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August 2010

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Abstract

This paper provides further evidence on the impact of crime on the job market using the time series data over the period 1980-2007 for Argentina. We also address methodological flaws by earlier crime studies by employing autoregressive distributed lag (ARDL) approach to cointegration advocated by Pesaran *et al* (2001). The results show that unemployment has a statistically positive effect on the crime rate, depending on the model used.

Resumen

Este trabajo provee evidencia del impacto del crimen en el mercado laboral utilizando series de tiempo en el periodo 1980-2007 para Argentina. Utilizamos la metodología de Autoregressive distributed lag (ARDL) desarrollada por Pesaran et al (2001) para establecer la relación de cointegración entre las variables. Los resultados muestran que desempleo tiene un efecto significativo positivo sobre crimen, dependiendo del modelo utilizado.

Keywords: Crime, Cointegration, ARDL

JEL Classification Codes: k42, K14, C32, E24

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1. Introduction

In July 2010 the Victimization Survey carried out by Universidad Torcuato Di Tella reports that 39% of the interviews families in 40 urban centers of Argentina were victims of a crime in the last 12 months. Even more, 26.5% of those families suffered a violent crime. These are the results of one of many opinion surveys, but they all have in common that crime is one of most important problems in Argentina.

It is widely recognized that socioeconomic determinants influence crime rates. The link between unemployment and crime has been largely debated. Becker postulated that unemployment is positively related to crime because when an individual is unemployed, the marginal return from legitimate earning activities are lower than before, hence one is more likely to engage in criminal activities.

However, there have been a few attempts to establish causality between unemployment and crime rates in Argentine: unemployment may explain crime, but crime may also be detrimental to legal activities in the sense that affect economic agents' decisions of, for example, how many resources to invest in human and non human capital.

The present paper aims to contribute to this debate by using a time series approach in order to determine the dynamic relationship among crime rate and macro economic variables. In particular, we will employ an Autoregressive Distributed Lag (*ARDL*, henceforth) approach to cointegration and error correction models, to determine whether there is evidence of causality in the short and long run between unemployment and crime rates in Argentine from 1980 to 2007. In our best of knowledge, there is no study which deals with crime rates and has used a dynamic econometric model such as the ARDL approach, especially in Argentina context.

An ARDL approach designed by Pesaran et al (2001), is employed to set the integration and cointegration status of the variables. We use this approach rather than Johansen`s since this method is more robust with small number of observations and with endogeneity of the variables. This paper aims to understand the links between crime and unemployment in Argentina, using annual data from 1980 to 2007, by means of ARDL.

[1] We thank Joaquín Alvarez for helpful research assistant. We gratefully acknowledge the support of the Consejo de Investigaciones de la Universidad Nacional de Tucumán (CIUNT) Grant 26/F 204. The views expressed herein are those of the authors and not necessarily those of the CIUNT

This paper is structured as follows: After the introduction, Section 2 reviews the empirical literature. Section 3 discusses the econometric methodology. Section 4 presents the data. Section 5 shows the empirical results. Section 6 concludes.

2. Theoretical And Literature Review

The hypothesis that unemployment, income distribution, and other variables characterizing the economic environment of the region affects crime can be traced out to Adam Smith. But it was not until the seminal paper of Gary Becker in 1968 that the first models of economics of crime upsurge.

Becker established that crime is an economically important activity and the decision to participate in it, is an economic choice taken by rational agents. This decision comes form a maximization problem in which agents have to compare costs and benefits of legal and illegal activities taking into accounts the probability of being arrested and punished.

Theoretical literature of crime emphasize on two fundamental aspects: the deterrence effect, related to the probability of being arrested and of being condemned and the social and macroeconomic effect of environment which generates an atmosphere prone to crime, measured by variables such as the unemployment rate, income per capita, inequality in income distribution, education, among others.

