ORIGINAL RESEARCH PAPER
Volume-6 | Issue-9 | September-2017 | ISSN No 2277 - 8179 | IF : 4.176 | IC Value : 78.46
INTERNATIONAL JOURNAL OF SCIENTIFIC RESEARCH

FACTORS AFFECTING CRIME RATES IN KENYA; A REGRESSION ANALYSIS

Statistics

Joel Chelule

Mr. Chris Muchwanju

ABSTRACT

In this paper, we use a special type Mixed Effects Regression Model, that is Hierarchical Linear Model to study factors affecting crime rates in Kenya. The study explores the effect of various factors on the crime rate in Kenya. We estimate a crime equation using a panel dataset of the provinces in Kenya for the period 1990 to 2010 employing the REML estimator. The parameter estimates for the variables Poverty Rate (0.95542), Unemployment rate (0.526), Young men (15-29) years(0.2394), Conviction Rate(-0.278), clear-up rate (-0.87) Probability of arrest (-2.65), and population Density (0.0414) are all significant at 95% confidence Interval in accounting for increase in Crime Rate against person with their expected signs. The parameter estimates for the variables Poverty Rate (0.127), Unemployment rate (0.0.414), School enrolment (-0.817), Probability of conviction (-0.126)),Probability of arrest (-4.32) and population Density (0.114) are all significant at 95% confidence Interval in accounting for increase in Crime Rate against property with their expected signs. Our empirical results further suggest that Poverty Rate, Unemployment rate, Probability of arrest, population Density and police rate are correlated to all typologies of crime rate considered.

KEYWORDS

Introduction

Crime is one of the major problems of any society. It causes disequilibrium in the social system. It is a complex phenomenon of social, political and economic impacts. More important, crime can be seen as an indirect symptom of failures in personal development, socialization and education of children- failures which represent very large losses of human potential.

The reasons why people are more or less law-abiding are manifold. Crime is as old as mankind itself, moreover, it has become a common societal phenomenon and many people view it as if it is a functional component of the organization of human groupings (Schafer, 1976).

Despite the large research literature addressing various aspects of these issues, there remains limited evidence giving both a broad picture of the range of anti-social activity and a detailed longitudinal picture of the development processes leading to criminal outcomes.

Since Becker (1968) published his seminal work on the economics of crime, a large empirical literature has been developed around estimation and testing of economic model of crime. Almost all of these contributions have used aggregate data, usually at state or national level. Economists have devoted considerable effort to determining its empirical validity.

Ideally, the economic model of crime should be estimated with individual level data since the model purports to describe the behavior of individuals. However, the expense and difficulty to create random sample which is large enough to include representative information about individual criminal activity has been, and still is a challenge. This challenge has continued to be obstacle for individual level analysis. Few literatures have used individual data, but empirical result failed to obtain the expected estimate, Christopher and Trumbull (1994).

In the absence of empirical work at the individual level, the estimation of the economic model of crime using aggregate data continues Craig (1987), Avio (1988) and Trumbull (1989). While estimation with aggregate data has been criticized, results from such estimation have influenced public policy.

The consensus of the empirical literature is that punishment (certainty and severity), Incarceration population, police rate and unequal opportunities have strong deterrents effect.

Estimates of the magnitude of deterrence effect vary, but it appears that an increase in law enforcement activity that increase the probability of punishment or the severity of punishment. Further empirical investigation is necessary in order to gain a more accurate estimate of the magnitude of this deterrent effect.

Objections to economic studies of criminal behavior have been many and occasionally fierce; see for example, Blumstein, Cohen and Nagin (1978), Orsagh (1979), Brier and Fienberg (1980), Prisching (1982), and Cameron (1988). In particular, studies based on aggregate data have been criticized. In addition to attacks on the assumption of rational behavior, the main criticism relates to interpretation of empirical results, method of estimation, statistical identification of equations, and unobserved heterogeneity, measurement errors, and operationalization of theoretical variables. The effects of various economic factors are less clear.

The vast majority of the research has been theoretical in emphasis (e.g. Stigler 1970, Posner 1977, Andreoni (1991), Kaplow and Shavell 1999). Less progress has been made in empirically testing the economic model of crime, although there are a number of notable attempt to do so (e.g. Ehrlich 1973, Witte 1980, Cameron 1988, Tauchen, Witte and Griensinger 1994). One major difficulty in testing the Becker (1968) model and its numerous extensions is that many of the predictions of the model are empirically indistinguishable from other competing models. For example, except under special circumstances, it is difficult to separate deterrence (the basis of the economic model).

Many supposed tests of the economic model of crime have little power to discriminate between competing models. Difficulty that arises in testing the economic model of crime is identifying exogenous sources of variation in the criminal justice system that is necessary to identify a causal link between response and deterrent variables. The early empirical literature in this area, lacking exogenous variation, yield results that are difficult to interpret and have been harshly criticized Fisher and Nagin (1978), Cameron (1988).

Cornwell and Trumbull (1994) point to the fact that aggregate cross-section econometric techniques do not control for unobserved heterogeneity. Addressing this problem by use of a panel data dataset of North Carolina counties, they obtain more modest deterrent effects of the arrest and conviction rates than those obtained from cross-section estimation.

