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Posted Date: 17 March 2026

doi: 10.20944/preprints202603.1227.v1

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Article

Spatiotemporal Impact of Education and Employment on Crimes at Sub-State Level: A Case Study of West Bengal Districts

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Abstract

Does Geographic Economy matter in forestalling Crimes? This study tried to answer this question by analyzing the spatial impact of education and employment on violence within the state of West Bengal. This research aims to create a Crime Severity Index to compare with the Crime Rate for the districts of West Bengal. To make the index more justified, the weights are generated based on the individual crime's respective imprisonment years and the likelihood of that incident. To identify the determinants of crime at a micro-level we considered a panel data structure of 19 cross-sections for 5 time points (from 2000 to 2020). The rank correlation coefficient among different crimes indicates the pattern of crimes has changed over time. A high & positive Moran's I score suggests that crime rates and the degree of violence are closely linked across different locations, especially at the border regions within the state. The spatial panel analysis outcome shows that factors like higher education among females, stable job placements, and unit of police stations have a substantial influence on regional crimes as well as the severity level over space.

Keywords: crime rate; Crime Severity Index; education & employment; LSDV; Moran's I; spatial panel regression; West Bengal

JEL Codes: K42; J21; C23; C21; C33

Background and Motivation of the Study

The negative economic externality utters that an individual's action or behaviour has a detrimental influence on those who are not directly engaged in the happening. And a crime comes under the radar of such a negative externality. It's important to comprehend crime rates in emerging nations like India for several reasons. Excessive crime rates can impede economic development, and raise expenses for the legal system, healthcare, and law enforcement. India's history of crime is complicated, shaped by cultural variety, socioeconomic disparities, and colonial domination. The Indian Penal Code was created in 1860 as part of the legal structure designed to systematically combat crime during British rule. India continues to tackle crime after gaining independence by implementing many laws and reforms to keep up with societal shifts. Because underprivileged populations are frequently more impacted by violence and insecurity, crime also propagates negative societal externalities worse by restricting access to necessary resources and services. Understanding crime rates enables policymakers to address the underlying socioeconomic causes that contribute to crime, create focused interventions, enhance public safety, and promote sustainable development.

In recent decades academic researchers from the various fields of law & management, sociology, and economics (Stickle & Felson, 2020) (Rudolph & Starke, 2020) (Hazra, 2019) (Aboya, et. al, 2022) (Ohlan, 2020) have shown interest in how crime rates could be tackled through social developments. Iniquities are complicated societal issues, and it is very important to understand their negative impact on social welfare. The contribution of the Government of India (GoI) in the implementation of several

initiatives like NCRB¹, CCTNS², modernization of police forces, Inter-Operable Criminal Justice System³ (ICJS), Skill Development and Employment Generation schemes (PMKVY, MGNREGA) that prevent the overall crime rate in India. According to the National Crime Records Bureau (NCRB) report 2022, crime against women and children has increased by 7.9% and 9.4% respectively from the previous year. The report mentioned the property crime rate including theft, robbery, and burglary shares almost 30% of all IPC crimes in India. Violent crimes like murder and kidnapping have shown a slight decline (0.8%) in 2022. NCRB's report also highlighted some key factors such as the unemployment rate, social inequalities, and urban population growth which influence the crime rate in India. Horrible kidnappings, sexual assaults, and killings of women and children were exposed by a string of murders and disappearances in Nithari, Noida (2006). Stronger regulations against sexual offenses resulted after the Nithari killings, which also prompted worries about police carelessness and child protection. In Mumbai (2008), a series of coordinated terror attacks, which resulted in 166 fatalities and hundreds of injuries, struck multiple locations. The attackers targeted famous buildings such as the Oberoi Hotel, the CST Railway Station, and the Taj Palace Hotel. Due to the attack's revelation of weaknesses in India's law enforcement and intelligence networks, security measures were strengthened and counterterrorism efforts were expanded. A savage gang rape and attack on a bus in Delhi killed a young lady called 'Nirbhaya (viz. fearless)', sparking widespread demonstrations and highlighting gender-based violence. The tragedy shocked the nation's conscience and prompted calls for justice for rape survivors. The outrage prompted changes in India's sexual assault legislation, including harsher fines and the formation of fast-track tribunals for such cases. The financial crime involves jewelry magnate Nirav Modi and Mehul Choksi (2018), who used forged Letters of Undertaking (LoUs) issued by PNB staff to get loans from other banks. The ₹11,000 crore scandal resulted in revisions to Indian banks' policies for granting Letters of Undertaking (LoUs) and Letters of Credit. The issue has prompted a review of India's banking sector supervision measures. Another infamous financial violence in India shocked the world in 2016 when the business tycoon Vijay Mallya, founder of Kingfisher Airlines, defaulted on loans of over ₹9,000 crore borrowed from multiple Indian banks. Despite repeated notices, Mallya left the country, leading to a legal pursuit by Indian authorities. Some unsolved million-dollar burglary cases such as 'The Great Train Robbery (2008)', 'The Sardar Patel Museum Heist (2012)', and 'Delhi Jewellery Store Heist (2016)' raised the question of the increasing violence level in India.