GDP per capita can also be important in the explanation of crime rate. An economic expansion (increase in GDP per capita) could reduce criminal activities but it can also make more attractive illegal activities since it presents better opportunities, although, the potential victims could neutralize this "richness" effect by destining more resources against crime (alarms, bars, etc.). So the expected sign of GDP per capita is ambiguous. In this context, it could be more appropriate the use of relative deprivation indicators (GINI coefficient)[2]

There are numerous studies on the relationship between crime and inequality. Many of these studies find that relative income impacts on crime (see Fajnzylber et al.,2002, Choe, 2008, Cerro and Meloni, 2001)). Hovewer other works fail to find a robust effect of inequality on crime (for instance, Neumayer, 2004).

From a theoretical point of view education may affect the criminal decision through several channels. First, higher levels of educational attainment are associated with higher returns on the market increasing the opportunity cost of crime. As noted by Usher (1997) that education perpetuates the values of society, enculturates people to serve their communities and promotes the virtues of hard work and honesty. Furthermore, Lochner and Moretti (2004) indicate that schooling generates beyond the private return received by an individual. Recent research tends to support the view that education is negatively correlated to crime rate (Buonnano and Montolio, 2006; Buonnano and Leonida, 2006; Lochner and Moretti, 2004). Additionally, several studies show that criminals tend to be less educated and from poorer economic families than non criminals (Freeman (1994), Lochner (1999))

Unemployment rates measure the absence of legal income opportunities and are central part of criminiometric of the Becker-Ehrlich type models (Entorf and Spengler, 2000). Unemployment, as it limits the rate of return of legal activities, is expected to increase illegal activities However, studies on the relation between crime and unemployment conclude that the effect of unemployment on crime is ambiguous and appears to be very sensitive to econometric specification. Freeman (1994) and Imrohoroglu et al (2001) research support this finding.

Freeman (1994) and Maciandaro (1999) set that the effect of job market on crime may be studied through time series, cross section and economic characteristic across people. Depending on the type of study performed it is likely to obtain different results (for instance, Witt et al (1998), Marselli and Vannini (2000))

Empirical applications for Argentina carried out by Kessler and Molinari (1997), Balbo and Posadas (1998) and Chambouleyrón and Willington (1998), show that socio-economic variables are not significant or weakly significant to explain criminal behavior. On the other hand, Cerro and Meloni (1999) in a panel study find a significant and positive effect of unemployment on criminal activities. They also found an important deterrence effect measured by the probability of arrest and sentence. The deterrence effect is well documented for the US and Europe (Levitt, 1998; Edmark, 2005; Entorf and Spengler, 2000).

The expected signs of deterrence variables are negative since they represent a cost to those who commits crimes. Therefore, as the rate of sentence and conviction increases, the crime rate is expected to decrease, ceteris paribus. Di Tella and Schargrodsky (2004) find a large deterrent effect of police on crime, by measuring the car thefts before and after an Argentinean exogenous event.

All these papers emphasize the causal effect of socioeconomic and deterrence variables on crime rate. However, there have been few attempts to establish the role of criminal activities as explanatory variable and to establish causality between economic activities and crime: unemployment, for example, may explain crime, but crime may also be detrimental to legal activities in the sense that affect economic agents' decisions.

The first contributions were due to Knack and Keefer (1995), who studied the impact of property rights on economic growth using indicators provided by country risk evaluators to potential foreign investors. Mauro (1995) also finds that corruption lower investment, thereby lowering economic growth.

Monte and Pagani (2001) for Italian dataset, Pshiva and Suarez (2006) for Colombia, Daniele and Marani (2008) for Italy, carried out different researches for different countries and periods but they all find that criminal activities have a detrimental effect on investment.

On the other hand, Forni and Paba (2000) examine the impact of murder in Italy, as a proxy of organized crime, on employment, finding a strong effect. Later on and extending the dataset, Peri(2004) also find a negative effect of crime on employment growth.

Cardenas (2007) studying the case of Colombia identifies that the deceleration of growth is a result of a reduction in productivity. At the same time, VAR and Granger Causality test results support the causal relationship between drug trafficking and violent crime and from crime to productivity.