Crime is among the most difficult of the many challenges facing Kenya. The country's crime rates are among the highest in the world and no Kenyan is insulated from its effects. Beyond the pain and loss suffered by crime victims, crime also has less direct costs. The threat of crime diverts resources to protection efforts, exacts health costs through increased stress, and generally creates an environment that is not conducive to productive activities relationship with returns from crime and non-crime activities. All of these effects are likely to discourage investment and stifle long-term growth in Kenya. The result of this finding will help policy makers and planners to target with feasible interventions and strategies to reduce crime in Kenya

1.2 Statement of the Problem

Crime is on the rise globally, but is more accelerating in African countries. In particular, Kenya ranked the second-highest after South Africa on the survey on economic crimes in the world (UN, 2009). Criminal behavior is steadily increasing and over half of the population worries about crime constantly and roughly 75% feel unsafe while at home (UN-Habitat, 2002).

Many factors have been attributed to the ever increasing crime rate in Kenya. Crime statistics in Kenya over the years has remained at the level of summary, tabulation and lacks scientific analysis that allows for prediction, planning and effective control. There is a need for a policy change towards crime reduction in the country. In this study we are going to consider provincial crime rate data for crimes against person and property in Kenya and determine the factors that affect crime rates.

Justification of the Study

The last quarter of the Twentieth Century witnessed an escalation of violent crime in Africa. Thus crime is mainly related to the increased intensity and complexity of urbanization. Obviously, specific features of urbanization have particularly contributed to the growth of criminal violence. Egypt, Nigeria and South Africa are the cities that feature most prominently in literature on violent crime in Africa (Albert 1998). There are other countries, however, whose violent crime rate is equally or relatively high or is fast becoming so. Kenya, is one of those countries. Because of this it is of interest that we study the factors affecting crime rate in Kenya so as to help policy makers and administrators understand why and how crime occur in the country and be able to plan, predict and prevent it. Since Kenya is divided into smaller regions called province, it is of interest that we analyze crime rate at these levels.

Literature Review

Becker (1968) published his seminal work on the economics of crime. Since then, an enormous literature has risen on the economic model of crime. The vast majority of this research has been theoretical in emphasis (e.g. Stigler 1970, Posner 1977, Polinksy and Shavell 1984, Andreoni 1991, Kaplow and Shavell 1999). Less progress has been made in empirically testing of the economic model of crime, although there are a number of notable attempts to do so (e.g. Ehrlich 1973, Witte 1980, Cameron 1988, Tauchen, Witte, Griesinger 1994), Cornwell and Trumbul (1994), Doyle et al. 1999, Gould et al. (2002), Witt et al. (1998, 1999), Carmichael and Ward (2000, 2001), Gillado and Cruz (2004) and Han et al. (2010).

One major difficulty in testing the Becker (1968) model and its numerous extensions is that many of the estimation of the model are empirically indistinguishable from other competing models. For example, except under special circumstances, it is difficult to separate deterrence (the basis of the economic model) from incapacitation effects (a reduction in crime rate that arises mechanically because criminal are behind bars, rather than due to behavioral response to changing incentives). Thus, many supposed tests of the economic model of crime have little power to discriminate between competing models.

Another difficulty that arises in testing the economic model of crime is identifying exogenous sources of variation in the criminal justice system that are necessary to identify a causal link between policies and changes in crime rates. The early empirical literature in this area lacking exogenous variation, yielded results that are difficult to interpret and have been harshly criticized, Fisher and Nagin (1978), Cameron (1988).

More recently, some progress has been made in this area. For instance, on the question of whether more police reduce crime, a series of papers using a range of different approaches have all come to a similar conclusion that more police substantially reduce crime, Marvell and Moody (1968), Levitt (1977) and Corman and Mocan (2000).

During the last 50 years economists have devoted considerable effort to determining its empirical validity since Becker's (1968) have published his seminal article on the economic model of crime and they have invaded the field using their all-embracing model of individual rational behavior, where a criminal act is preferred and chosen if the total pay-off, including that of sanctions and other costs, is higher than that of legal alternatives. Much of this research examines deterrence, the idea that policy can reduce crime by raising the expected costs, Erling (1999).

Methodological problems may also be the source of disagreement between studies Erling (1999). A large number of literatures have been done around estimating economic model of crime in previous studies. Much of these the existing empirical evidence contains biased and inconsistent estimates from failing to properly control for unobserved heterogeneity John (2001) and Best (2005). Several statistical techniques (equation specifications and estimation techniques) have been used and the studies have been based on data from countries and states down to counties, municipalities, campuses, and individuals to estimate economics of criminal behavior. But much the empirical result failed to obtain the expected estimate.

Recently, Spelman (2008) discussed in details the relationship between crime and explanatory variables comparing conclusions of 13 published studies on similar data using different technical specifications for the analysis. He shows that the discrepancies in the results depend on the methods rather than on real differences in the data sets. The conclusions of regressions on available data are thus considered with circumspection. Time series is too short to extract general conclusions. There is a long list of discrepancies between studies.

Objections to economic studies of criminal behaviour have been many and occasionally fierce, see for example, Blumstein, Cohen and Nagin (1978), Orsagh (1979), Brier and Fienberg (1980), Cornwell and Rupert (1988), Cameron (1988), and Ezekiel

Gaya (1999). In particular, studies based on aggregated data have been criticized. In addition to attacks on the assumption of rational behavior, the main criticism relates to interpretations of empirical results, method of estimation, statistical identification of equations, and unobserved heterogeneity, measurement errors, and operationalization of theoretical variables. The effects of various economic factors are less clear. There was fear of simultaneity and multicollinerity between explanatory variables and error term. These problems of correlation are not present in studies where individual data are employed, such as Witte (1980), Myers (1980) and Cornwell and Trumbul (1994).