In our study, we selected West Bengal state as our area of research for its distinct and complex socio-economic, cultural, and geographical profile than the other Indian states. The state combines a diverse landscape of urban and rural areas with sharp contrasts in income, education, and infrastructure, providing a valuable setting to examine how these factors impact crime and economic disparities. The high population density in some districts creates social pressures that may amplify economic stress and crime rates, while its strategic border location with Bangladesh (the world's fifth-longest land border, stretching 2,217 km with Bangladesh) introduces additional challenges, such as cross-border access and migration issues affecting the economic stability. West Bengal's political history marked by prolonged leftist governance followed by rapid change also shapes its crime scenario and economic policies, offering a unique political-economic context. Further, the state's longstanding labor movements, significant economic disparities, and high unemployment in certain sectors allow for an

¹ NCRB stands for the National Crime Records Bureau, established in the year 1986. The NCRB obtains and publishes the most comprehensive database on yearly criminal activity trends in Indian states and districts.

² CCTNS or the Crime and Criminal Tracking Network & Systems (2009) is established to enhance the effectiveness of police services through e-Governance.

³ The Inter-operable Criminal Justice System (ICJS) is an initiative of the e-Committee to enable seamless transfer of data and information among different pillars of the criminal justice system, like courts, police, jails and forensic science laboratories, from one platform (Source: e-Committee, Supreme Court of India).

in-depth investigation of the links between economic stress and crime. Its rich cultural diversity, blending backward class populations, tribal, and migrant communities, influences social dynamics and potentially affects crime patterns in ways distinct from other states. However, West Bengal state has no exception in reporting different types of violence compared to the other regions in India. In West Bengal, the overall crime rate per one lakh population in 2022 accounted for 266.6 (the national average is 486.5). Crime against women is even higher (66.7 per one lakh women) in West Bengal compared to the national average (64.5 per one lakh women). Crimes against children and property-related iniquities have also shown an increasing trend in West Bengal. Evidence from a few infamous real-life criminal activities since 2000, West Bengal has witnessed several high-profile crimes reflecting diverse social, political, and security challenges. Notable incidents include brutal assaults like the Park Street Rape Case (2012), the Kamduni rape and murder case (2013), and the current year's gruesome rape and murder case of a doctor ('Tilottama' case, 2024) at the R. G. Kar Hospital, Kolkata stirred the entire world for its brutality, these and many more cases underscored the issues with women's safety. Communal violence in Malda (2016) and Basirhat (2017) exposed vulnerabilities related to religious tensions and social media's role in inciting unrest. Political rivalries fueled violence in Parui (Birbhum, 2015), while the prolonged Gorkhaland agitation in Darjeeling (2017) intensified demands for regional autonomy. The Sharada Chit Fund scam in 2013 duped thousands of investors, and the recent political scam of teacher recruitment (2022) revealed deep-rooted corruption in the state. The Ranaghat convent attack (2015) and Burdwan (2014) blast highlighted security threats, with cross-border implications. Together, these incidents underscore ongoing challenges in law enforcement, public trust, and political stability in the state. In addition to the above crime cases, we might keep note of some contexts about the state of West Bengal. The overall literacy rate in West Bengal was 77.08% (the national average is 77.7%) in 2022, which includes the literacy rate among males at 82.6% and for females at 71.1% (India's average male literacy rate is slightly higher at 84.7%). According to the GlobalDataLab records, the mean years of education in West Bengal (6.83 years) was lower than the national average (7.38 years) in 2022. The urbanization rate is marked higher (32.4%) than the country's average (30.0%) in the same year. It should be noted that the percentage of households tagged as poor (according to the International Wealth Index value under 70) was much higher in West Bengal (69.2%) compared to the national value of 50.3%. The Gini coefficient of Wealth Inequality was also found to be slightly up in West Bengal in 2022. According to the PLFS report 2022-23, the unemployment rate in West Bengal was 2.2% which is lower than the all-India percentage of 3.2. A harsh situation is shown by the fact that almost 50% of West Bengal's population belongs to socially backward classes (SC/ST and OBC), according to the Census of India 2011, NCBC report, and the West Bengal government's reports. The NCRB report 2021 said that the percentage of violent crimes and kidnappings in West Bengal (57.2% of total cognizable crimes) is high compared to India's statistics (37.6% of total cognizable crimes).

