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Socio-economic Determinants of Crime: An Empirical Study of Pakistan

Awais Anwar[1]*, Noman Arshed[2], Sofia Anwar[3]

[1]Department of Economics, Center of Economic and Research, Shandong University Jinan, China, [2]Department of Economics, University of Management & Technology, Lahore, Pakistan, [3]Department of Economics, Government College University Faisalabad, Punjab, Pakistan. *Email: awaisanwar007@sdu.edu.cn

ABSTRACT

The objective of present study is to empirically examine the socio-economic determinants of crime in Pakistan. The analysis is carried out by using the annual time series data for the period 1973-2014. The dependent variable is total crime rate (per one million population), While the explanatory variables are unemployment, education, income inequality, per capita income, and deterrence variable. The study estimates, the long-run and short-run elasticities of supply of offense function by using autoregressive distributed lag model approach.

Keywords: Deterrence, Time Series, Crime Rate, Property Crime, Violent Crime
JEL Classifications: I24, N3, P46

1. INTRODUCTION

There is no single root cause of crime. Crime is outcome of multiple Social, economic, cultural and family conditions. To prevent crime it is important to understand the meaning and roots of crime. Causes of crime vary from country to country because of different social and cultural characteristics. The study of crime and economics started in 1960s when Fleisher (1966) concluded that low income and unemployment occasion the increase of crime rate in society. Becker (1968) introduces the rational behavior of a criminal in which an individual has to decide between legitimate and illegitimate activity on the basis of cost benefit analysis. His analysis shows that an individual commits crime when the expected utility of illegitimate activity increases as compared to the utility of legitimate activity. Ehrlich (1975) extended the work of Becker and found that time allocation to legal and illegal activity also influences the crime rate. Ehrlich's empirical investigation supports the findings of Fleisher (1966), a raise in income of median level family will lead to increase crimes like murder, and rape, assault and property crime, and he also found that unemployment was positively related to crime rate. The prior results disagree with Fleisher (1966) but the last finding is consistent with the result of Fleisher that income inequality relates positively with an offence rate. Both Ehrlich (1973) and Fleisher (1963) judge the consequence of unemployment with a misdemeanour rate by considering that unemployment in an area is complementary factor of income opportunity accessible in legitimate market[1].

However, Block and Heineke (1975) suggest another way of criminal preference problem by taking in consideration the theoretical model of Becker (1968), Ehrlich (1973), analyze the relationship between crime and inequality. They incorporate the fraction of population in an area earning less than half the median income as proxy of inequality. He argues that individual allocate his time in legitimate and illegitimate activity on the basis of expected return on these activities. In his model inequality induces crime because by placing an individual who have very minor return from legitimate work as compared to individual who have very high return from legitimate work. Block and Heinek (1975) employ the time allocation of legitimate and illegitimate activity in their utility function in the context of time allotment only implicitly through its consequences on wealth. They attempt to simplify the

1 In empirical investigation both authors Fleisher and Ehrlich shows consensus that income and distribution is dominant factor of committing an offence as compare to unemployment.

previous work done on "economic model of crime" in order to get such findings which are suitable, not in special cases alone. Most significantly, changes in wealth, the payoff to illegal activity, enforcement, punishment, and the degree of certainty surrounding punishment were seen to have no qualitative supply implications under traditional preference restrictions.

In addition, Ehrlich (1975) analyze that education does not have a uniform effect on legal and illegal opportunities. Education may enhance the self-productivity, whether it is in case of self-protection against conviction as well as against various legal occupational problems. Buonanno and Leonida (2005) explain effects of education on crime using panel data of different regions of Italy from 1980 to 1995. They slot in the enrolment of high school in their model. They explain that there is non-linearity between education and crime because where education is low, the increase in education lowers the crime rate because education promotes virtues of hard work, honesty and perpetuates the values of society but on the other side of coin where education is high, the increase in education promotes more crime rate like fraud and property crime. Consistent with the findings of Ehrlich (1975), Lance and Enrico (2004) empirically investigate the relationship between crime and education by using three types of data i.e. individual data, state level data and self-report data on crime and their findings come up with the conclusion that crime and education are related contrariwise.

Lochner (2007) argues that education gives two possible directions to reduce crimes. Firstly, good education increases the opportunity cost of crimes because criminals need time for criminal activity and that time can be used in other productive purposes like legitimate work because high education confirms the job opportunities in legal sector. Secondly, the criminals' time goes in waste while they are in prison. This cost is very high for criminals because they can raise their income by spending their time in other ways. Taking an account the empirical work of crime and education, Qadri and Kadri (2011) estimate the relationship between education and violent crime by using vector autoregressive (VAR) model. They incorporate expenditure on education in their model and their results suggest that education reduces violent crime because of education there will be hope for the provision of better life, employment in legitimate activity and optimistic expectation. In this way an individual will stop to involve in illegitimate activity.

Keeping in view the above mentioned determinants of crime like deterrence and education, income inequality also plays crucial role in determination of crime[2]. Considering the work on Pakistan study, Shuja (2008) proposes that crime rate can be identified with income inequality in Pakistan, because financial crisis leads a person to become an offender. The poor are unable to educate their children so there is a chance for them to involve in illegal activity because of the dearth of education and skills. Brush (2007) elucidates and compares the cross-section data of different states of the United States and Times Series data. He uses Gini coefficient in order to measure income in equality in his model and his result suggests that there is a positive relationship between crime and income inequality in cross-section data but they are negatively related in time series data. While Kelly (2009) estimates the relationship between crime and inequality. According to his findings, impact of inequality on violent and property crime is different. Property crime cannot be explained by the inequality but with the change in inequality violent crime changes with an elasticity >0.5.

