Crime and Unemployment in Malaysia: ARDL Evidence

Muzafar Shah Habibullah*
Faculty of Economics and Management, Universiti Putra Malaysia, 43400 UPM Serdang, Selangor, Malaysia

A.H. Baharom
Taylor's Business School, Taylor's University, No. 1, Jalan Taylor's, 47500 Subang Jaya, Selangor, Malaysia

Badariah Haji Din
College of Law, Government and International Studies, Universiti Utara Malaysia, 06010 Sintok, Kedah, Malaysia

Suriyani Muhamad
School of Social and Economic Development, Universiti Malaysia Terengganu, 21030 Kuala Terengganu, Terengganu, Malaysia

Suryati Ishak
Faculty of Economics and Management, Universiti Putra Malaysia, 43400 UPM Serdang, Selangor, Malaysia

*Corresponding author; email: muzafar@upm.edu.my

ABSTRACT

The purpose of the present study is to determine whether there is long-run relationship between crime rates and unemployment rate in Malaysia for the period 1973 to 2003. The autoregressive distributed lag bounds testing procedure was employed as the main tool to infer cointegration or the long-run relationship between unemployment and the crime rates. The results indicate that the unemployment rate, and crime rates: total crime rate, violent crime (murder, robbery, and assault), and property crime (daylight burglary, night burglary, and *motorcycle theft) are cointegrated. The estimated long-run coefficients suggest that unemployment rate has negative effect on violent crime, murder, robbery, assault, and motorcycle theft. The paper shows that jobless population in Malaysia as a result of recession tend to remain in or near homes and neighborhoods and this likely will reduce the occurrence of crime.*

Keywords: *crimes, unemployment, ARDL, Malaysia*

INTRODUCTION

In his theoretical paper, Becker (1968) assumes that criminals are rational and utility maximizing individuals and therefore, contended that an individual will decide whether to engage in crime by comparing the benefits and costs of committing crime. Becker (1968) emphasizes on how changes in the probability and severity of punishment can alter the individual's decisions to commit crime. The work by Becker was extended by Ehrlich (1973) by including the role of opportunity cost between illegal and legal work in the crime model. If legal income opportunities become scarce relative to potential gains from crime, the Becker-Ehrlich model predicts that crime will become more frequent. One such factor that could instigate individual into crime offenders is unemployment. Raphael and Winter-Ebmer (2001, p. 259) contended that, "The proposition that unemployment induces behavior is intuitively appealing and grounded in the basic notion that individuals respond to incentive. The decrease in income and potential earnings associated with involuntary unemployment increases the relative returns to illegal activity. Moreover, workers that experience chronic joblessness have less to lose in the event of an arrest and incarceration. Hence, straightforward economic reasoning suggests that unemployment is an important determinant of the supply of criminal offenders and hence, the overall crime rate."

Weatherburn (1992, p.1) further suggest that "if unemployment does anything, it reduces the capacity of an individual to earn income from legitimate activity" and "high rates of unemployment must surely weaken the social bonds between young people and the wider society. This, by itself, would increase the risk that the young will drift into deviant subcultures where involvement in crime of one form or another becomes a way of life."

Malaysia is no exception to crime offenders where the phenomenon of crime wave has received an increasing attention and the criminal activity has been given wide coverage in the newspaper and media. Murder, robbery, assault, rape, burglary and theft are common criminal offences in Malaysia. It seems that since the financial crisis, crime has increased significantly in Malaysia. Without doubt, there exists a deep sense of social alarm that has called for urgent measures from the government to reduce the levels of criminality. Despite this alarming event, Malaysia's criminal activity has received little attention and remains largely neglected by the economics of crime literature originally proposed by Becker (1968) and Ehrlich (1973).

Thus, the purpose of the present study is to fill this gap in the literature by providing some empirical evidence on the link between the crime rate in a developing economy, Malaysia and the economic adversity measured by the unemployment rate. In Malaysia, the public and the government have closely monitored the rate of unemployment and as such it is imperative that we look at the link between crime and unemployment. We intend to determine whether there exist a long run relationship between the crime rates and unemployment rate in Malaysia.