Mauro and Carmeci (2007), using data form Italian regions by means of ARDL approach suggest that crime has a negative long run effect on output level, rather than the other way round.

Masih and Masih (1996) using Australian data within a multivariate cointegrated system establish the direction of causality by means of a Granger Causality test, but they couldn't find an impact of crime on socioeconomic variables. Later Narayan and Smith (2004), also for Australia, examine Granger causality between different typologies of crime and socioeconomic variables. The results depend on the crime typology and the socioeconomic variable.

For the Malaysian case, Habibullah and Baharon (2008) find that the long run causal effect runs form economic activity to crime rates by means of an ARDL approach. On the other hand they fail to find causality neither in the long run nor in the short run among variables.

Detotto and Pulina (2009) using data from Italy, analyses how a set of economic variables and deterrence variables affect criminal activity and highlight that crime is also detrimental to economic activities, by means on an ARDL approach. These findings are also sustained by a Granger Causality test, in the sense that crime typologies affect legal activities, reducing employment rate.

3. METHODOLOGY

The model used in this paper assumes the following long-run relationship:

$$CR_t = \alpha_0 + \alpha_1 UNEMP_t + \alpha_2 GDP_t + \alpha_3 SENT + \varepsilon_t \qquad [1]$$

where *CR* = crime rate per 10.000 pop, *UNEMP*= Unemployment rate, *GDP* = income per capita and *SENT* =sentences rate per total crime. ε_t is the classical error term. All variables are expressed in natural logarithms.

The methodology employed here is borrowed from Pesaran et al. (2001). The choice of this methodology is based on several considerations: first, as shown by Pesaran et al (2001), this methodology yields consistent estimates of the long- run coefficients that are asymptotically normal irrespective of the underlying regressors are I(0) or I(1).

Second, this technique provides unbiased estimates of the long run model and valid t-statistics in presence of potential endogeneity of some regressors (Harris and Solis, 2003). It has also better statistical properties than the two- step Engle and Granger approach as the unrestricted error correction model does not push the dynamics into the residual term (Banerjee et al., 1998). Finally, it has good small sample properties as compared to alternative econometric techniques, multivariate cointegration (Narayan, 2005).

To implement this procedure, equation [1] is modeled as a conditional ARDL error correction model:

$$\Delta CR_t = \beta_0 + \sum_{j=1}^{n} \beta_j \Delta UNEMP_t + \sum_{j=1}^{n} \delta_j \Delta GDP_t + \sum_{j=1}^{n} \phi_j \Delta SENT_t + \eta_1 CR_{t-1} + \eta_2 UNEMP_{t-1} + \eta_3 GDP_{t-1} + \eta_4 SENT_{t-1} + \nu_t \qquad [2]$$

To get equation (2), one has to solve equation (1) for ε_t and lag the solution equation by one period. Eq (2) is a representation of the ARLD approach to cointegration.

The first step in the *ARDL* approach is to estimate Eq (2) by using Ordinary Least Squares (OLS). The second step is to test the presence of cointegration by restricting all the coefficients of the lagged level variables equal to zero. That is the null hypothesis of cointegration (*Ho*: $\eta_1 = \eta_2 = \eta_3 = \eta_4 = 0$), is tested against the alternative (*H₁*: $\eta_1 \neq 0, \eta_2 \neq 0, \eta_3 \neq 0, \eta_4 \neq 0$) by an *F* test with a non-standard distribution.

This test involves two asymptotic critical value bonds depending on the variables are I(0) or I(1) or a mixture of both. If the test statistic value exceeds their upper critical value, then there is evidence of cointegration, if below we cannot reject the null hypothesis of no cointegration and if it lies between bounds, inference is inconclusive. Once a long-run relationship has been established, equation (2) is estimated using an appropriate lag-selection criterion. The optimal lag lengths of the *ARDL* are selected by R bar criteria. At the second stage of the *ARDL* cointegration procedure, it is also possible to obtain the ARDL representation of the error-correction model. To estimate the speed with which the dependent variable adjusts to independent variables within the bounds-testing approach, following Pesaran *et al.*, the lagged-level variables in equation (2) are replaced by ecm_{t-1} as in equation (3):

$$\Delta CR_t = \beta_0 + \sum_{j=1}^{n} \beta_j \Delta UNEMP_t + \sum_{j=1}^{n} \delta_j \Delta GDP_t + \sum_{j=1}^{n} \phi_j \Delta SENT + \lambda ecm_{t-1} + \upsilon_t \qquad [3]$$

A negative and statistically significant estimation of λ not only represents the speed of adjustment but also provides an alternative means of supporting cointegration between the variables.