Baharom and Habibullah (2008) asserts that the lack of employment opportunities leads to illegitimate activity amongst the unemployed. An unemployed person needs to run his house by some means and when he does not find any legitimate source of income, he indulges in illegitimate activity. Imrohoroglu et al. (2001) model predict that 79% people involved in illegal activity are employed and only 21% are unemployed. These results are consistent with the data of the United States of America as of 1980. As a result, they draw a conclusion that the increase in unemployment rate does not have any impact on crime rate. Smith et al. (1992) estimate the relation between unemployment and seven different types of crime (Homicide, motor vehicle theft, fraud, break and enter robbery, stealing and assault) from 1964 to 2001 in Australia. He found that increase in unemployment would lead to increase in robbery and motor vehicle theft in short sun while in long run unemployment causes homicide, motor vehicle theft and fraud.

Myers and Samuel (1983) measure the association between crime and unemployment by using two different samples (Federal Prison Sample and Baltimore Sample) 1971-1972. They incorporate the sample of offenders released from federal prisons in 1972. In Federal prison sample both white and black offenders lowers the participation in illegal work with healthy opportunity of employment in legal market. While in Baltimore sample (area where people have low financial resources) employment opportunities leads them to higher survival rate from re arrest. So in both samples we have got same results so here we conclude those offenders who are already in prison and places where financial resources are not in sufficient amount to meet the requirement of people, by providing employment opportunity to both kinds of people in legal work we will be able to drive down crime.

In addition, taking an account the short run and long run association between crime and unemployment, Gumus (2004) scrutinizes short-term and long-term relationship between crime and unemployment. He uses the data of 75 US metropolitans. He concludes that in the short-term if person gets unemployed, he looks for a new job while in the long run if he person is unemployed then there is a possibility of him involving in an illegal activity. Considering the time series analysis between crime and unemployment, Chen (2009) implement VAR model in order to estimate the long run relationship between unemployment and crime from 1976 to 2005 in Taiwan. He found the long run relationship between unemployment and theft, fraud and total crime.

Kustepeli (2006) elaborate that gross domestic product (GDP) growth is positively related to crime because with the growth of GDP we move towards capital intensive technique because of which labor become unemployed and is driven towards

2 Confirm by Patterson (1991), Nilsson (2004).

an illegitimate activity. Therefore, we conclude that increase in growth of an economy leads towards more crime rate in a society. Habibullah and Baharom (2009) estimate the relationship between gross national product (GNP) and 15 different types of crime (total crime, violent, murder, attempted murder, armed robbery, robbery, rape, assault, property, daylight burglary, night burglary, lorry-van theft, car theft, motorcycle theft and larceny) in Malaysia from 1973 to 2003. He employed autoregressive distributive lag model (ARDL) by bound testing procedure in order to estimate the long run relationship. Result suggest that there is long run relationship between GNP and seven different types of crime (murder, armed robbery, rape, assault, daylight burglary and motorcycle theft).

In the light of the discussed literature, it is stated that causation between crime and socioeconomic indicators varies from region to region and country to country. The abovementioned studies incorporate panel data in order to estimate their respective model but causation between crime and economic indicators change with the change in nature of the data. The socioeconomic indicators of crime is meagrely studied in Pakistan, however some studies use only economic indicators of crime while the deterrence variable is absent in these studies. The objectives of study is to estimate the long run and short run elasticities of supply of offense function and estimate the effect of deterrence variable on crime.

This study organizes in to four sections. Section one includes the introduction, second section incorporates the theoretical frame work, third section takes an account the methodology and scrutiny and third section includes the stability of the model.

2. VARIABLES AND DATA DESCRIPTION

In supply of offense function, deterrence variable is important variable, which is discussed in most of the developed regions studies but other variables like unemployment, education, income inequality, per capita income, population density and poverty also affect the crime rate in Pakistan. Most of the studies in Pakistan discussed the other factors like unemployment, education and income inequality, which affect the crime rate in Pakistan except deterrence variable. This section will explore the factors affecting the crime rate in Pakistan.

In this study crime rate (crime/one hundred thousand populations) is regarded as dependant variable. Deterrence variable of crime plays important role in deciding for an individual to move in unlawful or lawful activity. For the estimation of supply of an offense function, deterrence variable is employs at aggregated and disaggregated level. Table 1 shows the description of variables.

2.1. Test for Stationarity

A series is said to be stationary if it mean, variance and covariance does not relate with time period or in other words it remains constant over time.

A series said to be non-stationary if it violates the any part of definition given below. There are many methods to test the hypothesis of unit root, but the most frequently used technique is Dickey–Fuller (DF) which estimates the following equation by method of ordinary least square (OLS) (Dickey and Fuller, 1979).

Table 1: Variables description

Variable	Description of notations
lX_{ac}	Crime rate at aggregated level (all reported crime/total population)
lD_{ac}	Cost of aggregated crime (strength of police/aggregated crime)
lU_{ac}	Unemployment rate
II_{ac}	Income inequality (Gini coefficient)
lE_{ac}	Education (secondary school enrolment/population)
lG_{ac}	Real GDP/population

$$Z_t = \Psi_1 Z_{t-1} + \mu_t \tag{1}$$

Where the error term of above equation μ_t is assumed to be white noised (0, σ^2). The series is said to be non-stationary if $\Psi_1 = 1$ and on the other hand it is said to be stationary if $\Psi_1 < 1$. Our null hypothesis (H_0: $\Psi_1 = 1$) and alternative hypothesis is (H_1: $\Psi_1 < 1$). The rejection of null hypothesis is sufficient condition for the series to be stationary and vice versa.

We will face two main problems with the estimation of Equation (1) by method of OLS. Method of OLS is valid if data is stationary and second in Equation (1) the lagged dependent variable act as independent variable, which make our estimator biased downwards in small samples due to conventional *t* statistics for Ψ_1 may not be appropriate. DF fills the above-mentioned gap by subtracting Z_{t-1} on both side of equation.

