AN EMPIRICAL ANALYSIS ON NON-LINEAR IMPACTS OF INCOME ON CRIME:AN ARDL APPLICATION

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AN EMPIRICAL ANALYSIS ON NON-LINEAR IMPACTS OF INCOME ON CRIME:AN ARDL APPLICATION

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ABSTRACT

AN EMPIRICAL ANALYSIS ON NON-LINEAR IMPACTS OF INCOME ON CRIME:AN ARDL APPLICATION

Özkan, Ezgi

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This thesis investigates the nonlinear impacts of income on crime. Through the econometric analysis, the role of income on crime in G7 countries over the period 1965–2010 is estimated. An ARDL (autoregressive distributed lag) model is used for identifying the role of income on crime in the long-run. The findings show that an inverted-U shaped relationship is the dominant form between income and crime in the long run, à la the Kuznets Curve Hypothesis (KCH). Hence it has been concluded that, in economies experiencing an increase in incomes, policy makers should not expect that crime rates will fall by default as income per capita rises. Accommodating policies are required to keep crime rates low in the early periods of growing incomes. This is a novel contribution, given that majority of the literature assumes a linear relationship between income and crime.

Keywords: Crime; Economic Development; ARDL.

ÖZET

GELİRİN SUÇ ÜZERİNDEKİ DOĞRUSAL OLMAYAN ETKİLERİNİN AMPİRİK BİR ÇALIŞMASI: ARDL UYGULAMASI

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Bu tez, gelirin suç üzerindeki doğrusal olmayan etkilerini incelemektedir. Ekonometri analizi uygulanarak, 1965-2010 zaman aralığında gelirin G7 ülkelerindeki etkisi tahmin edilmiştir. Gelirin ve işsizliğin suç üzerindeki uzun dönem etkisini belirleyebilmek için ARDL modeli uygulanmıştır. Yapılan analize göre uzun dönemde gelir ve suç arasında Kuznets Eğrisi Hipotezi'ne benzer olarak ters U-şekli baskın olarak bulunmuştur. Bu sayede, ekonomide gelir artışı yaşanırken, politika yapıcıların kişi başına düşen gelir artarken suç oranlarının düşmesini beklememesi gerekir sonucuna varılmıştır. Uyum politikaları, gelir artış yıllarının başlangıç dönemlerinde suç oranlarını düşük tutma üzerine kurulmalıdır. Bu sonuç alışılmışın dışında bir katkıdır, çünkü literatürdeki birçok çalışma gelir ve suç arasında doğrusal bir ilişki olduğunu varsaymaktadır.

Anahtar Kelimeler: Suç, Ekonomik Kalkınma, ARDL Modeli

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To my family

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1. INTRODUCTION

Since crime can impose great costs to the societies, the causes of crime have been studied by theorists from different fields such as economics, psychology, political science, history, and sociology. I believe that the role of economics on crime distinguishes from other sciences. Economics is generally described as being the study of the allocation of scarce resources, and crime is one of the many social problems toward which we need to allocate our limited resources. Therefore, the key objective of economists concerning cost of reducing crime is how these resources should be divided between different branches of the criminal justice system such as the police, courts, and prisons. From this perspective, the economist should create effective policies and strategies to reduce crime. In order to do that, it is necessary to explore the main determinants of criminal behaviors and find the relationships between crime and economic or socioeconomic variables.

At this point, it is crucial to explain the relationship between crime and economics. From an economic perspective, a criminal offender can be viewed as a "rational" individual that maximizes his/her utility allocating his/her time between legal and illegal activities given a budget constraint. Criminal individuals will decide to engage in criminal behaviors based on expected rewards, risks, and costs derived from a criminal act. As Becker (1968) indicates, a rational offender will commit an illegal activity when the marginal benefit deriving from crime, discounted by the expected value of the penalty, is higher than the marginal benefit deriving from a legal activity, *ceteris paribus.* Hence, poor people might commit more crime because the rewards are higher and the costs are lower for them than for wealthier people. For instance, the cost of losing freedom and being incarcerated is proportionally will be lower for individuals living in extreme poverty than for individuals in a good financial situation. Therefore, level of crime in developed countries with higher GDP per capita, is expected to be lower although favorable economic conditions can also trigger higher levels of illegal activity. Hence, altering levels of crime and its relation to income seem to be vague. In order to reveal this relationship, we need to profoundly analyze long-run patterns of income and crime in developed countries.

There have been number of studies focusing on the variables of income such as GDP and GNP per capita. Whilst Messner et al. (2002), Neumayer (2003) and Neapolitan (1998) find a negative relationship, Fajnzylber et al. (1998) find a positive relationship stressing that levels of crime tend to be higher in rich countries. However, Soares (2002) underlies that reporting rates of crime in developing countries can be misleading; thus, the studies may not always lead to positive correlations. Although aforementioned vague relationship between crime and major income variables does exist, it is possible to reanalyze the link by the help of ARDL framework. This approach has some methodological advantages in comparison to other cointegration procedures. The ARDL solves endogeneity problems and inability to test hypotheses on the estimated coefficients in the long-run associated with the Engle-Granger (1987) method. Furthermore, the long and short-run coefficients of the model are estimated simultaneously. At the same time, the ARDL approach to testing for the existence of a long-run relationship between the variables in levels is applicable irrespective of whether the underlying regressors are stationary I(0) or non-stationary I(1), or mutually cointegrated.

The aforementioned studies have been looking at linear relationship between income and crime. However, this model that will be used also will provide us to scrutinize non-linear relationship between these two variables. This leads to main question of my thesis to measure whether there is a linear or non-linear relationship between income and crime and in case of non-linearity, how income affects crime. This thesis will contribute the existing literature of economics of crime as well as suggest an empirical model for developed countries' crime reduction policies.

In existing literature, both Halicioglu and Habibullah *et* Baharom analyze long-run effects of income on crime by using an autoregressive distributed lag model. Halicioglu (2012) finalizes her result as a negative correlation in Turkish case. Habibullah and Baharom (2009) find that murder, rape, assault, and motorcycle theft in Malaysia are positively correlated whilst armed robbery is negatively bounded. Both approaches directly refer to linearity, yet this thesis will focus on non-linear effects of income. However, their analysis on the long-run impacts of income by this framework will be contributing to long-run approach.

Kuznets Curve Hypothesis[1] (KCH), which examines the non-linear relationship between income inequality and the level of development, gives us an idea about

[1] This hypothesis is originated by Kuznets (1955).

whether there is also a relationship between income inequality and crime. This is because the strong correlation between income inequality and crime causes a transitivity effect.[2] Therefore, if the KCH is regarded, it is natural to expect that crime will also first rise and then fall with rising income, or more generally, it might be nonlinear such as quadratic or cubic.

To analyze nonlinear impacts of income on crime, this thesis studies G7 countries (Canada, the United States, the United Kingdom, France, Germany, Italy and Japan) over the period 1965-2010 due to the following reasons: Firstly, whereas G7 countries have different sociological, ethnic and cultural background, their level of development is approximately similar and their income distribution is more homogenous than several developing and developed counties. Secondly, the rate of recorded crime and data availability in G7 countries are relatively higher than OECD countries.

This study is comprised of four chapters. Chapter two overviews the historical background concerning the early contributions to the economics of crime. Chapter 3 presents empirical analysis on long-run relationship between income per adult and crime per adult, and Chapter 4 concludes and suggests policy implications.

[2] The pure positive relationship between income inequality and crime is supported by Danziger and Wheeler (1975), Jacobs (1981), Freeman (1999), Fajnzylber, Lederman, and Loayza (1998, 2000a), Neapolitan (2003).

2. CRIME MACROECONOMICS LITERATURE

This chapter presents theoretical and empirical literature about how macroeconomic variables affect crime. Section 2.1 introduces the pioneering studies in economics of crime. Section 2.2 presents the studies on the link between crime and income. Section 2.3 examines the literature about crime and labor market, focusing on labor market opportunities and the role of unemployment rate. Section 2.4 discusses the literature about crime and income inequality.

2.1. Pioneering Studies on Economics of Crime

The relationship between criminal behavior and economic conditions has been promoted by many sociological theories; such as strain theory, control theory, neo-Marxist models, and labeling theory.[3] However, sociological theory views crime through economics models and this assumption is called *rational choice theory*. Rational choice theory considers criminal opportunities as part of a rational calculation of expected costs and benefits of actions. This theory introduced into the economics of crime literature by Fleisher (1966), Becker (1968) and Ehrlich (1973).

"The Effect of Unemployment on Juvenile Delinquency", which is written by Fleisher in 1966, is the first known published paper in the field of economics of

[3] Major studies in these approaches are as follows: Social strain theory (Merton, 1938; Cloward and Ohlin, 1960), social control theory (Hirshi, 1969; Thornberry and Christenson, 1984; Wilson, 1988, 1996; Silver and Miller, 2004), neo-Marxist models (Quinney, 1977) and labeling theory (Hughes and Carter, 1981).

crime. Fleisher (1966) analyzes the relationship between labor market condition and youth crime from public policy perspective. Fleisher emphasizes that “other aspects of the functioning of labor market, such as determination of levels and distributions of wages and determination of population distribution”, as well as considering that “the important effects upon the allocation of time among legitimate and illegitimate forms of activity” (p. 543). He finds that the effect of unemployment on juvenile delinquency is positively significant when the youths are over the age of sixteen.

Fleisher’s paper is also a pioneer in studies that investigating the role of income on criminal decisions. He claims that “the low income increases the tendency to commit crime is that it raises the relative cost of engaging in legitimate activity” and “the probable cost of getting caught is relatively low, since they (low-income individuals) view their lifetime earnings prospects dismally they may expect to lose relatively little earning potential by acquiring criminal records; furthermore, if legitimate earnings are low, opportunity cost of time actually spent in delinquent activity, or in jail, is also low (p. 120). However, he mentions that the expected income is not considered to be the sole income factor, but also income levels of potential victims are crucial. A rise in income level of potential victims leads to increase in motivation to commit crimes, particularly for property crimes. Thus, Fleisher points out that income has two effects on crime, which run opposite directions, also they do not need to have equal strength.

Fleisher's findings show that when the average family income is higher, young males are associated with less court appearances and lower number of arrests for robbery, burglary, larceny, and auto theft across 101 cities. He also finds that if the gap between the second lowest quartile of households and the highest quartile of households gets higher, the number of arrests and court-appearances tends to increase. However, when he estimates only for high-income families, the coefficient becomes statistically insignificant.

Even though it is widely accepted that Fleisher's work is remarkable in the literature of economics of crime, seminal paper of Becker (1968) is a milestone since introducing an econometric model to analyze the dynamics of crime control policies in the society. Becker claims that criminals are rational; when engaging a criminal activity, they compare the financial or other rewards from crime and the legal work and they consider the probability of apprehension, conviction and the severity of punishment. Thus, individual will decide how to allocate their time between legitimate and illegitimate activities, by taking account of cost-benefit analysis.

Becker proposes a framework for "supply of offences", by assuming that the expected utility of an offence exceeds the utility derived from legal activities. According to him, "Some persons become "criminals", therefore, not because of their basic motivation differs from that of other persons, but because their benefits and cost differ (p. 176).

Becker's economic model is presented as follows:

$$O_j = O_j(p_j, f_j, u_j)$$

Where Becker defines a supply of offences (O), the probability of conviction (p), the punishment if the individual is convicted (f), and a portmanteau variable (u) such as the income available to him in legal or other illegal activities (p.177).

Becker defines agent's choice under uncertainty as follows;

$$EU_j = p_j U_j(Y_j - f_j) + (1 - p_j)U_j(Y_j)$$

where Y_j is the income (monetary and psychic), $(1 - p_j)$ is the probability of success, f_j is "the monetary equivalent of the punishment", furthermore crime supply is decreasing in p and f.

He mentions that the main contribution of his study is to determine optimal policies for dealing with illegal behaviors, which is a necessary condition for allocating resources optimally. Moreover optimal policies accomplish to minimize the social loss from offences.

$$L = D(O) + C(p, O) + bpfO$$

where D is damage from crime, C cost of apprehension and conviction, and $bpfO$ is total social loss from punishments.

Becker minimizes the social loss from offences with respect to p and f; where p is the probability of arrest and f is punishment). If there is an increase in p which is compensated by the same percentage decrease in f, the expected income would not change but expected utility would be affected since the risk amount would change. In brief, when p increases, expected utility would decline and the number of offences would change; and when f increases, it would have greater effect for risk averse agents.

The extension of Becker's model is applied by Ehrlich (1973) by considering time allocation model when analyzing the effects of income levels and distribution on criminal propensity and crime rate. Ehrlich (1973) assumes that individual has fixed leisure time and remaining time covers legal and illegal activities. Because of legal activities consist of wage, personal training, ability, human capital, and other socio-economic variables, such as age, gender, race, religion and urbanization, income generated by legal activities can differ among individuals. When individuals, who participate in the criminal sector, maximize their expected utility in respect to the benefits and costs of illegitimate activities, if they find it larger than expected utility from legal sector, then criminals commit to crime. The author also suggests that for a given median income, income inequality could be a measure of the differential between legal and illegal activities. He employs a regression analysis of index crimes across the U.S. states in 1940, in 1950 and in 1960. He finds that higher median family income levels are correlated with higher rates of murder, rape, assault, and property crimes.

Schmidt and Witte (1984) extend the Becker's model by constructing four possible justice states, which of them has a certain probability. However, in these models, the effect of changes in sanctions and gains and losses of crime are more ambiguous than Becker's model. They claim the idea that unemployment leads to lower income, and individuals will have higher risk aversion, and thus expected utility of crime will decrease. Therefore, unemployment causes to increase in illegal activity if we make a standard assumption of decreasing absolute risk aversion.[4] However, if the individuals have neutral risk aversion, illegal activity is not affected by a change in the expected employment rate. After Ehrlich's study, replications and extensions have been studied by Forst (1976), Vandaele (1978), and Nagin (1978).

2.2. Crime and Economic Development

In the economics of crime literature, Gross Domestic Product (GDP) or Gross National Product (GNP) per capita is widely operationalized as an indicator of economic development. Several economists are heavily interested in answering the question of what the relationship between crime and income is.

Majority of contemporary studies find a negative relationship between crime and income per capita. For example, Messner *et al*. (2002) find that GDP growth rate is negatively associated with homicide rate by using a cross-sectional analysis covering 65 nations. Also, they find a consistent positive influence of income inequality on homicide rates after implementing various model specifications. Moreover, Messner *et al*. (2002) test the importance of quality of the Gini coefficient and they find a consistently positive association between the Gini and homicide in both high quality and low quality measures. Neapolitan (1998) also

[4] Standard assumption can be defined as the maximization of expected utility under Neumann–Morgenstern axioms.

stresses the negativity and find that nations with higher GDP per capita have lower crime rates.

Another important consideration for the effect of income on crime is presented by the paper of Neumayer (2003), investigating whether economic growth and the average income level are significant factors on the homicide rate or not. He finds that economic growth and the GDP per capita are associated with lower homicide rates. In another study, Neumayer (2005) observes a quadratic effect of the GDP per capita on robberies and violent thefts. He states that "Per capita income has a non-linear effect on violent property crime. An increase in income leads to an increase in violent property crime over a range of income, but at a decreasing rate, the positive link over a range of income levels could be either because higher income raises the value of things to be stolen, rendering violent property crime more attractive, or because reporting of crimes is higher in richer countries, as argued by Soares (2002)" (p.105, p.106).

Guillaumont and Puech (2006) follow the approach used by Neumayer. The main focus of their study is to discuss the effect of economic shocks or macro-economic instability on crime. They set a hypothesis that the number of robberies increases as average income increases because opportunities increase; however, as individuals get richer on average, desire to commit a robbery decreases. Therefore, they claim that there exists a Kuznets curve for robbery. The authors also suggest that disappointed anticipations arise during periods of rapid increase of income, which also generates frustration and crime. Moreover, they show that illegal activities are used by some agents in order to compensate their loss of income and smooth the consumption level. It mainly deals with the direct effect of instability on crime. However, they find that negative impact of growth on crime, because macro instability reduces the growth.

Additionally, extensive empirical literature has attempted to employ the international-level panel data to examine the effect of income on crime. For example, Fajnzylber *et al*. (1998) find a strong positive correlation between high levels of GDP per capita and intentional homicide and robbery crime rates by using a wide panel data set, compiled from the United Nations World Crime Surveys. Another study, done by Fajnzylber *et al*. (2000), indicates mixed result: income per capita has alternating signs and shows different significance in homicide and robbery rates. However, income growth is found significantly negative on both homicide and robbery when they undertake panel data analysis of 45 countries for homicides and 34 countries for robberies in the period 1970-1994. Furthermore, Fajnzylber *et al*. (2002a) show that the coefficient of per capita GNP is not statistically significant; homicides rates are not affected by economic development. However, Fajnzylber *et al*. (2002b) find that the average income appears with a negative sign but it is significant only for the smaller samples.

Although majority of the literature use the GDP as a measure of economic development, Arvanites and Defina (2006) build an alternative indicator, which is called inflation-adjusted per capita gross state product (GSP). Their empirical study shows that the strong economy of 1990s reduced all four index property crimes and robbery by reducing criminal motivation; it means crime increases with economic strength, but not to drive crime by increasing criminal opportunity. They also discuss that GSP might be a more valid proxy for economic strength than the unemployment rate.

