A Comprehensive Examination of Economic Crime in India

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Abstract:

Crime rates can rise for a number of causes. A portion of the population turns to illegal activities in order to support themselves when there is extreme inequality in the distribution of wealth and income, as well as unequal access to educational opportunities. The emergence and surge of economic crime in various Indian states could be explained by a number of macroeconomic variables, including per capita net state domestic product (which measures the states' economic health), the percentage of the population living below the poverty line (which measures the extent of poverty), the unemployment rate, and estimates of monthly per capita expenditure from the Lorenz ratio (which measures the degree of inequality). This research attempts to identify the elements that genuinely contribute to the incidence of economic crime in various Indian states throughout a range of time periods by conducting an empirical examination of these determinants. Findings suggest that the population living below the poverty line has a negative impact on the per capita incidence of economic crime in India, whereas the per capita net state domestic product has a large positive impact.

Keywords: *Economic crime, Poverty, Unemployment, Inequality.*

Introduction:

There is a strong link, according to a number of social scientists and economists, between the prevalence of crime and unemployment and poverty. It has frequently been observed that many people are compelled to look for work in the shadowy and illegal industries after failing to find employment and/or as a result of poor income levels.

An offense is defined as a criminal conduct or offense that is punishable by law and about which a police or magistrate complaint may be filed. Financial crime, or economic crime, is the term used to describe unlawful activities carried out by an individual or group of individuals with the intention of gaining a financial or professional benefit. Gaining money is the main motivation behind these kinds of crimes. Economic crime is seen to do significant harm to society. This is due to the fact that it not only has an impact on democratic institutions but also jeopardizes state treasure by reducing funding for the execution of public initiatives. Even when economic crime might not be violent in and of itself, it might have violent consequences.

Literature Review

The body of research on the relationship between crime and economic consequences is extensive. (Ehrlich, 1973: 521–565) looked at the relationship between crime and defense (collective law enforcement) and found that there was a direct link between income disparity and property crimes.

(Mauro, 1995: 681–712) discovered that political instability, bureaucracy, ineffective courts, and corruption hindered investment and growth.

(Goel and Nelson, 1998: 107–120) used both supply-side and demand-side incentives to study how the size of the government affects public official corruption. They have attempted to identify the kinds of government operations that might serve to discourage the misuse of public office, and they have calculated the correlation between the prevalence of corruption and the size of the federal government overall.

(Machin and Meghir, 2004: 958–979) examined how these financial incentives affect crime rates, concentrating on how wages at the bottom of the wage distribution fluctuate. Using data on police forces in England and Wales from 1975 to 1996, the authors discovered that a (relative) decline in low-wage workers' earnings correlates with an increase in crime rates. Empirical findings demonstrated a robust correlation between the low-wage labour sector and the crime rate.

The hypothesis examined in this paper — that is, that the implementation of an anti-money laundering policy deters potential criminals from engaging in illicit behaviour and so lowers the crime rate — was empirically explored by (Ferwerda, 2009: 903–929). International collaboration was the most significant policy action taken for lowering crime; other measures included the institutional framework, the function of legislation, and the private sector's law enforcement responsibilities.

(Liu and Lin, 2012: 163–186) examined the function of government auditing in reducing corruption using panel data from Chinese provinces between 1999 and 2008 and found a negative correlation between the post-audit rectification effort and the province's degree of corruption.

The research that we have previously evaluated primarily addressed the concerns surrounding the economic repercussions of corruption generally, and there is a great deal of room to investigate related issues in this field. There were none that we could find in the literature on economic crimes. By examining the factors that contribute to economic crime in general in India, this study closes this gap in the literature.

Data and Methodology

Data from India's National Crime Records Bureau (NCRB) is used in this study to examine various economic crimes committed by Indian states. The Reserve Bank of India's Handbook of Statistics on Indian States provides information on macroeconomic factors such as per capita net state domestic product, the percentage of the population living in poverty, and the unemployment rate. The Databook Planning Commission (2014) provides information on monthly per capita expenditure estimates based on the Lorenz ratio.