A REVIEW OF RELATED LITERATURE

Despite the numerous studies identifying the link between crime and unemployment, the empirical results has been mixed. Those analyses are contained in survey conducted by Chiricos (1987) and Box (1987). On one hand, Box (1987) reports 32 cross-sectional and 18 time series studies. Out of the 32 cross-sectional studies, he found out that only 19 cases supported the existence of a significant positive relationship between crime and unemployment. And out of the 18 time series studies, 13 cases suggested a positive association between unemployment and crime. On the hand, Chiricos (1987) reviewed 68 studies and argued that less than 50 percent of the cases indicate positive and statistically significant effects of the rate of unemployment on crime offences.

Recent studies have further inflated these controversies. Using data for unemployment and crime rate of the U.S. for the period 1960-90, Lester (1995) found that larceny and property crimes are positively link with the unemployment rate. Land et al. (1995) also found a positive relationship between unemployment and crime in post-war United States. This contention is further supported by Lessan (1991) who found out that annual change in black and white male unemployment rates exert positive effect upon imprisonment-rate changes, after controlling for variations in violent crime rates, prison capacity, and age structure. Using panel state data for the United States for the period 1970 to 1993, Raphael and Winter-Ebmer (2001) found that high unemployment rates are an important factor contributing substantially to both property and violent crime rates despite after taking into account for controlling alcohol consumption. A study by Becsi (1999) using a panel data regression analysis for the U.S. for the period 1971-1994, the results indicate that some states in the U.S. experienced high crime rates, which reflect relatively high unemployment rates, and low expected earnings from legitimate work for some population segment. This would suggest that higher unemployment rates suggest more economic distress and would expected to positively influence crime (Cantor and Land, 1985; Osborne et al., 1992; Doyle et al., 1999; Levitt, 1996; Gould et al., 2002).

Kapuscinski et al. (1998) found a strong positive relationship between unemployment and trends in homicide in Australia. Weatherburn et al. (2001), however, found no evidence of any relationship between unemployment and crime of, break, enter and steal, and motor vehicle theft in Australia. On the other hand, study by Chapman et al. (2002) on New South Wales (NSW), Australia crime data identify that unemployment amongst young males has a substantial effect on property crime. Chapman et al. (2002, p. 24) argue that elimination of male long term unemployment amongst male aged 15-24 by direct job creation would result in close to a 7 percent reduction in property crime in NSW per annum. Better still, if these individuals continued in formal education to the end of the year 12 the reduction in break, enter and steal over the course of a year would amount to almost 15 percent."

Field (1990, 1999) found no effect of unemployment on post-war British crime trends. Witt et al. (1998) examine the role exerted by earnings inequality and unemployment in the determination of crime using a panel of annual regional data from 1979 to 1993 for England and Wales. They found that continued falls in the relative wages of unskilled men and increases in male unemployment in England and Wales act as incentives to engage in criminal activity. Using the 1992 British Crime Survey, which sampled 11,713 households across England and Wales in 572 areas, and employing the Box-Cox flexible functional form approach, Elliot and Ellingworth (1998) also found a significant positive relationship between male unemployment and property crime. Pyle and Deadman (1994) have concluded that unemployment may be less important to crime than other indicators of economic activity in the U.K. Their contention supported Ehrlich (1973) earlier views that unemployment rate act as a complementary indicator of income opportunities available in the labor market. However, the result of Carmichael and Ward (2000) suggest that a systematic positive relationship between male unemployment and burglary, theft, fraud and forgery and total crime rates regardless of age in England and Wales for the period 1989 to 1996. Their model predicts that a given increase in adult unemployment will lead to a higher percentage increase in most crimes.

For crime data in New Zealand, Small and Lewis (1996) and Papps and Winklemann (1998) found that unemployment rate is important factor in affecting the crime rate in the country. In fact, results in Small and Lewis (1996) suggest that unemployment Granger cause crime offences in New Zealand. A study on Italian data by Scorcu and Cellini (1998, p. 287) for the period 1951-1994, found that "in all cases, economic variables (including unemployment) seem to cause crime rate in the long-run, whereas crime rates do not cause economic variables."