On one hand, data sources are not always reliable because crime data are not given, they contain gaps that are generally filled by the Agency collecting the data. One should care about how this is done, and whether the same methodology has been used for all the time covered by the analysis Targonski (2002). Graphic representations may prove to be useful when analyzing data, although they are not currently used Buenos Aires (2000). The estimates of the effects of gains to crime underscore the problem of finding good empirical measures for theoretical variables.

In this work, we propose a mixed effects model that takes into account the nested structure of our dataset hence a Hierarchical Linear Model is used. We estimate crime rate at provincial level and at country level, hence a two-level model and obtain the estimates of the parameters that are consistent and efficient.

Cornwell and Trumbul (1994) and Cruz (2004) point to the fact that aggregate cross-section econometric techniques do not control for unobserved heterogeneity. Addressing this problem by use of panel data set of North Carolina counties, they obtain more modest deterrent effects of the arrest and conviction rates than those obtained from cross-section estimation.

The study of crime has always been a multidisciplinary activity. Along history different school of thought have proposed different and sometimes convictive ways of considering time. Apart from criminologists, sociologists are perhaps the dominant group, but psychologists and political scientists have also long been prominent. Economists, econometricians and statistician are among the most recent entrants. With Becker's 1968 "Crime and Punishment: An Economic Approach," serving as the starting point for modern economists' work on crime and Cornwell and N. Trumbul (1994) and Marselli (1997) " Estimating the Economic Model of Crime with panel data." In the mid to late 1990's, there are renewed flurry of work by young economists who developed research agendas largely centered on the study of crime.

In this paper we review that economists and statisticians have done over the past years about the major determinants of crime. We consider both the policy variables related to deterrence and the more unconventional factors examined by economists.

Our empirical strategy consists mainly of plots that, one-by-one, compare crime rates with potential determinants; that is, we examine the univariate relation between crime and possible explanatory factors. This approach suffers too large defects: the right model of crime is undoubtedly multifactorial, and the raw correlation between crime and a potential determinant can be misleading in the presence of endogeneity.

This study will mainly focus on model estimation and also the effects of deterrence, socio-economic and demographic variables on crime rate in Kenya. The hypothesis considered is derived from economic models and uses statistical techniques commonly employed by economists and statisticians.

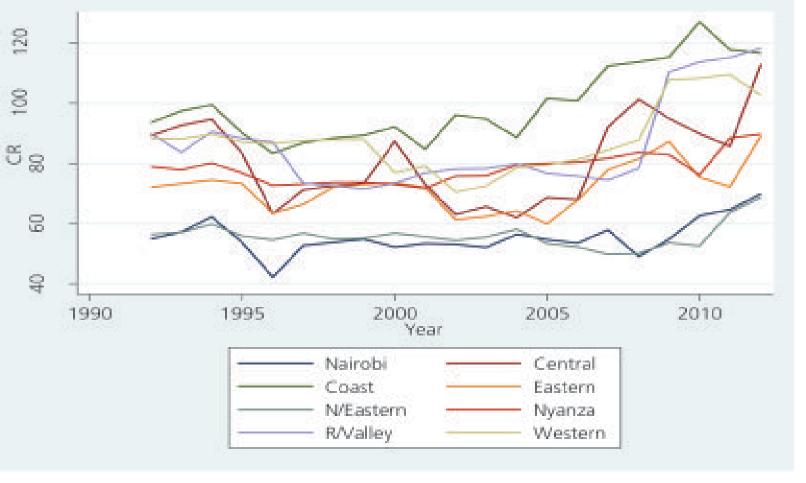
Crime is among the most difficult of the many challenges facing Kenya. The country's crime rates are among the highest in the world and no Kenyan is insulated from its effects (UN, 2002, 2009, 2011). Beyond the pain and loss suffered by crime victims, crime also has less direct costs. The threat of crime diverts resources to protection efforts, exacts health costs through increased stress, and generally creates an environment unconducive to productive activity.

Our paper differs from the existing literature in a number of ways. First, to our knowledge is the first paper on crime determinants in Kenya that uses provincial data, this allows us to better capture the nature of crime given that criminal activities are related to a specific area and its characteristics. Second, we explicitly consider in our analysis deterrence, demographic and socioeconomic factors. Third, we explicitly account for different levels in criminal activities. We estimate a hierarchical linear model of provinces crime rates using Restricted Maximum Likelihood estimator. This allows us to control for unobserved province-specific effects, the joint endogeneity of some of the explanatory variables of crime, and the existence of measurement errors afflicting in particular the crime data. Controlling for joint endogeneity is extremely important in order to obtain consistent estimates of the effect of socioeconomic and demographic variables on crime rates. Finally, the use of panel data allows us to control for the effect of unobserved variables that can be considered as province-specific effects, as systematic measurement errors of crime rate. By controlling for these specific effects, we are able to reduce the estimation bias due to the underreporting of crime. Fourth, differently from previous studies on crime in Kenya that use the overall crime rate to measure the level of criminal activity, we separate the crime measure into two broad crime types: property crimes and crimes against the person. This approach allows us to avoid aggregation bias, as stressed by Cherry and List (2002) "it is inappropriate to pool crime types into a single decision model...much of the existing empirical estimates suffers from aggregation bias" .