Here, we have tried to empirically examine the impact of ‘per capita net state domestic product at constant prices (in rupees)', 'population below poverty line (in %)' based on Mixed Reference Period consumption, 'rate of unemployment (per 1000)' based on Usual Status and 'Lorenz ratio estimates of monthly per capita expenditure' based on Mixed Reference Period on incidence of crime in case of 'economic crime'.

Due to paucity of data, period of our panel study is discrete, viz. 2004, 2009 and 2011. We have used annual data of 28 Indian states – Andhra Pradesh, Arunachal Pradesh, Assam, Bihar, Chhattisgarh, Goa, Gujarat, Haryana, Himachal Pradesh, Jammu & Kashmir, Jharkhand, Karnataka, Kerala, Madhya Pradesh, Maharashtra, Manipur, Meghalaya, Mizoram, Nagaland, Odisha, Punjab, Rajasthan, Sikkim, Tamil Nadu, Tripura, Uttar Pradesh, Uttarakhand and West Bengal, thereby amounting to 84 number of observations for these three points of time.

- **Economic Crime**

The variables that we have used in this section are described below:

ecocrime_pc → per capita incidence of economic crime

nsdp_pc → per capita net state domestic product at constant prices (in rupees)

pov → population below poverty line (in %)

unemp → rate of unemployment (per 1000)

lorenz → Lorenz ratio estimates of monthly per capita expenditure

Descriptive statistics are first obtained for each and every variable. The characteristics of the variables being studied are briefly summarized via descriptive statistics. They are employed to provide manageable quantitative descriptions. It would be difficult to understand what the data is revealing if we only presented our raw data, which is why descriptive statistics are crucial.

Panel regression is then performed. Enough observations are provided by panel data, which leads to increased sample variability, decreased collinearity, increased degrees of freedom, and more precise model parameter inference. Compared to a single cross-section or time series data, these models are more effective at capturing the complexity of human behaviour.

Models using panel data are more adept at capturing the heterogeneity present in every single unit. The panel data structure implies that the cross-sectional units — individuals, businesses, governments, or nations — are diverse. When these heterogeneous effects are present in empirical modeling, disregarding them produces biased and ineffective conclusions.

Cross-sectional models are not suitable for capturing behavioural dynamics since they are limited to determining the behaviour pattern at a specific time. Comparing changes in the behaviour of various economic agents is also impossible using time series data, which restricts itself to a single unit and offers information over a period of time. However, it becomes reasonably simple to assess the changes in the behavioural pattern using the data because panel data sets provide time series on each cross-sectional unit in a group.

In order to denote both individuals and time observations, panel data often refers to groups with the subscript i and time as the subscript t. For example, a panel data observation y_{it} is observed for all individuals $i = 1, 2, \ldots\ldots, N$ across all time periods $t = 1, 2, \ldots\ldots, T$.

Let us consider a simple linear model:

$$y_{it} = \alpha + \beta x_{it} + \epsilon_{it}$$

The representation above is a homogenous model:

- The constant, α, is the same across groups and time.
- The coefficient, β, is constant across groups and time.
- Any differences across groups enter the model only through the error term, ϵ_{it}.

$$y_{it} = \beta_0 + \beta_1 x_{it} + u_{it}$$

$$u_{it} = \mu_i + \epsilon_{it}$$

$$y_{it} = \beta_0 + \mu_i + \beta_1 x_{it} + \epsilon_{it}$$

The one-way random effect panel data model includes unobservable time-specific or individual-specific effects, which act like individual-specific stochastic error terms. It assumes that these effects are uncorrelated with the observed characteristics, x_{it}. It does not result in biased OLS estimates of coefficients but does lead to inefficient parameters and incorrect standard inference tools.

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The distinguishing feature of the random effect model is that μ_i does not have a true value but rather follows a random distribution with parameters that

The one-way fixed effect panel data model includes unobservable time-specific or individual-specific effects. These effects capture omitted variables. It assumes that individual-specific effects are correlated with the observed characteristics, x_{it}. Pooled Ordinary Least Squares (OLS) estimates for data generated by this process will be inconsistent.

we want to estimate. The random effect term, μ_i is uncorrelated with x_{it} and pooled OLS estimates of the model parameters will not be biased. It affects the covariance structure of the error component, implying that typical inference tools, such as the t-statistic, will not yield accurate results and pooled OLS estimates of the model parameters will be wasteful. Feasible Generalized Least Squares (FGLS) should be used to estimate the random effect model. The error structure — one that takes into consideration the error terms unique to each individual — can be added to the model by using FGLS.