We employ the supply of an offense function in logarithmic forms for the sake of getting elasticity's; this is represented by (L):

$$\Delta Z_t = (\Psi_1 - 1)Z_{t-1} + \mu_t \tag{2}$$

Method of OLS is employed in order to estimate the above-mentioned Equation (2). Now checked the Null hypothesis for unit root {($\Psi_1 - 1$) = 0} against the alternative hypothesis for no unit root {($\Psi_1 - 1$) < 0}. A series is said to be stationary if null hypothesis is rejected and vice versa.

Equation (2) exhibits simple first order auto regressive process with no deterministic component and zero mean. This means that if time equals to zero than $Z_0 = 0$. "Since, in a model with no deterministic component under the hypothesis of non-stationary, the mean of a series is determined by the initial observation, therefore, (2) is only valid when overall mean of the series is zero." So it is unknown whether ($Z_0 = 0$). So we incorporate constant term (β) as drift in Equation (2),

$$\Delta Z_t = \beta + (\Psi_1 - 1) Z_{t-1} + \mu_t \tag{3}$$

Null hypothesis of unit root is {H_0: (Ψ_1 – 1) =0} is verified against the alternative hypothesis of no unit root which is

$\{H_1: (\Psi_1 - 1) < 0\}$. The hypothesis of unit root is rejected if the value of calculated μ_t statistics is greater than critical value of μ_t statistics and vice versa. "Z_t is stationary with no trend. Using (3) to test for a unit root is not appropriate because it does not test both null and alternative hypothesis. So, including trend t, (3) becomes"

$$\Delta Z_t = \beta + \alpha_t + (\Psi_1 - 1) Z_{t-1} + \mu_t \tag{4}$$

Equation (4) is used for testing the unit root hypothesis, which shows that Z_t has both stochastic and deterministic trend. The t statistic is used to test the unit root hypothesis. Z_t is said to be non-stationary, if calculated t statistics is greater than critical value of t statistics.

From Equation (4), the null hypothesis of unit root and no trend $H_0: \{(\Psi_1 - 1) = \alpha = 0\}$ is checked against the alternative hypothesis of no unit root and trend $H_1: \{(\Psi_1 - 1) \neq \alpha \neq 0\}$ keeping in view Ψ_1 statistics. Z_t is said to be non-stationary with no trend, if calculated value of Ψ_1 is less than critical value and vice versa.

In DF we assume that μ_t is white noised. "If the error term is not white noise, there is autocorrelation in the residuals of OLS regression in (2-4). This will invalidate the use of DF statistic for unit root test. Two approaches are used to overcome this problem. First, the testing Equations (2-4) can be generalized."

"Second, DF statistic can be adjusted. First approach is commonly used, which is the augmented DF test (ADF). So, to make μ_t white noise, lagged values of dependent variable are included on right hand side of DF equations (2-4) which become,"

$$\Delta Z_t = (\Psi_1 - 1) Z_{t-1} + \sum_{i=1}^{k} \Omega_i \Delta Z_{t-1} + \propto_t \tag{5}$$

$$\Delta Z_t = \beta + (\Psi_1 - 1) Z_{t-1} + \sum_{i=1}^{k} \Omega_i \Delta Z_{t-1} + \propto_t \tag{6}$$

$$\Delta Z_t = \beta + \alpha t + (\Psi_1 - 1) Z_{t-1} + \sum_{i=1}^{k} \Omega_i \Delta Z_{t-1} + \propto_t \tag{7}$$

In ADF test and DF test we assume that there is only one unit root (Dickey and Fuller, 1979). Standard hypothesis testing procedure is used to test the unit root in the level of series "If hypothesis of unit root is not rejected, then first difference is tested for presence of second unit root and so on. This procedure continues until the null of unit root is rejected."

3. EMPIRICAL SPECIFICATION OF SUPPLY OF AN OFFENSE

For the specification of supply of an offense model the studies Gillani et al. (2009), Kustepeli (2006), Baharom and Habibullah (2008) have used linear model for the empirical estimation the linear specification of model derived from cost minimization and utility maximization technique.

3.1. Econometric Model for Supply of Aggregated Offense

$$\begin{aligned}
\Delta \log(X_{ac}) = {} & \beta_0 + \beta_1 \log(D_{ac_{t-i}}) + \beta_2 U_{ac_{t-i}} + \beta_3 I_{ac_{t-i}} \\
& + \beta_4 \log(E_{ac_{t-i}}) + \beta_5 \log(G_{ac_{t-i}}) + \beta_6 \log(P_{ac_{t-i}}) \\
& + \beta_7 O_{ac_{t-i}} + \phi_1 \log(X_{ac_{t-i}}) \\
& + \sum_{i=1}^{m} \alpha_1 \Delta \log(D_{ac_{t-i}}) + \sum_{i=1}^{m} \alpha_2 \Delta U_{ac_{t-i}} + \sum_{i=1}^{m} \alpha_3 \Delta I_{ac_{t-i}} \\
& + \sum_{i=1}^{m} \alpha_4 \Delta \log(E_{ac_{t-i}}) + \sum_{i=1}^{m} \alpha_5 \Delta \log(G_{ac_{t-i}}) \\
& + \sum_{i=1}^{m} \alpha_6 \Delta \log(P_{ac_{t-i}}) + \sum_{i=1}^{m} \alpha_7 \Delta O_{ac_{t-i}} \\
& + \sum_{i=1}^{m} \lambda_1 \Delta \log(X_{ac_{t-i}}) + \varepsilon_t
\end{aligned}$$

