Article:

Janko, Z. and Popli, G. (2015) Examining the link between crime and unemployment: a time-series analysis for Canada. Applied Economics, 47 (37). pp. 4007-4019. ISSN 0003-6846

https://doi.org/10.1080/00036846.2015.1023942

Examining the Link between Crime and Unemployment: A Time Series Analysis for Canada

Zuzana Janko
Department of Economics
San Francisco State University

Gurleen Popli*
Department of Economics
University of Sheffield

February 2015

Key words: crime rates in Canada, time series analysis, unemployment

JEL Classification: C22, K1

Abstract

We use national and regional Canadian data to analyze the relationship between economic activity (as reflected by the unemployment rate) and crime rates. Given potential aggregation bias, we disaggregate the crime data and look at the relationship between six different types of crimes rates and unemployment rate; we also disaggregate the data by region. We employ an error correction model in our analysis to test for short-run and long-run dynamics. We find no evidence of long-run relationship between crime and unemployment, both when we look at disaggregation by type of crime and disaggregation by region. Lack of evidence of a long-run relationship indicates we have no evidence of motivation hypothesis. For selected types of property crimes we find some evidence of significant negative short-run relationship between crime and unemployment, lending support to the opportunity hypothesis. Inclusion of control variables in the panel analysis does not alter the findings, qualitatively or quantitatively.

Acknowledgments: We are grateful to Mustafa Caglayan, Juan Carlos Cuestas, and the participants at the Royal Economic Conference (April 2014) for providing helpful comments. We would also like to thank an anonymous referee for very valuable comments, which have much improved the paper. The normal disclaimer applies.

* Corresponding author: Department of Economics, University of Sheffield, 9 Mappin Street, Sheffield, S1 4DT, UK. Email: g.popli@shef.ac.uk; Tel no. +44-114-2223485

1. Introduction

In this paper, we use Canadian data to analyze the relationship between macroeconomic activity, specifically the unemployment rate, and crime rates. We start our analysis by looking at the national level time series data to gather some insight into the relationship between aggregate crime and unemployment; this is followed by a disaggregated analysis, where we look at the relationship between six different types of crimes rates and unemployment. Finally, we conduct a panel data analysis to allow for disaggregation over different types of crimes and over different regions; where our panel consists of ten Canadian provinces. In our analysis we employ an error correction model to test short-run and long-run dynamics that occur in the relationship between unemployment and crime as a result of regional variations and the variations in the types of crime.

Since Becker's (1968) seminal paper, wherein he develops a theoretical model of crime behaviour to specifically address the role of deteriorating labour markets, a large literature has developed examining the relationship between crime and the economy. Becker argued that an individual will engage in criminal activities as long as the expected utility of committing crime is greater than the expected utility of engaging in other activities; hence, deteriorations in labor market opportunities make crime relatively more attractive. While Becker's analysis was at the micro level, we build on existing research to explore the link between crime and the state of the macro economy.

To capture the relationship between crime and the macro economy, researchers have made use of a number of different macroeconomic aggregates, such as real GDP and unemployment. Early analysis of the link between crime and the state of the economy cycle includes that of Cook and Zarkin (1985) who examine the role of real GDP; they find that expansions of economic activity (via a rise in real GDP) has a negative impact on property crimes. Wang and Minor (2002) look at the impact of job accessibility; they conclude that improvements in job accessibility occurring at times of economic expansions lower crime rates, however the relationship is stronger for property crimes than for crimes of violence. Alternatively, the unemployment rate is used in this literature, as it rises during contractions and falls during expansions and is more directly linked with the economic incentives of crime.

In our paper we use the unemployment rate to capture the link between the business cycle and crime rate. As part of our analysis, we specifically deal with the problem of aggregation bias; we start with an aggregated national level analysis, followed by disaggregation along the crime margin. The national level analysis is followed by a regional panel analysis, which is also disaggregated along the crime margin.

The issue of aggregation bias has been addressed in this literature before. An early example is the work by Cornwell and Trumbull (1994), who in their paper use county level data from North Carolina (US) to control for unobserved heterogeneity (which they call 'jurisdictional heterogeneity') and find that results based on national level data overstate the role of a number of explanatory variables. Levitt (2001) argues that national level data while useful for certain types of analysis are a 'crude tool' in exploring the link between unemployment and crime rates as the national crime statistics potentially remove useful variations. A similar argument holds for disaggregating unemployment rates, as those can differ substantially by regions. An argument can also be made that economic incentives across various kinds of crimes vary. Cherry and List (2002), using the same data, extend the work by Cornwell and Trumbull by allowing for different types of crimes, and find evidence of 'parameter heterogeneity' across crime types.

The structure of the paper is follows. Section 2 of the paper reviews the recent literature on the link between unemployment and crime. Section 3 presents a review of the different econometric specification used in the literature to identify the link between unemployment and crime using macro level data; we also discuss in detail the specification we use in our analysis. Section 4 presents the empirical analysis: data and results. Discussion and concluding comments are in section 5.

2. Background Literature

In their seminal work Cantor and Land (1985) developed a theoretical framework to explain the link between unemployment and crime. They suggested two important links: *opportunity* and *motivation*. The motivation hypothesis, similar to the Becker (1968) analysis, suggested that a decrease in viable economic prospects will increase the incentive to engage in crime; so the unemployed are more likely to engage in criminal activities; this suggests a positive relationship between crime and unemployment. The opportunity hypothesis (also referred to as the *guardianship* hypothesis) on the other hand suggested that a decrease in economic activity will decrease the availability of criminal targets (the unemployed are also more likely to stay at home thus decreasing their vulnerability to crime, especially property crime), and hence reduce the incentive to engage in crime; this suggests a negative relationship between crime and unemployment. The two effects are expected to work differently based on the type of crime; with the motivation hypothesis being more important for property crime and opportunity hypothesis being relevant for both property and violent crimes (though the effect is still expected to be stronger for the property crimes).

There are numerous empirical studies investigating the hypothesised theoretical relationship between crime and unemployment. The key finding from much of the literature suggests: unemployment matters for property crimes more than for other kinds of crime (for example, violent crimes); evidence in support of this relationship is seen across countries and time. However, the evidence on the direction of the relationship (positive or negative) is mixed, it often depends on the econometric specification being used and the type of crime being investigated.