Ultimately, following the execution of the panel data models with fixed effect and random effect, we turn our focus to the Hausman test to select the better model between the two. One way to refer to the Hausman test is as a model misspecification test. The Hausman test can assist us in selecting between the fixed effect model and the random effect model in panel data analysis. Random effect is the favoured model, according to the null hypothesis. The idea that the model is fixed effect is the alternative hypothesis. Essentially, the tests try to see if there is a correlation between the unique errors and the regressors in the model. The null hypothesis is that there is no correlation between the two.

Descriptive Statistics:

Table 1: Descriptive Statistics

Variable	*Mean*	*Standard Deviation*
ecocrime_pc	0.0000715	0.0000446
nsdp_pc	46028.48	36058.93
pov	25.71095	12.80943
unemp	80.52381	75.53767
lorenz	0.3111155	0.0584561

The results of the descriptive statistics for the variables under investigation are summarized in Table 1. One way to quantify variability is via the standard deviation. It is a measurement of the variation in values within a set of data.

During the sampling period, the average per capita incidence of economic crime (ecocrime_pc) in 28 Indian states is 0.0000715. In this case, the standard deviation is 0.0000446. During the sampling period, the average per capita net state domestic product at constant prices (nsdp_pc) for 28 Indian states is Rs. 46028.48, with a standard deviation of Rs. 36058.93. The states' economic situation is indicated by this variable.

Over the course of the sample period, the average percentage of people living below the poverty line (pov) in 28 Indian states is 25.71995%. Comparably, during the sampling period, the average percentage of people living over the poverty line in 28 Indian states is 74.28905 %. In this case, the standard deviation is 12.80943%. This variable shows the level of poverty among state residents. During the sampling period, the average rate of unemployment (unemp) for the states under consideration is 80.52381 per 1000. In this case, the standard deviation is 75.53767 per 1000. This variable shows the unemployment rate in each state for members of the labour force.

Over the course of the sample period, the average Lorenz ratio estimates of monthly per capita expenditure (lorenz) across 28 Indian states is 0.3111155. In this case, the standard deviation is 0.0584561. The degree of inequality between the Indian states is shown by this variable.

Results and Discussion

Once the nature of the variables of interest has been established, we attempt to estimate the model that focuses on economic crime, which is notationally represented as follows:

$$\boxed{ecocrime\_pc_{it} = \tau_0 + \varphi_i + \tau_1 nsdp\_pc_{it} + \tau_2 pov_{it} + \tau_3 unemp_{it} + \tau_4 lorenz_{it} + \omega_{it}}$$

τ_0, τ_1, τ_2, τ_3, τ_4: parameters to be estimated

ω_{it}: random white-noise error term, which is stochastic in nature

φ_i: unobserved heterogeneous factor

$ecocrime\_pc_{it}$: per capita incidence of economic crime

$nsdp\_pc_{it}$: per capita net state domestic product at constant prices (in rupees)

pov_{it}: population below poverty line (in %)

$unemp_{it}$: rate of unemployment (per 1000)

$lorenz_{it}$: Lorenz ratio estimates of monthly per capita expenditure

We can obtain a sense of how these parameters impact the dependent variable ($ecocrime\_pc_{it}$) by estimating the model mentioned above. We have first used a fixed effect panel model for this. Following is the regression outcome that the fixed effect model yielded:

Table 2: Regression Result of Fixed Effect Model for 'ecocrime_pc'

ecocrime_pc	*coefficient*	*t-statistic*	*p-value*
nsdp_pc	2.45e-10	2.82	0.007
Pov	-6.93e-07	-1.92	0.061
Unemp	-8.16e-09	-0.14	0.885
Lorenz	0.0000767	0.92	0.363
Constant	0.0000548	1.99	0.052

