Original Research Article

Do Macroeconomic Variables Drive Crime Types? A Long-Term Evidence from India

# ABSTRACT

Variables used:Total Crime, IPC Crimes, Violent crimes, Property crime, Economic crime, Inflation, Unemployment, Per capita real GDP

Objectives: Economists have long believed that macroeconomic variables influence crime. We test this conjecture using nearly universal data on crimes in India between the years 1991 and 2018. Specifically, we investigate if crimes like Total, IPC, Violent, Property, and Economic Crimes have any long-term link with economic factors like inflation, Real Per capita GDP, and unemployment.

Methods: Data related to economic variables were obtained from World Bank data source and crimes-related data were obtained from NCRB. In order to find out long run relation, ARDL Model has been used.

Results: The data tell an intriguing story. First, crime is strongly and causally related to unemployment in cross-sectional data. However, unemployment has no influence on crime in time series data. Second, income inequality increases economic crimes but reduces violent crimes. Third, inflation increases property crimes but has no impact on other kinds of crimes. Fourth, economic growth increases economic crimes but does not have impact on other kinds of crimes.

Conclusion: Overall, macroeconomic variables like unemployment, inflation, and economic growth influence particularly kinds of crimes. Put differently, macroeconomic conditions appear to determine allocation of criminal activity among different kinds of crimes rather change the total quantity of criminal activity in society.

**Key Words:** Crime,unemployment, inflation and real per capita GDP

**Introduction**

“Despite the increasing incidence and complexity of crime, the concept of crime had fascinated largely by Indian psychologists and sociologists who understood the problem as mainly psycho-social phenomena with little relevance to other disciplines whatsoever” (Gupta, 2024). “Though this is the case in India, the study of crime as an economic problem had been taken up in the western academic world nearly a century back” (Abraham, 2012). This study is devoted for the time series analysis to determine the role of macroeconomic variables like unemployment, inflation and real per capita GDP on various crimes in India. Time series data has been taken for the period 1991-2018[[1]](#footnote-1) on the basis of availability of relevant data.

Figure 1

 *Source: NCRB data*

Most forms of crime were found to have increased significantly over the research period (Figure 1). Because of this reason it is critical to identify the numerous factors of crime. “Thus, this study investigates if crimes such as Total Crimes, IPC Crimes, Violent Crimes, Property Crimes, and Economic Crimes have a long-term association with economic factors such as inflation, Real Per capita GDP, and unemployment. The main intention behind selecting the crimes like Total Crimes, IPC Crimes, Violent Crimes, Property Crimes, and Economic Crimes is the fact that they represent almost all important crimes in India, and economic variables like inflation, Real Per capita GDP (which has been used as a proxy for economic growth and prosperity), and unemployment selected due to the availability of data” (Bansal et al., 2023). It is critical to identify the elements that lead to increased crime rates because this will help develop strategies to reduce it. The impact of many factors on crime rates varies by economy. Thus, understanding the factors that influence crime rates in a specific economy would allow policymakers to better effectively execute crime-reduction programs. Thus, the purpose of this article is to examine the impact of the aforementioned factors on crime rates in India.

Crime and criminal behaviour in India have been subject to significant variations due to the influence of potential underlying macroeconomic conditions. Despite this influence, there lacks sufficient literature dealing with the impact of key macroeconomic variables like inflation, unemployment, and per capita real GDP on crimes in India. Inflation, by reducing purchasing power and inducing economic stress, can contribute to property-related crimes (Fajnzylber et al., 2002). Unemployment may push individuals toward illegal activities by limiting legitimate income-earning opportunities (Raphael & Winter-Ember, 2001). While an increase in per capita real GDP signals economic growth, it does not guarantee equitable distribution of income. In fact, growth in developing countries like India may exacerbate inequality, which is a known driver of crime (Chiu & Madden, 1998). However, the influence of these macroeconomic variables on crimes in India—and the direction and magnitude of these relationships—remain underexplored, particularly in underdeveloped contexts where such effects are likely to be pronounced (Narayan & Smyth, 2004). This article attempts to address this research gap by investigating how inflation, unemployment, and per capita real GDP affect crimes in India, thereby providing evidence-based insights for policymakers to develop strategic interventions to prevent crime.