Using US data, Cantor and Land (1985) find evidence for both crime opportunity and crime motivation, especially when considering crimes with a property component (such as robbery, burglary and larceny). Findings of Cantor and Land are confirmed by Philips and Land (2012), using relatively more recent and larger dataset for the US. Raphael and Winter-Ebmer (2001) and Gould et al. (2002), again using US data, report a statistically significant positive relationship between unemployment and property crimes, but not one between unemployment and crimes of violence. Using panel data for the 49 US states over the period 1974-2000 Lin (2008) finds elasticity of property crime, to changes in unemployment, as high as 4% (1% increase in unemployment leads to a 4% increase in crime); further, 33% of the change in property crimes over the period of analysis could be attributed to unemployment.

While a large body of evidence comes from the US, studies using data from other countries also find a similar (mostly positive) relationship between crime and unemployment. Reilly and Witt (1996), Witt et al. (1999) and Wu and Wu (2012)[1] look at the relationship between crime and unemployment for England and Wales; Papas and Winkelmann (2000) for New Zealand; Edmark (2005) and Oster and Agell (2007) for Sweden; Buonanno (1996) for Italy; and Altindag (2012) does a cross country analysis using a country-level panel data from European countries.

Andresen (2013) used data from Canadian provinces to look at the relationship between the state of the economy and crime; where the state of the economy is captured by: GDP, unemployment and low income. The key findings suggest a complex relationship between the state of the economy and crime; while the author concludes

[1] Wu and Wu (2012) find mixed results, with unemployment and fraud having a negative relationship and unemployment and drug offences having a positive relationship.

that the state of the economy matters for crime, there is no clear finding on the sign and magnitude of the estimated parameters.

Most of empirical analyses looking at economic motives for crime, in general, highlight the importance of controlling for other variables which influence crime rate. Following Ehrlich (1973), who made the first attempt to empirically operationalise Becker's model of crime and punishment, most commonly used control variables often reflect: deterrence mechanism, inequality of income, and demographic factors.

Corman and Mocan (2005) look at the crime-deterrence-unemployment relationship; where deterrence, as measured by size of police force and number of arrests for different crimes, is expected to have a negative effect on crime. Using data from the New York City, even after controlling for the deterrence variables, they find a significant positive relationship between crime (burglary and motor vehicle theft) and unemployment. Levitt (1996) looks at the impact of incarceration rates on crime across all US states. His findings suggest that an increase in incarceration rates has a negative impact on crime; further once the deterrence mechanism is controlled for he too finds a positive relationship between unemployment and crime.

Second set of control variables often reflect the level of inequality, which is used to capture the 'relative economic hardship' as a motivation for engaging in criminal behaviour (Andresen, 2013). Inequality is expected to impact crime in two ways: first, higher the inequality more rich the potential victim, hence higher returns for potential offenders; second, lower the relative income of the individuals at the bottom of the distribution, less the opportunity costs of engaging in crime for those at the lower end of the distribution (Wu and Wu, 2012). Both Witt et al. (1999) and Machin and Meghir (2004), using data from England and Wales, find that relative fall in the wages of the low-wage workers increases crime. Similarly, Entorf and Spengler (2000) use German data and find evidence that widening inequality increases the delinquent behaviour.

Third set of controls often reflect the demographics. There are distinct age and gender patterns to crime, with young males most likely to commit crime, be arrested and incarcerated (Steffensmeier and Allan, 1996; Freeman, 1999). Evidence from Levitt (1996, 1997) suggests that higher % of young population yields higher crime, with the 25-44 population having a larger impact. The impact of youth unemployment specifically however yields mixed results. Oster and Agell (2007), using Swedish data, find that while general unemployment significantly impacts crime, there is no evidence that youth unemployment impacts crime.

3. Econometric model

Cantor and Land (1985) not only suggested the two opposing links (opportunity and motivation) between crime and unemployment, they also argued that the timing of these two links differs; specifically, the opportunity effect has an immediate impact on crime, while the motivation effect occurs over time with sustained unemployment. The empirical specification they used to capture the two hypothesised effects is given by the following regression equation

$$\Delta C_t = \beta_0 + \beta_1 U_t + \beta_2 \Delta U_t + \varepsilon_t$$

where C_t is log of crime at time t; U_t is the unemployment rate at time t; Δ is the difference operator, such that $\Delta U_t \equiv U_t - U_{t-1}$; and ε_t is the stochastic error term. β_0, β_1, and β_2 are the parameters to be estimated; where β_1 captures the effect of the opportunity hypothesis (the short-run effect), which is expected to be negative ($\beta_1 < 0$), and β_2 captures the effect of the motivation hypothesis (the long-run effect), which is expected to be positive ($\beta_2 > 0$).[2]

[2] Most of the empirical studies which find a positive link between unemployment and crime (consistent with the motivation hypothesis) use annual date and are mainly looking at the relationship between first difference of crime and contemporaneous first difference of unemployment i.e. β_2. Cantor and Land argue in their 1985 paper that 'while the motivational effects of unemployment are lagged, they are of relatively short duration'. Thus, their interpretation of long-run is within a year.

While the theoretical economic model specified by Cantor and Land (1985) was not subject to criticism, their econometric specification claiming to capture the economic model came under heavy criticism early by Hale (1991) and Hale and Sabbagh (1991), and later by Greenberg (2001). The earlier criticism stemmed from the developments in co-integration methods, which showed that attempts to explain a stationary variable with a non-stationary variable leads to a model that is statistically misspecified and results in spurious regression. Hale (1991) and Hale and Sabbagh (1991) argued that while the first difference of crime was stationary, unemployment rate in levels was often (if not always) non-stationary. Consequently, they argue that to estimate the relationship one needs to check if the two series to be estimated are integrated of the same order, and use co-integration methods if appropriate.

Subsequently, Greenberg (2001) argued that the use of the difference term misspecifies the lag effect i.e. the long-run relationship is not captured, as differencing discards information about the long-run trend of the time series; thus arguing that to capture the long-run relationship a co-integration model is needed. Britt (2001) lays out the differences between the co-integration approach (argued for by Greenberg) and the first difference approach (argued for by Land et al., 1995). Britt states, that while co-integration captures the long-run relation, the first difference approach captures a short-run relationship.