On the other hand, some studies find no relationship between crime and income. For example, Lee and Bankston (1999) find no relationship between the GDP per capita and the homicide rate, by using as control variables the level of political rights, income inequality, the infant mortality rate, the percent male 15-29 year old, population size, population density, the percent urban, and population growth. Another important study conducted by Soares (2002) finds that per capita income is not associated with crime, like other control variables such as urbanization, police presence and religion. Indeed, Soares investigates the determinants of heterogeneity in crime rates across countries, by focusing on the importance of reporting rates. Soares suggests that the reason behind finding a positive relationship between development and crime found in previous studies is reporting rates. According to Soares, the correlation between reporting rates and development prompt researchers to find this positive effect; therefore, richer countries are likely to report a higher fraction of crimes and poor countries tend to underreport crime.

Whereas the majority of economics of crime literature proposes that income or income per capita is one of the main determinants of crime, some researchers advocate the inverse relation: crime affects economic growth rate. For instance, Peri (2004) uses provincial data from 1951 to 1999 and points out that the annual per capita income growth is negatively influenced by murders in Italy after controlling employment in private sector and per capita GDP. The results of Peri (2004) indicate that there could be some non-linearity among these variables. Also, Cardenas (2007) analyzed the relationship between crime and growth rate in an unbalanced panel of 65 countries during the period 1971–1999. By using country fixed effect specifications, Cardenas (2007) find strong negative relationship between crime and economic growth. Mauro and Carmeci (2007) use an overlapping generation exogenous growth model in order to investigate the link between crime, growth and unemployment for the regional data from 1963 to 1995. They use Pooled Mean Group (PMG) panel estimator which is proposed by Pesaran et al. (1999) and found that regional homicide rate has significantly negative long-run effects on the level of per-capita GDP, but not on its growth rate. Chen (2009) also analyzes long run and causal relationship of crime, growth, and unemployment in Taiwan by using Vector Autoregressive (VAR) model. Detotto and Otranto (2010) use large data with monthly frequency for the time period 1979-2002 and apply pure autoregressive (AR) model for Italy. Their findings indicate there could be small reductions in real GDP growth due to crime.

Although the literature exploring long run relationship between crime and economic development is still small, interest in this area is growing. For example, Scorcu and Cellini (1998) analyze the economic determinants of crime rates in Italy by using homicides and robbery data over the period 1951 to 1994. They suggest that cointegrating relationships make a connection for the long-run equilibrium levels of crime rates to economic factors by using endogenously determined structural breaks. They find that long-run pattern of homicides and robberies could be better explained by disposable income (consumption), while thefts are better explained by unemployment.

In order to investigate long run relationship, the growing literature is attempting to use Autoregressive Distributed Lag (henceforth, ARDL) bounds testing approach. For instance, Habibullah and Baharom (2009) apply an autoregressive distributed lag (henceforth, ARDL) model to analyze the relationship between economic variables including real GDP and different categories of crime in Malaysia, using data covering the period 1973-2003. They conclude that the long run causal effect runs from income to crime, as many other economic variables. On the other hand, Halicioglu *et al*. (2012), again employing an ARDL model to identify the causes of crime in Japan over the period 1964-2009, conclude that there exist co-integration between different crime categories and economic variables such as income, unemployment, divorce, urbanization and security expenditures. Moreover, their findings suggest that increasing urbanization, unemployment, and divorce rates have positive and significant effect on crime.

Although several studies have been done to find the link between economic development and crime, there is lack of studies relating to ARDL approach. Therefore, the implementation of this method sounds very intuitively appealing.

2.3. Crime and Unemployment

Some researchers prefer to use alternative indicators to measure economic conditions instead of using GDP or GNP per capita. For example, they suggest that labor market outcomes, unemployment rate or wage could be comparatively narrow measures of economic activity.

Most of the classic criminological studies find positive relationship between some aspects of unemployment and crime. For instance, anomie theory of Merton (1938) proposes that crime results in inability to obtain employment which contributes to material and cultural success. Also, social-control theories suggest that insufficient job stability and commitment cause criminal behavior among adults.[5] Similarly, economic theories of choice (Becker-Ehrlich type models) mention the negativity between employment and crime, stress the relative payoffs of conventional and illegal endeavors. However, social learning and differential association theories emphasize the learned values, attitudes, and behaviors resulted by interactions with other individuals at work when revealing the negative relationship between crime and employment. Even though each of the theories mention a different structure for the link between employment and crime, they present that employment might affect crime negatively.

The topic on how labor market incentives affect crime has pursued its popularity after the emerging of classical criminological theories. For example, Grogger (1991) find a strong and negative effect of legal income on arrest. Also, he

[5] For other social control theory studies, see Kornhauser (1978) and Sampson and Laub (1993).

provides evidence that employment and relatively minor criminal activities are complementary activities, and employment and serious crime are substitute activities. However, when these two crime types are pooled, he finds no effect on criminal activity.

Another important study has been conducted by Cornwell and Trumbull (1994). In their empirical analysis, using the panel data of North Carolina, authors show that high wages in legal activities are correlated with low crime rates. Similarly, Uggen and Thompson (1999) find that work and legal income have negative effects on illegal earnings. It is reported that illegal earnings decreased $100 and $200 per month due to increasing employment and every legal dollar earned reduced illegal earnings by nearly seven cents.

To address the importance of skill levels of labors, Machin and Meghir (2000) find that reductions in wages of unskilled workers increases the property crimes like burglary, theft, and vehicle crimes when analyzing a time-series study of England and Wales. However they emphasize the importance of using wage variable rather than unemployment rate because wage summarizes the labor market opportunities available to individuals.

Although the literature exploring relationship between crime and unemployment is vast, this link is still ambiguous. A wide range survey by Chiricos (1987) suggests that unemployment in most cases leads to an increase in crime. After review of 63 aggregate studies published in the fields of economics, sociology, and criminology journals, he finds that 31% of 288 estimates were positively and statistically significant and only 2% were negative and statistically significant. He also adds that most of the non-significant estimates were positive. Chiricos (1987) finds little support for how unemployment decreases the opportunity to commit criminal activity since fewer and better protected criminal targets. Freeman (1995) finds a similar result that wages from legitimate work have negative effects on crime. He states that "the question that traditionally motivated analyses of crime and the job market has been the effect of unemployment on crime. Many people believe that joblessness is the key determinant of crime, and have sought to establish a significant crime-unemployment trade-off". He also emphasizes that "most important, although the rate of unemployment drifted upwards from the 1950s to the 1990s, even the largest estimated effects of unemployment on crime suggest that it contributed little to the rising trend in crime" (p.1). On the contrary, Box (1987) reports 35 studies on the topic, out of which 20 find a positive relationship between crime and unemployment, while the others do not find a significant relationship.

One remarkable study is conducted by Cantor and Land (1985), hereafter C-L. They criticize the earlier studies for their weak and inconsistent findings since they have not considered the two possible ways unemployment may influence crime. Cantor and Land (1985) analyze the relationship between annual unemployment rates and crime rates in the United States. According to the authors, when people are unemployed, it can be expected that they have greater motivation to violate the law; this will lead to increase in the time to spend at their home. Hence, it will help to prevent burglaries and to reduce their vulnerability to robbery, assault, and homicide. This negative effect of unemployment on crime is called as the opportunity effect. C-L also suggest that opportunity effects should be instantaneous, although motivational effects are probably to be lagged because most workers are likely to save their savings and welfare benefits for insurance at the times they lose their jobs. The positive effect of unemployment on crime can be called as the motivational effect. However, the motivation effect is assumed to have lagged effect on crime since people would immediately commit crime feeling financial depressed when they are unemployed.

C-L suggest that the two possibilities need not be mutually exclusive: unemployment could lead to reduce the opportunities in order to violate the law, however at the same time, increase in motivation to do it. They note that if both effects are instantaneous, a coefficient of the net effect of unemployment on crime might be small and insignificant, though both effects are substantial. They find that the total effect of the unemployment rate is the sum of positive motivational and negative opportunity impacts. Their results show a negative partial effect across all the types of crimes, which are homicide, robbery, burglary, larceny-theft and motor vehicle theft indicating a significant effect. However, they find a positive partial effect especially for property crimes such as robbery, burglary and larceny. They conclude that the relationship between unemployment rates and crime rates might be positive, negative or null; it depends on the type of crime and the effects on criminal opportunity or criminal motivation.

On the other hand, Hale and Sabbagh (1991) criticize the methodology of the C-L's hypothesis in terms of omission of some essential exogenous variables. As an alternative, Hale and Sabbagh (1991) instruct a framework by using cointegration and error correction models for England and Wales. Greenberg (2001a, 2001b) also criticizes the C-L and other previous studies by using an updated dataset. Greenberg also considers the duration of unemployment to observe the motivation and the opportunity effect. However, he finds that both effects do not support the C-L's hypothesis. Moreover, his findings indicate that divorce is correlated with robbery and homicide with respect to negative error correction terms.

By summarizing findings of different panel-data studies at different levels like states, counties, and cities of the United States, Levitt (2001) comes to conclusion that "a 1% change in the unemployment rate is typically found to increase property crime by 1-2% contemporaneously but often has no systematic impact on violent crime". However, Levitt (2001) does not find a support for motivation effect, because the lagged unemployment rate has not influence on property and violent crime. Also, in their state-level panel data analysis investigating link between unemployment and crime in the US, Raphael and Winter-Ember (2001) find that unemployment is an important determinant of property crime rates. They suggest that percentage point decrease in unemployment causes 1-5% decline in property. Nevertheless, their findings indicate mixed results for violent crimes, and show a small positive effect of male unemployment rates on state rape rates.

Several researchers point out the endogeneity problem between crime and unemployment. For example, Thornberry and Christenson (1984) suggest that unemployment and crime mutually affect each other over the individual's life span. Their findings show that unemployment has significant instantaneous effects on crime, meanwhile crime has significant lagged effects on unemployment. Piehl (1998) also highlights the importance of endogeneity and states that, “The literature on economic conditions and crime needs empirical studies that use simultaneous models, so that the causality of crime on economics and that of economics on crime are both incorporated”. Also, Levitt (2001) and Bushway and Reuter (2001) both emphasize the significance of cope with endogeneity in their studies.

2.4. Crime and Income Inequality

From Becker (1968) to modern economist studying on crime, income inequality has been accepted as an indicator for measuring the difference between the gains from crime and its opportunity costs, especially by Fleisher and Ehrlich. Fleisher (1996) suggests that the size of the difference between the average income of the second lowest quartile and that of the highest quartile of households likely to increase city arrest and court-appearance rates. However, the coefficient is not statistically insignificant for high-income communities alone. Ehrlich (1973) proposes that crime also increases when income inequality increases. He finds that individuals at the lower end of the income distribution will have high probability to commit crime because the cost of crime, legal income given up is quite low.

An alternative approach for comprehending the positive link between inequality and crime is that in countries with higher income inequality, it will decrease in individuals' expectations about improvement of their social-economic status which is obtained by legal economic activities. Therefore, most of the empirical studies of economics of crime advocate the hypothesis that the higher income inequality in countries leads to increase in more crime. For instance, by using a wide panel dataset of crime rates from 1970 to 1994, Fajnzylber, Lederman, and Loayza (1998) find that income inequality is positively associated with crime rates, both on intentional homicide and robbery. However, the level of income per capita is not found as a statistically significant determinant of national crime rates. Also Freeman (1999) using US data find a positively significant relationship between the Gini coefficient and crime rates. Neapolitan (2003) also detects a positive effect of income inequality on robbery and burglary. For instance, he uses control variables such as the GDP per capita, the infant mortality rate, the level of democracy, and the urbanization rate income inequality and homicide rates.

Since the main reason to commit property crime differs from the reasons of committing to violent crime; some researchers believe that it is necessary to distinguish the partial effects of income inequality on property or violent crime. For example, by using data from all metropolitan counties of the US, Kelly (2000) finds that income inequality has no influence on property crime, but has a significant and robust effect on violent crime. Furthermore, poverty and police activity have significant effects on property crime, though the effect is relatively small on violent crime.

However some studies have found no relationship between crime and income inequality. For instance, Doyle, Ahmed, and Horn (1999) analyze the property crime in the US by using panel data from 1984 to 1993. They find that income inequality has no significant effect on crime rates. In addition, they propose that favorable labor market conditions have significant and negative effects on both property crime and violent crime. Allen (1996) using time series regression finds no significant effect of inequality on the overall crime.

Both Dahlberg and Gustavsson (2008) and Nilsson (2001) focus on property crime and income inequality in Sweden. Nilsson (2001) finds that an increase of one per cent in the proportion of households below 10% of the median income increases burglary by 5.9 per cent and auto theft by 22.1 per cent. On the other hand, Dahlberg and Gustavsson (2008) suggest that a 1% increase in income inequality leads to an increase in burglary and auto theft of 1.1 and 1.8 per cent, respectively. Moreover, they explain the reason behind why some economists have not found a relationship between crime and inequality. According to them, income inequality should be separated into two parts: transitory and permanent income inequality. Their findings show that an increase in permanent income inequality leads to increase property crime, but an increase in transitory income inequality has no effect on it. However, they find that measure of income (GDP or GNP) has no effect on crime.

3. THE NON-LINEAR IMPACTS OF INCOME ON CRIME

3.1. Introduction

On average, across the G7 countries, overall crime has declined from 97 to 78 crimes per thousand adults between 1992 and 2010. In the US, total number of crime has fallen by nearly half between 1991 and 2010. In Canada, throughout the same time period the total has dropped from 152 to 97 for every thousand adults. According to the British Crime Survey (2000), in 2010 recorded crime in the UK fell to its lowest level since records began in 1981. Similarly, in France, Official Crime Statistics (2010) showed that the overall crime rate in 2009 was at the lowest level since 1989. Crime figures have also fallen in Germany: official statistics show that the overall recorded number of crimes in 2010 was below 6 million for the first time since the country was reunified in 1991.[6] Considering the fact that G7 countries are the most advanced economies in terms of income levels, the pattern brings forward the question: "what is the role of income on crime at macro level?"

Fleisher (1966) is one of the pioneering studies on the effects of income on individuals' decisions to commit criminal acts:[7,8] he argues that the effect of

6 The two exceptions in crime statistics among G7 countries have been Japan and Italy. The Japanese crime rate has been converging to other developed countries by increasing from very low rates due to changing life style towards a quasi-Western society (cf., Halicioglu et al. (2012)). It is only Italy that crime rates did not fall in the period covered.
7 The economics of crime theory is generally associated with Becker (1968). Ehrlich (1973) extended the analysis of Becker by introducing time allocation into the model. One of the factors found playing a critical role in explaining crime is income.

higher levels of average income on crime is ambiguous, since income is correlated with both cost of engaging criminal activity (negative) and the expected payoff (positive) from crime. Accordingly, the literature has produced mixed evidence, irrespective of the nature of data and methodology. Take for example single-country studies. Reilly and Witt (1996) find that per capita household income has negative impact on the rate of burglary and theft, based on data from England and Wales over the period 1976-2005. Halicioglu (2012), employing an autoregressive distributed lag (henceforth, ARDL) model, conclude that income is negatively co-integrated with aggregate crime in Turkey over the period 1965-2009. Scorcu and Cellini (1998), using an endogenous structural break method in Italian data over the period 1951-1994, finds that long-run pattern in the rates of homicide and robbery could be explained by per capita consumption or disposable income, and sign of the relationship is negative until the mid-1960s, after which it turns to positive. Choe (2008), by analyzing 9 different types of crime categories in 50 states of the US from 1995 to 2004, shows that robbery and motor vehicle theft have a statistically significant and positive relationship with income. Finally, Habibullah and Baharom (2009), using an ARDL model, find that the long run causal effect runs from income to crime in Malaysia between the period 1973 and 2003, and that murder, rape, assault, and motorcycle theft are all positively correlated with income, whereas armed robbery has negative relationship with it.

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8 Some other studies considered the average earnings or wages instead of income. Using different wage measures, Gosling, Machin and Meghir (2000) find that decrease in wages of unskilled workers lead to increase in crime in England and Wales. Gould et al. (2002) examine the effect of wages and unemployment on crime in US between 1979-97 and conclude that both wages (negatively) and unemployment (positively) are correlated with crime. Narayan and Smyth (2004), on the other hand, find mixed results for Australia in the 1964-2001 period: Their estimates indicate that male youth unemployment and real male average weekly earnings are positively associated with fraud, homicide and motor vehicle theft but not with breaking and entering, stealing, robbery and serious assault in the long-run.

The extensive panel data studies on the issue also yield mixed evidence on the relationship between income and crime. For example, Fajnzylber *et al*. (1998) find a strong positive correlation between high levels of GDP per capita, and rates of intentional homicide and robbery, using a wide panel data set compiled from the United Nations World Crime Surveys. In contrast, several other studies show that panel evidence on the role of income in explaining crime is negative. For example, Fajnzylber *et al*. (2000) show that the coefficient of income growth is significantly negative on both homicide (45 countries) and robbery (34 countries) in the period 1970-1994s, and that the coefficient of income per capita has alternating signs for homicide and robbery. Fajnzylber *et al*. (2002b) find that the coefficient of average income is negative, but not necessarily always significant. Finally, Neumayer (2005) finds that higher income levels are associated with lower homicide rates, based on data from 59 countries between 1980 and 1997.