3.2. Econometric Model for Supply of Offense against Property

$$\begin{aligned}
\Delta \log(X_{pc}) = {} & \beta_0 + \beta_1 \log(D_{pc_{t-i}}) + \beta_2 U_{pc_{t-i}} \\
& + \beta_3 I_{pc_{t-i}} + \beta_4 \log(E_{pc_{t-i}}) + \beta_5 \log(G_{pc_{t-i}}) \\
& + \beta_6 \log(P_{pc_{t-i}}) + \beta_7 O_{pc_{t-i}} + \phi_1 \log(X_{pc_{t-i}}) \\
& + \sum_{i=1}^{m} \alpha_1 \Delta \log(D_{Pc_{t-i}}) + \sum_{i=1}^{m} \alpha_2 \Delta U_{Pc_{t-i}} + \sum_{i=1}^{m} \alpha_3 \Delta I_{Pc_{t-i}} \\
& + \sum_{i=1}^{m} \alpha_4 \Delta \log(E_{Pc_{t-i}}) + \sum_{i=1}^{m} \alpha_5 \Delta \log(G_{Pc_{t-i}}) \\
& + \sum_{i=1}^{m} \alpha_6 \Delta \log(P_{Pc_{t-i}}) + \sum_{i=1}^{m} \alpha_7 \Delta O_{Pc_{t-i}} + \\
& + \sum_{i=1}^{m} \lambda_1 \Delta \log(X_{Pc_{t-i}}) + \varepsilon_t
\end{aligned}$$

3.3. Econometric Model for Supply of Offense against Violence

$$\begin{aligned}
\Delta \log(X_{vc}) = {} & \beta_0 + \beta_1 \log(D_{vc_{t-i}}) + \beta_2 U_{vc_{t-i}} + \beta_3 I_{vc_{t-i}} \\
& + \beta_4 \log(E_{vc_{t-i}}) + \beta_5 \log(G_{vc_{t-i}}) + \beta_6 \log(P_{vc_{t-i}}) \\
& + \beta_7 O_{vc_{t-i}} + \phi_1 \log(X_{vc_{t-i}}) + \sum_{i=1}^{m} \alpha_1 \Delta \log(D_{vc_{t-i}}) \\
& + \sum_{i=1}^{m} \alpha_2 \Delta U_{vc_{t-i}} + \sum_{i=1}^{m} \alpha_3 \Delta I_{vc_{t-i}} + \sum_{i=1}^{m} \alpha_4 \Delta \log(E_{vc_{t-i}}) \\
& + \sum_{i=1}^{m} \alpha_5 \Delta \log(G_{vc_{t-i}}) + \sum_{i=1}^{m} \alpha_6 \Delta \log(P_{vc_{t-i}}) \\
& + \sum_{i=1}^{m} \alpha_7 \Delta O_{vc_{t-i}} + \sum_{i=1}^{m} \lambda_1 \Delta \log(X_{vc_{t-i}}) + \varepsilon_t
\end{aligned}$$

Above mentioned models shows the lag value of independent and dependent variable without differenced and summation and lag value of independent and dependent variable with differenced and summation. In econometric model for supply of aggregated offense X_{ac} (All reported crime rate) is the dependent variable and rest of variable are independent. However in econometric model for supply of offense against property and violent; X_{pc} (property crime rate) and X_{ac} (violent crime rate) act as dependent variable. The coefficients with differenced (Δ) tells us the short run dynamics of the model and coefficients without differenced tells us long run dynamics. In second step the existence of long-run relationship is tested through Bounds test procedure. For all three supply of offense function which is related to aggregated, property and violent crime rate. The null hypothesis for the existence of no long run relationship for three supply of offense function is given below:

H_0: $\beta_1 = 0$, $\beta_2 = 0$, $\beta_3 = 0$, $\beta_4 = 0$, $\beta_6 = 0$, $\beta_7 = 0$

Alternative hypothesis is:

H_1: $\beta_1 \neq 0$, $\beta_2 \neq 0$, $\beta_3 \neq 0$, $\beta_4 \neq 0$, $\beta_6 \neq 0$, $\beta_7 \neq 0$

For the joint significance of above mention variable which are β_1, β_2, β_3, β_4, β_5, β_6, β_7.

F statistics can be calculated from bounds test procedure and compare these values with the non-standard values of critical bounds developed by Pesaran et al. (2001) If calculated value lies above the upper bound than cointegration will establish and If critical value lies below the lower bound than cointegration will not established. However if the calculated value lies between upper and lower bound than F statistics become inconclusive.

However bounds test is applied irrespective of the fact whether regressors are $I(1)$ or $I(0)$. Pesaran et al. (2001) "tabulated the appropriate critical values for different number of regressors and whether the regressors contain an intercept and time trend."

The above-mentioned model is estimated keeping in view the lag criterion with the help of Akaike and Schwarz Bayesian criteria (SBC). With the completion of above procedure gives us the long run elasticities as well as enables the use of cumulative sum (CUSUM) and CUSUM sum of square test to the residuals of above mentioned equation for testing the long run elasticities along with short run dynamics.

4. ERROR CORRECTION MODEL (ECM)

The subsequent step is development of ECM. ECM describes the short run dynamics with the long run relationship. The term ECM (−1) is known as adjustment parameter, which tells us "the speed of adjustment and the negative sign and its highly statistical significant confirms cointegration and determines the LR causal effect. The negative sign of the adjustment parameter also ensures stability of the model. The negative and statistical significant sign of the coefficient of ECM_{t-1} also implies that the series are non-explosive and LR equilibrium is attained."