For other countries, Cerro and Meloni (2000) found positive and significant effect of unemployment on crime for a panel data from Argentina. Hojman (2002), however, found otherwise. He argues that in Argentina, unemployment does not play the same role as inequality. Lee (2003) found that, for Korea, the evidence suggest a long run equilibrium relationship between male unemployment and total crime, violent and property crime, and male unemployment Granger cause violent crime, while total crime and property crime Granger cause unemployment. For Japan, Lee's (2003) revealed that unemployment exhibit long run relationship with murder and rape, and unemployment Granger cause rape while murder Granger cause unemployment. In the case of Spain, a study by Andres (2002) indicates that the unemployment rate has a positive effect on crime rates. And for Taiwan, Denq et al. (1994) analyzed a time series data from 1964 to 1990, found that there is a positive association between burglary/larceny and unemployment suggests that unemployment is an immediate motivator for crime. In Malaysia, Meera and Jayakumar (1995) found out that unemployment show positive relationship with house-breaking, motor theft, total theft, murder, robbery, total crime rate, violent crime and rape.

METHODOLOGY

Testing for Cointegration: The Bounds Test

In this study, we specify crime-unemployment equation for Malaysia as follows:

$$crime_t = \alpha_0 + \alpha_1 unemp_t + \mu_t \tag{1}$$

where small letters indicate variables in natural logarithm and μ_t is the error term. The parameters $\alpha' s$ are to be estimated. It is a *priori* that we expect $\alpha_1<0$; or $\alpha_1>0$. Unemployment rate has a positive effect on crime rate. The unemployed are more highly motivated to commit crimes because they are out of work and have financial needs. When unemployment rates are low, more people will spend more time away from home engaging in work or in leisure activities and will be more likely to purchase new consumer goods, resulting in a larger number of more attractive opportunities for crime. On the other hand, a negative relationship between unemployment and crime that is based on routine activities theory hypothesizes that an immediate consequence of unemployment is to reduce crime because the unemployed generally find themselves in routine activities that are more home-based. When unemployment rate is high, the unemployed may be more likely to remain in or near their homes and neighborhoods, thus reduce rate of crime by reducing the overall number of opportunities for criminal acts to occur (Britt, 1997).

Estimating Equation (1) using OLS is not straight forward because the estimated equation is subject to the so-called spurious regression results (Granger & Newbold, 1974). According to Granger and Newbold (1974) a spurious regression resulted from estimating an equation containing non-stationary economic variables. Nevertheless, recent advances in time-series analysis have yielded new procedures for estimating long-run and short-run econometric relationships between non-stationary variables. One such procedure which has become widespread in the economic literature is the use of dynamic specification with an error-correction mechanism (ECM) in single-equation and multi-equation macroeconomic forecasting models. However, the ECM model is not of recent origin as it was introduced by Phillips (1954) and first used in economics by Sargan (1964). But, the ECM models have only gained recognition amongst the economists and econometricians since the published work of Davidson et al. (1978). In Davidson et al. (1978), the ECM models which include the dynamics of both short-run (changes) and long-run (levels) adjustment process was used to specify U.K.'s consumption function. The favorable performance of the ECM model relative to the traditional model has inspired other researchers to use the ECM approach in economic modeling. Although the work of Hendry (1979, 1983) and associates on aggregate consumption and money demand has been very influential, it was Granger (1981, 1986) who linked the time-series properties of economic time-series, in particular, to the concept of cointegration and the ECM modeling approach.

In this study, to test for cointegration and the ECM modeling, we employ the bounds test proposed by Pesaran et al. (2001) which is more appropriate for small sample study. Pesaran and Shin (1999) show that with the ARDL framework, the OLS estimators of the short-run parameters are -consistent and the ARDL based estimators of the long-run coefficients are super consistent in small sample sizes. As a matter of fact, Narayan (2005) has provided critical values for sample as small as 30 to 80 observations.

To test for cointegration by using the bounds test, we estimate the following conditional Autoregressive Distributed Lag (ARDL) unrestricted error-correction model (UECM) for the crime-unemployment equation, $crime_t$ as follows

$$\Delta crime_t = \alpha_0 + \sum_{i=1}^{k} \alpha_{1i} \Delta crime_{t-i} + \sum_{i=0}^{m} \alpha_{2i} \Delta unemp_{t-i} \quad (2)$$
$$+ \beta_1 crime_{t-1} + \beta_2 unemp_{t-1} + \nu_{1t}$$

where *k and m* are optimal lag length chosen; α_0 is a constant term and υ_{1t} is the disturbance term in the crime equation. According to Pesaran et al. (2001), an *F*-test for the joint significance of the coefficients of the lagged levels in the above Equation (2), that is the null hypothesis for non cointegration amongst variables in the equation, is $H_0: \beta_1 = \beta_2 = 0$

against the alternative H_α: $\beta_1 \neq \beta_2 \neq 0$; are employed to bounds test for cointegration or the existence of a long-run relationship between *crime* and *unemap*. This can be denoted as F_{crime} (*crime*|*unemap*) *or* F_{crime} (.) Rejection of the null hypothesis suggest cointegration between *crime* and *unemap* and therefore implies that *unemap* is *long-run forcing* for *crime.*