Andresen (2013) uses panel data from ten Canadian provinces over the period, 1981-2009, to test the Cantor and Land (1985) model. The specification they use is

$$C_{jt} = \beta_0 + \beta_1\left(U_{jt} - \overline{U}_j\right) + \beta_2\overline{U}_j + \beta_3 Trend + \varepsilon_t$$

where C_{jt} is log of crime in province j at time t. $U_{jt} - \overline{U}_j$ is the deviation of unemployment in province j at time t from the average unemployment in province j ($\overline{U}_j$) over the period of analysis. β_1 captures the short-run effect and is expected to be negative ($\beta_1 < 0$); and β_2, the coefficient of the average unemployment rate in province

j, captures the long-run effect and is expected to be positive ($\beta_2 > 0$). To address the issue of non-stationarity in the crime series the authors also include a deterministic trend (linear and non-linear) in their analysis; they however ignore the issue of potential non-stationarity in the unemployment series.

3.1 Our model and estimation strategy

We consider a somewhat unified approach. We make use of an error correction model that allows us to investigate whether unemployment has both short-run and long-run dynamics; we address the issue of non-stationarity in both the crime and unemployment series; lastly, we do both a time series (national level) analysis and a panel (regional) analysis. Thus, we build on the works of Cantor and Land (1985), Hale and Sabbagh (1991), Greenberg (2001), Levitt (2001) and Andresen (2013), and incorporate both short term and long term components in estimating a dynamic regression model.

We begin our analysis by looking at the national level time series data. We estimate an error correction model for crime incorporating both the long-run and the short-run dynamics, where short term dynamics are viewed as departures from long-run equilibrium that may last for short periods. The first relationship we aim to estimate is given by equation (1):

$$\Delta C_t = \beta_0 + \beta_1 \Delta U_{t-1} + \beta_2 \, Z_{t-1} + \beta_3 \Delta C_{t-1} + \varepsilon_t \qquad (1)$$

where $\beta_1 < 0$ is the coefficient which captures the short-run relationship (opportunity hypothesis) between change in crime rates and change in unemployment rates; ΔC_{t-1} is included to capture the dynamics/persistence in crime variables; and ε_t is the stochastic error term. $Z_{t-1} = C_{t-1} - \gamma \, U_{t-1}$ is the error correction term, it captures the long term relationship (the motivation hypothesis) between the variables of interest; β_2 (where $-1 < \beta_2 < 0$) is the speed of adjustment, which tells us how the variable of interest, here crime, adjusts to deviations from the long-run relationship. For a long term relationship to exist between crime and unemployment we require $\gamma \neq 0$. If, we find that statistically $\gamma = 0$ then we conclude that there is no long-run relationship between the variables of interest, in which case equation (1) will have no error correction term, and all we have is the short-run dynamics.

We estimate equation (1), first to capture the relationship between total national crime rates and national unemployment rates. Then, we disaggregate total crime into six types of crime (including property crimes and violent crimes) and look at the relationship, at the national level, between types of crimes and aggregate unemployment rate. In each case we test for the presence of the long term relationship.

After estimating the national level relationship(s), we disaggregate further allowing for regional differences, specifically considering crime rates and unemployment rates across the ten Canadian provinces. At the regional level we estimate a panel regression of the form:

$$\Delta C_{jt} = \beta_1 \Delta U_{jt-1} + \beta_2 Z_{jt-1} + \beta_3 \Delta C_{jt-1} + \theta_j + \varepsilon_{jt} \qquad (2)$$

where θ_j is the region specific fixed effect; and ε_{jt} is the stochastic error term. The estimated coefficients (β_1, β_2 and β_3) have the interpretation as in equation (1).

In our empirical estimation we use log of crime throughout, hence the estimated coefficients associated with change in unemployment, in both equations (1) and (2), are interpreted as semi-elasticities. We also test for number of lags, for both crime and unemployment, which should be included in equations (1) and (2). Since we are estimating an autoregressive distributed lag model, we also test for model misspecification. For our panel analysis we also include other control variables (discussed in section 2 above) in our analysis.

4. Empirical Analysis

4.1 Data and descriptive statistics

All data used in this paper were collected from CANSIM, a data base of Statistics Canada. We have annual data, which at the national and regional level covers the period of 1979 to 2006. Our data includes seven crime series. At the most aggregate level is the series of total crime rate (TC) for Canada and individual provinces. Total crime is then disaggregated into two types of crimes: Crimes of Violence (VIO) and Property Crimes (PC). The property crimes are then further disaggregated into four key components of crime: Breaking and Entering (BE), Robbery (ROB), Auto Theft (ATH), and Fraud (FR).

Canada has 13 regions: 10 provinces and 3 territories. In our panel analysis we include all the 10 provinces (see Table 1 for the list of provinces included in the study). We do not use the data on the three Canadian territories (Northwest Territories, Nanavut, and Yukon) due to the large demographical differences compared to the other provinces and due to the lack of data (for example, Northwest Territories was separated into Nanavut and the Northwest Territories in 1999, although Nanavut was already established in 1993, leading to missing data problems in the mid-1990s).

The additional control variables included in the panel analysis are: the incarceration rate (INCAR); % male, between the ages 18 to 24 years, of total population (PMALE18); % male, between the ages 25 to 44 years, of total population (PMALE25); and Gini coefficient (GINI) for each province over time. The incarceration rate is included to capture the deterrence mechanism[3]; we expect the coefficient for INCAR to be negative. We include GINI to capture the 'relative economic hardship' as a motivation for engaging in criminal behavior; inequality is

[3] Incarceration works in two ways: deterrence (threat of sanctions deters people from engaging in crime) and incapacitation (while incarcerated criminals are unable to commit crime). Incarceration rate is included with a lag to avoid the problem of reverse causality; see Corman and Mocan (2000, 2005) and Levitt (1996).

expected to have a positive impact on crime. We also control for the young (18-24) male population as well as the middle age (25-44) male population, to capture the age and gender patterns in crime; with the coefficients on these variables expected to be positive.