A few stylized facts about crime rate in Kenya

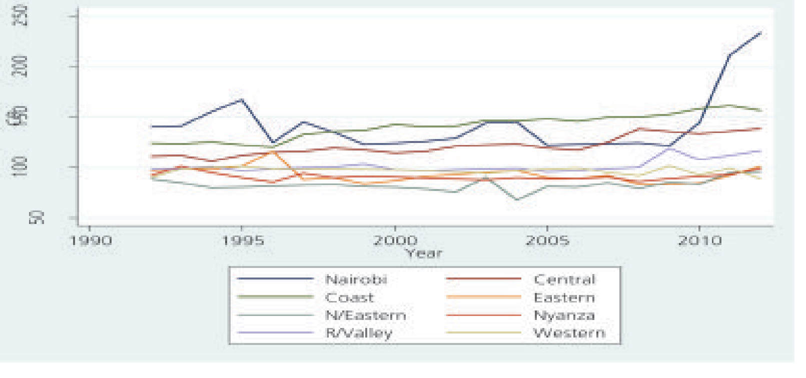
On the basis of the latest official statistics, the trend of crime against person and property in provinces in Kenya can be depicted as in Figure 1 and 2 below, over the period 1990-2010. Generally, there is a steady increase in crime rate over the period considered and therefore need intervention in order to reduce the crime rates.

For Crime Against person



Note: Own elaboration using data from KNBS

For Crime Against Property



Note: Own elaboration using data from KNBS

Research Gap

Crime threatens human security and rights, undermines economic, political and social development of various countries worldwide. Despite vast budgetary allocations by the government to fight crime, little has been achieved so far and this has impacted the country's development agenda negatively. According to official crime data provided, there has been a drastic rise in crime in the last three decades in most developing countries, Kenya included.

Indeed, Kenya has seen a tremendous growth in social, economic and political field, but unless there are clear policy guidelines to deal with issues of crime, the vision 2030 may not be realized. Crime is a pertinent issue in Kenya and has persisted thus needs a deeper study.

The heterogeneous report from the police and other law enforcement agencies leaves doubt on why such trends thrive. It is therefore, crucial to study crime rate and the reason why it increases, not only for academic purpose but also for designing and diligently prescribing effective policies for planning, predicting and preventing crime.

Despite its remarkable features, Kenya's criminal activity has received little attention and remains largely neglected by the economics of crime literature. There is huge potential to fill in such gaps in knowledge based quantitative research from the very rich and largely unexploited registered data that exists in African countries, Kenya in particular. Indeed, if one goes through this copious literature one will hardly find any allusion to Kenya or to any other African countries.

Methodology

Study area source of data and variables used for the analysis

Statistical View of Crime Rate

Crime rate is a function of many factors or variables called explanatory or independent or predictor variables. Thus, crime rate is the performance measure called the response or dependent variable. Hence, the relationship between crime rate and explanatory variables takes the form of a multiple regression model.

Review of Multiple Regression

In general, a multiple regression model takes the form;

$$Y = f(\xi_1, \xi_2, \ldots, \xi_k) + \varepsilon \qquad (3.1)$$

Where Y is the response variable, $\xi_1, \xi_2, \ldots, \xi_k$ are the independent variables and ε is a term that represents other sources of variability not accounted for in the function f. This ε may include effects such as measurement errors on the response, background noises and even effects of other variables. It is treated as statistical error $\sim N(0, \sigma^2)$.

Consequently;

$$E[Y| \xi_1, \xi_2, \ldots, \xi_k] = E[f(\xi_1, \xi_2, \ldots, \xi_k)] + E[\varepsilon| \xi_1, \xi_2, \ldots, \xi_k] = E[f(\xi_1, \xi_2, \ldots, \xi_k)] \qquad (3.2)$$

The variables $\xi_1, \xi_2, \ldots, \xi_k$ in equation (3.1) are called natural variables because they are expressed in the natural units in which the measurements being studied were made. It is convenient to transform these natural variables into coded variables, say $X_1, X_2, \ldots, X_k$, which are dimensionless with mean zero and some standard deviation. Accordingly, in terms of the coded variables, the response function (3.1) can be written as;

$$Y = f(x_1, x_2, \ldots, x_k) + \varepsilon \qquad (3.3)$$

where ε are random variables called error terms which are assumed to be identically and independently distributed, independent of X and normally distributed with zero mathematical expectation i.e. $E(\varepsilon) = 0$, and constant and finite variance i.e. $Var(\varepsilon) = \sigma^2 < \infty$. The explanatory variables X are assumed to be non-random.

Since the true response function f is unknown, it is approximated. In its approximation, the efficiency of the estimation procedure depends on the ability to develop a suitable approximation for this function. This tenability of an efficient approximation is usually the focus in modeling.

The Model

In light of the explanation provided in sub-sections (3.1) and (3.2), together with the reason that panel data may have group effects, time effects, or both, whereby these effects are either fixed or random, we propose a Mixed-Effects Regression Model that takes into account the two levels of analysis, that is at provincial level and at country level. We therefore propose a Hierarchical Linear Model of the form;

i). One at provincial level

Level 1: $Y_{ij} = \beta_{0j} + \beta_{ij}X'_{ij} + e_{ij}$ (1)

ii). At country level

Level 2:

$\beta_{0j} = \gamma_{00} + \mu_{0j}$

$\beta_{ij} = \gamma_{i0} + \mu_{ij}$ (2)

Where;

$Y_{ij}$is the crime rate for province i, at time j, X'_{ij} contains a set of control variables and deterrent variables, and μ_{0j} , $\mu_{ij}$and ε_{it} are error terms assumed to be iid with zero expectation and $\mathrm{Var}(\mu_{oj}) = \sigma^2_\mu$, $\mathrm{Var}(\mu_{ij}) = \sigma^2_\mu$ and $\mathrm{Var}(\varepsilon_{it}) = \sigma^2_\varepsilon$

In this mixed effects model, the effect of the independent variables are allowed to have varying effects across level 2 units because their coefficients in level 2 of the model includes the random error terms. It is these error variances that allow the effect of the independent variables to take on different values across level 2.