4.1. Aggregate Supply of Offense Function

$$\begin{aligned}\Delta\log(X_{ac}) = {} & \alpha_{10} + \varphi_1 \propto_{ac_t} + \sum_{i=1}^{m_1}\alpha_{1i}\Delta\log(D_{ac_{t-i}}) \\ & + \sum_{i=1}^{m_2}\alpha_{2i}\Delta U_{ac_{t-i}} + \sum_{i=1}^{m_3}\alpha_{3i}\Delta I_{ac_{t-i}} + \sum_{i-1}^{m_4}\alpha_{4i}\Delta\log(E_{ac_{t-i}}) \\ & + \sum_{i-1}^{m_5}\alpha_{5i}\Delta\log(G_{ac_{t-1}}) + \sum_{i-2}^{m_6}\alpha_{6i}\Delta\log(P_{ac_{t-i}}) \\ & + \sum_{i-2}^{m_7}\alpha_{7i}\Delta O_{ac_{t-i}} + \sum_{i-2}^{m_8}\alpha_{8i}\Delta\log(X_{ac_{t-i}}) + ecm_{1t-i}\end{aligned}$$

4.2. Supply of Offense Function against Violence

$$\begin{aligned}\Delta\log(X_{vc}) = {} & \alpha_{14} + \varphi_3 \propto_{vc_t} + \sum_{i=1}^{m_1}\alpha_{15i}\Delta\log(D_{vc_{t-i}}) \\ & + \sum_{i=1}^{m_2}\alpha_{16i}\Delta U_{vc_{t-i}} + \sum_{i=1}^{m_3}\alpha_{17i}\Delta I_{vc_{t-i}} + \sum_{t-1}^{m_4}\alpha_{18i}\Delta\log(E_{vc_{t-i}}) \\ & + \sum_{t-1}^{m_5}\alpha_{19i}\Delta\log(G_{vc_{t-1}}) + \sum_{t-1}^{m_6}\alpha_{20i}\Delta\log(P_{vc_{t-1}}) \\ & + \sum_{t-1}^{m_7}\alpha_{21i}\Delta O_{vc_{t-1}} + \sum_{t-2}^{m_8}\alpha_{22i}\Delta\log(X_{vc_{t-i}}) + ecm_{3t-i}\end{aligned}$$

4.3. Supply of Offense Function against Property

$$\begin{aligned}\Delta\log(X_{pc}) = {} & \alpha_7 + \varphi_2 \propto_{pc_t} + \sum_{i=1}^{m_1}\alpha_{8i}\Delta\log(D_{pc_{t-i}}) \\ & + \sum_{i=1}^{m_2}\alpha_{9i}\Delta U_{pc_{t-i}} + \sum_{i=1}^{m_3}\alpha_{10i}\Delta I_{pc_{t-i}} + \sum_{t-1}^{m_4}\alpha_{11i}\Delta\log(E_{pc_{t-i}}) \\ & + \sum_{t-1}^{m_5}\alpha_{12i}\Delta\log(G_{pc_{t-1}}) + \sum_{t-1}^{m_6}\alpha_{13i}\Delta\log(P_{pc_{t-1}}) \\ & + \sum_{t-1}^{m_7}\alpha_{14i}\Delta O_{pc_{t-1}} + \sum_{t-2}^{m_8}\alpha_{15i}\Delta\log(X_{pc_{t-i}}) + ecm_{2t-i}\end{aligned}$$

5. RESULTS AND INTERPRETATION

This section clarifies the results of empirical investigation and explains the relationship between socio-economic indicators and crime rate in Pakistan.

5.1. Causality and Dynamic Problems in ARDL Model

Pesaran et al. (2001) tells that autoregressive distributed lag model (ARDL) is applied, if the time series data is stationary at same or different level (some are integrated at order I(1) and some are integrated at level I(0). This technique also applied on small finite sample. Procedure allows us to find long run and short run dynamics.

5.2. Unit Root Test

In order to access the estimation of data, the initial step is unit root test for the stationarity of the data. ADF test is carried out for unit root testing. Table 2 tells us the results of ADF. The

Table 2: ADF test

Variables	ADF				Order of integration
	Level		First difference		
	Intercept	Trend and intercept	Intercept	Trend and intercept	
Total crime rate	0.100	0.438	6.472*	6.828*	I(1)
Property crime rate	2.563	2.501	6.553*	7.246*	I(1)
Violent crime rate	1.256	2.052	7.596*	8.149*	I(1)
Strength of police	0.304	1.385	5.071*	5.087*	I(1)
Poverty	2.167	2.241	6.248*	6.432*	I(1)
Population density	2.612***	4.983*	43.47*	4.320*	I(0)
Per capita income	1.548	1.540	4.695*	5.045*	I(1)
Secondary school enrolment	0.584	1.641	6.069*	5.979*	I(1)
Unemployment rate	1.770	1.968	5.610*	5.669*	I(1)
Income inequality	3.733*	3.898**	2.920**	3.208	I(0)

Here the lag length of each variable is determined through SBC. *; ** and *** reflects the rejection of null hypothesis of unit root problem (non-stationarity) of variables at 0.10, 0.05 and 0.01 level of significance. SBC: Schwartz and Bayesian criteria, ADF: Augmented Dickey–Fuller

ADF shows the presence of unit root problem in all variables at 1% level of significance except population density and income inequality. In order to check the stationarity of variables with drift and other factor, intercept term is employed for the specification of unit root. Pesaran et al. (2001) "found that SBC is preferable to Akaike information criterion (AIC), as it is a parsimonious model that selects the smallest possible lag length, while AIC selects the maximum relevant lag length." Results of above mentioned tables justified the employment of ARDL model technique because our dependant variable is stationary at first difference *I*(1) and independent variables are integrated at *I*(1) and *I(*0) at aggregated and disaggregated level.

5.3. Testing of Cointegration Using ARDL

When series is stationary at I(0) and I(1), ARDL is used in order to analyse and test the existence of cointegration. The results of stationarity obtained through unit root test and confirms that variables are stationary at I(0) and I(1) and thus ARDL technique is carried out.

Table 3 shows the F statistics of all three models exceeds the upper bound value which rejects the null hypothesis of "no long run relationship exists" at 1% and 5% level of significance. Thus existence of long run relationship is suggested between the variables.