However, despite the growing literature examining the role of income on crime at several levels of aggregations, the failure to establish a clear link may be due to one particular reason: The assumption in almost all the literature, of a linear relationship between income per capita and crime may be misleading, as it does not consider the Kuznets Curve Hypothesis (KCH).[9] We know from the hypothesis that inequality in an economy first increases and then decreases in the

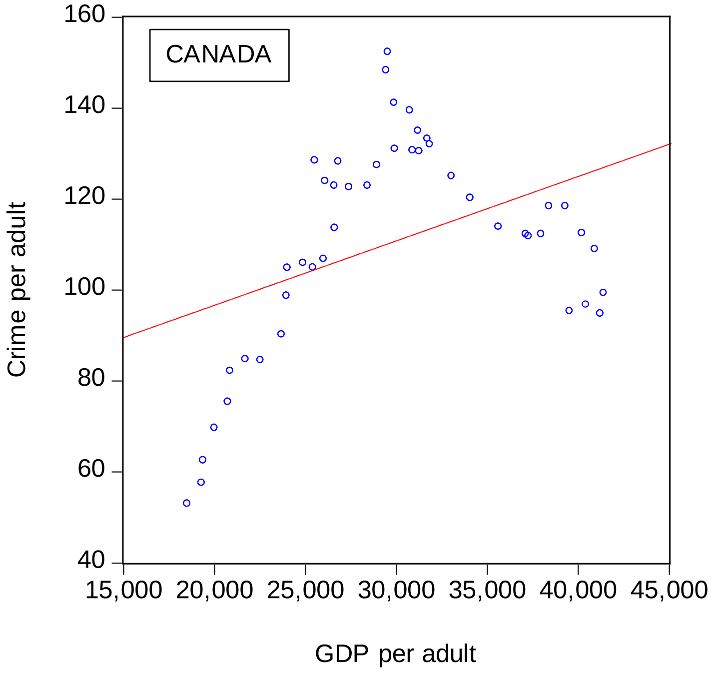
9 To our knowledge, there is only one exception to this. Neumayer (2005) assumes a non-linear relationship between income per capita and violent property crime by using the squared term of the log of per capita income as a control variable and finds that an increase in income leads to increase in violent property crime at a decreasing rate by employing data from 59 countries in the period 1980-1997. Though it is not income, another study having nonlinear vision is Bounanno and Leonida (2005), which assumes a nonlinear relationship between crime and education.

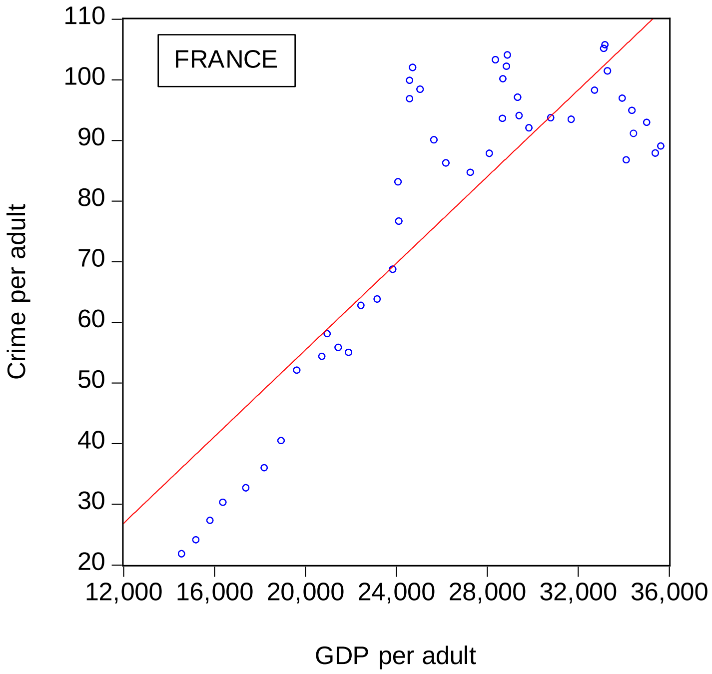
development process (cf., Kuznets, 1955). As several studies provide strong evidence that income inequality is positively associated with crime, it is natural to expect that income has a nonlinear relationship with crime via the income inequality.[10] Hence, if the KCH is taken into consideration, it is natural to expect that crime will also first rise and then fall with rising income, or more generally, it may take any non-linear form, e.g., quadratic or cubic.

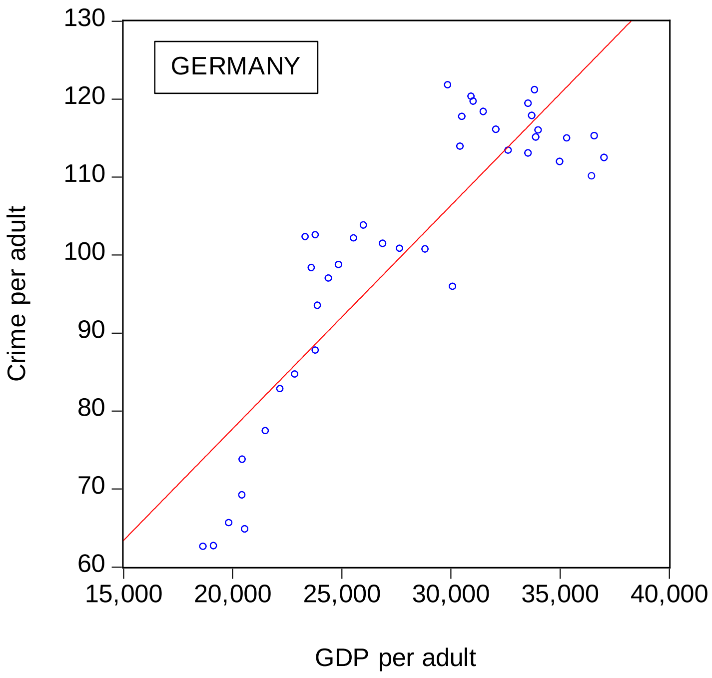
The obvious first step towards finding support for our hypothesis would be to scatter plot crime per adult against income per adult for each G7 country, which is shown in figure 1 below.[11] The raw data for each G7 country suggest a non-linear relationship between crime and level of development. Though visual analyses are not entirely reliable, our plots nonetheless highlight the possibility that the relationship between income and crime may not be linear.

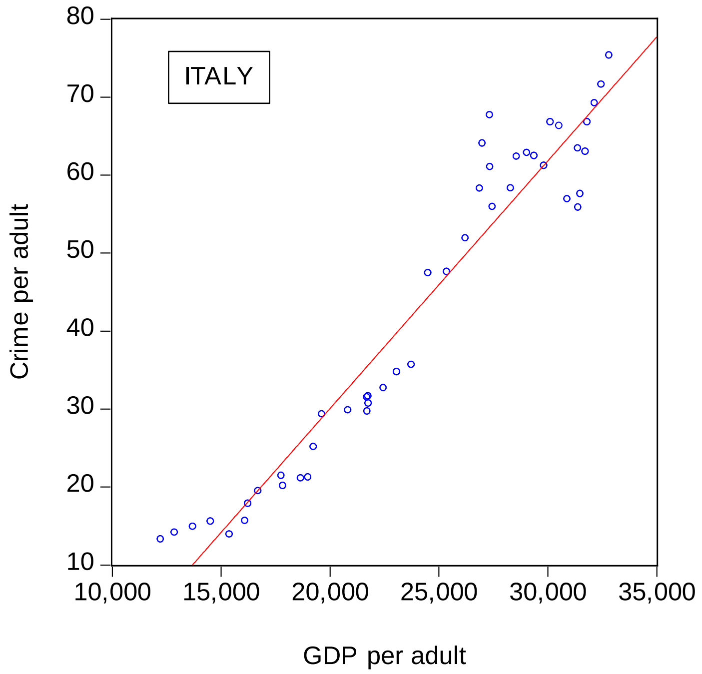
10 For theoretical studies regarding the impact of income inequality on crime, see Becker (1968), Ehrlich (1973), Block and Heineke (1975), Chiu and Madden (1998), Atkinson and Bourguignon (2000) and Imrohoroglu *et al*. (2000) and for the empirical studies, see Fleisher (1966), Ehrlich (1973), Allen (1996), Kelly (2000), Fajnzylber *et al*. (1998, 2002) and Demombynes and Özler (2005)

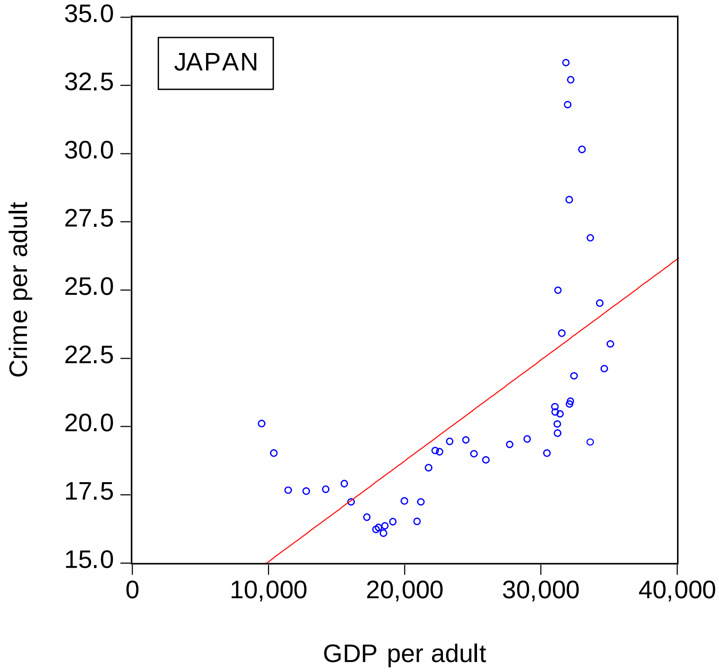
11 The data covers the period 1965-2010 for all but Germany, which starts in 1970. Authors can provide the data on request.

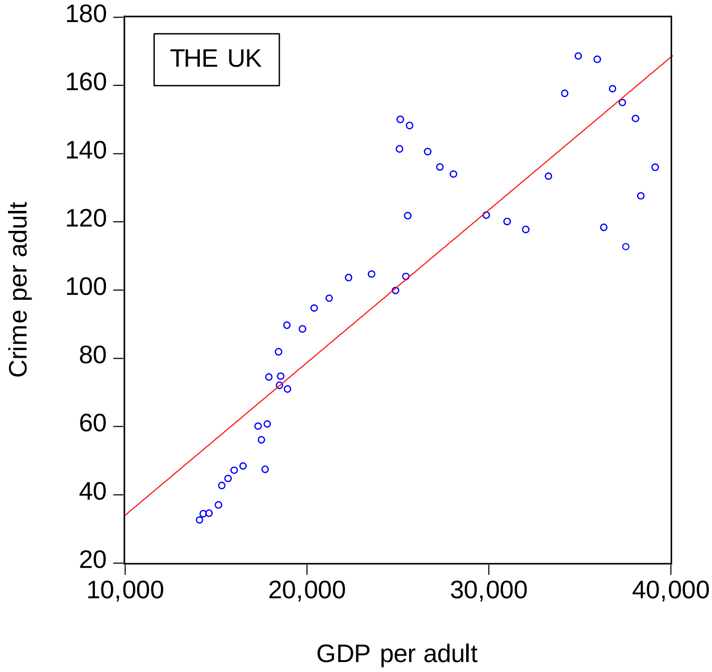

CANADA
160
140
120
100
80
60
40
Crime per adult
15,000
20,000
25,000
30,000
35,000
40,000
45,000
GDP per adult


FRANCE
110
100
90
80
70
60
50
40
30
20
Crime per adult
12,000
16,000
20,000
24,000
28,000
32,000
36,000
GDP per adult


GERMANY
Crime per adult
GDP per adult
130
120
110
100
90
80
70
60
15,000
20,000
25,000
30,000
35,000
40,000


ITALY
Crime per adult
GDP per adult
80
70
60
50
40
30
20
10
10,000
15,000
20,000
25,000
30,000
35,000


JAPAN
Crime per adult
GDP per adult
35.0
32.5
30.0
27.5
25.0
22.5
20.0
17.5
15.0
0
10,000
20,000
30,000
40,000


THE UK
Crime per adult
GDP per adult
180
160
140
120
100
80
60
40
20
10,000
20,000
30,000
40,000

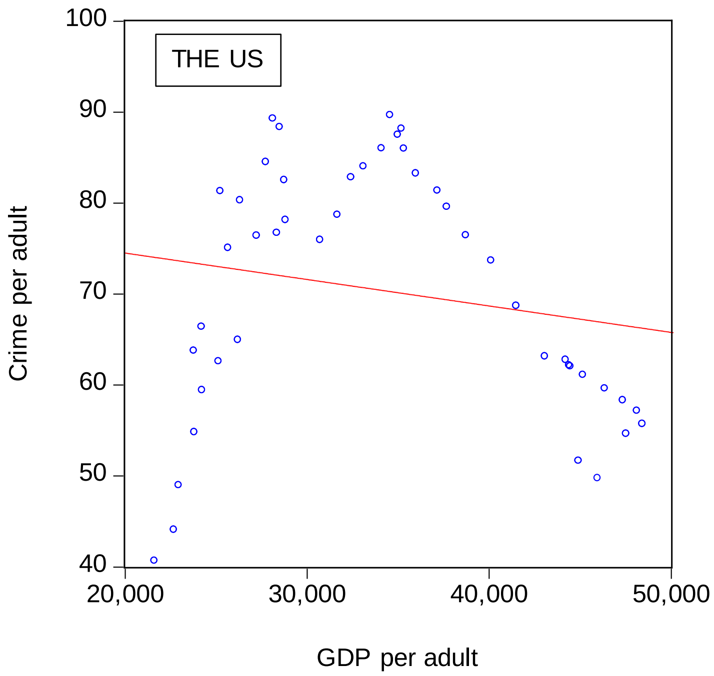


Figure 1 Crime per adult versus Income per adult

Source: Eurostat, Statistics of Canada (CANSIM), FBI statistics, Historical Statistics of Japan, and Heston et al. (2012)

Our aim in this paper is to determine econometrically whether the relationship between income and crime is truly linear or not. This is important for all (empirical) crime studies, as otherwise the role of income on crime cannot be identified correctly, at least due to the omitted variable bias. In addition, a (biased) linearity assumption would have an impact on appropriate policy implications.

To increase the reliability of our analysis, we will test three alternative possible relationships between income and crime: cubic, quadratic, and linear. A priori, we expect that a non-linear relationship, either cubic or quadratic, will be supported by the data and in particular we expect to find an inverted U-shaped relationship due to the Kuznets Curve Hypothesis. In order to increase the explanatory power of the income variable, in all runs we include in the equation the unemployment rate, which is a good proxy for legal income opportunities, as this has been highlighted as having a significant explanatory power on crime in several studies. In particular, Cantor and Land (1985) argue that the unemployment rate, like income, has two contradictory effects on crime: the opportunity effect and the motivation effect. While the former implies low unemployment rate (high economic activity) causes higher crime rates, the latter implies the reverse, i.e., lower unemployment rate causes lower crime.[12]

In our study, we purposefully focused on G7 countries due to the data limitations on crime statistics. We also refrain from cross sectional analysis because crime levels across countries may not be comparable.[13] We employ the bounds testing approach to cointegration and error correction testing within ARDL framework developed by Pesaran and Pesaran (1997), and Pesaran *et al*. (2001). The ARDL method fits our analysis for two reasons. First, as shown in the next section, crime data is I(0) while income data is I(1) in most instances. Second, the ARDL method provides a perfect environment for both long run relationship and short-run dynamics. Throughout our analysis, we show that the dominant type of relationship between income and crime is inverted-U shaped, as expected, in the long run. We also show that short run analyses indicate that income per adult is a

12 Some studies relating the opportunity effect concentrate on the absence of guardianship and suitable targets, e.g., Cohen and Felson (1979), Felson (1994), Land and Felson (1976), and Wilcox et al. (2003), there are other studies finding that that motivation effect dominates, e.g., Arvanites and DeFina (2006) and Hale and Sabbagh (1991). Some others, on the other hand, either find mixed results between unemployment and crime, such as Chiricos (1987), e.g., Lee (1993), Freeman (1995), Levitt (1996, 1997, 2001), Raphael and Winter-Ember (2001).
13 Cf., http://epp.eurostat.ec.europa.eu/statistics_explained/index.php/Crime_statistics.

strong determinant of crime rates among all G7 countries, with the exception of the US.

The organization of this section as follows: Section 3.2 introduces the data and the methodology. Section 3.3 is reserved for empirical analysis. We show that the long-run relationship between income per adult and crime per adult is non-linear rather than linear for most G7 countries.