The equation for the intercept β_{0j} consists of the overall mean intercept γ_{00} and a cluster-specific random intercept only μ_{0j}. The additional equations for the slopes β_{ij} consists of the overall mean slopes γ_{i0} and cluster specific random slopes μ_{ij}

Thus combining (1) and (2) above gives the overall mixed effects model;

$$Y_{ij} = \gamma_{00} + \mu_{0j} + (X'_{ij})(\gamma_{i0} + \mu_{ij}) + e_{ij}$$

$$Y_{ij} = \gamma_{00} + \gamma_{i0}X'_{ij}\mu_{ij} + \mu_{0j} + \mu_{ij}X'_{ij} + e_{ij} \qquad (3)$$

Estimation of HLM

We now describe the estimation techniques for our two-level hierarchical model. We now present notation which we use throughout this section. Consider the level 1, level 2 and combined models (using HLM) shown in (1), (2) and (3), respectively. Using matrix notation these models are represented as follows:

Level 1: $Y_i = \beta_j X'_j + e_j$ $\qquad$ j = 1,2 …,J $\qquad$ (4)

Where;

$$Y_{j=} \begin{bmatrix} Y_{1j} \\ Y_{2i} \\ Y_{nj} \end{bmatrix}, \qquad X_j = \begin{bmatrix} 1 & X_{1j} \\ 1 & X_{2j} \\ 1 & X_{3j} \end{bmatrix}, \qquad \beta_{j=} \begin{bmatrix} \beta_{oj} \\ \beta_{1j} \end{bmatrix}, \qquad \varepsilon_{j=} \begin{bmatrix} \varepsilon_{1j} \\ \varepsilon_{2i} \\ \varepsilon_{nj} \end{bmatrix}$$

Level 2: $\beta_j = \gamma + \mu_j$ $\qquad$ (5)

Where;

$$\beta_{j=} \begin{bmatrix} \beta_{oj} \\ \beta_{1j} \end{bmatrix}, \qquad \gamma_j = \begin{bmatrix} 1 & \gamma_{00} \\ 1 & \gamma_{10} \\ 1 & \gamma_{11} \end{bmatrix}, \qquad \mu_{j_{j=}} \begin{bmatrix} \mu_{oj} \\ \mu_{1j} \end{bmatrix}$$

Combined model; $Y_{ij} = \gamma X'_j + \mu_j X'_j + \varepsilon_{ij}$ $\qquad$ (6)

X is a design matrix, γ is a vector of fixed effects, μ_j is a vector of random effects and ε_{ij} is a vector of random errors. The assumptions are as outlined below;

$$\varepsilon_{ij} \sim N(0, R), \qquad R_j = \delta^2 I_{nj}$$

$$\mu_j \sim N(0, G), \; G = \begin{bmatrix} \tau_{00} & \tau_{01} \\ \tau_{10} & \tau_{11} \end{bmatrix} \qquad (7)$$

Several estimation techniques are used in hierarchical linear modeling since the model comprises different types of parameters. Specifically, the level 1 coefficient, β_j can be fixed, that is equal to a constant β_{1j}, non-randomly varying (that is across level 2).

The level 2 coefficients, γ, are considered fixed effects and the level 1 and level 2 variances and covariances (δ^2 , τ_{00} , τ_{11} and τ_{11}) are called the covariance components.

The estimation techniques for each type of parameter are outlined below.

Estimating Fixed Effects(γ)

Weighted least squares (WLS) or generalized least squares (GLS) is used to estimate γ as shown

below:

$$\hat{\gamma} = (A^T\hat{V}^{-1}A)\widehat{^{-1}A^T V}\widehat{^{-1}}Y \qquad (8)$$

$$V = \mathrm{Var}\,(Y) = XGX^T + R \qquad (9)$$

A is a N x 4 design matrix with $= \sum_{j=1}^{J} n_j$, and $\hat{V}$ is V with G and R replaced by their Maximum Likelihood Estimates. The elements of G and R (that is δ^2 , τ_{00} , τ_{11} and τ_{11}) are called the variance covariance components and are estimated by Maximum Likelihood or Restricted (ML) or restricted maximum likelihood (REML) as described below

The variance of the estimator $\hat{\gamma}$ in (8) is estimated by

$$\widehat{Var}(\hat{\gamma}) = (A^T \widehat{V^{-1}} A)^{-1} \quad (10)$$

Estimating Covariance Components(R and G)

If the design is perfectly balanced (that is, $n_j$all equal and the distribution of level 1 predictors

within each level 2 unit, there are closed-form formulae for estimating the variance-covariance parameters. When the design is unbalanced, iterative numerical procedures are used to obtain the estimates. Usually these procedures are based on maximum

likelihood estimation techniques. Maximum likelihood (ML) estimates of G and R are found by maximizing the following log-likelihood function

$$l_{ML}(G, L) = -\frac{1}{2}\log|V| - \frac{N}{2}\log r^T V^{-1} r - \frac{N}{2}\left(1 + \log\frac{2\pi}{N}\right) \quad (9)$$