The next step is to estimate long run relationship between the variables and the associated ECM by using ARDL model approach. The distributed lag order of dependent variables is one which is selected through SBC[3]. The lag order of ARDL for aggregated supply of offense function is (1, 1, 0, 0, 0, 3, 2, 0), supply of offense against property is (1, 1, 0, 0, 0, 2, 2, 0) and the supply of offense function against violence is (3, 2, 0, 2, 1, 3, 3, 1). The order of lag length is selected through SBC criteria.

5.4. Long Run Elasticity's

In order to estimate the responsiveness of supply of offense function and its determinants, the concept of elasticity is considered. In order to investigate the nature of supply of offense functions at aggregate and disaggregate level and its determinants. We utilized and estimate the elasticity. To observe the more responsive behavior of supply of offense function short run and long run elasticity is estimated. Long run elasticities are estimated with the help of ARDL model and short run elasticities are estimated through ECM.

Table 4 shows deterrence variable of crime is estimated with the help of strength of police. The increase in deterrence variable of crime lowers the expected utility of illegitimate activity as compare to legitimate activity Becker (1968) Whereas in case of unemployment Cantor and Land (1985) states that unemployment creates less crime in the society because increase in unemployment lowers the consumption expenditures of household so opportunity of earning from crime become lowers and it discourages a person from committing a crime. An unemployed person spend most of his time at home so an individual allocate less time to illegitimate activity and it lowers the crime rate[4].

However, the per capita income affects the aggregated crime rate positively and insignificantly while education shows positive and significant effect on aggregated crime rate. However income inequality shows negative but insignificant impact on aggregated crime rate[5].

However, Parsley (2001) across the states of US finds positive association between poverty and crime. According to him increase in poverty motivates a person to commit crime, in order to satisfy the basic requirements of life. Consistent with the finding of study Jalil and Iqbal (2010) also find the positive association between crime and population density because increase in population will lead to more people involve in unlawful activity. CUSUM and CUSUM Square test which exist within 5% level (showed by two straight lines) thus indicating that long run relationships are stable among the variables of aggregated supply of offense function.

Table 5 reports the supply of offense function against property. All other economic indicators affect the property crime rate significantly except unemployment, Income Inequality, population

3 Pesaran et al. (2001) "found that SBC is preferable to AIC, as it is a parsimonious model that selects the smallest possible lag length, while AIC selects the maximum relevant lag length."

4 Confirmed by Myers and Samuel (1983).

5 Confirmed by Omotor (2010), Brush, (2007).

Table 3: F statistics for the joint significance of variable

Supply of offence functions	Model 1, 2 and 3	F statistics	I (0)	I (I)
Aggregated supply of an offense function	$X_{ac} = \beta_0 + \beta_1 I_{ac} + \beta_2 G_{ac} + \beta_3 P_{ac} + \beta_4 O_{ac} + \beta_5 E_{ac} + \beta_6 D_{ac} + \beta_7 U_{ac} + \varepsilon_t$	3.99	2.22	3.39
Supply of offense against property	$X_{pc} = \beta_0 + \beta_1 I_{pc} + \beta_2 G_{pc} + \beta_3 P_{pc} + \beta_4 O_{pc} + \beta_5 E_{pc} + \beta_6 D_{pc} + \beta_7 U_{pc} + \varepsilon_t$	3.56	2.22	3.39
Supply of offense function against violence	$X_{vc} = \beta_0 + \beta_1 I_{vc} + \beta_2 G_{vc} + \beta_3 P_{vc} + \beta_4 O_{vc} + \beta_5 E_{vc} + \beta_6 D_{vc} + \beta_7 U_{vc} + \varepsilon_t$	4.16	2.22	3.39

Table 4: Estimated long run elasticity of aggregated supply of offense function based on ARDL approach

Explanatory variables	Coefficient (1, 1, 0, 0, 0, 3, 2, 0)	Standard error	t-value	P value
Income inequality	−0.09	0.078	−1.20	0.236
Log (per capita)	0.00002	0.00001	1.07	0.292
Log (population density)	1.76**	1.018	1.73**	0.092
Poverty	0.005**	0.002	1.85**	0.073
Log (education)	0.471*	0.147	3.19*	0.003
Log (deterrence variable)	−0.467*	0.226	−2.06*	0.047
Unemployment rate	−0.054*	0.017	-3.14*	0.003
Validity test				
Breusch Godfrey test serial correlation LM test	**Breusch Pagan Godfrey test for Hetroscedascity**	**F statistics**	**Durbin–Watson statistics**	
Obs*R²: 4.75	Obs*R²: 11.235	44.68	1.749	
P Chi-square (4): 0.313	P Chi-square (7): 0128	P (F-statistics): 0.000		

Dependent variable is total crime rate per one hundred thousand population. *,**Represent statistical significance at the 0.10, and 0.05, respectively. ARDL: Autoregressive distributive lag

Table 5: Estimated long run elasticity of supply of offense function against property based on ARDL approach

Explanatory variables	Coefficient (1, 1, 0, 0, 0, 2, 2, 0)	Standard error	t value	P value
Income inequality	−0.081	0.117	−0.69	0.496
Log (per capita)	0.00005**	0.00002	1.90**	0.065
Log (population density)	0.184	1.525	0.12	0.904
Poverty	0.010*	0.004	2.33*	0.026
Log (education)	1.577*	0.221	7.12*	0.000
Log (deterrence variable)	−0.192	0.339	−0.56	0.575
Unemployment rate	−0.009	0.026	−0.380	0.706
Validity test				
Breusch Godfrey test serial correlation LM test	**Breusch Pagan Godfrey test for hetroscedascity**	**F-statistics**	**Durbin Watson statistics**	
Obs*R²: 2.122	Obs*R²: 8.185	18.88	1.832	
P Chi-square (2): 0.345	P Chi-square (7): 0.316	P (F-statistics): 0.000		

Dependent variable is total crime rate per one hundred thousand population. Significant at significant at *5%, **10%. ARDL: Autoregressive distributive lag

density and deterrence variable. Unemployment shows negative but insignificant effect on property crime rate.