3.2. Data and Methodology

We construct dataset for G7 countries over the period 1965-2010. The dependent variable is the total number of crime per adult (recorded by police departments) in the age range between 15 and 64. Aggregate crime data contains all crime categories, including homicide, violent crime, robbery, domestic burglary, theft of a motor vehicle, and drug trafficking. The crime data is compiled from Eurostat, Statistics of Canada, FBI statistics, and Historical Statistics of Japan. The working age population is obtained from OECD Stat. The income data (at 2005 international dollars) are drawn from the Heston et al. (2012) dataset. Income per adult is introduced in the linear, quadratic, and cubic forms in the analysis.[14] The unemployment rate is used to increase the explanatory power of the model, representing a good proxy for legal income opportunities.[15] All variables are

14 We use income per adult and GDP per adult interchangeably throughout the study.
15 Numerous studies use unemployment in explaining crime. Some of these studies find that unemployment rate is positively associated with crime, e.g., Ehrlich, 1973; Freeman, 1995; Scorcu and Cellini, 1998; Gould, Weinberg, and Mustard, 2002; Arvanities and DeFina 2006. Some other studies find mixed results between crime and unemployment, e.g., Chricos, 1987; Levitt, 1996, 2001; Allen, 1996; Britt, 1997; Entorf and Spengler, 2000.

expressed in their natural logarithmic levels. Table 1 presents the descriptive statistics of crime per adult and income per adult for G7 countries.

Table 1 Descriptive Statistics of Data

		Crime per adult (cr)				GDP per adult in 2005 I$ (y)				Unemployment rate (u)			
Country	**# of Obs./ Period Incl.**	**Mean**	**Max.**	**Min.**	**SD**	**Mean**	**Max.**	**Min.**	**SD**	**Mean**	**Max.**	**Min.**	**SD**
Canada	46 (1965-2010)	4.68	5.03	3.97	0.24	10.28	10.63	9.83	0.23	2.00	2.47	1.22	0.30
France	46 (1965-2010)	4.28	4.66	3.08	0.44	10.15	10.48	9.59	0.25	1.85	2.51	0.34	0.64
Germany	41 (1970-2010)	4.60	4.80	4.13	0.20	10.22	10.52	9.83	0.20	1.89	2.56	-0.22	0.66
Italy	46 (1965-2010)	3.63	4.32	2.58	0.56	10.06	10.40	9.41	0.28	2.09	2.48	1.68	0.28
Japan	46 (1965-2010)	3.01	3.50	2.78	0.19	10.08	10.47	9.17	0.35	0.93	1.68	0.09	0.49
United Kingdom	46 (1965-2010)	4.50	5.13	3.48	0.49	10.07	10.58	9.56	0.33	1.68	2.46	0.34	0.58
United States	46 (1965-2010)	4.23	4.50	3.70	0.21	10.41	10.79	9.98	0.25	1.75	2.26	1.22	0.26

Note: SD denotes standard deviation. All series are in their natural logarithmic levels.

The following econometric models are employed to test whether, in the long run, the relationship between crime per adult and income per adult is cubic, quadratic, or linear:[16]

$$Ln(cr_t) = \lambda_{c0} + \lambda_{c1} Ln(y_t) + \lambda_{c2}\, Ln(y_t)^2 + \lambda_{c3}\, Ln(y_t)^3 + \lambda_{c4} Ln(u_t) + \epsilon_{ct} \qquad \text{(1a)}$$

$$Ln(cr_t) = \lambda_{q0} + \lambda_{q1} Ln(y_t) + \lambda_{q2}\, Ln(y_t)^2 + \lambda_{q3} Ln(u_t) + \epsilon_{qt} \qquad \text{(1b)}$$

$$Ln(cr_t) = \lambda_{\ell 0} + \lambda_{\ell 1} Ln(y_t) + \lambda_{\ell 2} Ln(u_t) + \epsilon_{\ell t} \qquad \text{(1c)}$$

where the coefficients $\lambda_{cj},\ j = 1,2,3$ are the long-run elasticity estimations of crime per adult (cr_t) with respect to GDP per adult (y_t), to the square of GDP per adult (y_t^2), and to the cube of GDP per adult (y_t^3), respectively. The subscripts c, q and ℓ refer to cubic, quadratic, and linear specifications respectively.

If the data do not support a cubic relationship, or if no statistically significant evidence is found via (1a), we run (1b) to test quadratic pattern of CKC. In (1b), the coefficients $\lambda_{qi},\ i = 1,2$ stand for the long-run elasticity estimations of cr_t with respect to y_t and to the square of it. Likewise, if the data do not support a quadratic relationship, or if no statistically significant evidence is found via (1b), we run (1c) to test linear pattern of CKC. In (1c), the coefficients $\lambda_{\ell k},\ k = 1$ stand

16 While a quadratic specification may show either a U-shaped curve or an inverted U-shaped CKC, the cubic specification may yield an S-shaped or an inverted S-shaped CKC.

for the long-run elasticity estimations of cr_t with respect solely to y_t. In addition, ϵ_t and the subscript t denote the error term and the time period index, respectively.

3.3. Empirical Analysis

3.3.1. Unit Root Tests

Basic econometric method for analyzing stationarity in the time series data is to use unit root tests. The critical bounds test of Pesaran *et al*. (2001) or Narayan (2005) requires that the order of integration of our series ought to be either I(0) or I(1). In this paper, two different unit root tests are used for robustness, namely, Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP). The Schwarz Information Criterion (SIC) is employed as lag selection criteria. Newey–West Bartlett kernel method is selected as the bandwidths for PP.

The unit root test results of the series for G7 countries are shown in the table 2a-2g below. The tests cover an intercept in the levels, and an intercept and a linear trend in first difference.

Table 2 Unit Root Tests

Table 2a Unit Root Test Results for Canada

Variables	ADF-test	PP-test
Panel A: Level (Intercept , no trend)		
Lncr	-2.950(2)**	-3.749(2)***
Lny	-1.178(1)	-1.603(2)
Lny^2	-1.101(1)	-1.489(2)
Lny^3	-1.025(1)	-1.379(2)
Lnu	-3.337(1)**	-2.311(6)
Panel B: First difference (Intercept & trend)		
Lncr	-5.497(1)***	-3.346(43)*
Lny	-4.912(0)***	-4.764(5)***
Lny^2	-4.884(0)***	-4.731(5)***
Lny^3	-4.858(0)***	-4.700(5)***
Lnu	-5.393(0)***	-5.555(10)***

Table 2b. Unit Root Test Results for France

Variables	ADF-test	PP-test
Panel A: Level (Intercept and no trend)		
Lncr	-4.605(6)***	-4.702(1)***
Lny	-4.894(0)***	-4.894(0)***
Lny^2	-4.614(0)***	-4.894(0)***
Lny^3	-4.341(0)***	-4.027(1)***
Lnu	-3.431(0)**	-3.431(0)**
Panel B: First difference (Intercept & trend)		
Lncr	-4.165(5)**	-4.547(1)***
Lny	-5.205(0)***	-5.205 (0)***
Lnya^2	-5.214(1)***	-5.220(1)***
Lny^3	-5.216(0)***	-5.223(1)***
Lnu	-5.034(0)***	-4.939(5)***

Table 2c. Unit Root Test Results for Germany

Variables	ADF-test	PP-test
Panel A: Level (Intercept , no trend)		
Lncr	-2.785(0)*	-2.781(2)*
Lny	-1.741(0)	-2.663(10)*
Lny^2	-1.634(0)	-2.4785(10)
Lny^3	-1.529(0)	-2.297(10)
Lnu	-3.478(1)**	-5.189(6)***
Panel B: First difference (Intercept, no trend)		
Lncr	-5.879(0)***	-5.940(4)***
Lny	-5.338(0)***	-6.149(13)***

Lny^2	-5.376(0)***	-6.192(13)***
Lny^3	-5.414(0)***	-6.237(13)***
Lnu	-4.177(0)**	-3.856 (11)**

Table 2d. Unit Root Test Results for Italy

Variables	ADF-test	PP-test
Panel A: Level (Intercept , no trend)		
Lncr	-1.879(0)	-1.822(1)
Lny	-4.455(0)***	-5.316(5)***
Lny^2	-4.235(0)***	-4.998(5)***
Lny^3	-4.022(0)***	-6.437(0)***
Lnu	-2.104(0)	-2.162(1)
Panel B: First difference (Intercept, no trend)		
Lncr	-5.724(0)***	-5.678(3)***
Lny	-6.521(0)***	-6.705(6)***
Lny^2	-6.485(0)***	6.661(6)***
Lny^3	-4.688(5)***	-6.597(6)***
Lnu	-6.593(1)***	-6.389(6)***

Table 2e. Unit Root Test Results for United Kingdom

Variables	ADF-test	PP-test
Panel A: Level (Intercept , no trend)		
Lncr	-2.246(1)	-2.526(1)
Lny	-0.691(1)	-0.647(2)
Lny^2	-0.595(1)	-0.533(2)
Lny^3	-0.501(1)	-0.424(2)
Lnu	-2.090(2)	-2.486(4)
Panel B: First difference (Intercept & trend)		
Lncr	-4.882(0)***	-4.850(2)***
Lny	-4.534(0)***	4.588(1)***
Lny^2	-4.507(0)***	-4.562(1)***
Lny^3	-4.484(0)***	-4.541(1)***
Lnu	-4.251(1)***	-8.843(3)***

Table 2f. . Unit Root Test Results for United States

Variables	ADF-test	PP-test
Panel A: Level (Intercept , no trend)		
Lncr	-1.238(2)	-2.171(3)
Lny	-1.325(0)	-1.374(6)
Lny^2	-1.239(0)	-1.264(5)
Lny^3	-0.751(1)	-1.169(5)
Lnu	-3.307(1)**	-1.621(6)

Panel B: First difference (Intercept & trend)		
Lncr	-6.576(1)***	-3.530(28)**
Lny	-5.255(0)***	-5.155(11)***
Lny^2	-5.206(0)***	-5.077(10)***
Lny^3	-5.157(0)***	-5.001(9)***
Lnu	-5.571(1)***	-4.445(19)***

Table 2g. Unit Root Test Results for Japan

Variables	ADF-test	PP-test
Panel A: Level (Intercept , no trend)		
Lncr	-2.186(1)	-1.451(4)
Lny	-6.636(0)***	-5.740(3)***
Lny^2	-6.164(0)***	-5.556(2)***
Lny^3	-5.715(0)***	-5.199(2)***
Lnu	-0.886(1)	-0.860(2)
Panel B: First difference (Intercept & trend)		
Lncr	-2.536(0)	-2.584(1)
Lny	-4.413(0)***	-4.306(2)***
Lny^2	-4.570(0)**	-4.573(1)***
Lny^3	-4.714(0)***	-4.725(1)***
Lnu	-4.668(0)***	-4.723(1)***

Notes: The null hypothesis is the existence of unit root for ADF and PP tests. In the tables, superscripts ***, **, * denote the rejection of the null hypothesis at 1%, 5% and 10% significance levels, respectively. ADF and PP critical values are due to MacKinnon (1996). Lag lengths for ADF test and bandwidths for PP test are in parentheses.

Unit root test results show that all variables are either I(0) or I(1) at varying significance levels, except for Japan: crime per adult is non-stationary in levels and in first differences. As it violates the fundamental requirements of the critical bounds test of Pesaran et al. (2001) and Narayan (2005), Japan is eliminated from our analyses.

Following ADF and PP unit root tests, we run Zivot and Andrews (hereafter, ZA) unit root test (1992), hereafter ZA, for determining the structural breaks in the data. Perron (1989) states that the absence of structural break point may cause a bias that weakens the ability to reject a false unit root null hypothesis. To overcome this problem, the ZA testing procedure suggests determining a structural break endogenously from the data, either in the intercept, in the linear trend, or in both, and the determination of the order of integration of a series simultaneously. The table 3a-3f below shows the results of ZA unit root tests for the series in the study for six countries.

Table 3 Zivot Andrews Unit Root Tests

Table 3a ZA Unit Root Test Results for Canada

Panel A:Level	**Intercept**	**Trend**	**Int&Tr**
Lny	-3.659(1) [1990]	-	-3.615(1) [1980]
Panel B: First Difference	**Intercept**	**Trend**	**Int&Tr**
Lny	-5.405*** (0) [1993]	-4.956***(0) [2001]	-5.422**(0) [1997]

Table 3b. ZA Unit Root Test Results for France

Panel A:Level	**Intercept**	**Trend**	**Int&Tr**
Lny	-2.971 (1) [1976]	-3.049(1) [2001]	-3.00(1) [2001]
Panel B: First Difference	**Intercept**	**Trend**	**Int&Tr**
Lny	-5.908***(0) [1975]	-5.570***(0) [1976]	-5.85***(0) [1998]

Table 3c. ZA Unit Root Test Results for Germany

Panel A:Level	**Intercept**	**Trend**	**Int&Tr**
Lny	-3.697 (1) [2002]	-4.172***(1) [1997]	-5.066*(1) [1990]
Panel B: First Difference	**Intercept**	**Trend**	**Int&Tr**
Lny	-5.642***(1) [1991]	-5.289***(1) [1991]	-5.562**(1) [1991]

Table 3d. ZA Unit Root Test Results for Italy

Panel A:Level	**Intercept**	**Trend**	**Int&Tr**
Lny	-2.117 (0) [2003]	-3.164(0) [2001]	-3.093(0) [2001]
Panel B: First Difference	**Intercept**	**Trend**	**Int&Tr**
Lny	-6.032***(1) [1986]	-	-6.035***(1) [1978]

Table 3e. ZA Unit Root Test Results for United Kingdom

Panel A:Level	**Intercept**	**Trend**	**Int&Tr**
Lny	-4.048 (3) [1979]	-3.596(3) [1981]	-4.045(3) [1979]
Panel B: First Difference	**Intercept**	**Trend**	**Int&Tr**
Lny	-5.116**(1) [1983]	-4.927***(1) [2001]	-5.174**(1) [1997]

Table 3f. ZA Unit Root Test Results for United States

Panel A:Level	**Intercept**	**Trend**	**Int&Tr**
Lny	-3.537 (1) [1996]	-3.478(1) [2003]	-4.019(1) [1999]
Panel B: First Difference	**Intercept**	**Trend**	**Int&Tr**
Lny	-5.917***(1) [1983]	-5.587***(1) [2000]	-5.869***(1) [1983]

Notes: The null hypothesis is the existence of unit root with a structural break in intercept. The critical values are due to Zivot and Andrews (1992). Superscripts ***, **, * denote the stationarity for the ZA unit root test at 1%, 5% and 10% critical levels, respectively. Lag lengths are in parenthesis and the date in square brackets denote the time of the structural change. "-" represents cases in which a result cannot be obtained due to data problems. Finally, Int&Tr stands for Intercept and Trend.

The ZA tests for the six countries indicate that the series of income per adult are non-stationary at levels, but stationary in first differences for all but Germany, although at different significance levels. Hence, the series of income per adult are integrated of order one for the five countries, and integrated of order zero for Germany.

3.3.2. ARDL Cointegration Analysis[17]

The Autoregressive distributed lags (ARDL) bounds testing approach of cointegration was developed by Pesaran and Shin (1999) and Pesaran *et al.* (2001). In our dynamic single equation regression model, which includes the lagged values of the dependent variable, the current and lagged values of the explanatory variables are embodied so as to estimate short-run elasticities, directly and indirectly, and the long-run equilibrium relationship (Wang *et al.*, 2011). ARDL specification has some advantageous features over both the residual-based Engle and Granger (1987) test, and the maximum likelihood test of Johansen (1988) and Johansen and Juselius (1990). With this method, there is no longer any

[17] This sub-section heavily draws from Kılınç, Onater and Yetkiner (2013).

need for variables to be of the same order of integration, the series can be either I(0) or I(1). This technique allows the series in the system to have different optimal lag orders; therefore, it provides efficient estimates, even when the samples are small, and there is an endogeneity problem.[18]

The selection of the optimal lag length is important since lag lengths might influence the ARDL results. Our optimal lag selection is based on Schwarz – Bayesian information criterion (SBIC).[19] After this step, the ARDL test follows the bounds testing approach of cointegration, and then following equations are employed to determine the linear and nonlinear (cubic or quadratic) relationship between crime and economic development in the long-run:

$$\Delta Lncr_t = \alpha_{c1} + \sum_{i=1}^{p} \beta_{c1i}\, \Delta Lncr_{t-i} + \sum_{j=0}^{r} \gamma_{c1j}\, \Delta Lny_{t-j} + \sum_{k=0}^{s} \varphi_{c1k}\, \Delta Lny_{t-k}^2 + \sum_{m=0}^{z} \rho_{c1m}\, \Delta Lny_{t-m}^3 + \sum_{n=0}^{h} \psi_{c1n}\, \Delta Lnu_{t-n} + \zeta_{c1} Lncr_{t-1} + \zeta_{c2} Lny_{t-1} + \zeta_{c3} Lny_{t-1}^2 + \zeta_{c4} Lny_{t-1}^3 + \zeta_{c5}\, Lnu_{t-1} + \eta_{c1t} \tag{2a}$$

$$\Delta Ln\, cr_t = \alpha_{q1} + \sum_{i=1}^{p} \beta_{q1i}\, \Delta Ln\, cr_{t-i} + \sum_{j=0}^{r} \gamma_{q1j}\, \Delta Lny_{t-j} + \sum_{k=0}^{s} \varphi_{q1k}\, \Delta Lny_{t-k}^2 + \sum_{n=0}^{h} \psi_{q1n}\, \Delta Lnu_{t-n} + \zeta_{q1} Lncr_{t-1} + \zeta_{q2} Lny_{t-1} + \zeta_{q3} Lny_{t-1}^2 + \zeta_{q4}\, Lnu_{t-1} + \eta_{q1t} \tag{2b}$$