Where,

$$r = Y - A\,(A^T V^{-1} A)^T A^T V^{-1} Y$$

If the number of level 2 units, J is large then the estimates generated through maximum likelihood are approximately equal to estimates generated through restricted maximum likelihood (REML). REML estimates of the covariance components are based on residuals which are computed after estimating the fixed effects (8) by WLS or by GLS and are estimates based on maximizing a marginal likelihood. REML estimates take into account the degrees of freedom used in estimating the fixed effects when estimating the covariance components. REML estimates of G and R are found by maximizing the following log-likelihood

$$l_{REML}(G, R) = -\frac{1}{2}\log|V| - \frac{1}{2}\log\left|A^T V^{-1} A\right| - \frac{(N-p)}{2}\log r^T V^{-1} r - \frac{(N-p)}{2}\left[1 + \log\frac{2\pi}{(N-p)}\right] \quad (10)$$

Where;

$r = Y - A(A^T V^{-1} A)^T A^T V^{-1} Y$and p = rank(A)

HLM generates REML estimates by default and uses the EM algorithm to maximize (10).

EstimatingRandom Effects (μ)

Random effects are estimated using shrinkage estimators. The estimates of random effects are generated according to the following:

$$\hat{\mu} = \hat{G} X^T \widehat{V^{-1}} (Y - A\hat{Y})$$

It is generally of interest to estimate the individual random coefficients. These can simply be obtained by substitution.

Study Area

This research project makes use of the panel data set of crime rate for the eight provinces of Kenya for the period 1990-2010. Crime rate, the response variable is defined as the number of offences per 100,000 populations. The crimes considered are against person and against property.

Data Collection

The data was obtained from annual Statistical abstract and reports from KNBS, Kenya Police annual report and the World Bank Reports. Since crime is influenced by a number of factors, or variables, we determine these variables and give a brief description of the variables.

Variables used in the analysis

The Dependent variable is the crime rate of each province expressed in number of crimes per 100,000 citizens. The definition and expected signs of each individual independent variable used in the analysis is given in Table 1.

Table 1: Independent variables included in Equation 1 with their definitions and expected signs of their coefficients.

Independent Variable	Definition	Expected Sign of Coefficients
Population Density	which is the province population divided by county land area	Positive
Unemployment Rate	Unemployment rate per province	Positive
Education	Percent of people over the age of 25 with a college education	Negative
Young men	the percentage of the province's population that is male and between the ages of 15 and 29	Positive
Probability of conviction	which is measured by the ratio of convictions to arrests	Negative
Clear-up	The number of crimes cleared by police to the total number of crimes reported	Negative
Police	the number of police per capita as a measure of the county's ability to detect crime (Police	Negative
Probability of arrest	which is measured by the ratio of arrests to offences	Negative
Poverty	Percentage of people below the poverty line	Positive

The variable population density measures how dense the population of a given province is. Population density is measured on a population per square mile basis. This variable is included to capture the effect of the degree of urbanization on the crime rate. As Machin and Meghir discussed, theoretically there is more crime in urban areas which would make this variable to have a positive effect on the

The variable, unemployment rate, measures the unemployment rate in a province. This is a measure of economic incentives relating to crime. When unemployment is high, the opportunity cost of committing crime is much lower because people do not have jobs to provide them with income. Allison (1972) includes the unemployment rate among the male labor force between the age of 15 to 24 in his model and finds the coefficient on this variable to have a positive and significant effect on crime rate. Machin and Meghir (2004) also argue for the inclusion of unemployment rate among the set of independent variables.

Education is the percentage of people over the age of 25 that have at least a college education. The theory behind the inclusion of this variable is that when people are less educated are more likely to commit crimes. The reason is that more educated individuals have higher levels of income resulting in a higher marginal cost of committing crime. Allison (1972) includes the average number of years of education for males over the age of 25 in his model and finds the coefficient of this variable to have a negative and significant effect on crime rate.

The variable, Young men is included because young men are said to be more prone to engage in criminal activities than the rest of the population, this means that the participation to crime is higher at the initial stage of adulthood. (Freeman, 1991; Grogger, 1998).

The variable Poverty measures the percentage of the population below the poverty line. This variable is included to capture the effect of income distribution on crime rate. Merlo (2003) discusses the idea of income distribution being an important factor when talking about the crime rate in a particular state. The more people impoverished the more crime there should be in a particular state. This is because people that are impoverished have much less to lose from committing crime and more to gain.

Results and Discussions

Our data was analyzed using stata version 13 to analyze the factors that influence crime rate in Kenya. HLM regression was used to estimate the parameters and then interpretation was made. Crime rate was disaggregated into crime against person and crime against property.

The model and its Interpretation

Table 1.HLM coefficients of fixed effects for crime against person

Crime Rate	Coef.	Std.Err.	Z	P>|Z|	[95% Confidence Interval]	
					Lower	Upper
Intercept	10.11775	14.21819	0.71	0.004*	17.98489	37.7494
Poverty rate	0.95542	0.17758	5.38	0.000*	0.6073664	1.303476
Unemployment Rate	0.526087	0.1087708	4.84	0.000*	0.3129002	0.739274
School enrolment	-0.302063	0.1647508	1.83	0.067	-0.0208426	0.6249686
Young men(15-29 years)	0.239432	0.1473421	1.62	0.006*	0.05045783	0.5288657
Conviction Rate	-0.277573	0.1178335	1.86	0.018*	-0.0466233	0.508522
Clear-Up Rate	-0.870728	0.4126044	-2.11	0.035*	-1.679418	-0.062038
Probability of arrest	-2.653541	1.1685032	-1.27	0.023*	-4.943764	-0.363129
Population Density	0.0413675	0.1283256	1.22	0.001*	0.0162306	0.0664576

Interpreting the variables for crime against person

From table 1 above for estimation of fixed effects, the parameter estimates for the variables Poverty Rate (0.95542), Unemployment rate (0.526), Young men (15-29) years(0.2394), Conviction Rate(-0.278), clear-up rate (-0.87) Probability of arrest (-2.65), and population Density (0.0414) are all significant at 95% confidence Interval in accounting for increase in Crime Rate against person with their expected signs. The variable school enrolment rate, with the expected sign in the coefficient (-0.302) was not significant in explaining the crime rate against person in the provinces.