# DATA AND METHODOLOGY

Data related to economic variables is obtained from World Bank data source and crime related data was obtained from NCRB. In order to find out this long run relation, Auto Regressive Distributed Lag Model (ARDL Model) has been used. The ARDL co-integration approach is selected because the research deals with variables integrated in various orders, I(0), I(1), or a mix of the two. In the research, certain variables were stationary at the level (inflation), while others were stationary at the first difference. In this time series study, the researcher employed the ARDL model to determine the long- and short-run relationships between crimes and chosen economic factors such as inflation, unemployment, and per capita real GDP.

The basic form of an ARDL regression model is:

$y\_{t} = β\_{0} +β\_{1}y\_{t-1} + .......+ β\_{k}y\_{t-p}+α\_{0}x\_{t} +α\_{1}x\_{t-1} +α\_{2}x\_{t-2} + ....... + α\_{q}x\_{t-q} + ε\_{t}$
 (1)

where εt is a random "disturbance" term, which is assumed to be white noise.

In this study, the ARDL model is specified as follows:

$Δy\_{t} =β\_{0} +Σ β\_{i}Δy\_{t-i} +Σγ\_{j}Δx\_{1t-j} +Σδ\_{k}Δx\_{2t-k} +Σω\_{m}Δx\_{3t-m}+ θ\_{0}y\_{t-1} + θ\_{1}x\_{1t-1} +θ\_{2} x\_{2t-1} +θ\_{3} x\_{3t-1}+ e\_{t}$ (2)

Akaike Information Criterion (AIC) has been used to determine the appropriate lags. To identify and correct for autocorrelation Breusch-Godfrey Serial Correlation LM Test has been used. Bounds Test has been performed to see if there is any evidence of a long-run relationship between the variables. An F-test of the hypothesis (H0:  θ0= θ1 = θ2 = θ3= 0) is conducted against the alternative that H0 is not true. This tests for the absence of a long-run equilibrium relationship, which corresponds to zero coefficients for yt-1, x1t-1, x2t-1 and x3t-1 in equation (2). Rejection of H0 implies a long-run relationship. Pesaran et al. (2001) provide bounds on the critical values for the F-statistic, with lower bounds assuming all variables are I(0) and upper bounds assuming all are I(1). If the F-statistic falls below the lower bound, the variables are I(0) and no cointegration is possible (Pesaran et al., 2001). If it exceeds the upper bound, cointegration is confirmed. If it falls between the bounds, the test is inconclusive.

Assuming cointegration is confirmed, estimate the long-run equilibrium relationship

yt = α0 + α1x1t + α2x2t + α3x3t + vt  (3)yt​=α0​+α1​x1t​+α2​x2t​+α3​x3t​+vt​(3)

and the ARDL model:

Δyt = β0 + Σ βiΔyt-i + ΣγjΔx1t-j + ΣδkΔx2t-k + Σ$ω\_{m}$Δx3t-k + φzt-1 + et (4)

where zt-1 = (yt-1 -a0 - a1x1t-1 - a2x2t-1), and the a's are the OLS estimates of the α's in (3)

ARDL Cointegrating and Long-Run Form Test has been conducted to assess the significance of individual coefficients in the long run.

We can "extract" long-run effects from the ARDL. Looking back at equation (2), and noting that at a long-run equilibrium,  Δyt = 0, Δx1t= Δx2t= Δx3t= 0, we see that the long-run coefficients for x1, x2 and x3 are -(θ1/ θ0), -(θ2/ θ0) and -(θ3/ θ0) respectively.

**Results and Discussion**

# STATIONARITY TEST

Stationarity test was used to determine whether the time series is stationary. This ensures model validity, reliable forecasting, drawing reliable statistical inference and avoiding spurious regression. The ADF Unit root test has been used to check the presence of unit root. The functional form of ADF is that;

$$∆y\_{t}=β\_{1}+δy\_{t-1}+\sum\_{i=1}^{m}γ\_{i}Δy\_{t-i}+u\_{t}$$

The hypothesis (H0:$δ=0$) has been tested against the alternative hypothesis (H1: $δ\ne 0$). This test is conducted to check for the presence of a unit root. By rejecting the null hypothesis, we can confirm that none of the variables are integrated of order 2 (I(2)), which would otherwise invalidate the methodology. Consequently, this implies that the series is stationary.

The results obtained were summarized in Table 1.