18 Menyah and Wolde-Rufael (2010) suggests that ARDL model corrects the endogeneity problem of explanatory variables even in small samples

19 Pesaran and Shin (1999) state that SBIC is more consistent than Akaike Information Criterion (AIC) and Hannan–Quinn information criterion (HQ). In addition, Monte Carlo evidence shows that SBIC and AIC determines reliable lag order (Panopoulou and Pittis, 2004; Emran *et al.*, 2007).

$$\Delta Ln\, cr_t = \alpha_{\ell 1} + \sum_{i=1}^{p} \beta_{\ell 1i}\, \Delta Ln\, cr_{t-i} + \sum_{j=0}^{r} \gamma_{\ell 1j}\, \Delta Lny_{t-j} + \sum_{n=0}^{h} \psi_{\ell 1n}\, \Delta Lnu_{t-n} + \zeta_{\ell 1} Lncr_{t-1} + \zeta_{\ell 2} Lny_{t-1} + \zeta_{\ell 3}\, Lnu_{t-1} + \eta_{\ell 1t} \tag{2c}$$

where η_{c1t}, η_{q1t}, and $\eta_{\ell 1t}$ denote the white noise error terms for cubic, quadratic, and linear forms of the model respectively, and Δ is the first difference operator. The parameters β, γ, φ, and ψ are the short-run coefficients, and ζ_{cx}, $x = 1,2,3,4,5$, ζ_{qy}, $y = 1,2,3,4$ and $\zeta_{\ell z}$, z=1,2,3 are the long-run coefficients of the ARDL model. The bounds testing approach is based on the joint F or Wald statistics, testing the significance of the lagged levels of the variables via the null hypothesis of no cointegration, $\mathrm{H_0}: \zeta_{\mathrm{c1,c2,c3,c4,c5}} = 0$ against the alternative of the existence of cointegration, $\mathrm{H_1}: \zeta_{\mathrm{c1,c2,c3,c4,c5}} \neq 0$. If the cointegrating relation is not found for cubic specification, the same procedure is applied for quadratic specification, e.g., the null hypothesis of no cointegration, $\mathrm{H_0}: \zeta_{\mathrm{q1,q2,q3,q4}} = 0$ against the alternative of the existence of cointegration, $\mathrm{H_1}: \zeta_{\mathrm{q1,q2,q3,q4}} \neq 0$. Similarly, if the cointegrating relation is not found for quadratic specification, the same procedure is applied for linear specification, e.g., the null hypothesis of no cointegration, $\mathrm{H_0}: \zeta_{\ell 1,\ell 2,\ell 3} = 0$ against the alternative of the existence of cointegration, $\mathrm{H_1}: \zeta_{\ell 1,\ell 2,\ell 3} \neq 0$. The asymptotic distributions of two sets are given in Pesaran *et al*. (2001), and its modified version for small samples, ranging from 30 to 80, is presented in Narayan (2005). This study employs the critical values of Narayan (2005) for the bounds F-statistics, due to the limited annual time series data on crime per adult and income for the seven countries. The results of the bounds F-test for cointegration, together with critical values are reported in Table 4.

Table 4 The bounds F-test for cointegration for the estimated ARDL Specification

Cubic Specification				**Quadratic Specification**				**Linear Specification**			
Country	**Period**	**Model**	**F-Statistics**	**Country**	**Period**	**Model**	**F-Statistics**	**Country**	**Period**	**Model**	**F-Statistics**
Italy	**1965-2010**	**1, 0, 0, 0,0**	**3.789***	**Canada**	**1965-2010**	**1, 1, 0, 0**	**5.694****	United Kingdom	1965-2010	2, 2, 0	3.577
United Kingdom	**1965-2010**	**1, 1, 1, 1,0**	**7.697*****	**France**	**1965-2010**	**2, 1, 1, 0**	**5.838****				
				Germany	**1970-2010**	**1, 1, 0, 0**	**6.542*****				
				United Kingdom	1965-2010	1, 1, 1, 0	3.481				
				United States	**1965-2010**	**2, 1, 1, 0**	**4.976****				
		I(0)	I(1)			I(0)	I(1)			I(0)	I(1)
Critical values at 1%		4.280	5.840	Critical values at 1%		4.614	5.966	Critical values at 1%		5.155	6.265
Critical values at 5%		3.058	4.223	Critical values at 5%		3.272	4.306	Critical values at 5%		3.538	4.428
Critical values at 10%		2.525	3.560	Critical values at 10%		2.676	3.586	Critical values at 10%		2.915	3.695

Notes: F-statistics are obtained from the ARDL cointegration test. The critical values for the lower I(0) and upper I(1) are due to Narayan (2005): see Case II in appendix for n=30 and k=4 for cubic relationship, for k=3 for quadratic relationship, k=2 for linear relationship. The superscripts ***, **, * in bold denote significance levels at 1%, 5%, and 10%, respectively

The F-test has a non-standard distribution that relies on (i) the number of independent variables, (ii) whether the variables in the system are I(0) or I(1), and (iii) whether the model contains an intercept and/or a trend (Narayan, 2005). The critical values for I(1) are considered as the upper bound values and the critical values for I(0) are referred to as the lower bound values (Pesaran *et al.*, 2001). If the F- test statistics exceeds their upper bound values, then we could conclude that the null hypothesis is rejected at the significance level of the respective bound and the cointegration exists among variables. In contrast, if the F- test statistics is below their lower bound values, the null hypothesis fails to be rejected, and we can infer that there is no cointegration among variables. If the F-test statistics falls between the critical values, an inconclusive test result is implied. In this paper, the bounds F-test for cointegration analysis provide evidence of a cubic CKC for Italy and United Kingdom, and a quadratic CKC for Canada, France, Germany and United States (see table 4). However, the bounds test does not provide an evidence of either a quadratic or linear relationship for United Kingdom.

After verifying the cointegration among the variables, we employ the subsequent procedure to estimate the long-run coefficients, (Equations 3a, 3b), and the short-run coefficients (Equations 4a, 4b) by the ARDL approach and the Error-Correction Model (ECM) for the associated ARDL:

$$Ln\,cr_t = \alpha_{c2} + \sum_{i=1}^{p} \beta_{c2i}\, Ln\,cr_{t-i} + \sum_{j=0}^{r} \gamma_{c2j}\, Lny_{t-j} + \sum_{k=0}^{s} \varphi_{c2k}\, Lny_{t-k}^2 + \sum_{m=0}^{z} \rho_{c2m}\, Lny_{t-m}^3 + \sum_{n=0}^{h} \psi_{c2n} Ln\,u_{t-n} + \eta_{c2t} \tag{3a}$$

$$Ln\, cr_t = \alpha_{q2} + \sum_{i=1}^{p} \beta_{q2i}\, Ln\, cr_{t-i} + \sum_{j=0}^{r} \gamma_{q2j}\, Lny_{t-j} + \sum_{k=0}^{s} \varphi_{q2k}\, Lny_{t-k}^{2} + \sum_{n=0}^{h} \psi_{q2n} Ln\, u_{t-n} + \eta_{q2t} \quad (3b)$$

$$Lncr_t = \alpha_{\ell 2} + \sum_{i=1}^{p} \beta_{\ell 2i}\, Lncr_{t-i} + \sum_{j=0}^{r} \gamma_{\ell 2j} Lny_{t-j} + \sum_{n=0}^{h} \psi_{\ell 2n} Lnu_{t-n} + \eta_{\ell 2t} \quad (3c)$$

$$Lncr_t = \alpha_{c3} + \sum_{i=1}^{p} \beta_{c3i}\, \Delta Lncr_{t-i} + \sum_{j=0}^{r} \gamma_{c3j}\, \Delta Lny_{t-j} + \sum_{k=0}^{s} \varphi_{c3k}\, \Delta Lny_{t-k}^{2} + \sum_{m=0}^{z} \rho_{c3m}\, \Delta Lny_{t-m}^{3} + \sum_{n=0}^{h} \psi_{c3n} Lnu_{t-n} + \mu\, ECT_{t-1} + \eta_{c3t} \quad (4a)$$

$$Lncr_t = \alpha_{q3} + \sum_{i=1}^{p} \beta_{q3i}\, \Delta Ln\, cr_{t-i} + \sum_{j=0}^{r} \gamma_{q3j}\, \Delta Lny_{t-j} + \sum_{k=0}^{s} \varphi_{q3k}\, \Delta Lny_{t-k}^{2} + \sum_{n=0}^{h} \psi_{q3n} Lnu_{t-n} + \mu\, ECT_{t-1} + \eta_{q3t} \quad (4b)$$

$$Lncr_t = \alpha_{\ell 3} + \sum_{i=1}^{p} \beta_{\ell 3i}\, \Delta Ln\, cr_{t-i} + \sum_{j=0}^{r} \gamma_{\ell 3j}\, \Delta Lny_{t-j} + \sum_{n=0}^{h} \psi_{\ell 3n} Ln\, u_{t-n} + \mu\, ECT_{t-1} + \eta_{\ell 3t} \quad (4c)$$

where μ is the coefficient of the Error-Correction term (hereafter ECT) and is expected to be significantly negative.[20] The long run and the short run coefficients are presented in Table 5.

---

20 The ECT specifies the convergence speed of the variables to the steady state equilibrium values. ECT equations for cubic, quadratic and linear specifications are defined as follows:
$ECT_t = Lncr_t - \sum_{i=1}^{p} \beta_{c2i}\, Lncr_{t-i} - \sum_{j=0}^{r} \gamma_{c2j} Lny_{t-j} - \sum_{k=0}^{s} \varphi_{c2k} Lny_{t-k}^{2} - \sum_{m=0}^{z} \rho_{c2m} Lny_{t-m}^{3} - \sum_{n=0}^{h} \psi_{q3n} Lnu_{t-n}$,
$ECT_t = Lncr_t - \sum_{i=1}^{p} \beta_{q2i}\, Lncr_{t-i} - \sum_{j=0}^{r} \gamma_{q2j} Lny_{t-j} - \sum_{k=0}^{s} \varphi_{q2k} Lny_{t-k}^{2} - \sum_{n=0}^{h} \psi_{q3n} Lnu_{t-n}$;
$ECT_t = Lncr_t - \sum_{i=1}^{p} \beta_{q2i}\, Lncr_{t-i} - \sum_{j=0}^{r} \gamma_{q2j} Lny_{t-j} - \sum_{n=0}^{h} \psi_{q3n} Lnu_{t-n}$.

Table 5 The Estimated Long run and Short run coefficients

Indicator/Country	**Canada**	**France**	**Germany**	**Italy**	**United States**
Structural Break	1993	1975	1991	1986	1983
Estimated Long-run Elasticities					
Lny	86.6670 (3.91)***	31.8860 (3.16)***	34.2976 (3.11)***	-1404.6 (-2.30)**	73.0497 (7.28)***
Lny^2	-4.2193 (-3.90)***	-1.5451 (-3.14)***	-1.6543 (-3.08)***	141.4530 (2.30)**	-3.5265 (-7.35)***
Lny^3	-	-	-	-4.7396 (2.30)**	-
Lnu	-0.30047 (-1.10)	0.1622 (1.80)***	0.0962 (1.91)*	0.0187 (0.11)	-0.1765 (-1.58)***
Constant	-439.4134 (-3.89)***	-160.2887(-3.10)***	-173.2139 (-3.06)***	4644.1 (2.29)**	-373.4820 (-7.13)***
Dummy	-0.1054 (-0.59)	-0.1671 (-2.24)***	-0.04072 (-0.89)***	-0.1855 (-1.10)	0.0576 (0.99)

Notes: Year Dummy is the time of the significant structural break in intercept for the series Lnya that is obtained from ZA unit root test. (-1) refers one lag of the associated variable. '-'denotes that variable does not take place in the model. The United Kingdom is eliminated from our analyses as all long run coefficients are insignificant; irrespective of degree of non-linearity T-statistics for coefficients are in parenthesis. RSS is the residual sum of squares. The superscripts ***, **, * denote significance at 1%, 5%, and 10% respectively.

Table 5 (continued)

Indicator/Country	**Canada**	**France**	**Germany**	**Italy**	**United States**
Structural Break	1993	1975	1991	1986	1983
Estimated Short-run Elasticities					
$\text{Lncr}(-2)$	-	0.4545 (3.06)***	-	-	0.3651 (2.90)***
$\text{Lny}(-1)$	16.0637 (2.99)***	-40.6673 (-1.87)*	14.7286(2.41)***	-613.1148(-1.71)*	-4.8275 (-0.53)
$\text{Lny}^2(-1)$	-0.8206 (-3.14)***	1.9716(1.85)*	-0.7435 (-2.49)***	61.7439 (1.71)*	0.1949 (0.44)
$\text{Lny}^3(-1)$	-	-	-	-2.0688 (-1.71)*	
$\text{Lnu}(-1)$	-0.0584 (-1.53)***	0.0686 (1.47)	0.0432 (1.70)*	0.0081 (0.11)	-0.0463 (-2.05)***
$\text{ECT}(-1)$	-0.1945 (-2.55)***	-0.4228(-4.40)***	-0.4495(-4.12)***	-0.4365 (-3.32)***	-0.2626 (-3.91)***
ARDL Estimates					
Model	1,1,0,0	2,1,1,0	1,1,0,0	1,0,0,0,0	2,1,1,0
Adjusted R^2	0.9811	0.9856	0.9658	0.9834	0.9742
RSS	0.0343	0.0677	0.0341	0.1873	0.9742

Notes: Year Dummy is the time of the significant structural break in intercept for the series Lnya that is obtained from ZA unit root test. (-1) refers one lag of the associated variable. '-'denotes that variable does not take place in the model. The United Kingdom is eliminated from our analyses as all long run coefficients are insignificant; irrespective of degree of non-linearity T-statistics for coefficients are in parenthesis. RSS is the residual sum of squares. The superscripts ***, **, * denote significance at 1%, 5%, and 10% respectively.

Our results show that Italy has a cubic CKC in the form of an inverted S-shaped ($\gamma < 0$, $\varphi > 0$ and $\rho < 0$) and that all coefficients are significant at the 5% level in the long-run.[21] The inverted S-shape implies that, in Italy, aggregate crime first declines then increases and finally decreases in response to an increase in income. On the other hand, the crime data of Canada, Germany, France and United States support quadratic CKC in the form of an inverted U-shaped ($\gamma > 0$, $\varphi < 0$). The long run coefficients are significant at 1% for all these countries. Here, the relationship between income inequality and level of development in the original Kuznets hypothesis is reproduced by the relationship between crime and level of development, which we call the "transitivity effect". Finally, crime data for the United Kingdom fails to yield any statistically significant coefficient in its long run relationship between income and crime; therefore, the United Kingdom is eliminated from our analyses as all long run coefficients are insignificant, irrespective of degree of non-linearity. We also find that the long-run coefficients of unemployment indicate mixed but patterned results: while the coefficient of unemployment rate is positive in France, Germany, and Italy, it is found to be negative in the United States and Canada. We argue that the difference on the impact of unemployment rate on crime between continental Europe and North America is due to the varying labor market structure in these two groups of countries. Recall that we have already discussed the two countervailing effects of unemployment on crime: the opportunity effect (negative) and the motivation effect (positive). It is widely accepted that rigid labor markets, such as those in Europe, could result in higher levels of unemployment than more flexible markets,

[21] In the literature, there are numerous examples of S-shaped and inverted S-shaped patterns of Kuznets Curve in the form of Environmental Kuznets Curve and Gender Kuznets Curve, e.g., Harbaugh et al. (2002), Eastin and Parakash (2013), and Kılınç et al. (2013).

such as those of the US and Canada.[22] The rigid market in Europe leads to a higher unemployment rate, causing the motivation effect to dominate the opportunity effect, increasing the crime rate. On the other hand, the reverse holds in US and Canada, and therefore the crime rate declines as unemployment rate increases. Finally, as expected, the estimated ECT coefficients are negative and statistically significant at the 1% level for Canada, France, Germany, Italy, and United States. The error correction terms highlight that, within the cointegration model, there is a correction of the disequilibrium conditions at the following speeds: Canada 19%, France 42%, Germany 45%, Italy 44%, and the USA 27%. In other words, the speed of adjustment towards long-run equilibrium is approximately 5.3 years in Canada, 2.4 years in France, 2.2 years in Germany, 2.3 years in Italy and 3.4 years in the United States.

3.3.3. Stability of Long run and Short run Coefficients

As discussed in section 3.1, the ZA unit root test results have shown that there are structural breaks in the regressors. The cumulative sum (CUSUM) and cumulative sum squares (CUSUMSQ) tests due to Brown et al. (1975) are applied for the stability of the short run and long run coefficients. Figure 2 shows the plot of CUSUM and CUSUMSQ test statistics that fall inside the critical bounds of 5% significance level. This implies that the estimated parameters are stable over the period.