Figure 1 shows a plot of all the time series, at the national level. A casual inspection reveals that unemployment rose during the recessions in early 1980's and 1990's, with only a modest rise in unemployment during the slowdown in the early 2000's. [4] A close look at the total crime rates suggest that we may not obtain strong findings of a link between crime and unemployment when looking at aggregate data, however when we look at the disaggregated data we do find some interesting patterns. The robbery series mimics the unemployment series most closely, it exhibits peaks during the recession of the 1980's and 1990's with a modest increase in the early 2000's. With respect to fraud, there is a sharp rise prior to the recession in the 1980's, however it continues to stay high into the early 1990s, at which point it falls with a slight increase in early 2000's. Thus, while it does not exhibit a sharp decline prior to the 1990's recession, it does show similar patterns in the other time periods. Similarly, breaking and entering shows only a modest decline in the mid 1980's as compared to the sharp drop following the 1990's recession. Theft falls in the early 1980's, however it rises sharply in the mid 1980's reaching a peak in the 1990's recession. Overall, the observation of the data suggests that crime rates in Canada have fallen in recent years. [5]

The descriptive statistics of all variables at the national level are given in Table 2. On average, Breaking and Entering is the largest crime committed in Canada. The average unemployment rate over this time period is 8.8%. Table 3 gives the descriptive statistics of the variables at the regional level. Overall, evidence within each province is

[4] The recession dates mentioned are those obtained from the work done by the Economic Cycle Research Institute (ECRI) and empirical research by Louis and Simons (2005).

[5] Criminologists have observed a falling trend in crime rates in other countries as well. Levitt (2004) analyzes the causes of decreases in crime rates in US from 1991-2001. Ward and Carmichael (2001) consider the case of England and Wales. Similar trends are observed for Canada, see Boyce et al. (2014).

the same, with breaking and entering being the biggest crime. Newfoundland and Labrador has the highest level of unemployment but the lowest level of total crime. The highest total crime is in British Columbia (province with the highest inequality, as measured by Gini) followed by Saskatchewan, both are western provinces. The incarceration rate is the highest is Saskatchewan.

4.2 National level analysis

A casual observation of the data in Figure 1 suggests that the series might be non-stationary. We conduct an ADF test to check for non-stationarity and report our results in Table 4. We find all the series, with the exception of log of robbery, to be non-stationary.

Before we can estimate equation (1) we need to check whether or not the variables are co-integrated. If we do find co-integration then we will estimate the error correction model as specified in (1); if we find no co-integration then we estimate the specification without the error correction term. Table 5 reports the results of the co-integration test. We check for co-integration between the total crime rate and the unemployment rate, as well as each of the six disaggregated crime series and the unemployment rate. Our results indicate that for Canada there is no long-run relationship between unemployment rate and crime at the aggregate level (this is similar to the findings of Hale and Sabbagh, 1991, for England and Wales); hence we focus on short-run dynamics only.

The results for the short-run dynamics are reported in Table 6. With the exception of robbery there is a degree of persistence in growth of crime rate (first row, Table 6). Column (1) of Table 6 shows the findings for aggregate total crime at the national level. The results indicate that there is no significant relationship between growth in total crime rate and change in unemployment rate. Once we separate total crime into the two main categories, violent crime and property crime, we still find no significant relationship with unemployment (columns 2 and 3, Table 6).

Next, we disaggregate property crime further into BE, FR, ATH, and ROB. Our findings indicate that fraud and robbery have a significant link with unemployment, and the estimated coefficient is negative, lending support to the 'opportunity hypothesis'. For example, consider robbery (column 7, Table 6), the estimated coefficient, $\hat{\beta}_1 = -0.03$, which indicates that for each one point change in the unemployment rate there is a decrease of 0.03 percent in robbery rate.

Overall, although our analysis does yield some significant results at the national level, due to the low number of observations, we extend our sample to a panel, thus allowing for another margin of disaggregation; and it allows us to include control variables.

4.3 Regional level analysis

We start our analysis for the regional level data by first checking for unit root in all variables. We use the Fisher-type test which combines the p-values from a unit root test (we use the ADF tests) for each cross section (Baltagi, 2013). The results are reported in Table 7. Most of the series have a unit root, so we use the first difference of all series in our analysis. Next we do a panel co-integration test between each of the seven crime series and unemployment, and similar to the national level results we find no long-run relationship at the regional level.[6] We then go on to analyze the short-run dynamics in the panel data.

In Table 8 we use the same model as used for the national level. To make sure we have no serial correlation in the error term we include two lags of unemployment. We find some persistence in growth of crime rate, at the regional level as well, for all

[6] The panel co-integration test was done using the xtwest command of STATA (Persyn and Westerlund, 2008). Results are available from authors on request.

the series with the exception of auto theft and fraud (see row 1).[7] We find a significant negative relationship between change in unemployment and growth in total crime rate. When total crime is disaggregated into property crime and violent crime, we see that the relationship between total crime and unemployment is driven by the negative relationship between property crime and unemployment. Further disaggregation of property crime provides additional insight into the type of crime that is linked with unemployment (see columns 4 to 7). Growth in auto theft and breaking and entering have a statistically significant negative relationship with change in unemployment, which is consistent with the opportunity hypothesis predictions.

Next, we estimate the panel model with control variables (presented in Table 9). Our findings are robust to the inclusion of control variables i.e. there is no qualitative difference in the relationship between crime and unemployment, with or without controls (comparing Tables 8 and 9). We still find a significant relationship between unemployment and total crime, and property crimes; in both cases the coefficient is negative. With respect to the crime of violence, results here are in line with those of Gould et al. (2002) and Donohue and Levitt (2001), among others, who do not find any significant link between violent crime and unemployment. Disaggregating property crime, it's still growth in breaking and entering and auto theft which show a significant negative relationship with change in unemployment.

For the control variables, we find a significant negative relationship between changes in incarceration rates and growth in violent crimes; however, we find no evidence of deterrence effects (as captured by incarceration rates) for growth in property crimes. Increase in the proportion of young males (18 to 24 years old) in the population increases the incidence of robbery; on the other had an increase in the proportion of intermediate age males (25 to 44 years old) in the population is related positively with

[7] Glaeser et al (1996) and Machin and Meghir (2004) also find significant persistence in crime over time across areas.

the incidence of violent crimes and other property crimes (breaking and entering and fraud). Change in inequality in the region (as measured by changes in GINI) has no significant impact on growth in crime rates.

5. Discussion and conclusion

We use national and regional Canadian data to analyze the relationship between economic activity (as captured by the unemployment rate) and crime rates. Our analysis takes into account two potential sources of aggregation bias. First, we disaggregate the crime data and look at the relationship between six different types of crimes rates and unemployment rate as well as the total aggregates. Second, we look at regional disaggregation; we do analysis both at the national level and for ten provinces of Canada.