Table 1 List of variables for ADF and first difference

|  |  |  |
| --- | --- | --- |
| Variables | Level | First Difference |
|  |  | ADF | P value | ADF | P value |
| i | Total Crime | -2.681441 | 0.0902 | -5.756089\*\* | 0.0001 |
| ii | IPC Crimes | 2.644075 | 1.0000 | -3.234222\* | 0.0293 |
| iii | Violent crimes | -0.395511 | 0.8965 | -5.265426\*\* | 0.0002 |
| iv | Property crime | 0.876364 | 0.9935 | -4.672714\*\* | 0.0010 |
| v | Economic crime | 0.935525 | 0.9943 | -3.542579\* | 0.0151 |
| vi | Inflation | 3.026497\*\* | 0.0450 | -6.789861\*\* | 0.0000 |
| vii | Unemployment | -2.626706 | 0.1006 | -3.158142\* | 0.0345 |
| viii | Per capita real GDP | 1.881512 | 0.9996 | -4.234213\*\* | 0.0029 |

Note: \*\* and \* denote statistical significance at 1percent and 5 percent level respectively.

*Source: Researcher Calculation from World Bank and NCRB data*

It can be observed that all variables except inflation were non-stationary at level. However, the variables included in the first difference were stationary. After determining that inflation was stationary at I(0) and other variables were stationary at I(1), the ARDL model was utilized.

# UNEMPLOYMENT

According to economic theories of crime, when unemployment rates rise, so do crime rates (Ehrlich, 1973; Levitt, 1996). While official crime statistics from many countries show that unemployed people have high crime rates and that communities with a high unemployment rate experience a high level of crime, this cross-sectional relationship is rarely found in time-series studies of unemployment and crime (Kapuscinski et al., 1998; Wilson & Herrnstein, 1985). ARDL Co-integrating and Long Run Form Results Related to Unemployment were depicted in Table 2.

Table 2 ARDL Co-integrating and Long Run Form Results Related to Unemployment

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Models | Variable | Coefficient | t-Statistic | Prob. |
| Total crimes | Unemployment  | 3574353.525275 | 2.033301 | 0.0977 |
| IPC crimes | Unemployment | -92508.910026 | -0.440179 | 0.6683 |
| Property crimes | Unemployment | 346460.721029 | 1.444938 | 0.2220 |
| Economic crimes | Unemployment | -39737.038129 | -1.039594 | 0.3572 |
| Violent crimes | Unemployment | -406819.941017 | -0.684157 | 0.5194 |

*Source: Researcher Calculation from World Bank and NCRB data*

ARDL model findings reveal that unemployment has no statistically significant link with total crimes, IPC crimes, property crimes, economic crimes, or violent crimes, despite the fact that the models are statistically significant. The association between crime and unemployment is visible in cross-sectional data, but not in time series data. This is due to unemployment's cyclical nature, which has a short-term impact. The collected findings support this.

# INFLATION

This study clearly shows that there is a causal relationship between inflation and criminal activity. This is mostly because an increase in the general price level reduces people's real income. When real income falls, people's purchasing power suffers, particularly those in the lowest income stratum. This condition leads them to seek an additional source of income. Crime is the most convenient way for them to earn money to fulfill their fundamental necessities. Teles, Tang and Lean, and Gillani have all conducted empirical research that support this claim (GILLANI et al., 2009; Tang & and Lean, 2007; Teles & Shieh, 2004).ARDL Co-integrating and Long Run Form Results Related to Inflation were presented in Table 3.

Table 3 ARDL Co-integrating and Long Run Form Results Related to Inflation

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Models | Variable | Coefficient | t-Statistic | Prob. |
| Total crimes | Inflation | 123579.903877 | 3.116861 | 0.0263 |
| IPC crimes | Inflation | 14871.322472 | 2.433001 | 0.0332 |
| Property crimes | Inflation | 13955.192348 | 2.565238 | 0.0623 |
| Economic crimes | Inflation | -1739.058321 | -1.854528 | 0.1373 |
| Violent crimes | Inflation | -69293.919640 | -1.753782 | 0.1300 |

*Source: Researcher Calculation from World Bank and NCRB data*

The ARDL test findings suggest that there is a long-run equilibrium link between crime and inflation in India. The model discovered that inflation has a long-term equilibrium connection with total crimes, IPC crimes, and property crimes. The inflation co-efficient and sign indicate that inflation has a positive influence on overall crimes, IPC offenses, and property crimes in India. It shows that when inflation rises, so do overall crimes, IPC offenses, and property crimes in India. It has also been discovered that inflation has no meaningful association with violent crimes. In general, violent crimes are motivated by spontaneous provocation, disagreements, and political rivalry, rather than economic motives.