The ARDL approach does not require the pretesting of the variables included in the model, for unit roots, unlike other techniques such as the Johansen approach (Pesaran et al., 2001). However, we test for the presence of unit roots to exclude the possibility of I(2) variables. In presence of such variables, the F test critical values are not more valid because they are based on the assumption that variables are I (0) or I(1). Augmented Dickey Fuller (ADF) tests (Dickey and Fuller, 1981) were used to test for unit roots in the variables.

4. DATA

Annual data for Argentina in the period 1980-2007 were used in the empirical analysis. GDP per capita[3] (in constant pesos), and unemployment were extracted from the Instituto Nacional de Estadísticas y Censos (INDEC). Data on reported Crime and Sentence come from Dirección Nacional de Política Criminal. Crime rates are defined as the number of reported offences per 10.000 inhabitants. According to official statistics, the reported crime rate in Argentina increased 287 % in the period that span from 1980 to 2007, i.e., it increased at an average annual rate of 5.14%. However the growth rate was not even during the whole period. During the two deep crises Argentina went thought in this period, the 1989-1990 and 2001-2002; the crime rate grew faster, and reached a peak in 1989 of 202 crimes per 10000 inhabitants and in 2002 of 358 crimes per 10000 inhabitants.

After that it experienced a slight fall until 2007 when its value was 310. Unfortunately, statistics on crime are no longer available, but we conjecture that it has been increasing in the last years.[4] Even more, the victimization survey of Universidad Di

[3] We do not use Gini coefficient or other inequality measure for Argentina, since they are not obtainable from the official statistics at over the whole period under consideration.

[4] As many statistics are not reported by the present administration.

Tella, reports a victimization rate for 2008 of 28.4%, in 2009 of 34.1% and up to august 2010, 33.3%.

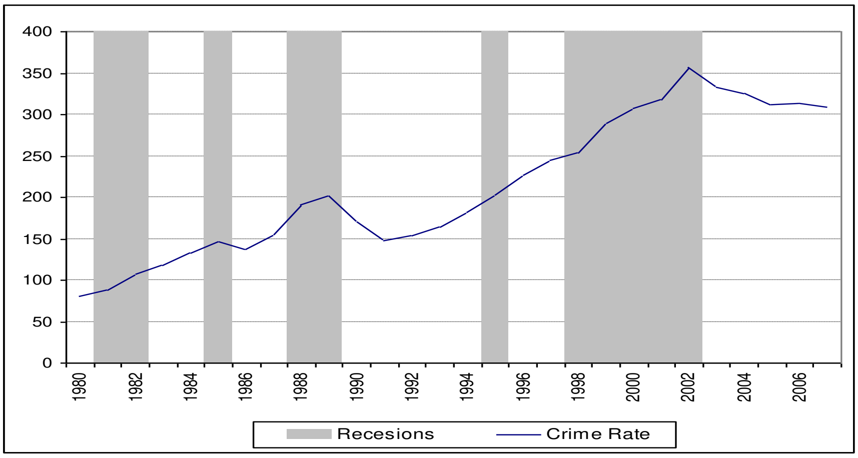
Argentina is a country characterized by huge volatility in its economic activity and in its judicial system. Analyzing the rate of crime in Argentina, we can identify different periods, that lead us think that deterrence and macroeconomic effect are both very important to explain crime.