The asymptotic distribution of critical values is obtained for cases in which all regressors are purely $I(1)$ as well as when the regressors are purely $I(0)$ or mutually cointegrated. Because the critical value of the test depends on the order of integration of the variables, $I(d)$, where $0 \leq \mathrm{d} \leq 1$, the test utilizes a critical range such that values exceeding the range are evidence of rejection, values less than the range are evidence of non-rejection, and values within the range are inconclusive. In other words, if the *F*-statistics exceed their respective upper critical values; we can conclude that a long-run relationship exists, without a need to know the order of integration of the regressors. If the *F*-statistics fall below the lower critical values, we cannot reject the null hypothesis of no cointegration and estimation can continue assuming no long-run relationship. If the *F*-statistics falls between the two bounds, the result is inconclusive. As such one needs to know the order of the integration of the underlying variables to proceed further. Further, if $\beta_1 < 0$, the long-run relationship between the level of $crime_t$ and $unemp_t$ is said to be stable (Pesaran et al., 1996).

Having found that $crime_t$ with respect to $unemp_t$ are cointegrated after estimating Equation (2), the following ARDL equation is estimated to arrive at the Autoregressive Distributed Lag-Restricted Error-Correction Model (ARDL-RECM):

$$crime_t = \gamma_0 + \sum_{i=1}^{p} \gamma_{1i} crime_{t-i} + \sum_{i=0}^{q} \gamma_{2i} unemp_{t-i} + \eta_t \qquad (3)$$

All the variables are previously defined. The optimal lag length in Equation (3) is selected using Schwartz Bayesian Criterion (SBC) as suggested by Pesaran et al. (1996). In the presence of cointegration, the following ARDL-RECM equation can be specified as follows:

$$\Delta crime_t = \delta_0 + \sum_{i=1}^{p} \delta_{1\mathrm{i}} \Delta crime_{t-i} + \sum_{i=0}^{q} \delta_{2\mathrm{i}} \Delta unemp_{t-i} \qquad (4)$$
$$+ \lambda ECM_{t-1} + \omega_t$$

where ECM_t s the error-correction term define as

$$ECM_t = crime_t - [\gamma_0 + \sum_{i=1}^{p} \gamma_{1i} crime_{t-i} + \sum_{i=0}^{q} \gamma_{2i} unemp_{t-i}] \quad (5)$$

Thus, from Equation (4), the significant of parameter λ indicative of cointegration, long-run causality and weak exogeneity of $crime_t$ Furthermore, parameter λ measures the speed of adjustment.

Further, the long-run coefficient (elasticities) can be obtained from Equation (3) as follows:

$$crime_t = \theta_0 + \theta_1 unemp_t + \mu_t \quad (6)$$

where $\theta_0 = \gamma_0 / 1 - \sum_{i=1}^{p} \gamma_{1i}$, $\theta_1 = \sum_{i=0}^{q} \gamma_{2i} / 1 - \sum_{i=1}^{p} \gamma_{1i}$, and μ_t is white noise.

Testing for Time-Series Properties

Although the bounds test proposed by Pesaran et al. (1996, 2001) do not require testing for the order of integration of the time-series involve in the analysis, we endeavour to check for the robustness of the order of integration for all the variables used in the present study. Ouattara (2004) argues that in the presence of *I*(2) variables the computed test statistics provided by Pesaran et al. (2001) are no more valid because they are based on the assumption that the variables are *I*(0) or *I*(1); therefore, the implementation of unit root tests in the ARDL procedure might still be necessary in order to ensure that none of the variables is integrated of order 2 or beyond. In this study, we employed the standard Augmented Dickey and Fuller (1979) (ADF) procedure for unit root test. The conventional augmented Dickey-Fuller (ADF) regression is of the following form

$$\Delta crime_t = \alpha crime_{t-1} + x_t' \delta + \sum_{i=1}^{p} \beta_i \Delta crime_{t-i} + \varpi_t \quad (7)$$

where x_t are optional exogenous regressors which may consist of constant or a constant and trend, α, δ, and β are parameters to be estimated, and ϖ_t are assumed to be white noise. The null of a unit root (H_0: $\alpha = 0$ *vs* $H_\alpha : \alpha < 0$) is rejected if the *t*-statistic of α is statistically significant from zero.