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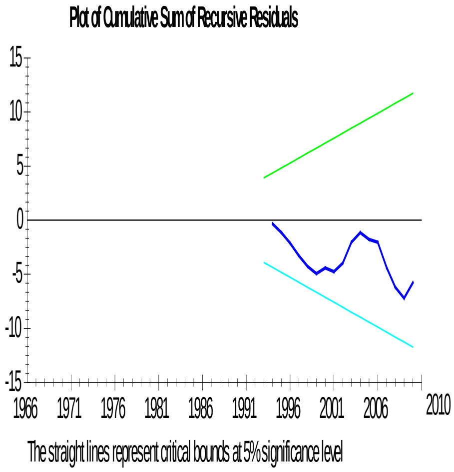
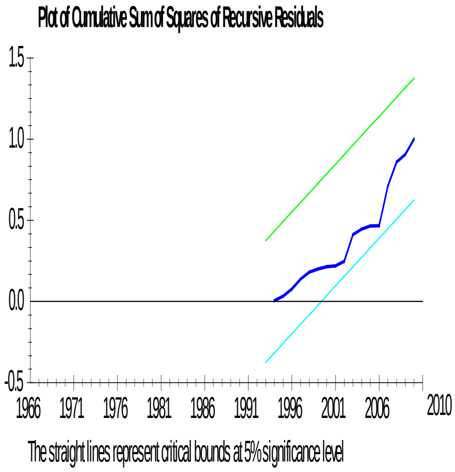
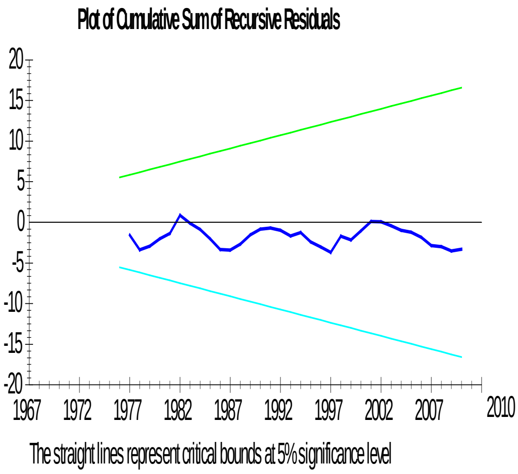
22 Extensive literature concerns the positive relationship between labor market institutions (labor market rigidity) and unemployment in general, e.g., Scarpetta (1996), Nickell (1997), Layard and Nickell (1999), Buchele and Christiansen (1999), Belot and Van Ours (2001), Botero et al. (2004); and Feldmann (2009) and see Nickell *et al*. (2005) on the high unemployment in Europe due to its rigid labor market and Bassanini and Duval (2006) on the low unemployment rate in US and Canada due to its flexible labor market.

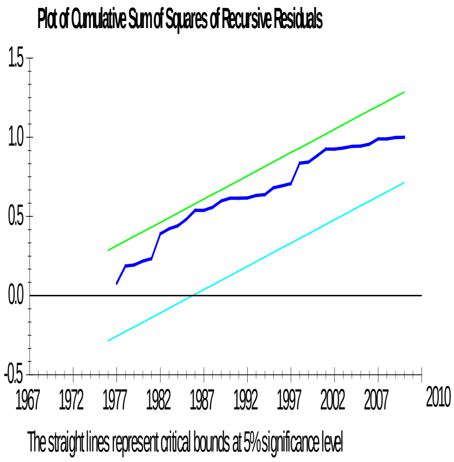
Canada



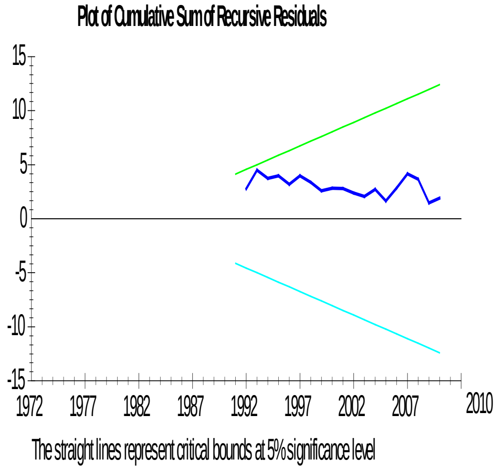


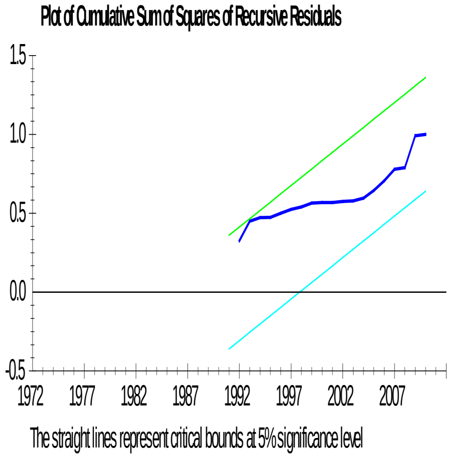
France



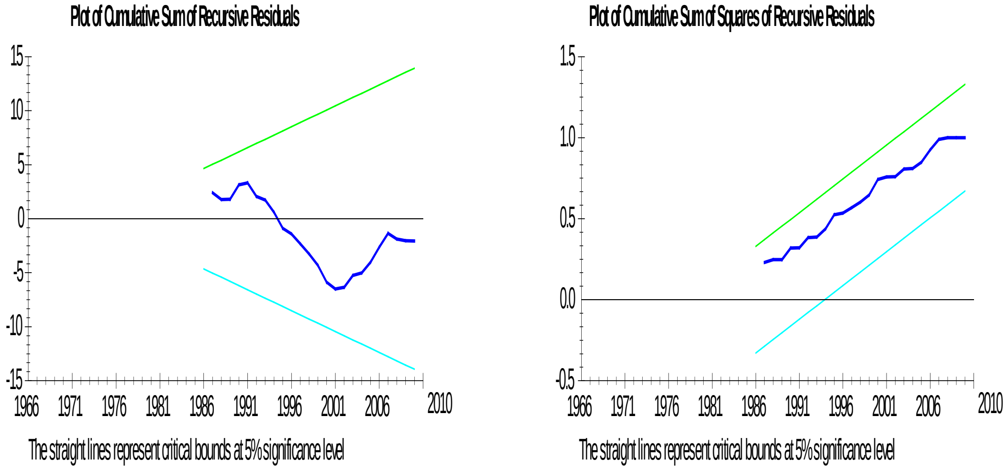


Germany





Italy



United States

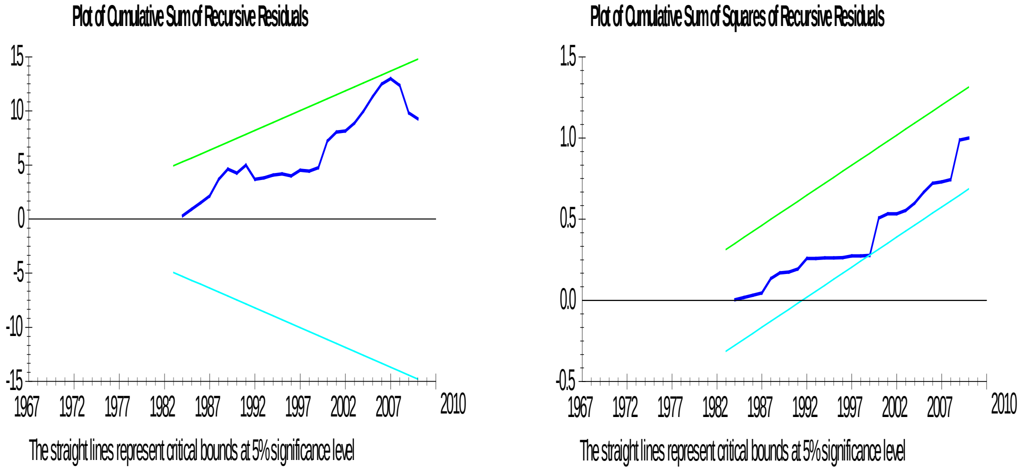


Figure 2 CUSUM and CUSUMSQ Patterns

3.4. Concluding Remarks

Recall that our study aims at identifying the long run role of income on crime at aggregate in G7 countries over the period 1965–2010 through the bounds testing approach to cointegration. We conjectured that an inverted-U shaped relationship must be expected between the two variables, à la the Kuznets Curve Hypothesis (KCH). This finding has important implications. First, policy makers in economies in which incomes are increasing should not expect that, as income per capita rises, crime rates will decrease by default. Policy makers should aim to develop accommodating policies to maintain non-accelerated crime rates in the early periods of income growth, in order to prevent crime rates following the income rise, due to increasing inequality of income distribution in this period. Second, rising income may keep unemployment low, which, policy makers may hypothesize, may contribute to lower crime rates. Our analyses have shown, however, that there is mixed evidence on the role of unemployment. This result again calls for active crime control against the complacency that rising income and falling unemployment rates will naturally cause a fall in crime rates.

3.5. Policy Implications

This chapter aimed at identifying the role of income on crime in G7 countries at macro level over the period 1965–2010. We employed the bounds testing approach to cointegration in order to identify the true role of income in explaining crime in the long-run. This study was motivated by the need to prevent two fundamental misconceptions in this area of research. Firstly, in terms of econometrics, this study addresses the issue of the omitted variable. Secondly, as regards economics, by avoiding the assumption of a linear relationship, the study presents a more accurate approach to the calculation of the role of income on crime. Our analyses yielded that an inverted-U shaped relationship is the dominant form between income and crime in the long run, à la the Kuznets Curve Hypothesis (KCH). In particular, we found that:

(i) Canada, France, Germany, and United States showed an inverted U-shaped relationship between income and crime;

(ii) Italy showed an inverted S-shaped relationship between income and crime;

(iii) The long-run coefficients of unemployment indicate mixed results: while the coefficient of unemployment rate is positive in France, Germany, and Italy, it is found to be negative in the United States and Canada.

We conclude that policy makers of economies having increasing incomes should not expect that crime rates will decrease by default as income per capita rises. This policy should prioritize the development of accommodating policies to maintain lower crime rates in the early periods of income growth. Given that majority of the literature expects a linear relationship between income and crime, whether positive or negative, this study represents a significant departure from the accepted view.

4. CONCLUSION

Crime is still a major issue of public concern and is major part of public expenditure. Despite the technology advances during the last decades, forecasting of the direction of crime rates is very limited. Therefore, criminologists, sociologists and economists have been investigating the determinants of crime.

Criminologists are likely to suggest that a decrease in income leads people to commit more crimes. Then, the economic anxiety of bad times causes to more property crime and robbery, and more domestic violence. However, economists investigate whether better economic conditions cause to increase in crime or not. Although several studies have examined the role of income on crime since 1960s, this relationship is still unclear. Economists have investigated this link by using different econometric regression analysis on different data sets over different time periods, but earlier studies consider linear relationship between income and crime. However, this assumption may be misleading in efforts to find the accurate link. They do not take notice of the Kuznets Curve Hypothesis, which suggests that income inequality in an economy first increases and then decreases in the development process. Since several studies indicate strong positive impact of income inequality on crime, it is natural to expect that income has a nonlinear relationship with crime via transitivity effect of the income inequality.

This thesis contributes to better understanding of the non-linear effects of income on crime within in the example of G7 countries over the period 1965-2010. The explicit analysis of behavior of crime in correspondence with increasing levels of income is a novel contribution in the economic literature.

Using an ARDL approach to cointegration framework of Pesaran *et al*. (2001) has several advantages. Firstly, endogeneity problem between crime and unemployment, which is mentioned by Christenson (1984), Piehl (1998), Levitt (2001) and Bushway and Reuter (2001), has been solved. Secondly, the long and short-run impacts of income on crime are estimated simultaneously. Furthermore, in the cointegration framework, estimated error correction terms (ECT) give us opportunity to specify the convergence speed of the variables to the steady state equilibrium values.

The results from Chapter 3 show that the relationship between income and crime seems to be nonlinear across G7 countries. The evidence from that section also shows that an inverted-U shaped relationship is the dominant form between income and crime in the long run. Whereas Canada, France, Germany, and United States show an inverted U-shaped, Italy shows an inverted S-shaped relationship between income and crime. However, the long-run coefficients of unemployment indicate mixed results; while it is positive in France, Germany, and Italy, it is found to be negative in the United States and Canada. The labor market flexibilities can be an explanation of these mixed results. For example, the rigid market in Europe leads to a higher unemployment rate, causing the motivation effect to dominate the opportunity effect, increasing the crime rate, while more flexible market in US and Canada cause to lower crime rate as unemployment rate increases.

These findings are crucial for implementation of crime reduction policies. It indicates that an increase in income per adult does not automatically lead to a decrease in crime per adult. Hence, policy makers should make more realistic assessments of the costs of crime and the consequences of the relationships between crime and policing, punishment and other deterring policies. The results also imply that it may be welfare improving to spend a larger share on law enforcement in the initial periods of development and of larger share in judicial expenses in the later periods of development.

From this point of view, there are several areas in which further research is necessary. Long-run analysis of different crime types instead of overall crime will help us to divide the effects of income on crime types. Economists generally believe that property crimes are better explained by economic models of crime than violent crimes. Therefore, this analysis would increase the efficiency of crime policies. Also, there can be other important factors determining the level of crime. For example, urbanization might have some crucial role in rising crime rates, especially in the cities. Further research implications may be to analyze this relationship in Organization for Economic Co-operation and Development (OECD) countries.

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APPENDIX A: Econometric Results

The Non-Linear Impacts of Income on Crime (quadratic form)

First Step: VAR ANALYSIS: to obtain the maximum lag length (you can see the VAR analysis named “table01” in Eviews Workfiles).

Canada:	2
France:	2
Germany:	2
Italy:	1
Japan:	3
UK:	2
the USA:	2

Second Step: Obtaining the lag orders based on maximum lag lengths

Canada:	2 1 0 0
France:	2 1 1 0
Germany:	1 1 0 0
Italy:	1 0 0 0
Japan:	3 0 0 0
UK:	2 2 1 0
USA:	2 1 1 0

Third Step: F test for cointegration analysis in E-views (check F values from Narayan(2005) for case 2 restricted intercept, and no trend, for degrees of freedom=2(3-1) and n=30 for robustness

Table 6 Narayan (2005) Critical Bounds

		I(0)	I(1)
Critical values at 1%		5.155	6.265
Critical values at 5%		3.538	4.428
Critical values at 10%		2.915	3.695

CANADA:

Wald Test:
Equation: Untitled

Test Statistic	Value	df	Probability
F-statistic	4.716429	(4, 32)	0.0042
Chi-square	18.86572	4	0.0008

Null Hypothesis: C(7)=C(8)=C(9)=C(10)=0
Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(7)	-0.282492	0.095930
C(8)	15.37100	6.518729
C(9)	-0.747088	0.314316
C(10)	0.011923	0.050239

Restrictions are linear in coefficients.

There is cointegration at %5

FRANCE:

Wald Test:
Equation: Untitled

Test Statistic	Value	df	Probability
F-statistic	5.838234	(4, 31)	0.0013
Chi-square	23.35293	4	0.0001

Null Hypothesis: C(8)=C(9)=C(10)=C(11)=0
Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(8)	-0.585337	0.122999
C(9)	15.98726	6.179465
C(10)	-0.769460	0.300234
C(11)	0.164273	0.061218

Restrictions are linear in coefficients.

There is cointegration at %5

GERMANY:

Wald Test:
Equation: Untitled

Test Statistic	Value	df	Probability
F-statistic	6.541814	(4, 29)	0.0007
Chi-square	26.16726	4	0.0000

Null Hypothesis: C(6)=C(7)=C(8)=C(9)=0
Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(6)	-0.567315	0.130849
C(7)	18.88507	7.035063
C(8)	-0.910658	0.340503
C(9)	0.041745	0.028944

Restrictions are linear in coefficients.

There is cointegration at %1

ITALY:

Wald Test:
Equation: Untitled

Test Statistic	Value	df	Probability
F-statistic	2.837620	(4, 35)	0.0388
Chi-square	11.35048	4	0.0229

Null Hypothesis: C(5)=C(6)=C(7)=C(8)=0
Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(5)	-0.314799	0.114283
C(6)	-0.559504	5.317149
C(7)	0.053758	0.263105
C(8)	0.083355	0.068931

Restrictions are linear in coefficients.

There is no cointegration.

JAPAN:

Wald Test:
Equation: Untitled

Test Statistic	Value	df	Probability
F-statistic	2.638902	(4, 33)	0.0513
Chi-square	10.55561	4	0.0320

Null Hypothesis: C(6)=C(7)=C(8)=C(9)=0
Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(6)	-0.220578	0.070629
C(7)	-5.352599	3.093204
C(8)	0.267528	0.153161
C(9)	0.040287	0.033038

Restrictions are linear in coefficients.

There is no cointegration.

THE UK:

Wald Test:
Equation: Untitled

Test Statistic	Value	df	Probability

F-statistic	5.348035	(4, 30)	0.0023
Chi-square	21.39214	4	0.0003

Null Hypothesis: C(9)=C(10)=C(11)=C(12)=0
Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(9)	-0.429750	0.107673
C(10)	10.20997	5.556127
C(11)	-0.482974	0.271819
C(12)	0.078908	0.045166

Restrictions are linear in coefficients.