At the beginning of the 80's, Argentina crime rate was very low. We conjecture that deterrence effect was quite strong, given that the country was under a Military Government regime. In 1983, with the upcoming of the democracy, important modifications took place in the Criminal Code (especially to laws 11179, 23050 and 23057 and in 1984 the law 23077 was enacted) and in the Criminal Code Procedures (law 2372) that implied considerable reductions in the punishment to criminal activities. Consequently with those modifications we see sustained increases in the crime rate.

On the other hand in 2003, some members of the Supreme Court were designed. Some of them were "garantistas" in the sense that relaxed penalties to criminal, especially to young people. We can observe that despite the huge economic recovery after 2001 crisis, the crime rate keeps high.

On the other hand, we can observe that during recessions, especially those deep, crime rate peaks, which let us conjecture that crime is related to economic activity.

Figure 1. Rate of Reported Crime (per 10.000 pop). Argentina 1980-2007



Source: Dirección Nacional de Política Criminal

4. EMPIRICAL RESULTS

In this paper, we employed the Augmented Dickey Fuller-GLS test (ADF-GLS) proposed by Elliot, Rothenberg and Stock (1996) and the Philips-Perron to test the stationarity of the variables.[5]Unit root results are reported in Table 1. It comes out of these results that the conditions for applying the ARDL cointegration approach are satisfied. In other words, none of the variables included in equation (1) is I(2) or of greater order.

[5] It has been documented that ADF by Dickey and Fuller perform badly in presence of small samples as the ones used in this paper

Table 1. Unit root results: Argentina 1980-2007

Variables (all in log)	Decision		ADF-GLS (level) (1)	Critical Value (2)	Phillips Perron (PP)	Critical Value (2)	PP difference
Crime Rate	I(1)	c,t,1	-2.903	-3.423	-1.556	-3.557	-3.81**
Sentence Rate	I(1)	c,t,1	-2.186	-3.423	-2.071	-3.557	-3.88***
GDP per capita	I(1)	c,t,1	-2.466	-3.423	-1.312	-3.557	-3.67**
Unemployment Rate	I(1)	c,1	-0.839	-2.463	-2.686	-2.944	-4.57***

Note: (1)Elliot, Rothenbert and Stock,
(2) 95% simulated critical value using 28 obs and 1000 replications
*, **, *** Significant at 10% , 5% and 1% respectively
Constant (c), time trend (t) and order of lag

Cointegration and Empirical Results

We first test for the existence of a level relationship among the variables in the *ARDL* model, independently on the integration order of the variables. It can be seen from Table 2 that when causality is assumed from unemployment to crime, the F statistic indicates the presence of long run relationship. When causality is assumed to be in the opposite direction, there is also evidence of a stable long run relationship between both variables.

Table 2. ARDL Cointegration Test. Upper and lower bounds

Dependent Variables (in First Differences)	Statistic F (4,17)	Conclusion
Crime Rate	3.917	Reject Ho at 90%
Sentence Rate	2.388	Accept Ho
GDP per capita	3.167	Inconclusive
Unemployment Rate	4.649	Reject Ho at 90%

Note: Ho: no long run relationship among variables.
Lags=1

Critical Bounds-Case II*	95%	90%
Upper Bound	4.049	3.574
Lower Bound	2.850	2.425

*Intercept and No Trend

Critical Bounds are constructed by stochastic simulations using 20000 replications

We then estimate the Autoregressive Distributed Lag (ARDL)[6]. In all models, we include interaction Dummies variables for the period 1999-2007 to control for structural break; these dummies are very significant in almost all cases.

The long run coefficients of the regressions in the ARDL approach are presented in Table 3. The sign of GDP coefficient is negative but not significant. Unemployment has a positive and significant relationship, indicating that an increase in unemployment increases the rate of crime. There is also a negative and significant deterrence effect on the crime rate: an increase in the sentence rate decreases illegal activities.

On the other hand, Table 3 does show no long run effect of crime on either GDPpc or Unemployment.