# PER CAPITA REAL GDP

When per capita real GDP grows, it indicates that the country's economy is growing. It never implies that the extra revenue is divided in a fair manner. Growth always helps the wealthy portions of society, and this type of growth is known as ruthless growth (Todaro & Smith, 2020). This type of circumstance is commonly known as inequity. The trickledown impact of economic expansion is gradual in many developing nations, including India. Chancel and Piketty convincingly demonstrate this development in wealth disparity in their working paper "Indian income inequality, 1922-2014," which is headlined "From British Raj to Billionaire Raj?". Increased inequality leads to a rise in crime rates (Chancel & Piketty, 2019). There is a wealth of research in the field of crime that suggests that economic disparity and deprivation are positively associated to crime (Blau & Blau, 1982; MESSNER, 1982, 1983; Williams, 1984). Income disparity has a considerable favorable influence on property and economic crime rates, but a negative impact on violent crime (Hooghe et al., 2011). This is also true in India, and the results of the ARDL model support this. ARDL Co-integrating and Long Run Form Results Related to Per Capita Real GDP were presented in Table 4.

Table 4 ARDL Co-integrating and Long Run Form Results Related to Per Capita Real GDP

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Models | Variable | Coefficient | t-Statistic | Prob. |
| Total crimes | Per capita real GDP | -252.019646 | -1.790531 | 0.1334 |
| IPC crimes | Per capita real GDP | 1217.508587 | 31.104920 | 0.0000 |
| Property crimes | Per capita real GDP | 191.747889 | 5.006875 | 0.0075 |
| Economic crimes | Per capita real GDP | 68.763682 | 15.158285 | 0.0001 |
| Violent crimes | Per capita real GDP | -243.724292 | -1.733712 | 0.1337 |

*Source: Researcher Calculation from World Bank and NCRB data*

The t statistics and p values for per capita real GDP show a long-term statistically significant link with IPC crimes, property crime, and economic crime. The positive sign of the per capita real GDP co-efficient indicates a favorable influence of per capita real GDP on IPC, property, and economic crimes. Per capita real GDP has no meaningful link with violent crime since violent crimes are not influenced by economic considerations. IPC crimes, economic crimes, and property crimes are all affected by economic conditions.

# CONCLUSION

In this empirical study, we examined long-term time series data to determine the long-term relationships between different types of crimes, including total crimes, IPC crimes, violent crimes, property crimes, and economic crimes. We also looked at the long-term relationships between these crimes and economic variables, such as unemployment, real per capita GDP, and inflation in India. According to this investigation, economic circumstances play a significant role in shaping criminal behaviour. The ARDL model introduced the noteworthy long-term link between economic factors and criminal activity.

First, the cross-sectional data show a substantial and causal relationship between unemployment and crime. However, the time series data show that unemployment has little effect on crime. Targeted job creation and skill development programmes, focussing on youth and marginalized communities could be helpful for reducing the immediate economic pressures leading to criminal behaviour. Government initiating such a drive along with evaluation of the effectives of these actions over time can to a large extent calm down unemployment-caused crimes in the country.

Second, while violent crimes decline, economic crimes rise as a result of wealth inequality. Emerging of wealth inequality induced economic crimes signals the need to address disparities in income and opportunities. Policy measures intended towards this cause like progressive taxation, wealth redistribution policies, social welfare programmes, and strengthening of education, healthcare, and economic opportunities in underserved areas were required to mitigate the conditions that drive economic crimes.

Third, while it has no effect on other types of crimes, inflation raises property crimes. This alerts the mechanism to effectively tackle the inflation problem. Strengthening monetary policy can be one of the solutions. But monetary policy has to be certainly complemented by social safety nets, such as subsidies for people living in lower strata of income, and controlled price for necessary items was inevitable to reach desirable results.

Hence the findings of the study partially align with the hypothesis that macroeconomic variables like inflation, unemployment and per capita real GDP have impact on crime and criminal behaviour in India. But we can find complexities in these relationships which are not fully anticipated. Unemployment, reflecting its cyclical nature, exhibit lack of a significant link, refuting the hypothesis. Positive long-run alignment of inflation with total, IPC, and property crimes supports the hypothesis, but we cannot find inflation having any link with violent crimes, highlighting crime type specificity. Per capita real GDP is found to be positively linked with IPC, property, and economic crimes, but contradicts with the anticipated crime-reducing effect, suggesting opportunity-driven crime.

