outweighs the effect of a corresponding increase in illegal income opportunities. The introduction of $p$ and $y$ has little impact on the

\textsuperscript{8} They also included a measure of relative income (or income inequality), which was assumed to have a positive effect on crime.

\textsuperscript{9} The full set of regression results is available from the authors upon request.
### Table 3
Extended Model (two way fixed effects model)

<table>
<thead>
<tr>
<th></th>
<th>( un )</th>
<th>( p )</th>
<th>( y )</th>
<th>( F )-test</th>
<th>Hausman test</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total offences</td>
<td>0.088*</td>
<td>-0.019</td>
<td>-1.048*</td>
<td>8.14</td>
<td>0.186</td>
</tr>
<tr>
<td></td>
<td>(0.047)</td>
<td>(0.100)</td>
<td>(0.380)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Violent offences</td>
<td>0.075</td>
<td>0.584*</td>
<td>-2.002*</td>
<td>22.01</td>
<td>0.327</td>
</tr>
<tr>
<td></td>
<td>(0.059)</td>
<td>(0.244)</td>
<td>(0.584)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Drug and anti-social offences</td>
<td>-0.037</td>
<td>0.286*</td>
<td>-4.409*</td>
<td>30.79</td>
<td>0.259</td>
</tr>
<tr>
<td></td>
<td>(0.104)</td>
<td>(0.109)</td>
<td>(0.849)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dishonesty offences</td>
<td>0.156*</td>
<td>0.701*</td>
<td>-0.581</td>
<td>5.57</td>
<td>0.101</td>
</tr>
<tr>
<td></td>
<td>(0.091)</td>
<td>(0.307)</td>
<td>(0.804)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Property damage offences</td>
<td>0.037</td>
<td>-0.162*</td>
<td>-1.251*</td>
<td>14.15</td>
<td>6.748</td>
</tr>
<tr>
<td></td>
<td>(0.044)</td>
<td>(0.073)</td>
<td>(0.374)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Property abuse offences</td>
<td>0.093</td>
<td>-0.404*</td>
<td>-0.572</td>
<td>24.09</td>
<td>0.183</td>
</tr>
<tr>
<td></td>
<td>(0.072)</td>
<td>(0.084)</td>
<td>(0.578)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sexual offences</td>
<td>0.326*</td>
<td>-0.586*</td>
<td>-1.011</td>
<td>12.12</td>
<td>3.873</td>
</tr>
<tr>
<td></td>
<td>(0.104)</td>
<td>(0.171)</td>
<td>(0.811)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Administrative offences</td>
<td>0.576*</td>
<td>0.222</td>
<td>-5.182*</td>
<td>18.06</td>
<td>0.549</td>
</tr>
<tr>
<td></td>
<td>(0.144)</td>
<td>(0.152)</td>
<td>(1.370)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Distribution under \( H_0 \)

<table>
<thead>
<tr>
<th>Critical value (( \alpha = 0.05 ))</th>
<th>( F(2,177) )</th>
<th>( \chi^2(1) )</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>3.00</td>
<td>3.84</td>
</tr>
</tbody>
</table>

**Notes:**
The number of observations is 208.
Estimated standard errors are in parentheses (covariance matrix estimator with regional heteroskedasticity).
An asterisk indicates statistical significance at the 10\% significance level.
The null hypothesis is that deterrence and income are jointly insignificant.
The null hypothesis of the Hausman test is that the clearance rate is uncorrelated with the regression error.

The estimated effect of the unemployment rate on crime. Most importantly, though, the significance of \( \hat{\beta} \) has increased for the total crime rate, leading to a rejection of the null hypothesis of no effect at the 10\% level. Thus, there is some evidence that increased legal income opportunities, be they through lower unemployment levels or higher income, lead to a substitution away from criminal activities.
5. Conclusions

So, having muddied further the already turbid waters of research into the unemployment-crime relationship, what has this study contributed? Evidence has been found that tends to confirm earlier conclusions reached by Small and Lewis for New Zealand. Results indicate that the total rate of crime remains significantly affected by the unemployment rate, once complicating factors are controlled for. In particular, unemployment was found to have a significant relationship to the number of dishonesty crimes committed. This is the category that includes the economic crimes of theft, fraud, car conversion, receiving and burglary that much of the previous literature, including Small and Lewis (1996), has focussed on.

Furthermore, this study indicates several possibilities for further research. In particular, the introduction of additional regressors that may explain crime, for example income inequality, may alleviate any remaining omitted variable bias.

The unemployment-crime relationship is an old issue. No consensus has been reached by economists during the past three decades, nor does one seem likely to emerge in the near future. Perhaps an observation by McDowell and Webb (1995) on this area of research has particular relevance: that it is an “urge to achieve a certainty which simply does not exist”. Or perhaps with superior data and superior techniques, a conclusive model of the crime decision may be found and, in the process, bring credibility to application of economic principles to social issues.
### Appendix: Definitions of offence groups

**Violent offences (O1)**  
- Homicide  
- Grievous assaults  
- Minor assaults  
- Group assemblies  
- Robbery  
- Kidnapping/abduction  
- Serious assaults  
- Intimidation/threats

**Drug and anti-social offences (O2)**  
- Drugs (not cannabis)  
- Drugs (cannabis only)  
- Gaming  
- Liquor offences  
- Disorder  
- Vagrancy offences  
- Family offences

**Dishonesty offences (O3)**  
- Theft  
- Fraud  
- Car conversion  
- Receiving  
- Burglary

**Property damage offences (O4)**  
- Destruction of property  
- Endangering

**Property abuse offences (O5)**  
- Firearms offences  
- Littering  
- Post, rail and fire abuses  
- Animals  
- Trespass

**Sexual offences (O6)**  
- Sexual attacks  
- Abnormal sex  
- Sexual affronts  
- Immoral behaviour  
- Immoral behaviour/miscellaneous  
- Indecent videos

**Administrative offences (O7)**  
- Against justice  
- Against national interest  
- Births, deaths and marriages  
- Immigration  
- Race relations  
- By-law breaches
References