Table 3. Long Run estimates: 1980-2007

Dependent Variable	Crime ARDL (2,2,1,2)	t Ratio	Unemployment ARDL (0,2,2,1)	t Ratio)
Crime			-2.457	-1.296
GDPpc	-0.276	-1.181	-7.939	-0.805
Unemployment	0.249***	5.092		
Sentence	-0.437***	-7.575	-2.598	-1.079
DCrime		-0.671		
DGDPpc	-0.081	6.217		
DUnemployment	0.263***	4.10		
DSentence	0.476***	2.723		
constant	5.557**	-1.181	-76.750	-0.98

Notes: All variables in log
* Significant at 10%
** Significant at 5%
*** Significant at 1%
ARDL lags order selected based on R-BAR Squared Criterion (crime, GDPpc, Unemployment, Sentence)
D stands for dummy variable

To complete the analysis it is also important to look at the results related to the short run dynamics. In this regard, the error correction representations for the respective selected ARDL models are presented in Table 4. All the terms in the estimated model are statistically significant (excepting unemployment) and with the expected sign. There is a short run dynamic that is significant in the crime rate explanation. In addition, the estimated coefficient of the error correction term is significant, thus confirming our previous results that there is a long run relationship between our variables. Furthermore, the magnitude of the estimate of the error correction term suggests a relatively high speed of adjustment from short run disequilibrium (1.042).

[6] ARDL estimations are in TableIA in Appendix

Table 4. Error Correction Representation for the Selected ARDL Model.

Dependent Variable	Delta Crime	Delta Unemployment
Delta Crime		-0.097
DeltaCrime (- 1)	0.562**	1.188*
DeltaGDPpc	-0.907**	-2.465***
DeltaGDPpc (-1)	0.820**	2.815***
DeltaUnemployment	-0.116	
DeltaUnemployment(-1)		0.564**
DeltaSentence	-0.348***	0.218
DeltaSentence (-1)	0.211**	
DeltaDCrime		
DeltaDGDPpc	-0.084	
DeltaDUnemployment	0.273**	
DeltaDSentence	0.496**	
ecm(-1)	**-1.042*** **	**-0.039**
R-Bar-Squared	0.833	
D-W	2.048	
ecm= Crime+0.276*GDPpc-0.249*Unemployment+0.437*Sentence-5.557 +0.081* DGDPpc-0.262* DUnemployment -0.476* DSentence		
ecm= Unemployment+7.939* GDPpc-2.457* Crime+2.599* Sentence-76.75		

Note: All variables in log
* Significant at 10%
** Significant at 5%
*** Significant at 1%

The relationship between unemployment (as dependent variable) and crime is not clear. By one side, Table 2 shows a cointegration relationship, but according to Table 4 there is no long run relationship between unemployment and crime (the estimated coefficient is negative and not significant). Table IV also shows no relationship between these variables, neither in the long run nor in the sort run.

Granger Causality Test

The null hypothesis of this test is that a variable or a set of variables do not Granger cause another variable. Granger (2000) suggests including the error correction term to examine the potential short-term causality and long term equilibrium relations. Including the error correction term allow testing the long run equilibrium relationship.

The main findings of the multivariate Granger causality test, are presented in Table 5. Unemployment and Crime lagged do Granger cause Crime. The ecm term is indicating a long run relationship. In the overall, we reject the non causality hypothesis.

Table 5. Granger Causality Tests

Dependent Variable	Delta Crime	Delta Unemployment
Delta Crime (-1)	1.899***	
Delta Unemployment (-1)	-0.363**	0.332
Delta Unemployment (-2)		-0.160
ecm (-1)	-1.814***	
All F(3,26)	6.017***	2.278

Note: All variables in log
* Significant at 10%
** Significant at 5%
*** Significant at 1%

However, neither Crime nor Unemployment lagged do Granger cause Unemployment, We could not find a long run relationship, given that the ecm term was not significant. We find that crime do not Granger Cause unemployment.

V. CONCLUSIONS

It is widely recognized that socioeconomic determinants influence crime rates. The link between unemployment and crime has been largely debated. However, there have been a few attempts to establish causality between unemployment and crime rates in Argentine: unemployment may explain crime, but crime may also be detrimental to legal activities in the sense that affect economic agents' decisions.