Macroeconomic factors that affect specific types of crimes include unemployment, inflation, and economic growth. Stated differently, macroeconomic factors seem to influence how criminal activity is distributed across various types of crimes rather than altering the overall amount of criminal activity in society. This necessitates specific interventions for violent crime, property crime and economic crime rather than general policies to curb overall crimes. Community-based programmes promoting social cohesion and resolving conflicts could be adopted for reducing violent crimes. Strengthening neighbourhood watch programmes and improving urban planning can enhance security, leading to a decline in property crimes. The economic crimes can be tackled to a large extend by investing in cybercrime units and financial crime investigation capabilities to address modern challenges. Thus, crime-specific strategies have to be developed for effectively tackling the problems related to crime and criminal behaviour along with controlling macroeconomic variables which crucially influence the motive behind committing crimes.

Ethical Approval:

As per international standards or university standards written ethical approval has been collected and preserved by the author(s).

Disclaimer (Artificial intelligence)

Option 1:

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc.) and text-to-image generators have been used during the writing or editing of this manuscript.

Option 2:

Author(s) hereby declare that generative AI technologies such as Large Language Models, etc. have been used during the writing or editing of manuscripts. This explanation will include the name, version, model, and source of the generative AI technology and as well as all input prompts provided to the generative AI technology

Details of the AI usage are given below:

1. ChatGPT version 4.o has been used for language correction in some areas. The input prompt used is “correct and improve language”.

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**Appendix**

Table 5 Time series data taken for the period 1991-2018

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  |  |  |  |  |  |
| Year | **Total Crime**  | **IPC Crimes** | **Property Crime** | **Economic Crimes** | **Violent Crime** |
| 1991 | 5052550 | 1678375 | 495015 | 49428 | 246252 |
| 1992 | 5252000 | 1689341 | 477863 | 52455 | 251952 |
| 1993 | 5433574 | 1629936 | 443454 | 50846 | 232554 |
| 1994 | 5512254 | 1635251 | 425100 | 50581 | 235228 |
| 1995 | 5993172 | 1695696 | 410813 | 48384 | 249087 |
| 1996 | 6296562 | 1709576 | 400082 | 51987 | 242900 |
| 1997 | 6411259 | 1719820 | 390396 | 52533 | 249200 |
| 1998 | 6180996 | 1778815 | 407227 | 52781 | 255128 |
| 1999 | 49,11,730 | 1764629 | 383203 | 58204 | 238081 |
| 2000 | 51,67,750 | 1771084 | 393235 | 60211 | 238381 |
| 2001 | 53,44,538 | 1769308 | 381654 | 61208 | 230930 |
| 2002 | 55,26,528 | 1780330 | 3,70,629 | 61820 | 221810 |
| 2003 | 54,94,814 | 1716120 | 3,63,181 | 62965 | 1,96,550 |
| 2004 | 60,28,781 | 1832015 | 3,91,644 | 67644 | 2,08,736 |
| 2005 | 50,26,337 | 1822602 | 3,88,867 | 69580 | 2,02,640 |
| 2006 | 51,02,460 | 1878293 | 392352 | 73881 | 205656 |
| 2007 | 57,33,407 | 1989673 | 376261 | 83061 | 215613 |
| 2008 | 59,38,104 | 2093379 | 410503 | 86057 | 228663 |
| 2009 | 66,75,217 | 2121345 | 416265 | 91979 | 230500 |
| 2010 | 67,50,748 | 2224831 | 420491 | 98266 | 241986 |
| 2011 | 62,52,729 | 2325575 | 433304 | 107420 | 256329 |
| 2012 | 60,41,559 | 2387188 | 430299 | 114455 | 275165 |
| 2013 | 66,40,378 | 2647722 | 516648 | 129306 | 300357 |
| 2014 | 45,71,663 | 2851563 | 600861 | 1,42,560 | 330754 |
| 2015 | 47,10,676 | 2949400 | 625279 | 1,50,170 | 335901 |
| 2016 | 48,31,515 | 2975711 | 675225 | 1,43,524 | 429299 |
| 2017 | 50,07,044 | 3062579 | 775263 | 1,27,430 | 426825 |
| 2018 | 50,74,634 | 3132955 | 8,02,372 | 1,34,546 | 428134 |

 *Source: NCRB data*

1. The COVID-19 pandemic significantly influenced crime rates in India from 2019 to 2022, leading to abnormally low crime levels. As using data from this period may result in misleading conclusions, our study focuses on the long-term impact of macroeconomic variables on crime, excluding data after 2018. [↑](#footnote-ref-1)