Sources of Data

Following the suggestion by Cherry and List (2002), we used disaggregate data on crime. According to Cherry and List (2002, p. 81), "it is inappropriate to pool crime types into a single decision model and that much of the existing empirical evidence suffers from aggregation bias." Since we recognized that deterrence effect of unemployment is quite heterogeneous across crime types, in this study, we have disaggregated crime offences into twelve sub-categories of crime, violent and property crime rates, namely: murder, attempted murder, armed robbery, robbery, rape, assault, daylight burglary, night burglary, lorry-van theft, car-theft, motorcycle theft and larceny. In fact, earlier studies by Cherry (1999), and Cornwell and Trumbull (1994) have pointed out that unobserved heterogeneity in the unit of observation may lead to spurious relationships that incorrectly imply or exaggerate deterrent effects.

Data on crime and their sub-categories for the period 1973 to 2003 were collected from the Royal Police of Malaysia (PDRM). The total crime activities are classified into 12 categories: murder, attempted murder, armed robbery, robbery, rape and assault (these comprise the violent crime); daylight burglary, night burglary, lorry-van theft, car theft, motorcycle theft and larceny (comprise the property crime). For the unemployment rate, the data were collected from the various issues of the Statistical Yearbook published by the Department of Statistics Malaysia.

RESULTS AND DISCUSSIONS

Results of the order of integration of each of the variables are presented in Table 1. Our main purpose is to determine the absence of $I(2)$ variables as their presence will invalidate the use of ARDL approach. As seen in Table 1, when the series are in their levels, they are clearly $I(1)$. When the series are in their first-differences, the ADF unit root test suggest that they are $I(0)$. Therefore, generally, we can say that the variables are stationary after differencing once.

Table 1

Results of ADF unit root test

Crime rate category	Level (Intercept and Trend)	First difference (Intercept)
Crime:	-2.35 [0.39]	-3.24 [0.02]
Violent:	-2.75 [0.22]	-3.71 [0.00]
Murder	-3.56 [0.05]	-4.69 [0.00]
Attempted murder	-2.20 [0.46]	-4.49 [0.00]
Armed robbery	-2.32 [0.40]	-4.48 [0.00]
Robbery	-2.17 [0.48]	-3.47 [0.01]
Rape	-3.31 [0.08]	-4.97 [0.00]
Assault	-2.87 [0.18]	-3.21 [0.02]
Property:	-2.29 [0.42]	-3.19 [0.03]
Daylight Burglary	-3.31 [0.08]	-3.20 [0.03]
Night Burglary	-3.06 [0.13]	-3.71 [0.00]
Lorry-van theft	-2.41 [0.36]	-4.25 [0.00]
Car theft	-2.01 [0.56]	-3.39 [0.01]
Motorcycle theft	-2.19 [0.47]	-3.00 [0.04]
Larceny	-2.38 [0.37]	-3.34 [0.02]
Unemployment rate	-1.82 [0.66]	-3.23 [0.02]

Notes: All unit root estimations were done using EViews. EViews select lag 1 as default and were used throughout the analysis. The square brackets [.] contain the *p-values*.

Having determined the order of integration of all the variables involve, we next test for cointegration using the ARDL framework as suggested by Pesaran et al. (2001). This involves estimating Equation (2) by OLS, and then using general to specific criteria to determine the number of optimal lagged differences of *k,m.* Table 2 shows the results of the bounds test using the *F*-test statistics for cointegration among *crime* and *unemp*. In this study, we have tested for cointegration for $F_{crime}(.)$. As for the lag length; *k, m,* we have limit the maximum number of lag to two periods due to our short span of time-series observations. According to Pesaran et al. (1996, 2001) the ARDL approach is flexible to the choice of dynamic lag structure when allowing for differential lag lengths on the lagged level variables and the short-run feedbacks, without affecting the asymptotic results of the bounds test. As shown in Panel B, in the cases of $F_{crime}(.)$. that we found cointegration with bounds *F*-statistic statistically significant at least at the 10 percent level. The bounds test for cointegration suggest that unemployment rate are cointegrated with total crime rate, violent crime, murder, robbery, assault, property crime, daylight burglary, night burglary, and motorcycle theft. Further, the conditional ECM Equation (2) do not suffer from serial correlation problem which is important for the validity of the bounds test.