We find no evidence of a long-run relationship between crime and unemployment, both when we look at disaggregation by type of crime and disaggregation by region. This finding is different from that of Andresen (2013) for Canada, who finds a long-run relationship in his panel analysis; the difference in the result is likely due to the difference in the methodology used to identify the long run relationship. Lack of evidence for a long-run relationship indicates we have no evidence of motivation hypothesis. This is probably not surprising, as to be able to observe a long-run relationship between unemployment and crime in the macro data we would expect substantial proportion of population to routinely move in and out of crime (Cohen and Felson, 1979) – possibly an unrealistic assumption. Freeman (1999) further speculates that the weak long run relationship between unemployment and crime could be due to coexistence of legitimate work and crime; with '*some criminals shift*(ing) *between crime and work over time, depending on opportunities.*' (Freeman, 1999, p. 3543).

For property crimes we do find some evidence of a significant negative short-run relationship between crime and unemployment, lending support to the opportunity hypothesis. This finding is in accord with that of Levitt (2001) for the US and Andresen (2013) for Canada. Our findings are robust, qualitatively and quantitatively, to the inclusion of control variables for deterrence, inequality and demographics.

For the type of property crime that has a significant relationship with unemployment, results vary by level of disaggregation used: while at the national level we find a significant relationship between unemployment and fraud and robbery, at the regional level the relationship is significant between unemployment and breaking and entering and auto theft. We peculate here that the results of panel data are more robust; we are better able to capture the variations in crime and unemployment (which are lost when aggregating the data to national level); and we are able to estimate a more complete model with control variables.

Our analysis also shows that careful attention needs to be paid to the time series properties of the data at hand. This is important for both the long-run relationship (when we check for stationarity and co-integration) and for the short-run relationship (when we carefully choose the lags of dependents and independent variables to be included in the analysis).

References

Altindag, D. T. (2012) Crime and unemployment: Evidence from Europe. *International Review of Law and Economics*, **32(1)**, 145-157.

Andresen, M.A. (2013) Unemployment, business cycle, crime, and Canadian provinces. *Journal of Criminal Justice,* **41**, 220-27.

Baltagi, B. H. (2013) Econometric Analysis of Panel Data. 5th ed. Chichester, UK: Wiley.

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

Boyce, J., Cotter, A., and Perreault, S. (2014) Police-reported crime statistics in Canada, 2013. *Juristat*, **34(1)**. Statistics Canada Catalogue no. 85-002-X.

Buonanno, P. (2006) Crime and labour market opportunities in Italy (1993–2002). *Labour*, **20(4)**, 601-624.

Britt, C. L. (2001) Testing theory and the analysis of time series data. *Journal of Quantitative Criminology*, **17**, 343-57.

Cantor, D. and Land, K.C. (1985) Unemployment and crime rates in the post-World War II United States: A theoretical and empirical analysis. *American Sociological Review*, **50**, 317-32.

Cherry, T.L. and List, J.A. (2002) The aggregation bias in the economic model of crime. *Economic Letters*, **75**, 81-86.

Cohen, L.E. and Felson, M. (1979) Social change and crime rate trends: A routine activity approach. *American sociological review*, **44(4)**, 588-608.

Cook, P.J. and Zarkin, G.A. (1985) Crime and the business cycle. *Journal of Legal Studies*, **14**, 115-28.

Corman, H. and Mocan, H. N. (2000) A Time-Series Analysis of Crime, Deterrence, and Drug Abuse in New York City. *American Economic Review*, **90(3)**, 584-604.

Corman, H. and Mocan, H. N. (2005) Carrots, Sticks, and Broken Windows. *Journal of Law and Economics*, **48(1)**, 235-266.

Cornwell, C. and Trumbull, W.N. (1994) Estimating the economic model of crime with panel data. *The Review of Economics and Statistics*, **76**, 360-66.

Donohue, J. and Levitt, S. (2001) Legalized abortion and crime. *Quarterly Journal of Economics*, **116**, 379-420.

Edmark, K. (2005) Unemployment and crime: Is there a connection? *The Scandinavian Journal of Economics*, **107(2)**, 353-373.

Ehrlich, I. (1973). Participation in illegitimate activities: A theoretical and empirical investigation. *The Journal of Political Economy*, **81(3)**, 521-565.

Entorf, H. and Spengler, H. (2000) Socioeconomic and demographic factors of crime in Germany: evidence from panel data of the German states. *International Review of Law and Economics*, **20(1)**, 75-106.

Freeman, R. (1999) The Economics of Crime. In *Handbook of Labor Economics*, Vol 3c Amsterdam, Netherlands: North Holland Publishers; Chapter 52.

Glaeser, E. L., Sacerdote, B. and Scheinkman, J. A. (1996) Crime and Social Interactions. *Quarterly Journal of Economics*, **111(2)**, 507-548.

Gould, E., Weinberg, B. and Mustard, D. (2002) Crime rates and local labor market opportunities in the United States: 1979-1991. *Review of Economics and Statistics*, **84**, 45-61.

Greenberg, D. (2001) Time series analysis of crime rates. *Journal of Quantitative Criminology*, **17**, 291–327.

Hale, C. (1991) Unemployment and crime: Differencing is no substitute for modeling. *Journal of Research in Crime and Delinquencies*, **28**, 426–29.

Hale, C. and Sabbagh, D. (1991) Testing the relationship between unemployment and crime: A methodological comment and empirical analysis using time series data from England and Wales. *Journal of Research in Crime and Delinquencies*, **28**, 400–17.

Land, K. C., Cantor, D. and Russell, S. T. (1995) Unemployment and crime rate fluctuations in the post-World War II United States: Statistical time series properties and alternative models. In Hagan, J., and Peterson, R. D. (eds.), *Crime and Inequality*, Stanford University Press, Stanford, CA, 55–79.

Levitt, S. (1996) The effect of prison population size on crime rates: Evidence from prison overcrowding litigation. *Quarterly Journal of Economics*, **111**, 319-52.

Levitt, S. (1997) Using electoral cycles in police hiring to estimate the effect of police on crime. *American Economic Review*, **87**, 270-90.

Levitt, S. (2001) Alternative strategies for identifying the link between unemployment and crime. *Journal of Quantitative Criminology*, **17**,377-90.