Here, the dependent variable is 'ecocrime_pc' and the independent variables are 'nsdp_pc', 'pov', 'unemp' and 'lorenz'. We want to estimate the impact of 'per capita net state domestic product at constant prices', 'population below poverty line', 'rate of unemployment' and 'Lorenz ratio estimates of monthly per capita expenditure' on 'per capita incidence of economic crime' in Indian states. Our null hypotheses are:

$\tau_0 = 0,\ \tau_1 = 0,\ \tau_2 = 0,$
$\tau_3 = 0, \tau_4 = 0;$

against the alternatives:

$\tau_0 \neq 0,\ \tau_1 \neq 0,\ \tau_2 \neq 0,$
$\tau_3 \neq 0, \tau_4 \neq 0.$

It is evident from the results (Table 2) that the probability value for "nsdp_pc" is less than 0.1 at the 10% level of significance, less than 0.05 at the 5% level of significance, and even less than 0.01 at the 1% level of significance. This suggests that the variable is statistically significant at all significance levels (1%, 5%, and 10%), leading to the acceptance of the alternative hypothesis and the rejection of the null hypothesis. Now that we are aware of the substantial correlation between "nsdp_pc" and "ecocrime_pc," we can turn our attention to the coefficient's value. Here, we observe that the two have a positive relationship. This indicates that in Indian states, the incidence of economic crime increases (declines) by 2.45e-10 units per capita for every unit of per capita net state domestic product that grows or falls.

Likewise, it is also evident that the probability value for "pov" is less than 0.1 at the 10% level of significance, less than 0.05 at the 5% level of significance, and larger than 0.01 at the 1% level of significance. At the 1% and 5% levels of significance, the variable is statistically inconsequential, but at the 10% level of significance, it is statistically significant. As a result, the alternative hypothesis is accepted at a 10% level and the null hypothesis is rejected. Now that we are aware of the substantial correlation between "pov" and "ecocrime_pc," we can turn our attention to the coefficient's value. Here, we observe that the two have a bad relationship. This suggests that in Indian states, the per capita incidence of economic crime rises or falls by 6.93e-07 units for every unit of population living below the poverty line.

Additionally, it is evident that the probability value for "unemp" is higher than 0.01 at the 1%, 0.05 at the 5%, and even higher than 0.1 at the 10% levels of significance. This suggests that the variable is statistically insignificant at all significance levels (1%, 5%, and 10%), leading to the acceptance of the null hypothesis and the rejection of the alternative hypothesis. This indicates that in Indian states, there is no discernible correlation between the rate of unemployment and the incidence of economic crime per capita.

Once more, the probability value for "lorenz" is larger than 0.01 at the 1%, 0.05 at the 5%, and even greater than 0.1 at the 10% significance levels. This suggests that the variable is statistically insignificant at all significance levels (1%, 5%, and 10%), leading to the acceptance of the null hypothesis and the rejection of the alternative hypothesis. This indicates that the estimates of monthly per capita expenditure obtained from the Lorenz ratio and the per capita incidence of economic crime in Indian states do not significantly correlate.

Ultimately, the constant term is statistically significant at the 5% and 10% levels of significance because the probability value is found to be less than or equal to 0.05 and less than 0.1, respectively, but statistically insignificant at the 1% level of significance because the probability value is greater than 0.01. As a result, at the 5% and 10% levels, the alternative hypothesis is accepted and the null hypothesis is rejected.

The random effect panel model was then conducted. The following is the regression outcome that the random effect model yielded:

Table 3: Regression Result of Random Effect Model for 'ecocrime_pc'

ecocrime_pc	*coefficient*	*z-statistic*	*p-value*
nsdp_pc	2.37e-10	2.88	0.004
Pov	-7.26e-07	-2.28	0.023
Unemp	-2.53e-08	-0.52	0.601
Lorenz	0.0001004	1.43	0.152
Constant	0.0000501	2.06	0.040

It is evident from the results (Table 3) that the probability value for "nsdp_pc" is less than 0.1 at the 10% level of significance, less than 0.05 at the 5% level of significance, and even less than 0.01 at the 1% level of significance. This suggests that the variable is statistically significant at all significance levels (1%, 5%, and 10%), leading to the acceptance of the alternative hypothesis and the rejection of the null hypothesis. Now that we are aware of the substantial correlation between "nsdp_pc" and "ecocrime_pc," we can turn our attention to the coefficient's value. Here, we observe that the two have a positive relationship. This indicates that in Indian states, the incidence of economic crime increases (declines) by 2.37e-10 units per capita for every unit of per capita net state domestic product that rises or falls. This shows that as states' economies have improved, people's disposable income has increased and they are willing to take risks and commit financial crimes to increase their earnings by a small amount.