Cohen et al. (1980) states that unemployment and property crime like robbery, burglary; larceny and motor vehicle theft are inversely associated with crime for two reasons. First increase in unemployment will lead to increase in the population stay at home due to which they can protect their property and reduce property crime.

However in case of income inequality, Blanco and Villa (2008) suggest that increase in income inequality motivates low income people to participate in unlawful activity because of low income as compare to other people[6]. Whereas taking in account the effect of education.

Cardenas and Rozo (2010) implement VAR model and suggest that increase in education motivates a person to involve in illegal activities because education provide better opportunity for an individual to safe himself from conviction and apprehension[7]. Per capita income shows positive and significant impact on crime rate. Baharom and Habibullah (2008) employ ARDL model and finds long run relationship exist between GNP and property crime rate in Malaysia from 1973 to 2003.

Keeping in view the variable poverty, Fedderke and Luiz (2008) find positive association between property crime and poverty. Offense against property is financially motivated crime; In order to attain money poor people usually commit property crime. While in case of population density CUSUM and CUSUM Square test which exist within 5% level (showed by two straight lines) thus indicating that long run relationships are stable among the variables of supply of offense function against property.

After considering the aggregated and property supply of offense function, we estimate the long run elasticities of supply of offense function against violence. Table 6 all explanatory variables show significant impact on violent crime rate except per capita

6 Confirmed by Chiu and Madden (1998).

7 Confirmed by Imrohoroglu et al. (2001).

income, population density, income inequality and unemployment. Education and deterrence variable show negative and significant impact on violent crime rate whereas poverty shows positive and significant impact on crime rate. Whereas keeping in view the effect of education on crime rate Lance and Enrico (2004) argues that increase in education increases the returns of lawful market as compare to unlawful market, which lowers the opportunity to commit crime.

However, Choe (2008) argue that poverty relates positively with violent crime rate because poor people do not have any legal source to satisfy the basic needs of his house. While in case of income inequality Narayn and Smyth (2004) found positive impact on violent crime rate.

While in case of population density CUSUM and CUSUM square test which exist within 5% level (showed by two straight lines) thus indicating that long run relationships are stable among the variables of supply of offense function against violence.

5.5. Short Run Elasticity's

After estimating the long run coefficients with the help of ARDL model, the next step is to estimate the short run coefficients by taking into account the ECM. The coefficient of ECM provides the information regarding speed of adjustment. "The coefficient of ECM provides the speed with which variable returns to its equilibrium position in the long run so the value of ECM should be negative and statistically significant." The negative sign of ECM indicates the convergence in the short run dynamics. The short run relationship of aggregated supply of offense function is mentioned in Table 7.

From Table 7, show that all explanatory variables show insignificant relationship with aggregated crime rate except education and unemployment. The deterrence variable of crime and Income inequality shows the negative but insignificant impact on crime rate while education shows positive and significant association with crime rate. However Unemployment shows the negative and significant impact on crime rate. Table 7 shows the value of ECM is −0.96 and highly significant in aggregated supply of offense function, which shows that deviation from long run equilibrium to short run dynamics is corrected by about 96% after each year. The t-value of ECM coefficient is −4.20 which is significant in aggregated supply of offense function and shows the convergence to the long run equilibrium. CUSUM and CUSUM square test which exist within 5% level (showed by two straight lines) thus indicating that that short run relationships are stable among the variables of aggregated supply of offense function.

The short run elasticity of supply of offense function against property is presented in Table 8. Table 8 shows that all explanatory variables show insignificant impact on property crime rate except per capita income and education. However income inequality, population density and Deterrence variable shows negative but insignificant impact on property crime rate, Table 8 shows the coefficient of ECM (speed of adjustment)

Table 6: Estimated long run elasticity of supply of offense function against violence based on ARDL approach

Explanatory variables	Coefficient (3, 2, 0, 2, 1, 3, 3, 1)	Standard error	t value	P value
Income inequality	−0.011	0.066	−0.177	0.860
Log (per capita)	0.000005	0.00001	0.357	0.723
Log (population density)	0.411	0.861	0.476	0.636
Poverty	0.011*	0.002	4.492*	0.005
Log (education)	−0.389*	0.124	−3.119*	0.004
Log (deterrence variable)	−0.389*	0.191	−2.029*	0.05
Unemployment rate	−0.023	0.014	−1.581	0.124

Validity test

Breusch Godfrey test serial correlation LM test	Breusch Pagan Godfrey test for hetroscedascity	F-statistics	Durbin Watson statistics
Obs*R^2: 3.062	Obs*R^2: 11.82	19.99	1.44
P Chi-square (2): 0.216	P Chi-square (7): 0.106	P (F-statistics): 0.000	

Dependent variable is total crime rate per one hundred thousand population. Significant at significant at *5%. ARDL: Autoregressive distributive lag

Table 7: Estimated short run elasticity of aggregated supply of offense function based on ECM approach

Explanatory variables	Coefficient (0, 0, 0, 0, 0, 2, 2, 0)	Standard error	t value	P value
Income inequality	−0.069	0.085	−0.815	0.424
Log (per capita)	0.000007	0.00002	0.248	0.806
Log (population density)	1.617	1.202	1.344	0.193
Poverty	0.004	0.007	0.593	0.559
Log (education)	0.820*	0.330	2.479*	0.021
Log (deterrence variable)	−0.196	0.394	−0.497	0.624
Unemployment rate	−0.040*	0.016	−2.378*	0.027
ECM(−1)	−0.963	0.229	−4.201	0.000

Validity test

Breusch Godfrey test serial correlation LM test	Breusch Pagan Godfrey test for hetroscedascity
Obs*R^2: 2.647	Obs*R^2: 5.240
P Chi-square (4): 0.265	P Chi-square (7): 0.969

Dependent variable is total crime rate per one hundred thousand population. Significant at significant at *5%. ECM: Error correction model is negative and significant in ECM of supply offense function against property. The value of ECM is −0.90 which shows that deviation from the long run equilibrium following by the short run dynamics is corrected by about 90% after each year. The convergence to the long run equilibrium occurs in supply of offense function against property because t-value of ECM is −4.26. CUSUM and CUSUM square test which exist within 5% level (showed by two straight lines) thus indicating that short run relationships are stable among the variables of supply of offense function against property.