Table 2: HLM estimates for variance components for crime against person

Random Effects Parameters	Estimate.	Std.Err.	[95% Confidence Interval]	
			Lower	Upper
Sd(_Cons)	3.253485	0.3660632	0.1067542	5.9962413
Sd(residual)	5.241192	0.4217241	4.5706615	6.0700878

From the table 2 above, the variance estimate at level 2, that is country; labeled sd (_cons) = 3.253485 and at level 1 , that is province; labeled sd (Residual) = 5.241192. These are standard deviations by default and must be squared in order to give the variances. We can only interpret these variances by calculating the Intra-class correlation coefficient (ICC), that is we can estimate what proportion of the unexplained variance is attributed to each level included.

The ICC is the proportion of variance in the outcome variable that is explained by the grouping structure of the hierarchical model. It is calculated as a ratio of group level error variance over the total error variance;

$$\rho = \frac{\sigma^2_{\mu_0}}{\sigma^2_{\mu_0} + \sigma^2_e}$$

Where $\sigma^2_{\mu_0}$is the variance of level 2 residual and σ^2_e is the variance of level 1 residuals.

From the results above the ICC is ;

$$\text{ICC} = \frac{3.253485^2}{3.253485^2 + 5.241192^2} = 0.2782$$

This means 27.82% of the total variance in crime rate is represented at the country level (i.e level 2). If the ICC were to be less than 0.1 then it indicates that we need not to consider the level in representing the variance of the outcome- there is no design effect. In this case we could go on to use OLS regression as usual.

Table 4: HLM coefficients of fixed effects for crime against property

Crime Rate	Coef.	Std.Err.	Z	P>|Z|	[95% Confidence Interval]	
					Lower	Upper
Intercept	56.71834	20.95356	2.71	0.000	15.65013	97.78656
Poverty rate	0.1269488	0.267851	0.47	0.003	-0.3980295	0.6519271
Unemployment Rate	0.4138228	0.166533	2.48	0.013	0.0874239	0.7402216
School enrolment	-0.817401	01252243	1.24	0.001	-0.3230138	1.3117891
Young men(15-29 years)	0.2274576	0.226324	1.00	0.316	0.216456	6.2695743
Conviction Rate	-0.125609	0.1799497	0.70	0.484	-0.2268339	0.4785558
Clear-Up Rate	-1.174315	0.6309484	-1.86	0.063	-2.410946	0.06232633
Probability of arrest	-4.322889	1.7880862	1.42	0.016	-4.183052	8.2747352
Population Density	0.1139867	0.1952754	0.28	0.000	0.2705476	4.9562314

From table 4 above for estimation of fixed effects, the parameter estimates for the variables Poverty Rate (0.127), Unemployment rate (0.0.414), School enrolment (-0.817), Probability of conviction (-0.126)),Probability of arrest (-4.32) and population Density (0.114) are all significant at 95% confidence Interval in accounting for increase in Crime Rate against property with their expected signs. The variables young men (15-29 years) with coefficient 0.227 and clear-up rate with coefficient -1.174were not significant in explaining the crime rate against property in the provinces although they had the expected sign in the coefficient.

Table 5: HLM estimates for variance components of crime against property

Random Effects Parameters	Estimate.	Std.Err.	[95% Confidence Interval]	
			Lower	Upper
Sd (_cons)	5.325168	0.4272981	1.68017587	7.206519
Sd (Residual)	7.407854	0.5185894	2.5328572	8.571946

From the table above, the variance estimate at level 2, that is country; labeled sd (_cons) = 5.325168 and at level 1 , that is province; labeled sd (Residual) = 7.407854. These are standard deviations by default and must be squared in order to give the variances.

The ICC is the proportion of variance in the outcome variable that is explained by the grouping structure of the hierarchical model. It is calculated as a ratio of group level error variance over the total error variance;

$$\rho = \frac{\sigma^2_{\mu_0}}{\sigma^2_{\mu_0} + \sigma^2_e}$$

Where $\sigma^2_{\mu_0}$ is the variance of level 2 residual and σ^2_e is the variance of level 1 residuals.

From the results above the ICC is ;

$$\text{ICC} = \frac{5.325168^2}{5.325168^2 + 7.407854^2} = 0.341$$

This means 34.1% of the total variance in crime rate is represented at the country level (i.e level 2). If the ICC were to be less than 0.1 then it indicates that we need not to consider the level in representing the variance of the outcome- there is no design effect. In this case we could go on to use OLS regression as usual.

Summary, Conclusions and Recommendations

Summary

The objectives of the research were met. we considered secondary panel data set of crime rate against person and property for the eight provinces in Kenya. The findings from the analysis will help the administrators and leaders in various levels understand the major factors influencing crime rates and help reduce crime in the country.