At the 1% level of significance, the probability value for "pov" is also larger than 0.01, but it is less than 0.1 at the 10% level of significance and even less than

0.05 at the 5% level of significance. This indicates that while the variable is statistically significant at the 5% and 10% levels of significance, it is statistically insignificant at the 1% level. As a result, at both the 5% and 10% thresholds, the alternative hypothesis is accepted and the null hypothesis is rejected. Now that we are aware of the substantial correlation between "pov" and "ecocrime_pc," we can turn our attention to the coefficient's value. Here, we observe that the two have a bad relationship. This suggests that in Indian states, the per capita incidence of economic crime rises or falls by 7.26e-07 units for every unit of population living below the poverty line. This suggests that the haves rather than the have-nots in a state are essentially responsible for the per capita incidence of economic crime. Put another way, economic crime is essentially white-collar crime that is committed by the rich.

Additionally, it is evident that the probability value for "unemp" is higher than 0.01 at the 1%, 0.05 at the 5%, and even higher than 0.1 at the 10% levels of significance. This suggests that the variable is statistically insignificant at all significance levels (1%, 5%, and 10%), leading to the acceptance of the null hypothesis and the rejection of the alternative hypothesis. This indicates that in Indian states, there is no discernible correlation between the rate of unemployment and the incidence of economic crime per capita. Put another way, the per capita incidence of economic crime is unaffected by changes in the unemployment rates of the Indian states.

Once more, the probability value for "lorenz" is larger than 0.01 at the 1%, 0.05 at the 5%, and even greater than 0.1 at the 10% significance levels. This suggests that the variable is statistically insignificant at all significance levels (1%, 5%, and 10%), leading to the acceptance of the null hypothesis and the rejection of the alternative hypothesis. This indicates that the estimates of monthly per capita expenditure obtained from the Lorenz ratio and the per capita incidence of economic crime in Indian states do not significantly correlate. Stated differently, this suggests that the degree of disparity among the Indian states is not related to the prevalence of economic crime per capita.

Ultimately, the constant term is statistically significant at the 5% and 10% levels of significance since the probability value is less than 0.05 and 0.1, respectively, but statistically insignificant at the 1% level of significance because it is bigger than 0.01. As a result, at the 5% and 10% levels, the alternative hypothesis is accepted and the null hypothesis is rejected.

We have performed the Hausman test to determine which of the two fixed effect and random effect models is the most suited.

The probability value, as determined by the results, is 0.7715, which is higher than 0.01 at the 1% level of significance, greater than 0.05 at the 5% level of significance, and somewhat higher than 0.1 at the 10% level of significance. This indicates that it is not statistically significant at the 1%, 5%, or 10% levels. As a result, the alternative hypothesis is always rejected and the null hypothesis is always accepted. Thus, we can say that the random effect panel model is the proper model that might be considered fit in this particular situation. For empirical analysis, the results shown above (Table 3) have been taken into consideration.

Conclusion

Based on empirical evidence, it may be said that the incidence of economic crime increases (declines) by 2.37e-10 units per capita for every unit of per capita net state domestic product that rises or falls. Subsequently, the per capita incidence of economic crime rises (falls) by 7.26e-07 units for every unit of population below the poverty level. Furthermore, there is no discernible link between the per capita incidence of economic crime and the unemployment rate. Lastly, estimates of monthly per capita expenditure using the Lorenz ratio and the incidence of economic crime per capita do not significantly correlate.

In summary, we can say that the population living below the poverty line has a negative impact on the per capita incidence of economic crime in India, whereas the per capita net state domestic product has a large positive impact.

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