Table 2

Results of bounds F-test for cointegration

Panel A: Critical value bounds of the *F*-statistic: Case III (unrestricted intercepts and no trends)						
	90% level		95% level		99% level	
T	$I(0)$	$I(1)$	$I(0)$	$I(1)$	$I(0)$	$I(1)$
30 (see Narayan, 2005)	4.29	5.08	5.39	6.35	8.17	9.28

Panel B: Calculated *F*-statistic:			
Crime Types:	*ARDL(k,m)*	$F_{crime}(.)$	Serial correlation (*p-values*)
Crime	1,0	8.01**	0.19
Violent	0,0	7.96**	0.63
Murder	0,0	9.81***	0.51
Attempted Murder	0,0	3.13	0.35

(continued)

Crime Types:	*ARDL(k,m)*	$F_{crime}(.)$	Serial correlation (*p-values*)
Armed Robbery	0,0	3.34	0.16
Robbery	0,1	9.24**	0.67
Rape	0,0	3.51	0.96
Assault	0,0	5.25*	0.29
Property	1,0	6.78**	0.36
Daylight Burglary	1,0	7.39**	0.23
Night Burglary	1,0	5.19*	0.60
Lorry-van Theft	0,0	1.02	0.71
Car Theft	0,1	4.14	0.65
Motorcycle Theft	0,1	15.95***	0.99
Larceny	0,0	1.70	0.49

Notes: Asterisks (***), (**), (*) denote statistically significant at the 1%, 5% and 10% level respectively.

Our main interest is to determine the sign and the size of the long-run parameter estimates, θ_1 in Equation (6). Column 2 in Table 3 shows the optimal lag length chosen for the ARDL model used to derive the long-run model specified by Equation (6); and estimate the short-run error-correction model as per Equation (4). The long-run elasticities are shown in column 3, while the *t*-statistics of the ECM term is shown in column 4 in Table 3.

Table 3

Results of long-run coefficients/elasticities and ECM model

Dependent variables:	ARDL (P,q)	θ_1	ECM's *t*-statistics
Crime	2,1	-0.3587 (1.6996)	-3.32***
Violent	1,1	-0.5826 (2.0429)*	-2.75**
Murder	1,1	-0.1977 (1.9144)*	-3.51***
Robbery	1,2	-0.7767 (2.2050**	-2.84***
Assault	1,0	-0.4120 (1.9445)*	-2.71**
Property	2,1	-0.3986 (1.5152)	-2.83***
Daylight Burglary	2,0	-0.1898 (1.1225)	-3.59***
Night Burglary	2,0	0.0927 (0.5693)	-2.72**
Motorcycle Theft	1,2	-2.1710 (4.9410)***	-4.07***

Notes: Asterisks (***), (**), (*) denote statistically significant at the 1%, 5% and 10% level respectively. Figures in round brackets are *t*-statistics.

Interestingly, in all cases the ECM term are negative, between zero and one, and are statistically significantly different from zero, thus supporting cointegration between unemployment rates and the total crime rate, violent crime, murder, robbery, assault, property crime, daylight burglary, night burglary, and motorcycle theft which was found cointegrated earlier using the bounds test.

More importantly, the result of the long-run elasticities indicates that unemployment rates are statistically significant at least at the 10 percent level in 5 out of 9 cases. The result suggests that there is an inverse relationship between unemployment and violent crime, murder, robbery, assault, and motorcycle theft. For example, a one percent increase in the unemployment rate; violent crime rate will reduce by 0.5 percent. On the other hand, a one percent increase in the unemployment rate; the motorcycle theft will decrease by 2.1 percent.

CONCLUSION

The purpose of the present study is to investigate the long-run relationship between unemployment rate and several categories of the criminal activities in Malaysia for the period 1973 to 2003. Due to the short span of data, we employ the Autoregressive Distributed Lag (ARDL) procedure suggested by Pesaran et al. (2001), which is more suited and robust for small sample size. In this study we have investigated twelve categories of criminal activities, namely: murder, attempted murder, armed robbery, robbery, rape, assault, daylight burglary, night burglary, lorry-van theft, car-theft, motorcycle theft and larceny.