Conclusion

In this work, we estimate a crime equation using a panel dataset of provinces in Kenya for the period 1990 to 2010, employing the REML estimator. In this analysis, we use a provincial dataset; and explicitly consider factors that influence crime rates. Furthermore, instead of using the overall crime rate to measure the level of criminal activity, we separate the crime measure into property crimes and crimes against the person.

Recommendations

In light of the results of this study, we have various recommendations to prevent the upsurge of crime in Kenya. The recommendations may help the government in formulation of policies that can be appropriate in crime prevention and move away from tradition way of crime reduction to preventive way. Increase in conviction in the long run appear to deter crime, hence the sure way to sustain it is by strengthening of the judicial system in Kenya which ensures that persons committing crimes are convicted. Police should make more arrests whenever crime is committed so as to reduce crime levels in the locality. The community at large should also educate the youth and occupy them with work. For further studies, we recommend the use Hierarchical Linear Models to analyze crime determinants at even lower levels like Districts, locations and villages in order to better reduce crime at all levels effectively.

REFERENCES

1. Akom, B. a. (1990). On Efficient Estimation with Panel Data: An Empirical Comparison of Instrumental Variables Estimators . Journal of Applied Econometrics, Vol.,5, No. 4 , 401- 406.John Wiley and Sons.
2. Andreoni. (1991). Reasonable Doubt and Optimal magnitude of fines: should the punishment fit crime? RAND Journal of Economics, 22 (3), 385-395.
3. Baltagi and Akom. (1990). On Efficient Estimation with Panel Data: An Empirical Comparison of Instrumental Variables Estimators. Journal of Applied Econometrics, Vol.5,No.4 , 401-406.John Wiley & Sons.
4. Becker, G. (1968). Crime and Punishment: An Economic Approach. The Journal of Political Economy,76/2 , 169-217.
5. Becker, G. (1993). Noble Lecture: The economic way of looking at behaviour. Journal of political econmy 101 , 385-409.
6. Best, G. (2005). Statistical Modelling and Crime Prediction in Nigeria: An Analysis of Key Indicators in Crime Statistics. Jos Journal of Social Issues,Vol.1.No.1 .
7. C.Cornwell and N.Trumbul. (1994). Estimating the Economic Model of Crime with panel Data. The Review of Economics and Statistics,Vol.76.No.2(May,1994) , 360-366.
8. Cameron. (1968). The Economics of crime deterrence : A survey of theory and evidence. Kyklos 41 , 301-323.
9. Ehrlich. (1999). Crime,Punishement,and the Market for Offenses. The Journal of Economic Perspectives,Vol.10.1 , 43-67.
10. Ehrlich, I. (1973). Participation in Illegitimate Activities: A Theoretical and Empirical Investigation. The Journal of POlitical Economy,81/3 , 521-565.
11. Entorf and Spengler. (2002). Crime in Europe: Causes and Consequences. Springer.
12. Entorf, H. and Spengler, H. (2000). Socioeconomic and Demographic Factors of Crime in Germany: Evidence From The Panel Data of the German States. International Review of Law and Economics,20 , 75-106.
13. Hale, C. (1998). Crime and Business Cycle in Post-War Britain Revisited, British Revisited. British Journal of Criminology,38/4 , 681-698.
14. Levitt, S. (2001). Alternative Strategies for Identifying the Link Between nemployment and Crime. Journal of Quantitative Criminology,17/4 , 377-390.
15. Levitt, S. (1996). The Effect of Prison Population Size on Crime Rates: Evidence from Prison Overcrowding Litigation. The Quarterly JOurnal of Economics,111/2 , 319-351.
16. Marselli and Vannini. (1997). Estimating a Crime Equation in the Presence of Organized Crime:Evidence from Italy. International Review of Law and Economics 17 , 89-113.
17. Myers. (1983). Estimating the Economic Model of Crime: Employement versus Punishment Effects. Quaterly Journal of Economics , 157-175.
18. N.Trumbull, W. (1989). Estimation of the Economic Model of Crime Using Aggregate and Individual level Data. Southern Economic Journal,Vol.56.No.2 , 423-439.
19. Orsagh. (1979). Empirical Criminology: Interpreting Results Derived From Aggregate Data. Journal Of Research in Crime and Deliquency , 294-306.
20. Raphael, S. and Winter-Ebmer, R. (2001). Identifying the Effect of Unemployment on Crime. JOurnal of Law and Economics,XLIV , 259-283.
21. Saridakis, G. (2004). Violent Crime in the United States of America: A Time-Series Analysis between 1960-2000. European JOurnal Of Law and Economics,18/2 , 203-221.
22. Schafer. (1976). Fear of Crime and Criminal Victimizations: Gender-based Contrasts. Journal of Criminal Justice,Vol.34 , 285-301.
23. Shavell, K. a. (1999). Economic Analysis of Law. National Bureau of Economic Research , p. Working paper No.6960.
24. Witt, R., Clarke, A. and Fielding, N. (1999). Crime and Economic Activity: A Panel Data Approach. British Journal of Criminology , 391-400.
25. Witte, A. D. (1980). Estimating the Economics Model of Crime with Individual Data . The quarterly journal of economics, Vol. 94, No. 1. , 57-84.
26. Witte, A. D. (1980). Estimating the Economics Model of Crime with Individual Data. The Quarterly Journal of Economics, Vol.94,No.1.(Feb.,1980) , 57-84.
27. Wolpin, K. (1978). An Economic Analysis of Crime and Punishment in England and Wales,1847-1967. The Journal of Political Economy,86/5 , 815-840.