Therefore, all of these discussed criminal incidents (Section I) and a lack of studies focusing on the acts of violence in West Bengal motivated us to investigate the pattern of severity of crimes across the districts in West Bengal. So in this paper, we have tried to investigate the pattern of crime rate over time and level of violence severity using a spatial panel analysis approach. Our paper is structured as the review of existing literature, the significance of our work, and the study objectives are defined in Section II. The data and methodology used in our research are explained in Section III followed by Section IV which includes the empirical results. Conclusions, Policy Recommendations, and Limitations of our study are pointed out in Section V.

A Brief Review of Literature and the Significance of the Study

The very first country-level crime index i.e. the Global Organized Crime Index was formulated by the Global Initiative Against Transnational Organized Crime (GI-TOC) in the year 2019. GI-TOC is used to calculate the country-level criminality score by combining three dimensions: criminal markets, criminal actors, and resilience, which encompass 193 nations. Several previous studies at the international level have evidence that the level of education is highly associated with criminal

activities. According to the studies by Isaac (1975), Selke (1980), Lochner (1999, 2020), Groot, et al. (2010), Hjalmarsson, et al. (2012), Fella, et al. (2014), Bell, et al. (2022), Miller & Alves (2023) it is concluded that completing higher studies significantly reduces the crime rates. A positive correlation between the unemployment rate and income inequality to unlawful offenses has been studied by several researchers including Paternoster, et al. (2001), Raphael, et al. (2001), Edmark (2005), Lin (2008), Andresen (2012). Many studies on the issue of reducing iniquities through educational attainment and increasing the labor force participation rate in India have been done in the recent past (Chaudhuri, et al. 2015; Rakshit et al., 2020; Mishra & Mishra, 2021; Nagasubramaniyan, 2024; Sharma & Sunder, 2024). Increasing employment possibilities and higher educational achievements of youth cohort across the districts of West Bengal significantly diminishes the crime incidents against women and children are also discussed in several research works including Deb, et al. (2005), Ghosh & Kar, (2008), Pandit & Halder (2023). Except for the education and income-generating factors, several socioeconomic explanatory variables have a significant impact on the crime rate in India. Studies like Drèze & Khera (2000), Kumar (2004), Dutta & Husain (2009), Hazra (2019), and Ahmad (2022) have investigated the positive correlation between urbanization rate and the percentage of socially backward class to the crime rate in India. However, there is a scanty number of studies that explored crime in India using spatial economics. Studies including those by Mazeika & Kumar (2017), Kabiraj (2022), and Mukherjee, et al. (2024) have shown that a few socioeconomic parameters do have a spatial effect on crime prevalence. Another study by Bhattacharyya, et. al. (2022) explored the spatial determinants of crimes against women in India, particularly focusing on dowry deaths, rape, molestation, and torture, using spatial panel data regression across 24 states from 1995–2015. The research finds that certain crimes exhibit spatial dependency, influenced by neighborhood effects, especially in dowry deaths. Key factors like female workforce participation and the presence of police stations reduce dowry deaths, indicating that improved economic empowerment and law enforcement are significant deterrents. Additionally, socio-economic disparities across states contribute to variations in crime incidence, underscoring the need for localized policy interventions to address gender-based violence effectively. They added that Micro-level spatiotemporal exploration of crime could lead to a more prominent understanding.