The bounds test for cointegration suggest that unemployment rate exhibit long-run relationship with total crime rate, violent crime, murder, robbery, assault, property crime, daylight burglary, night burglary and motorcycle theft. Before testing for cointegration using the ARDL bounds *F*-tests, we subject the variables to unit root testing and found out that all variables are $I(1)$. This is further supported by the results from the error-correction models.

Our long-run model suggests unemployment has a negative effect on violent crime, murder, robbery, assault, and motorcycle theft. It implies that during recession, when unemployment rates are relatively high, people who lost their job, may be more likely to remain in or near their homes and neighborhoods, thus, reducing the number of opportunities for crime.

REFERENCES

Andres, A. R. (2002). *Crime in Spain: An empirical investigation*. Unpublished manuscript, University of Southern Denmark, Denmark.

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

Besci, Z. (1999). Economics and crime in the States. *Economic Review, 84*(1), 38-57.

Box, S. (1987). *Recession, crime and punishment*. London: MacMillan.

Britt, C.L. (1997). Reconsidering the unemployment and crime relationship: Variation by age group and historical period. *Journal of Quantitative Criminology, 13*(4), 405-428.

Cantor, D., & Land, K. (1985). Unemployment and crime rates in the post-World War II United States: A theoretical and empirical analysis. *American Sociological Review, 50*, 317-332.

Carmichael, F., & Ward, R. (2000). Youth unemployment and crime in the English regions and *Wales. Applied Economics, 32*, 559-571.

Cerro, A.M., & Meloni, O. (2000). Determinants of the crime rate in Argentina during the '90s. *Estudios de Economia, 27*(2), 297-311.

Chapman, B., Kapuscinski, C.A. & Roussel, S. (2002). *Unemployment duration, schooling and property crime*. Department of Education, Employment and Training, State Government of Victoria, Australia.

Cherry, T.L. (1999). Unobserved heterogeneity bias when estimating the economic model of crime. *Applied Economics Letters, 6*, 753-757.

Cherry, T.L. & List, J.A. (2001). Aggregation bias in the economic model of crime. *Economics Letters, 75*(1), 81-86.

Chiricos, T. (1987). Rates of crime and unemployment: An analysis of aggregate research evidence. *Social Problems, 34*, 187-211.

Davidson, J., Hendry, D.F., Sbra, F. & Yeo, S. (1978). Econometric modeling of aggregate time series relationship between consumer's expenditure and income in the United Kingdom. *The Economic Journal, 88*, 661-692.

Denq, F., Vaughn, M.S. & Huang, F.F.Y. (1994). Correlates of crime in Taiwan: A time-series analysis from 1964 to 1990. *Crime, Law & Social Change, 21*, 267-285.

Dickey, D.A. & Fuller, W.A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association, 74*, 427-431.

Doyle, J.M., Ahmed, E., & Horn, R.N. (1999). The effects of labor markets and income inequality on crime: Evidence from panel data. *Southern Economic Journal, 65*, s717-738.

Ehrlich, I. (1973). Participation in illegitimate activities: A theoretical and empirical investigation. *Journal of Political Economy, 81*, 521-564.

Field, S. (1990). Trends in crime and their interpretation: A study of recorded crime in postwar England and Wales. *Home Office Research Study 119*, Home Office, London.

Field, S. (1999). Trends in crime revisited. *Home Office Research Study 195*, Home Office, London.

Elliot, C. & Elingworth, D. (1998). The relationship between unemployment and crime: A cross-sectional analysis employing the British Crime Survey 1992. *International Journal of Manpower, 17*, 81-88.

Gould, E.D., Weinberg, B.A., & Mustard, D.B. (2002). Crime rates and local labor market opportunities in the United States: 1979-1995. *The Review of Economics and Statistics, 84*(1), 45-61.

Granger, C.W.J. (1981). Some properties of time series data and their use in econometric model specification. *Journal of Econometrics, 16,* 121-130.

Granger, C.W.J. (1986). Developments in the study of cointegrated economic variables. *Oxford Bulletin of Economics and Statistics, 48*, 213-228.

Granger, C.W.J. & Newbold, P. (1974). Spurious regression in econometrics. *Journal of Econometrics, 2*, 111-120.

Hendry, D.F. (1979). Predictive failure and econometric modelling in macroeconomics: The transactions demand for money. In P. Omerod (ed.), *Economic modelling*. London: Heinemann.