There is cointegration at %5

THE US

Wald Test:
Equation: Untitled

Test Statistic	Value	df	Probability
F-statistic	4.976270	(4, 31)	0.0032
Chi-square	19.90508	4	0.0005

Null Hypothesis: C(8)=C(9)=C(10)=C(11)=0
Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(8)	-0.272872	0.108613
C(9)	15.74458	7.612590
C(10)	-0.763006	0.365883
C(11)	-0.008027	0.033706

Restrictions are linear in coefficients.

There is cointegration at 5%

Fourth Step: We found cointegration for Canada, France, and Germany in the 3rd step, so we will present the ARDL and ECM models only for these countries. (Canada, France, Germany, the UK, the US)

CANADA

Autoregressive Distributed Lag Estimates
ARDL(2,1,0,0) selected based on Schwarz Bayesian Criterion
****
Dependent variable is X5
44 observations used for estimation from 1967 to 2010
****

Regressor	Coefficient	Standard Error	T-Ratio[Prob]
X5(-1)	1.1860	.12487	9.4980[.000]
X5(-2)	-.46819	.12962	-3.6121[.001]
X1	21.2485	4.9499	4.2927[.000]
X1(-1)	.58179	.19402	2.9986[.005]
X2	-1.0570	.23964	-4.4106[.000]
X3	-.027244	.034846	-.78184[.439]
CON	-111.2734	25.4487	-4.3725[.000]
DUMMY	.0018518	.028973	.063916[.949]

****

R-Squared	.98507	R-Bar-Squared	.98216
S.E. of Regression	.026472	F-stat. F(7, 36)	339.2312[.000]
Mean of Dependent Variable	4.7097	S.D. of Dependent Variable	.19821
Residual Sum of Squares	.025228	Equation Log-likelihood	101.7742
Akaike Info. Criterion	93.7742	Schwarz Bayesian Criterion	86.6375
DW-statistic	1.7643		

****

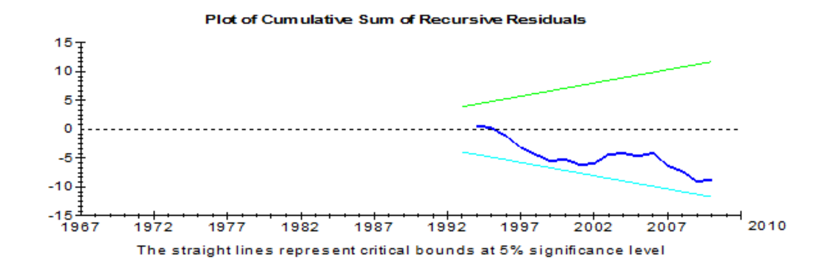
Diagnostic Tests
****

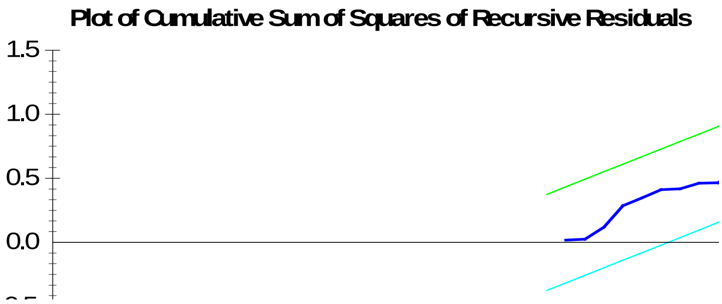
Test Statistics	LM Version	F Version
A:Serial Correlation	CHSQ(1)= 1.3160[.251]	F(1, 35)= 1.0791[.306]
B:Functional Form	CHSQ(1)= 2.8704[.090]	F(1, 35)= 2.4426[.127]
C:Normality	CHSQ(2)= .61061[.737]	Not applicable
D:Heteroscedasticity	CHSQ(1)= .0021384[.963]	F(1, 42)= .0020413[.964]

****

A:Lagrange multiplier test of residual serial correlation
B:Ramsey's RESET test using the square of the fitted values
C:Based on a test of skewness and kurtosis of residuals
D:Based on the regression of squared residuals on squared fitted values

CUSUM





Estimated Long Run Coefficients

Estimated Long Run Coefficients using the ARDL Approach
ARDL(2,1,0,0) selected based on Schwarz Bayesian Criterion
****

Dependent variable is X5
44 observations used for estimation from 1967 to 2010
****

Regressor	Coefficient	Standard Error	T-Ratio[Prob]
X1	77.3642	12.4702	6.2039[.000]
X2	-3.7458	.60630	-6.1780[.000]
X3	-.096549	.13738	-.70277[.487]
CON	-394.3413	63.8501	-6.1760[.000]
DUMMY	.0065627	.10224	.064187[.949]

Error Correction Representations

Error Correction Representation for the Selected ARDL Model
ARDL(2,1,0,0) selected based on Schwarz Bayesian Criterion
****
Dependent variable is dX5
44 observations used for estimation from 1967 to 2010
****

Regressor	Coefficient	Standard Error	T-Ratio[Prob]
dX51	.46819	.12962	3.6121[.001]
dX1	21.2485	4.9499	4.2927[.000]
dX2	-1.0570	.23964	-4.4106[.000]
dX3	-.027244	.034846	-.78184[.439]
dCON	-111.2734	25.4487	-4.3725[.000]
dDUMMY	.0018518	.028973	.063916[.949]
ecm(-1)	-.28218	.071251	-3.9603[.000]

****
List of additional temporary variables created:
dX5 = X5-X5(-1)
dX51 = X5(-1)-X5(-2)
dX1 = X1-X1(-1)
dX2 = X2-X2(-1)
dX3 = X3-X3(-1)
dCON = CON-CON(-1)
dDUMMY = DUMMY-DUMMY(-1)
ecm = X5 -77.3642*X1 + 3.7458*X2 + .096549*X3 + 394.3413*CON -
.0065627*DU
MMY
****

R-Squared	.75164	R-Bar-Squared	.70334
S.E. of Regression	.026472	F-stat. F(6, 37)	18.1581[.000]
Mean of Dependent Variable	.011792	S.D. of Dependent Variable	.048603
Residual Sum of Squares	.025228	Equation Log-likelihood	101.7742
Akaike Info. Criterion	93.7742	Schwarz Bayesian Criterion	86.6375
DW-statistic	1.7643		

****
R-Squared and R-Bar-Squared measures refer to the dependent variable

dX5 and in cases where the error correction model is highly

restricted, these measures could become negative.

FRANCE

Autoregressive Distributed Lag Estimates
ARDL(2,1,1,0) selected based on Schwarz Bayesian Criterion
****
Dependent variable is X5
44 observations used for estimation from 1967 to 2010
****

Regressor	Coefficient	Standard Error	T-Ratio[Prob]
X5(-1)	1.0009	.13294	7.5294[.000]
X5(-2)	-.38299	.14383	-2.6628[.012]
X1	-42.9286	20.4347	-2.1008[.043]
X1(-1)	56.9778	19.0494	2.9911[.005]
X2	2.0675	1.0020	2.0634[.047]
X2(-1)	-2.7504	.93441	-2.9434[.006]
X3	.030172	.046309	.65153[.519]
CON	-70.5734	25.2195	-2.7984[.008]
DUMMY	-.11714	.035821	-3.2702[.002]

****

R-Squared	.98949	R-Bar-Squared	.98709
S.E. of Regression	.041700	F-stat. F(8, 35)	411.9821[.000]
Mean of Dependent Variable	4.3390	S.D. of Dependent Variable	.36701
Residual Sum of Squares	.060861	Equation Log-likelihood	82.4006
Akaike Info. Criterion	73.4006	Schwarz Bayesian Criterion	65.3717
DW-statistic	2.2827		

****

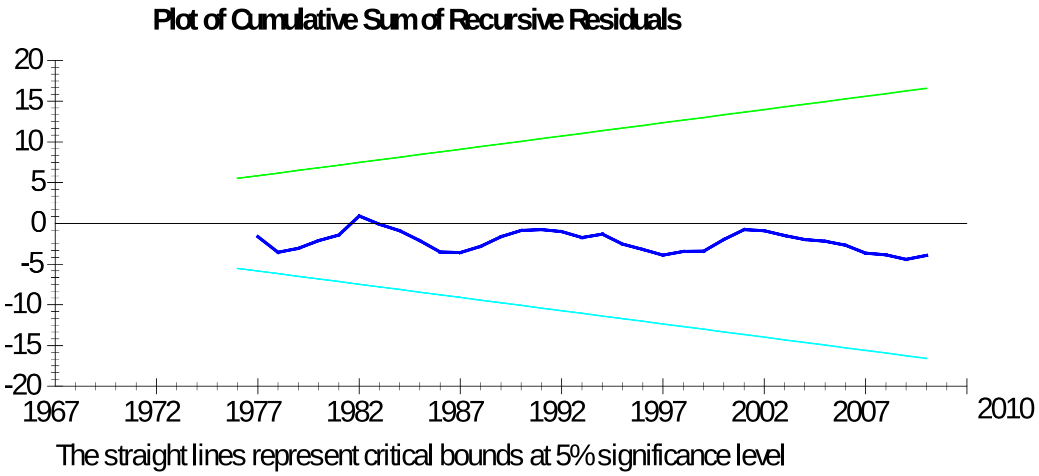
Diagnostic Tests
****

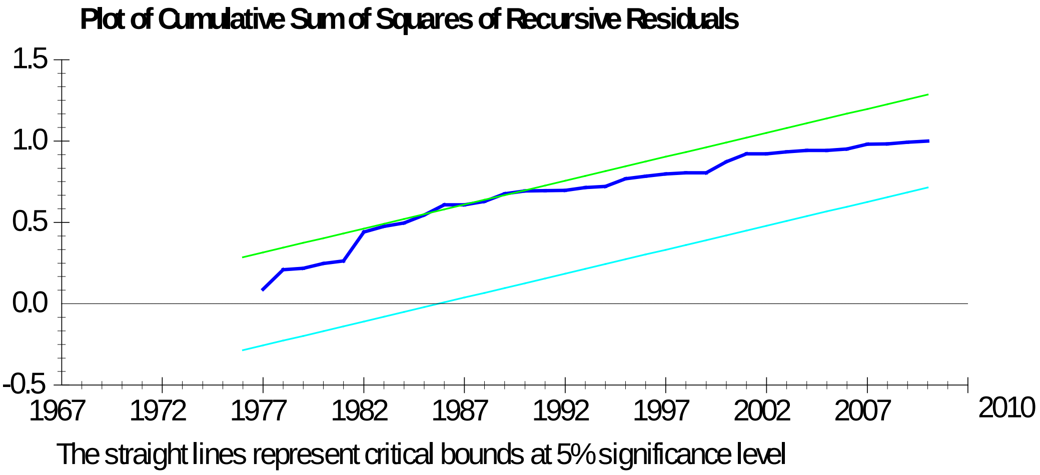
Test Statistics	LM Version	F Version
A:Serial Correlation	CHSQ(1)= 2.1245[.145]	F(1, 34)= 1.7249[.198]
B:Functional Form	CHSQ(1)= 1.4574[.227]	F(1, 34)= 1.1647[.288]
C:Normality	CHSQ(2)= 14.2727[.001]	Not applicable
D:Heteroscedasticity	CHSQ(1)= .64218[.423]	F(1, 42)= .62207[.435]

****

A:Lagrange multiplier test of residual serial correlation
B:Ramsey's RESET test using the square of the fitted values
C:Based on a test of skewness and kurtosis of residuals
D:Based on the regression of squared residuals on squared fitted values

CUSUM





Estimated Long Run Coefficients

Estimated Long Run Coefficients using the ARDL Approach
ARDL(2,1,1,0) selected based on Schwarz Bayesian Criterion
****
****
Dependent variable is X5
44 observations used for estimation from 1967 to 2010
****
****

Regressor	Coefficient	Standard Error	T-Ratio[Prob]
X1	36.7726	10.8526	3.3884[.002]

X2	-1.7874	.53000	-3.3725[.002]
X3	.078972	.10962	.72043[.476]
CON	-184.7195	55.4088	-3.3338[.002]
DUMMY	-.30661	.12229	-2.5073[.017]

****

Error Correction Representations

Error Correction Representation for the Selected ARDL Model
ARDL(2,1,1,0) selected based on Schwarz Bayesian Criterion

****

Dependent variable is dX5
44 observations used for estimation from 1967 to 2010

****

Regressor	Coefficient	Standard Error	T-Ratio[Prob]
dX51	.38299	.14383	2.6628[.011]
dX1	-42.9286	20.4347	-2.1008[.043]
dX2	2.0675	1.0020	2.0634[.046]
dX3	.030172	.046309	.65153[.519]
dCON	-70.5734	25.2195	-2.7984[.008]
dDUMMY	-.11714	.035821	-3.2702[.002]
ecm(-1)	-.38206	.090865	-4.2047[.000]

****

List of additional temporary variables created:
dX5 = X5-X5(-1)
dX51 = X5(-1)-X5(-2)
dX1 = X1-X1(-1)
dX2 = X2-X2(-1)
dX3 = X3-X3(-1)
dCON = CON-CON(-1)
dDUMMY = DUMMY-DUMMY(-1)
ecm = X5 -36.7726*X1 + 1.7874*X2 -.078972*X3 + 184.7195*CON + .30661*DU
MMY

****

R-Squared	.69200	R-Bar-Squared	.62160
S.E. of Regression	.041700	F-stat. F(6, 37)	13.1062[.000]
Mean of Dependent Variable	.030297	S.D. of Dependent Variable	.067789
Residual Sum of Squares	.060861	Equation Log-likelihood	82.4006
Akaike Info. Criterion	73.4006	Schwarz Bayesian Criterion	65.3717
DW-statistic	2.2827		

****

R-Squared and R-Bar-Squared measures refer to the dependent variable dX5 and in cases where the error correction model is highly restricted, these measures could become negative.

THE UNITED STATES

Autoregressive Distributed Lag Estimates
ARDL(2,1,1,0) selected based on Schwarz Bayesian Criterion
****
Dependent variable is X5
44 observations used for estimation from 1967 to 2010
****

Regressor	Coefficient	Standard Error	T-Ratio[Prob]
X5(-1)	1.0831	.13028	8.3132[.000]
X5(-2)	-.36295	.12913	-2.8107[.008]
X1	-3.1693	9.0334	-.35085[.728]
X1(-1)	24.3818	8.8572	2.7528[.009]
X2	.12005	.43432	.27642[.784]
X2(-1)	-1.1436	.42610	-2.6838[.011]
X3	-.038736	.023378	-1.6569[.106]
CON	-108.5758	27.7593	-3.9113[.000]
DUMMY	-.020448	.032773	-.62394[.537]

****

R-Squared	.97859	R-Bar-Squared	.97369
S.E. of Regression	.029210	F-stat. F(8, 35)	199.9283[.000]
Mean of Dependent Variable	4.2564	S.D. of Dependent Variable	.18009
Residual Sum of Squares	.029863	Equation Log-likelihood	98.0641
Akaike Info. Criterion	89.0641	Schwarz Bayesian Criterion	81.0353
DW-statistic	1.4431		

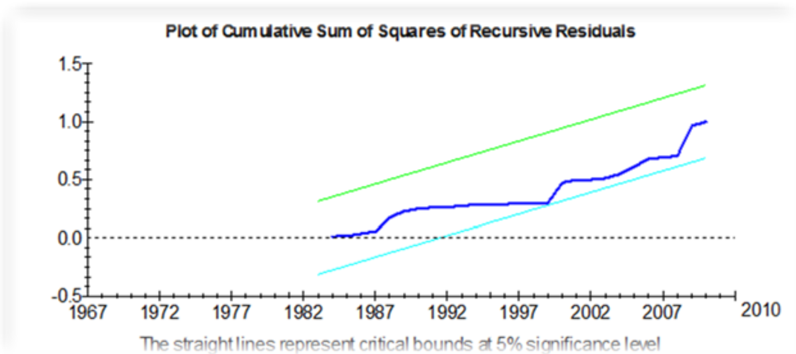
****

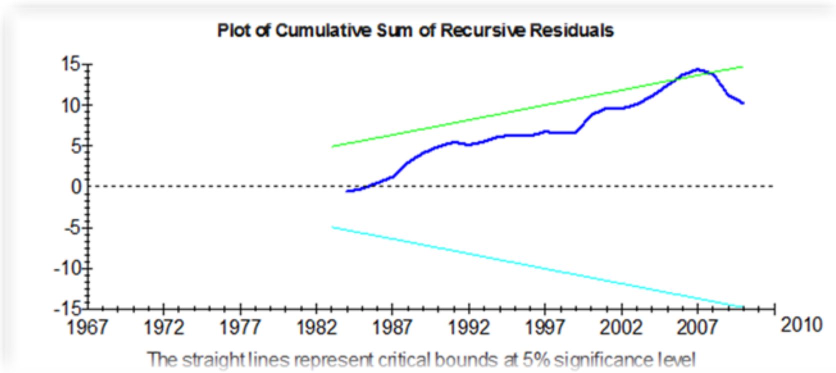
Diagnostic Tests
****
* Test Statistics * LM Version * F Version *
****
* * * *
* A:Serial Correlation*CHSQ(1)= 6.5426[.011]*F(1, 34)= 5.9387[.020]*
* * * *

* B:Functional Form *CHSQ(1)= .0098550[.921]*F(1, 34)=
.0076169[.931]*
* * * *
* C:Normality *CHSQ(2)= 1.8206[.402]* Not applicable *
* * * *
* D:Heteroscedasticity*CHSQ(1)= .63279[.426]*F(1, 42)= .61284[.438]*
****