Significance of the Study

This study addresses critical gaps in the existing literature on crimes by examining the spatiotemporal effects of socioeconomic factors, specifically education and employment, on crime patterns in West Bengal, India. Crime research in India often lacks micro-level analysis, with most studies focusing on broad, aggregated crime patterns at the state or national levels. This can obscure regional variations and specific local determinants, which are essential for policy interventions. By concentrating on inter-district variations, our study seeks to provide a deep understanding of crime patterns within West Bengal, a region characterized by significant socioeconomic diversity.

Previous studies have largely focused on isolated types of crime, such as dowry-related deaths, human assault, or crimes against women, which, while valuable, do not offer a comprehensive view of the overall crime landscape. Additionally, much of the existing research has relied primarily on crime rate metrics, which measure only the frequency of crimes without considering their severity or the degree of violence involved. Our study introduces a Crime Severity Index (CSI) that captures both the frequency and intensity of crimes across districts, providing a more accurate reflection of the crime landscape in terms of both prevalence and impact. By quantifying the severity of crimes alongside frequency, our study offers a novel perspective that can reveal deeper insights into the nature and distribution of criminal activity, offering a clearer indication of areas most in need of intervention.

The advantage of this study is its use of spatial econometric techniques to analyze crime patterns. Spatial econometrics allows us to examine not only the direct effects of socioeconomic factors on crime within a given district but also the spillover effects that neighboring regions may exert. Moreover, national border-specific regional impacts on crime are addressed in the study. For

example, low educational attainment or limited employment opportunities in one district could have an indirect influence on crime rates in neighboring districts. This regional interdependency is rarely addressed in traditional macro-level crime studies, which often assume that each area is an isolated unit. Our spatiotemporal approach acknowledges the interconnected nature of districts, aligning with real-world scenarios where socioeconomic conditions and crime do not adhere to administrative boundaries. Considering the role of education and employment in influencing crime, recognizing that these factors are crucial determinants of economic and social stability. By examining their impact on crime patterns, we aim to highlight potential pathways for reducing violence through targeted improvements in these areas.

In summary, this study’s integration of crime frequency and severity, coupled with a spatiotemporal framework, provides a valuable and previously underexplored perspective on crime patterns in West Bengal. The findings are intended to guide policymakers by highlighting the importance of addressing both the spatial dimensions and severity levels of crime, offering actionable insights that can inform more effective, locally targeted strategies for crime reduction. By filling the gaps in micro-level crime analysis, our study aims to contribute to safer, more equitable communities in West Bengal, with implications for similar regions across India.

Research Gaps and Objectives of the Present Study

Our review of existing research reveals the research gaps that only a few studies have examined crime patterns in India, especially at the micro-level. Focusing on a specific criminal activity like Dowry death (Bhattacharyya, et. al., 2022), Human Assault (Abraham, 2012), or Crime against women (Lolayekar, 2022), etc. creates some gaps in understanding the complete crime scenario. Prior studies focused on analyzing the crime rate (Chaudhuri, 2013) only without addressing the degree of violence or severity of different crimes. The utilization of spatial econometrics to explore crime patterns over geographic locations is rare on the shelf. To fill these identified gaps this study attempted to investigate the spatio-temporal impacts of education and workforce participation on violence at the micro-level. This study provides a new perspective by integrating crime frequency with the degree of violence, distinguishing it from traditional approaches. Notably, research examining the spatial spillover effects of socioeconomic factors on crime remains limited. By employing spatiotemporal analysis to investigate the regional determinants of both crime rates and the severity level, this study makes a substantial contribution to the literature in this area.