Levitt, S. (2004) Understanding why crime fell in the 1990s: Four factors that explain the decline and six that do not. *The Journal of Economic* Perspectives, **18**, 163-90.

Lin, M. J. (2008). Does unemployment increase crime? Evidence from US data 1974–2000. *Journal of Human Resources*, **43(2)**, 413-436.

Louis, R. J. and Simons, D. (2007) Is there a North American business cycle? An analysis of the period 1963-2002. *Applied Econometrics and International Development*, **7**, 109-120.

Machin, S. and Meghir, C. (2004) Crime and economic incentives. *Journal of Human Resources*, **39**, 958-79.

Oster, A. and Agell, J. (2007) Crime and Unemployment in Turbulent Times. *Journal of the European Economic Association*, **5(4)**, 752-775.

Papps, K. and Winkelmann, R. (2000) Unemployment and crime: New evidence for an old question. *New Zealand Economic Papers*, **34(1)**, 53-71.

Persyn, D. and Westerlund, J. (2008) Error-correction-based cointegration tests for panel data. *The Stata Journal*, **8**, 232-41.

Phillips, J. and Land, K.C. (2012) The link between unemployment and crime rate fluctuations: An analysis at the county, state, and national levels. *Social Science Research*, **41**, 681-94.

Raphael, S. and Winter-Ebmer, R. (2001) Identifying the Effect of Unemployment on Crime. *Journal of Law and Economics*, **44(1)**, 259-283.

Reilly, B. and Witt, R. (1996) Crime, deterrence and unemployment in England and Wales: An empirical analysis. *Bulletin of Economic Research*, **48(2)**, 137-159.

Steffensmeier, D. and Allan, E. (1996) Gender and crime: Toward a gendered theory of female offending. *Annual Review of Sociology*, **22**, 459-87.

Wang, F. and Minor, W.W. (2002) Where the jobs are: employment access and crime patterns in Cleveland. *Annals of the Association of American Geographers*, **92**, 435-50.

Ward, R. and Carmichael, F. (2001) Male unemployment and crime in England and Wales. *Economic Letters*, **73**, 111-15.

Witt, R., Clarke, A. and Fielding, N. (1999). Crime and economic activity: A panel data approach. *British Journal of Criminology*, **39(3)**, 391-400.

Wu, D. and Wu, Z. (2012) Crime, inequality and unemployment in England and Wales. *Applied Economics*, **44(29)**, 3765-3775.

Table 1: Variable names and codes

SERIES TITLE	CODE
TOTAL CRIME, ALL INCIDENTS; RATE PER 100,000 POPULATION	LTC
1. CRIMES OF VIOLENCE; RATE PER 100,000 POPULATION	LVIO
2. PROPERTY CRIMES; RATE PER 100,000 POPULATION	LPC
2.1 BREAKING AND ENTERING; RATE PER 100,000 POPULATION	LBE
2.2 FRAUDS; RATE PER 100,000 POPULATION	LFR
2.3 THEFT, MOTOR VEHICLES; RATE PER 100,000 POPULATION	LATH
2.4 ROBBERY; RATE PER 100,000 POPULATION	LROB
All crime variables are in natural logarithms	
UNEMPLOYMENT rate, for age 15 years and over	UEM
INCARCERATION; RATE PER 100,000 ADULTS (*in natural logarithms*)	LINCAR
% MALE, between ages 18 to 24 years, of total population	PMALE18
% MALE, between ages 25 to 44 years, of total population	PMALE25
Gini Coefficient, after tax income	GINI
PROVINCE	
NEWFOUNDLAND AND LABRADOR	NFL
PRINCE EDWARD ISLAND	PEI
NOVA SCOTIA	NS
NEW BRUNSWICK	NB
QUEBEC	QU
ONTARIO	ON
MANITOBA	MA
SASKATCHEWAN	SK
ALBERTA	AB
BRITISH COLUMBIA	BC

Table 2: Descriptive statistics: National level
(Time period: 1979-2006)

	Mean	Standard Deviation
LTC	9.14	0.10
LVIO	6.78	0.18
LPC	8.51	0.16
LBE	7.10	0.21
LFR	5.94	0.21
LATH	6.10	0.23
LROB	4.56	0.09
UEM	8.79	1.66

Table 3: Descriptive statistics: Regional level
(Time period: 1979-2006)

Province		LTC	LVIO	LPC	LBE	LFR	LATH	LROB	UEM	PMALE18	PMALE25	GINI	LINCAR
AB	MEAN	9.29	6.90	8.64	7.08	6.20	6.24	4.45	6.90	6.11	17.12	0.369	4.74
	SD	*0.12*	*0.14*	*0.16*	*0.22*	*0.15*	*0.23*	*0.14*	*2.39*	*1.16*	*0.83*	*0.01*	*0.17*
BC	MEAN	9.54	7.12	8.93	7.44	6.05	6.42	4.79	9.28	5.34	16.01	0.374	4.35
	SD	*0.10*	*0.13*	*0.12*	*0.21*	*0.22*	*0.32*	*0.17*	*2.54*	*0.75*	*0.91*	*0.02*	*0.10*
MA	MEAN	9.38	7.10	8.70	7.29	6.00	6.45	4.86	6.87	5.62	14.99	0.356	4.77
	SD	*0.10*	*0.36*	*0.14*	*0.18*	*0.43*	*0.51*	*0.28*	*1.62*	*0.74*	*0.88*	*0.01*	*0.13*
NB	MEAN	8.93	6.63	8.10	6.73	5.75	5.38	3.14	11.93	5.71	15.43	0.351	4.23
	SD	*0.08*	*0.27*	*0.11*	*0.16*	*0.19*	*0.14*	*0.19*	*1.71*	*0.84*	*0.99*	*0.01*	*0.19*
NFL	MEAN	8.77	6.70	7.93	6.61	5.59	4.74	2.49	17.13	5.97	15.09	0.343	4.30
	SD	*0.07*	*0.29*	*0.12*	*0.12*	*0.14*	*0.18*	*0.36*	*1.99*	*0.78*	*0.97*	*0.02*	*0.11*
NS	MEAN	9.07	6.76	8.31	6.82	5.95	5.42	3.82	11.10	5.60	15.24	0.356	4.02
	SD	*0.10*	*0.30*	*0.11*	*0.14*	*0.25*	*0.24*	*0.31*	*1.85*	*0.96*	*1.02*	*0.01*	*0.18*
ON	MEAN	9.03	6.71	8.39	6.86	5.93	5.85	4.28	7.60	5.55	15.89	0.367	4.46
	SD	*0.16*	*0.16*	*0.23*	*0.26*	*0.27*	*0.25*	*0.16*	*1.71*	*0.87*	*0.81*	*0.02*	*0.05*
PEI*	MEAN	8.93	6.44	8.09	6.57	5.79	5.14	2.59	13.23	5.53	14.30	0.341	4.49
	SD	*0.16*	*0.30*	*0.12*	*0.20*	*0.25*	*0.19*	*0.34*	*2.00*	*0.74*	*0.81*	*0.01*	*0.16*
QU	MEAN	8.91	6.45	8.37	7.22	5.68	6.23	4.91	10.68	5.52	16.21	0.358	4.07
	SD	*0.10*	*0.18*	*0.18*	*0.25*	*0.23*	*0.22*	*0.27*	*1.80*	*1.00*	*0.97*	*0.01*	*0.11*
SK	MEAN	9.45	7.05	8.71	7.37	6.32	6.16	4.21	6.38	5.62	14.19	0.367	5.07
	SD	*0.20*	*0.41*	*0.11*	*0.14*	*0.24*	*0.34*	*0.44*	*1.25*	*0.72*	*0.92*	*0.01*	*0.10*