The present paper aimed to contribute to this debate by using a time series approach in order to determine the dynamic relationship among crime rate and macro economic variables. In particular, we will employ an Autoregressive Distributed Lag (*ARDL*, henceforth) approach to cointegration and error correction models, to determine whether there is evidence of causality in the short and long run between unemployment and crime rates in Argentine from 1980 to 2007. We use an ARDL approach rather than Johansen`s since this method is more robust with small number of observations and with endogeneity of the variables.

Results do not let us conclude about the effect of crime on unemployment, since we obtained mixed results.

In cointegration equation (Table II) we find a relationship in both directions. In ARDL (Table 1A) we accept a relationship among variables, however only lagged once unemployment has a significant effect on crime, but not the other way round.

Lon run coefficients estimates by ARDL approach (Table III), we find a positive significant relationship from unemployment to crime, but not from crime to unemployment.

Table IV, Error Correction Model reinforces that variables explain crime in the long run, but not unemployment, however short run dynamic is not clear.

Lately Granger Causality test point to a relation of unemployment to crime but not the other way round.

The main results are not as conclusive as those obtained by Masih and Masih (1996) for Australia, who found no relationship from crime to unemployment, nor those obtained by Mauro and Carmeci (2007), Detotto and Pulina (2009), for Italy, or for the Malaysian case (Habibullah and Baharon (2008)) who find a strong relationship from crime to unemployment. Further research is needed to let us conclude about the dynamic relationship between crime and unemployment.

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APPENDIX

Table IA. Autoregressive Distributed Lag Estimates

Dependent Variable	Crime (2,2,1,2)	Sentence (2,1,0,2)	GDPpc (2,0,1,1)	Unemployment (2,2,2,2)
Sentence	-0.348***		0.145**	-0.169
Sentence(-1)	0.103	0.967***	-0.055	-0.15
Sentence(-2)	-0.210**	-0.398		-0.344
GDPpc	-0.907**	0.844		-2.52***
GDPpc(-1)	1.439**	-1.617**	1.247***	5.695***
GDPpc(-2)	-0.820**		-0.48***	-3.945***
Crime		-1.276***	-0.013	-0.974
Crime(-1)		1.396*		0.920
Crime(-2)		-0.852		-1.188*
Unemployment	-0.116	0.143	-0.147***	
Unemployment(-1)	0.375**		0.244***	1.757***
Unemployment(-2)				-0.587***
DGDPpc	-0.084		-0.159*	0.532
D Crime			-0.103*	
D Sentence	0.495**	-0.149		
D Unemployment	0.273**			0.275
c	5.79**	8.728	2.249	10.522*

Note: All variables in log
* Significant at 10%
** Significant at 5%
*** Significant at 1%

Testing for existence of a level relationship among the variables in the ARDL model.
Null hypothesis: no level effect

Dependent Variable	F-statistic	Null Hypothesis
Crime (2,2,1,2)	7.912	Reject at 95%
Sentence (2,1,0,2)	2.226	Can´t be rejected
GDPpc (2,0,1,1)	2.584	Can´t be rejected
Unemployment (2,2,2,2)	1.633	Can´t be rejected

Diagnostic Tests (F Version)

Test Statistics	Crime (2,2,1,2)	Sentence (2,1,0,2)	GDPpc (2,0,1,1)	Unemployment (2,2,2,2)
Serial Correlation	F(1,11)=0.067	F(1, 14)=5.291**	F(1, 15)=0.567	F(1, 11)=0.003
Functional Form	F(1,11)=4.798*	F(1, 14)= 0.049	F(1, 15)= 0.074	F(1, 11)= 0.184
Heteroscedasticity	F(1,24)=4.886**	F(1, 24)=1.395	F(1, 24)=5.491**	F(1, 24)= 0.111

Note: * Significant at 10%
** Significant at 5%
*** Significant at 1%