Following the facts of socioeconomic circumstances within the state of West Bengal discussed in the introduction part, our primary objective of this research is to investigate the inter-district crime pattern within the state and explore the socioeconomic determinants that could abate the violence. The objectives of this study can be summarized as, to develop a *Crime Severity Index (CSI)* over a five-year gap for the West Bengal districts, using a robust statistical framework that reflects the crime scenario in terms of their severity level. Secondly, to observe the existence of spatial correlation in regional crimes across the districts over time. Finally, to investigate the potential educational, employment, and regional determinants of crime using spatial panel regression. Thus, this study aims to shed light on the complex spatial links between socioeconomic variables and crime rates in West Bengal, providing suggestive implications to help policymakers create safer neighborhoods.

Methodology and Data Sources

Following the primary objective of this study, the Index of Crime’s Severity (CSI) is constructed using the NCRB’s crime statistics for the West Bengal districts. This study tried to cover different criminal activities by selecting seven unlawful actions given in the following Table 1.

Table 1. Selected Crime Variables to Develop the Crime Severity Index.

Sr. No.	Criminal Activity
1.	Murder

	(Homicide/Attempted to Murder/Kidnapping and Abduction to Murder)
2.	Crime against Women (Rape/Attempted to Rape/Kidnapping/Assault/Outraging her Modesty)
3.	Offense against Property (Theft/Robbery/Burglary)
4.	Causing Death by Negligence (Hit & Run and Other Road Accidents)
5.	Offense against Documents or Property Marks (Breach of Trust/Forgery/Cheating/Fraud)
6.	Miscellaneous IPC Crimes (Ransome/Arson/Dowry Death/Rash Driving, Cruelty by Husband or Relatives)
7.	Simple Hurt or Grievous Hurt (Use of Dangerous Weapons/Acid Attacks/ Endangering the Life or Safety of Others)

Source: Authors merged these different types of crime from the NCRB database.

These crime variables are provided as the unit values i.e. the total number of specific crime incidents has happened within a region. To make it comparative across the districts we converted them into the total number of incidents per 1 lakh population. These comparable values are then normalized by applying the UNDP Goalpost method. The normalization process followed the equation (1),

$$C'_{ijt} = \frac{(c_{ijt} - Min(c_{ij}))}{(Max(c_{ij}) - Min(c_{ij}))} \dots\dots (1)$$

C'_{ijt} represents the normalized score for the i^{th} crime indicator and j^{th} district in t^{th} year. c_{ijt} is the actual value of the i^{th} crime and j^{th} district in t^{th} year. Max and Min of c_{ij} are the maximum and minimum values of the i^{th} crime indicator and j^{th} district respectively considering all time points. By using this normalization procedure, each crime indicator is transformed into zero to one range, where 1 denotes the highest crime rate and 0 designates no crimes.

Construction of Crime Severity Index (CSI)

Results could be misleading if the above-normalized scores are used for further analysis. We should keep in mind that the severity of violence like rape or murder is not equivalent to a theft or forgery crime. Furthermore, crimes like murder happen less frequently than deaths due to negligence, such as those caused by car accidents. Thus, while constructing the Crime Severity Index (CSI), we must consider the frequency and the degree of violence for each of these specific unlawful behaviors. By estimating a correct weightage for the individual crimes in terms of their severity level and probability of occurrence we could make the index more valid. According to our methodology, the number of years a criminal will be incarcerated determines how severe the offense is. It would partially lessen the imbalances among the variables because a higher degree of violence is linked to a higher level of imprisonment (years). According to the relevant IPC Acts, the maximum number of years for imprisonment is shown in Table 2.

Table 2. Selected Crimes and their Respective Maximum Years of Imprisonment.