Hendry, D.F. (1983). Econometric modelling: The consumption function in retrospect. *Scottish Journal of Political Economy, 30*, 193-220.

Hojman, D.E. (2002). Explaining crime in Buenos Aires: The roles of inequality, unemployment and structural change. *Bulletin of Latin American Research, 21*(1), 121-128.

Kapuscinski, C.A., Braithwaite, J., & Chapman, B. (1998). Unemployment and crime: Toward resolving the paradox. *Journal of Quantitative Criminology, 14*(3), 215-243.

Land, K.C., Cantor, D., & Russell, S.T. (1995). Unemployment and crime rate fluctuations in the post-World War II United States: Statistical time-series properties and alternative and alternative models. In J. Hagan and R.D. Peterson (eds.), *Crime and inequality*. Stanford, CA: Stanford University Press.

Lee, Y.D. (2003). *Income inequality and crime. Cointegration analysis and causality Tests.* Unpublished manuscript, Shippensburg University.

Lessan, G.T. (1991). Macro-economic determinants of penal policy: Estimating the unemployment and inflation influences on imprisonment rate changes in the United States, 1948-1985. *Crime, Law and Social Change, 16*, 177-198.

Lester, B.Y. (1995). Property crime and unemployment: A new perspective. *Applied Economics Letters, 2*, 159-162.

Levitt, S. (1996). The effect of prison population size on crime rates: Evidence from prison overcrowding litigation. *Quarterly Journal of Economics, 111*, 319-351.

Meera, A.K., & Jayakumar, M.D. (1995). Determinants of crime in a developing country: A regression model. *Applied Economics, 27*, 455-460.

Narayan, P.K. (2005). The saving and investment nexus for China: Evidence from cointegration tests. *Applied Economics, 37*, 1979-1990.

Osborne, D.R., Trickett, A., & Elder, R. (1992). Area characteristics and regional variates as determinants of area property crime levels. *Journal of Quantitative Criminology, 8*(3), 265-285.

Papps, K., & Winkelmann, R. (1998). Unemployment and crime: New answer to an old questions. Institute for the Study of Labor Discussion Paper No. 25. Bonn: Germany.

Pesaran, M.H., Shin, Y. & Smith, R.J. (1996). Testing for the existence of a long-run relationship. DAE Working Papers No. 9622. University of Cambridge. U.K.

Pesaran, M.H. & Shin, Y. (1999). An autoregressive distributed lag modeling approach to cointegration analysis. In S. Storm (ed.), *Econometrics and Economic Theory in the 20th Century: The Ragnar Frisch Centennial Symposium*. Cambridge: Cambridge University Press.

Pesaran, M.H., Shin, Y., & Smith, R.J. (2001). Bounds testing approaches t the analysis of level relationships. *Journal of Applied Econometrics, 16*, 289-326.

Phillips, A.W. (1954). Stabilisation policy in a closed economy. *The Economic Journal, 64*, 290-323.

Pyle, D.J., & Deadman, D. (1994). Crime and unemployment in Scotland: Some further results. *Scottish Journal of Political Economy, 41*(3), 314-324.

Raphael, S. & Winter-Ebmer, R. (2001). Identifying the effect of unemployment on crime. *Journal of Law and Economics, 44*, 259-283.

Sargan, J.D. (1964). Wages and prices in the United Kingdom: A study of econometric methodology. In P.E. Hart, G. Mills & J.K. Whittakers (eds.), *Econometric Analysis for National Planning*. London: Butterworths.

Small, J. & Lewis, C. (1996). Economic crime in New Zealand: Causation or coincidence? Working Paper #158, University of Auckland, Australia.

Scorcu, A.E., & Cellini, R. (1998). Economic activity and crime in the long-run: An empirical investigation on aggregate data from Italy, 1951-1994. *International Review of Law and Economics, 18*, s279-292.

Weatherburn, D., Lind, B. & Ku, S. (2001). The short-run effects of economic adversity on property crime. *Australian and New Zealand Journal of Criminology, 34*, 134-147.

Weatherburn, D. (1992). Economic adversity and crime. *Trends & issues in crime and criminal justice no. 40*. Australian Institute of Criminology, Australia.

Witt, R., Clarke, A., & Fielding, N. (1998). Crime, earnings inequality and unemployment in England and Wales. *Applied Economics Letters, 5*, 265-267.