*Prince Edward Island data are not available for 2005.

Table 4: Results of the ADF test: National level

Variable	No trend		With trend	
	ADF statistic	**p-value**	**ADF statistic**	**p-value**
LTC	-2.188	0.2108	-2.220	0.4789
LVIO	-2.482	0.119	-1.600	0.7924
LPC	-0.744	0.8349	-2.837	0.1838
LBE	-0.337	0.9201	-2.329	0.4178
LFR	-0.699	0.8469	-2.841	0.1825
LATH	-1.446	0.5598	-1.694	0.7534
LROB	-3.227	0.0185	-3.224	0.0797
UEM	-2.558	0.1020	-3.030	0.1239

Reported statistics, for all variables, are from the Dickey-Fuller regression with a constant and one lag. Choice of one lag was made based on the diagnostics done on the residuals from the Dickey-Fuller regression, for all variables. All the residuals were found to be white noise (Q-test) and the null hypothesis of 'no serial correlation' could not be rejected (Breusch-Godfrey LM test for autocorrelation).

Table 5: Results of the co-integration test: National level

In each case below we are testing for CI between unemployment and the crime variable		
Crime Variable	**Hypothesis: rank = 0 Trace Statistics (5% critical value = 12.53)**	**Hypothesis: rank <=1 Trace Statistics (5% critical value = 3.84)**
LTC	5.781	0.001
LVIO	8.5299	0.2929
LPC	6.0436	0.5067
LBE	8.5297	0.7633
LFR	6.4065	0.4274
LATH	6.7766	0.0594
LROB	4.8784	0.2666

Reported trace statistics are for Johansen's test with two lags, in all case. Different orders of lags were tested, the results do not change.

Table 6: National level results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	LTC	LVIO	LPC	LBE	LFR	LATH	LROB
	ΔC_t	ΔC_t	ΔC_t	ΔC_t	ΔC_t	ΔC_t	ΔC_t
ΔC_{t-1}	0.51*** (0.19)	0.79*** (0.15)	0.66*** (0.19)	0.61*** (0.17)	0.59*** (0.20)	0.40** (0.19)	0.43 (0.28)
ΔU_{t-1}	-0.01 (0.01)	-0.01 (0.01)	-0.02 (0.01)	-0.01 (0.01)	-0.02* (0.01)	-0.02 (0.02)	-0.03** (0.02)
Constant	-0.00 (0.01)	0.00 (0.00)	-0.01 (0.01)	-0.01 (0.01)	-0.01 (0.01)	0.01 (0.01)	0.00 (0.01)
N	28	28	28	28	28	28	28

Standard errors in parentheses; * p<0.10, ** p<0.05, *** p<0.01

The number of lags included, in each of the seven series, was selected after doing the misspecification test.

Table 7: Results of the panel unit root test: Regional level

Variable	No trend		With trend	
	Z	P	Z	P
LTC	0.0025	0.0033	0.6552	0.7174
LVIO	0.0844	0.1540	0.9961	0.9821
LPC	0.8367	0.5648	0.0091	0.0012
LBE	0.8024	0.0143	0.1762	0.0232
LFR	0.9484	0.9320	0.0348	0.0143
LATH	0.5191	0.6020	0.6056	0.7658
LROB	0.2844	0.1059	0.2787	0.3658
UEM	0.0903	0.1212	0.0143	0.0307
LINCAR	0.1403	0.0567	0.0934	0.0348
PMALE18	0.3431	0.2196	0.4002	0.3105
PMALE25	0.0580	0.1911	0.7423	0.2323
GINI	0.9950	0.9938	0.5596	0.4362

Reported p-values, for all variables, are from the Fisher-type ADF test for panel unit root. The ADF regression includes a constant and two lags. The null hypothesis is 'all panels contain unit roots'; the alternative hypothesis is 'at least one panel is stationary'. We report p-values from two different test statistics: Z, which has an inverse normal distribution, and P which has the inverse chi-square distribution.

TABLE 8: Regional Level Results, no control variables: 1979-2006

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	LTC	LVIO	LPC	LBE	LFR	LATH	LROB
	ΔC_t	ΔC_t	ΔC_t	ΔC_t	ΔC_t	ΔC_t	ΔC_t
ΔC_{t-1}	0.23**	0.27**	0.34***	0.23**	-0.04	0.09	-0.35**
	(0.08)	(0.11)	(0.08)	(0.08)	(0.15)	(0.09)	(0.15)
ΔU_{t-1}	-0.01**	-0.00	-0.01***	-0.01**	-0.00	-0.03***	0.01
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)
ΔU_{t-2}	-0.00	-0.00	0.00	0.00	-0.00	0.01	-0.02
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
Constant	0.00***	0.02***	-0.01***	-0.01***	-0.01***	0.00***	0.03***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
N	270	270	270	270	270	270	270
R-square within	0.09	0.08	0.13	0.06	0.00	0.05	0.13

Standard errors in parentheses; * p<0.10, ** p<0.05, *** p<0.01
The results presented are for the fixed effect model. Hausman's test for specification was done, which rejected the random-effect model.