After the detection of long run elasticity of supply offense function against violence, short run elasticities are mentioned in Table 9. In short run all variable shows insignificant impact on violent crime rate. However deterrence variable and education shows negative and insignificant impact on violent crime rate while remaining variables shows positive but insignificant impact on violent crime rate. Lance and Enrico (2004) argue that education raises the opportunity cost of crime by raising the abilities of individual and skills in lawful market. Benefits of education are not only the benefits of an individual but also social benefits. Another similar result is consistent with the data of US prisoner population in 1996. Table 9 shows the coefficient of speed of adjustment is negative and significant, which shows the strong evidence regarding convergence to long run equilibrium. The coefficient value of ECM −0.62 is negative which shows that "in every year 62% of the error is adjusted in the previous year and 62% of the short run fluctuations are acceptable in long run trend."

CUSUM and CUSUM square test which exist within 5% level (showed by two straight lines) thus indicating that short run relationships are stable among the variables of supply of offense function against violence.

6. CONCLUSION AND SUMMARY

This study analysis the time series data from 1973 to 2010 by using ARDL model and ECM in order to estimate the long run and short run relationship between socio economic indicators and crime rate at aggregate and disaggregate level (property and violent crime rate). Violent crime includes murder, attempted murder, forcible rape, robbery and assault while property crime is a combination of burglary, theft, cattle theft and dacoity. Dependent variables are aggregated, property and violent crime rate while the independent variable includes the deterrence variable (strength of police), Secondary school enrolment, unemployment rate, Gini coefficient, head count ratio (poverty), Per capita income and population density.

The results of bounds test procedure suggest that all the above mentioned models show the existence of long run relationship between the socio economic indicators and crime rate at aggregated and disaggregated level. In case of aggregated supply of offense function, all variables show the significant impact on aggregated crime rate except per capita income and income inequality. Unemployment and deterrence variable (strength of police) shows the negative and significant impact on aggregated crime rate. The

Table 8: Estimated short run elasticity of supply of offense function against property based on ECM approach

Explanatory variables	Coefficient (0, 1, 0, 0, 0, 2, 2, 0)	Standard error	t value	P value
Income inequality	−0.044	0.116	−0.382	0.705
Log (per capita)	0.00009*	0.00003	2.517*	0.019
Log (population density)	−0.690	1.994	−0.346	0.732
Poverty	0.007	0.009	0.767	0.450
Log (education)	0.826**	0.424	1.945**	0.064
Log (deterrence variable)	−0.733	0.498	−1.470	0.154
Unemployment rate	0.010	0.023	0.471	0.641
ECM−1)	−0.908*	0.212	−4.268*	0.000
Validity test				
Breusch Godfrey test serial correlation LM test		Breusch Pagan Godfrey test for hetroscedascity		
Obs*R^2: 0.369		Obs*R^2: 8.71		
P Chi-square (2): 0.157		P Chi-square (12): 0.726		

Dependent variable is total crime rate per one hundred thousand population. Significant at significant at *5%, **10%. ECM: Error correction model

Table 9: Estimated short run elasticity of supply of offense function against violence based on ECM approach

Explanatory variables	Coefficient (0, 2, 0, 1, 1, 3, 2, 1)	Standard error	t value	P value
Income inequality	0.008	0.088	0.100	0.921
Log (per capita)	0.00001	0.00002	0.539	0.596
Log (population density)	3.332	3.968	0.839	0.413
Poverty	−0.02	0.040	−0.537	0.598
Log (education)	−0.561	0.441	−1.270	0.222
Log (deterrence variable)	−0.232	0.341	−0.681	0.505
Unemployment rate	0.010	0.016	0.638	0.532
ECM(−1)	−0.623*	0.296	−2.101*	0.051
Validity test				
Breusch Godfrey test serial correlation LM test		Breusch Pagan Godfrey test for hetroscedascity		
Obs*R^2: 0.026		Obs*R^2: 21.52		
P Chi-square (2): 0.986		P Chi-square (18): 0.253		

Dependent variable is total crime rate per one hundred thousand population. Significant at significant at *5%,. ECM: Error correction model coefficient of ECM in aggregated supply of offense function is negative and significant, which shows the convergence to the long run equilibrium.

In addition, the long run relationship of "supply of offense function against property" illustrates that socio economic indicators shows insignificant impact on property crime rate except per capita income, poverty and education. Increase in education motivates a person to involve in illegal activities because education provide better opportunity for an individual to safe himself from conviction and apprehension from white collar crime. Increase in income inequality motivates low income people to participate in unlawful activity because of low income as compare to other people. While speed of adjustment shows that deviation from the long run equilibrium following by the short run shock is corrected by about 90% within each year.

After the discussion of aggregated and property crime rate, the supply of offense function against violence demonstrate that the deterrence variable, education and poverty shows significant impact on violent crime rate, while remaining variable shows insignificant impact on violent crime rate, The convergence towards long run equilibrium occurs because coefficient of ECM is negative and significant.

The economics of crime is associated with many similar field of study like sociology, psychology and geography but particularly, we focus our attention towards the empirical investigation of socioeconomic consequences of crime such as unemployment rate, strength of police, Gini coefficient, secondary school enrolment, poverty (head count ratio), population density and per capita income. This allows us to draw conclusion that investigation of criminal behavior is a complex phenomenon, which is based on several other socioeconomic factors.

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