A:Lagrange multiplier test of residual serial correlation
B:Ramsey's RESET test using the square of the fitted values
C:Based on a test of skewness and kurtosis of residuals
D:Based on the regression of squared residuals on squared fitted values

CUSUM





Estimated Long Run Coefficients

Estimated Long Run Coefficients using the ARDL Approach
ARDL(2,1,1,0) selected based on Schwarz Bayesian Criterion
****
Dependent variable is X5
44 observations used for estimation from 1967 to 2010
****

Regressor	Coefficient	Standard Error	T-Ratio[Prob]
X1	75.7878	9.0695	8.3563[.000]
X2	-3.6568	.43437	-8.4186[.000]
X3	-.13840	.098379	-1.4068[.168]
CON	-387.9191	47.2499	-8.2099[.000]
DUMMY	-.073058	.12023	-.60766[.547]

****

Error Correction Representations

Error Correction Representation for the Selected ARDL Model
ARDL(2,1,1,0) selected based on Schwarz Bayesian Criterion
****
Dependent variable is dX5
44 observations used for estimation from 1967 to 2010
****

Regressor	Coefficient	Standard Error	T-Ratio[Prob]
dX51	.36295	.12913	2.8107[.008]
dX1	-3.1693	9.0334	-.35085[.728]
dX2	.12005	.43432	.27642[.784]
dX3	-.038736	.023378	-1.6569[.106]
dCON	-108.5758	27.7593	-3.9113[.000]
dDUMMY	-.020448	.032773	-.62394[.536]
ecm(-1)	-.27989	.065323	-4.2848[.000]

****
List of additional temporary variables created:
dX5 = X5-X5(-1)
dX51 = X5(-1)-X5(-2)
dX1 = X1-X1(-1)
dX2 = X2-X2(-1)
dX3 = X3-X3(-1)
dCON = CON-CON(-1)
dDUMMY = DUMMY-DUMMY(-1)
ecm = X5 -75.7878*X1 + 3.6568*X2 + .13840*X3 + 387.9191*CON + .073058*D
UMMY

****

R-Squared	.75864	R-Bar-Squared	.70347
S.E. of Regression	.029210	F-stat. F(6, 37)	18.3354[.000]
Mean of Dependent Variable	.0027559	S.D. of Dependent Variable	.053641
Residual Sum of Squares	.029863	Equation Log-likelihood	98.0641
Akaike Info. Criterion	89.0641	Schwarz Bayesian Criterion	81.0353
DW-statistic	1.4431		

****

R-Squared and R-Bar-Squared measures refer to the dependent variable dX5 and in cases where the error correction model is highly restricted, these measures could become negative.

GERMANY

Autoregressive Distributed Lag Estimates

ARDL(1,1,0,0) selected based on Schwarz Bayesian Criterion

****

Dependent variable is X5

39 observations used for estimation from 1972 to 2010

****

Regressor	Coefficient	Standard Error	T-Ratio[Prob]
X5(-1)	.56212	.10639	5.2838[.000]
X1	12.1962	5.8940	2.0693[.047]
X1(-1)	.55832	.28862	1.9345[.062]
X2	-.61427	.28923	-2.1238[.042]
X4	.046644	.025112	1.8575[.072]
CON	-64.2281	30.5376	-2.1032[.043]
DUMMY	.046482	.034692	1.3399[.190]

****

R-Squared	.97207	R-Bar-Squared	.96684
S.E. of Regression	.032181	F-stat. F(6, 32)	185.6375[.000]
Mean of Dependent Variable	4.6188	S.D. of Dependent Variable	.17671
Residual Sum of Squares	.033140	Equation Log-likelihood	82.5377
Akaike Info. Criterion	75.5377	Schwarz Bayesian Criterion	69.7152
DW-statistic	2.2172	Durbin's h-statistic	-.90750[.364]

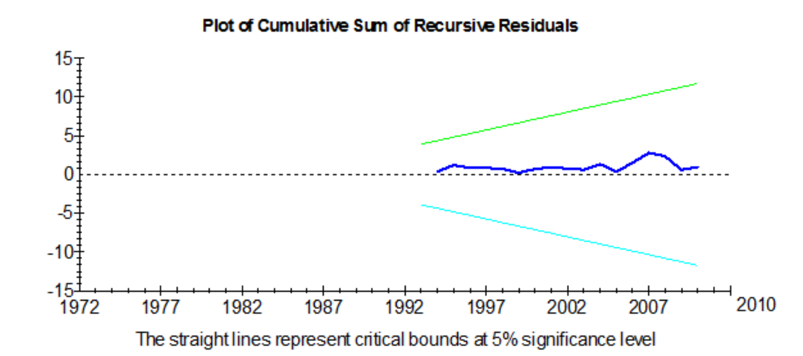
****

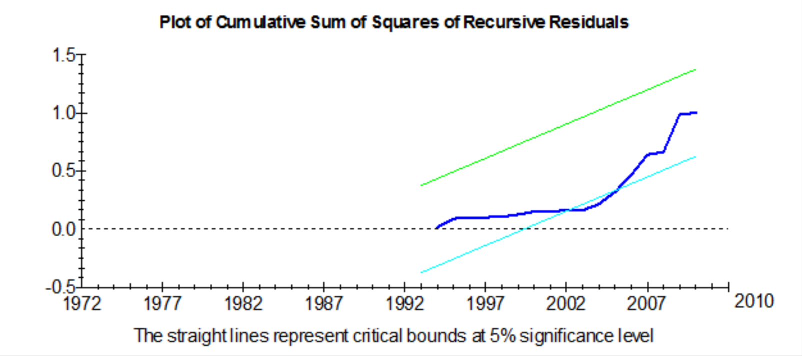
Diagnostic Tests

```
*******************************************************************
*************
*   Test Statistics  *      LM Version       *       F Version        *
*******************************************************************
*************
*               *                    *                    *
* A:Serial Correlation*CHSQ(   1)=   1.5805[.209]*F(   1,  31)=   1.3094[.261]*
*               *                    *                    *
* B:Functional Form   *CHSQ(   1)=   .90649[.341]*F(   1,  31)=   .73769[.397]*
*               *                    *                    *
* C:Normality       *CHSQ(   2)=   6.5271[.038]*      Not applicable       *
*               *                    *                    *
* D:Heteroscedasticity*CHSQ(   1)=   .78666[.375]*F(   1,  37)=   .76168[.388]*
*******************************************************************
*************
```

A:Lagrange multiplier test of residual serial correlation
B:Ramsey's RESET test using the square of the fitted values
C:Based on a test of skewness and kurtosis of residuals
D:Based on the regression of squared residuals on squared fitted values

CUSUM





Estimated Long Run Coefficients

Estimated Long Run Coefficients using the ARDL Approach
ARDL(1,1,0,0) selected based on Schwarz Bayesian Criterion

****

Dependent variable is X5
39 observations used for estimation from 1972 to 2010

****

Regressor	Coefficient	Standard Error	T-Ratio[Prob]
X1	29.1278	11.1886	2.6033[.014]
X2	-1.4028	.54440	-2.5768[.015]
X4	.10652	.051111	2.0841[.045]
CON	-146.6800	57.4019	-2.5553[.016]
DUMMY	.10615	.083054	1.2781[.210]

Error Correction Representations

Error Correction Representation for the Selected ARDL Model
ARDL(1,1,0,0) selected based on Schwarz Bayesian Criterion

****

Dependent variable is dX5
39 observations used for estimation from 1972 to 2010

****

Regressor	Coefficient	Standard Error	T-Ratio[Prob]
dX1	12.1962	5.8940	2.0693[.046]
dX2	-.61427	.28923	-2.1238[.041]
dX4	.046644	.025112	1.8575[.072]
dCON	-64.2281	30.5376	-2.1032[.043]

dDUMMY .046482 .034692 1.3399[.189]
ecm(-1) -.43788 .10639 -4.1159[.000]
****
List of additional temporary variables created:
dX5 = X5-X5(-1)
dX1 = X1-X1(-1)
dX2 = X2-X2(-1)
dX4 = X4-X4(-1)
dCON = CON-CON(-1)
dDUMMY = DUMMY-DUMMY(-1)
ecm = X5 -29.1278*X1 + 1.4028*X2 -.10652*X4 + 146.6800*CON -
.10615*DUM
MY
****

R-Squared	.51189	R-Bar-Squared	.42037
S.E. of Regression	.032181	F-stat. F(5, 33)	6.7117[.000]
Mean of Dependent Variable	.014450	S.D. of Dependent Variable	.042269
Residual Sum of Squares	.033140	Equation Log-likelihood	82.5377
Akaike Info. Criterion	75.5377	Schwarz Bayesian Criterion	69.7152
DW-statistic	2.2172		

****
R-Squared and R-Bar-Squared measures refer to the dependent variable

dX5 and in cases where the error correction model is highly

restricted, these measures could become negative.

THE UNITED KINGDOM

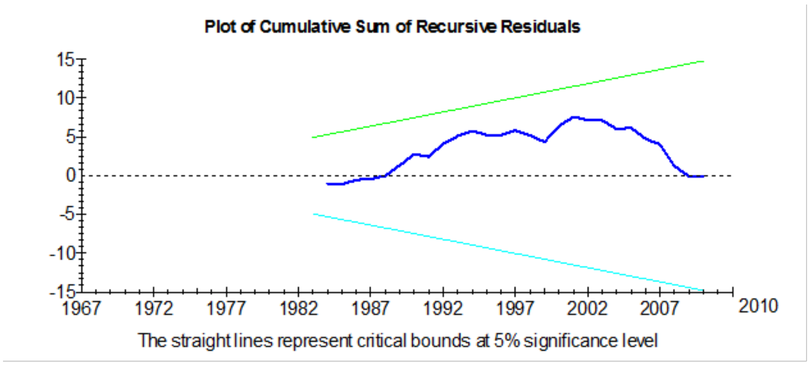
Autoregressive Distributed Lag Estimates
ARDL(2,2,1,0) selected based on Schwarz Bayesian Criterion
****
Dependent variable is X5
44 observations used for estimation from 1967 to 2010
****

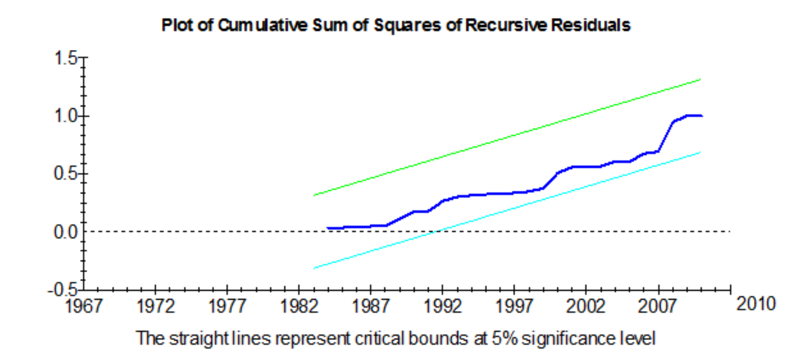
Regressor	Coefficient	Standard Error	T-Ratio[Prob]
X5(-1)	1.2549	.13295	9.4385[.000]
X5(-2)	-.52512	.13991	-3.7534[.001]
X1	-27.0905	12.3917	-2.1862[.036]
X1(-1)	34.3009	11.4291	3.0012[.005]

```
 X1(-2)              -1.1027          .45191          -2.4401[.020]
 X2                 1.2822          .61077          2.0994[.043]
 X2(-1)              -1.5724          .56556          -2.7802[.009]
 X4                .059143          .036764          1.6087[.117]
 CON                -30.9161          25.4039          -1.2170[.232]
 DUMMY               -.031191          .058284          -.53517[.596]
*******************************************************************
*************
 R-Squared                 .98932   R-Bar-Squared               .98649
 S.E. of Regression          .052684   F-stat.    F(  9,  34)  349.9974[.000]
 Mean of Dependent Variable    4.5479   S.D. of Dependent Variable      .45335
 Residual Sum of Squares      .094371   Equation Log-likelihood       72.7503
 Akaike Info. Criterion       62.7503   Schwarz Bayesian Criterion     53.8294
 DW-statistic                1.9367
*******************************************************************
*************


                         Diagnostic Tests
*******************************************************************
*************
*    Test Statistics  *        LM Version        *         F Version          *
*******************************************************************
*************
*                  *                     *                     *
* A:Serial Correlation*CHSQ(   1)=  .067996[.794]*F(   1,  33)=  .051076[.823]*
*                  *                     *                     *
* B:Functional Form   *CHSQ(   1)=   2.5858[.108]*F(   1,  33)=   2.0604[.161]*
*                  *                     *                     *
* C:Normality        *CHSQ(   2)=   .26220[.877]*       Not applicable       *
*                  *                     *                     *
* D:Heteroscedasticity*CHSQ(   1)=   .26448[.607]*F(   1,  42)=   .25398[.617]*
*******************************************************************
*************
   A:Lagrange multiplier test of residual serial correlation
   B:Ramsey's RESET test using the square of the fitted values
   C:Based on a test of skewness and kurtosis of residuals
   D:Based on the regression of squared residuals on squared fitted values
```

CUSUM





Estimated Long Run Coefficients

Estimated Long Run Coefficients using the ARDL Approach
ARDL(2,2,1,0) selected based on Schwarz Bayesian Criterion
****
****
Dependent variable is X5
44 observations used for estimation from 1967 to 2010
****
****

Regressor	Coefficient	Standard Error	T-Ratio[Prob]
X1	22.6001	16.7981	1.3454[.187]
X2	-1.0737	.82950	-1.2944[.204]
X4	.21885	.12852	1.7028[.098]
CON	-114.3994	84.7597	-1.3497[.186]
DUMMY	-.11542	.22142	-.52127[.606]

Error Correction Representations

Error Correction Representation for the Selected ARDL Model
ARDL(2,2,1,0) selected based on Schwarz Bayesian Criterion
****
Dependent variable is dX5
44 observations used for estimation from 1967 to 2010
****

Regressor	Coefficient	Standard Error	T-Ratio[Prob]
dX51	.52512	.13991	3.7534[.001]
dX1	-27.0905	12.3917	-2.1862[.035]
dX11	1.1027	.45191	2.4401[.020]
dX2	1.2822	.61077	2.0994[.043]
dX4	.059143	.036764	1.6087[.116]
dCON	-30.9161	25.4039	-1.2170[.232]
dDUMMY	-.031191	.058284	-.53517[.596]
ecm(-1)	-.27025	.084220	-3.2088[.003]

****
List of additional temporary variables created:
dX5 = X5-X5(-1)
dX51 = X5(-1)-X5(-2)
dX1 = X1-X1(-1)
dX11 = X1(-1)-X1(-2)
dX2 = X2-X2(-1)
dX4 = X4-X4(-1)
dCON = CON-CON(-1)
dDUMMY = DUMMY-DUMMY(-1)
ecm = X5 -22.6001*X1 + 1.0737*X2 -.21885*X4 + 114.3994*CON + .11542*DU
MMY
****

R-Squared	.62029	R-Bar-Squared	.51978
S.E. of Regression	.052684	F-stat. F(7, 36)	7.9347[.000]
Mean of Dependent Variable	.027063	S.D. of Dependent Variable	.076026
Residual Sum of Squares	.094371	Equation Log-likelihood	72.7503
Akaike Info. Criterion	62.7503	Schwarz Bayesian Criterion	53.8294
DW-statistic	1.9367		

****
R-Squared and R-Bar-Squared measures refer to the dependent variable dX5 and in cases where the error correction model is highly restricted, these measures could become negative.

APPENDIX B: Definition of Crimes

Murder. The willful (non-negligent) killing of one human being by another.

Forcible rape (*Sexual assault*). The carnal knowledge of a female forcibly and against her will. Assaults or attempts to commit rape by force or threat of force are also included; however, statutory rape (without force) and other sex offenses are excluded.

Robbery. The taking or attempt to take anything of value from the care, custody, or control of a person or persons by force or violence and/or by putting the victim in fear.

Assault (*Aggravated assault*). The unlawful attack by one person upon another for the purpose of inflicting severe or aggravated bodily injury. (This type of assault is usually accompanied by the use of a weapon or by means likely to produce death or great bodily harm.)

Burglary. The unlawful entry of a structure to commit a felony or theft. (The use of force is not required to classify an offense as burglary.)

Larceny (*Theft*). The unlawful taking, carrying, leading, or riding away of property from the possession or constructive possession of another. It includes such crimes as shoplifting, pocket-picking, purse-snatching, thefts from motor vehicles, thefts of motor vehicle parts or accessories, bicycle thefts, etc., in which no use of force, violence, or fraud occurs. (This crime category does not include embezzlement, confidence games, forgery, and worthless checks. Motor vehicle theft is a separate category.)

Motor vehicle theft. The theft or attempted theft of a motor vehicle, includes the stealing of automobiles, trucks, buses, motor cycles, motor scooters, snowmobiles, etc.

Crimes against persons (*Violent crimes*). Total of all crimes of homicide, forcible rape, robbery, and aggravated assault.

Crimes against property. Total of all crimes of burglary, larceny-theft, and motor vehicle theft.