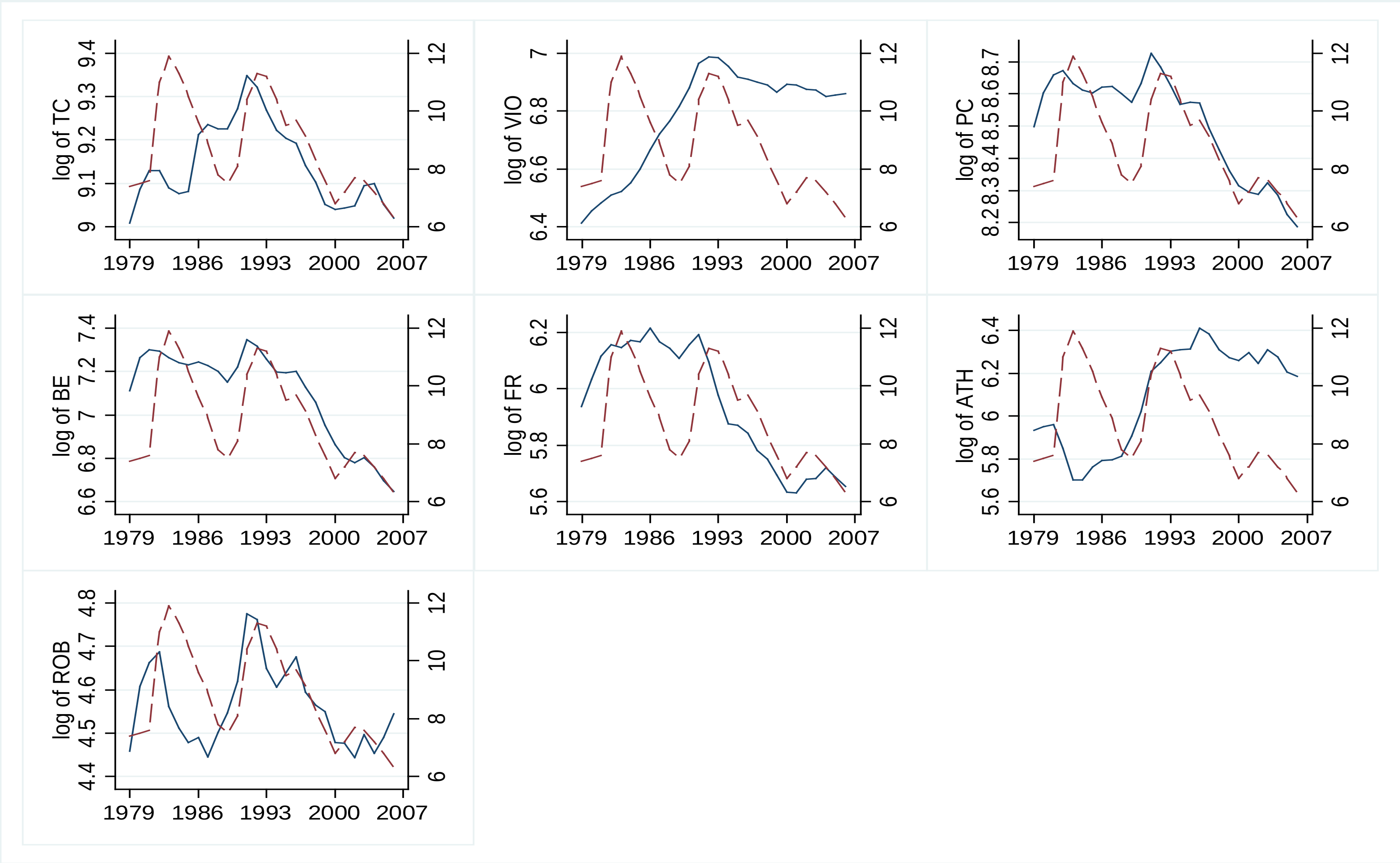
TABLE 9: Regional Level Results, with control variables: 1979-2006

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	LTC	LVIO	LPC	LBE	LFR	LATH	LROB
	ΔC_t	ΔC_t	ΔC_t	ΔC_t	ΔC_t	ΔC_t	ΔC_t
ΔC_{t-1}	0.15*	0.16	0.27***	0.20***	-0.11	0.06	-0.37**
	(0.08)	(0.09)	(0.07)	(0.06)	(0.11)	(0.10)	(0.16)
ΔU_{t-1}	-0.01**	-0.00	-0.02***	-0.01**	-0.00	-0.02***	0.01
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
ΔU_{t-2}	-0.00	-0.01	-0.00	-0.00	-0.00	0.01	-0.02
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
$\Delta PMALE18_t$	-0.01	0.00	0.04	0.03	0.10	-0.04	0.19*
	(0.02)	(0.03)	(0.03)	(0.03)	(0.08)	(0.07)	(0.08)
$\Delta PMALE25_t$	0.07***	0.09***	0.07***	0.09***	0.16***	-0.03	0.06
	(0.00)	(0.02)	(0.01)	(0.02)	(0.03)	(0.02)	(0.06)
$\Delta LINCAR_{t-1}$	-0.04	-0.05*	0.05	-0.04	-0.12	-0.12	-0.09
	(0.04)	(0.02)	(0.06)	(0.05)	(0.09)	(0.13)	(0.07)
$\Delta GINI$	-0.34	-0.22	-0.33	-0.09	-0.43	0.49	1.36
	(0.40)	(0.36)	(0.45)	(0.84)	(0.92)	(1.02)	(0.81)
CONSTANT	0.00*	0.02***	-0.00	-0.01**	-0.00	0.00	0.04***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
N	269	269	269	269	269	269	269
R-square within	0.16	0.18	0.18	0.10	0.10	0.06	0.14

Standard errors in parentheses; * p<0.05, ** p<0.01, *** p<0.001

The results presented are for the fixed effect model. Hausman's test for specification was done, which rejected the random-effect model.

Figure 1: Unemployment rate and Crime at the National Level (1979-2006)



Notes: The solid line gives the crime rate (left hand side axis); the dashed line gives the unemployment rate (right hand side axis).