Sr. No.	Type of Criminal Activity	Under Section (IPC Act.)	Years of Imprisonment		Maximum Custody (Years)
			Min	Max	
1.	Murder	302; 307; 354	2	Life Time	27*
2.	Crime against Women	376; 511	10		
3.	Offense against Property	379; 392; 393; 394; 397; 398; 380	3	14	14
4.	Causing Death by Negligence	304A; 304 Part II	2	10	10
5.	Offense against Documents	420; 465; 468-471	7	7	7

6.	Miscellaneous IPC Crimes	279; 498A	0.5	3	3
7.	Simple Hurt or Grievous Hurt	337; 338	0.5	2	2
Total Possible Tenure of Custody (Years)					63

Source: The Indian Penal Code, GoI (*Click here for the: List of Sections & IPC Acts.*) * Author’s estimation:
The tenure of lifetime imprisonment is assumed to range between 18 years (*as per The Juvenile Justice (Care and Protection of Children) Act, 2015*) to 72 years (*as per Life Expectancy at Birth in WB, 2022*). The reason to take the juvenile age of 18 years as the lower margin is because the tenure of confinement is different up to the juvenile age and for the sake of simplicity, we presumed that the mentioned criminal activities have occurred after the adolescent age. Based on SRS data, the upper ceiling is set at 72 years, which is the life expectancy at birth in West Bengal in 2022. Thus the sentenced year of lifetime imprisonment may vary between 18 to 72 years. The maximum year of lifetime imprisonment is taken as the average of the maximum jail time of 54 years (*when someone committed murder/rape at the age of 18 i.e. (72 – 18) = 54 Years*) and the minimum jail time of 0 years (*if someone attempted murder/rape at the age of 72 that becomes equal to the expected life at birth i.e. (72 - 72) = 0 Year*). Thus, the maximum year of lifetime custody is taken as the average of these two extreme cases i.e. (54+0)/2 = 27 years.

The relative severity level of each crime is calculated using the formula,

$$SL_{c_i} = \frac{Years_{c_i}^{Max Custody}}{\sum_{i=1}^7 Years_{c_i}^{Max Custody}} \dots\dots\dots (2)$$

where, SL_{c_i} = Severity level of the i^{th} crime, $Years_{c_i}^{Max Custody}$ denotes the maximum years of imprisonment for the i^{th} crime, which is an overall of 63 years. This will make the degree of severity relative in nature across the selected crimes i.e. $\sum SL_{c_i} = 1$.

The final index will be somewhat biased-free if just the predicted severity is assigned as the weights. We should take into account both the severity and likelihood of each crime within the state to better justify the weighting technique. We also keep in mind that the higher the level of severity, the lesser will be the frequency of that specific crime. The relative likelihood and the relative severity are shown in Table 3.

The relative frequency of each crime is calculated using the equation,

$$F_{c_i} = \frac{c_i}{\sum_{i=1}^7 c_i} \dots\dots\dots (3)$$

F_{c_i} = Relative frequency of crime c_i

Table 3. Relative Severity Level of Crimes and their Relative Frequency of Occurrence.

Sr. No.	Type of Criminal Activity	Relative Severity Level (SL_{c_i})	Relative Frequency of Crime (%) (F_{c_i})
1.	Murder	0.429	10.13
2.	Crime against Women	0.429	1.4
3.	Offense against Property	0.222	6.98
4.	Causing Death by Negligence	0.159	3.5
5.	Offense against Documents	0.111	13.5
6.	Miscellaneous IPC Crimes	0.048	47.21
7.	Hurt	0.032	17.27

Source: Authors’ estimation.

The final weights are measured by multiplying the equations (2) and (3) i.e.,

$$W_{c_i} = (SL_{c_i} * F_{c_i}) \dots\dots\dots(4)$$

Using the following formula the final weights are normalized to range between 0 to 10 levels of severity,

$$W'_{c_i} = \left[\left(\frac{W_{c_i}}{\sum_{i=1}^7 W_{c_i}} \right) \times 10 \right] \dots\dots (5)$$

The final distribution of standardized weights across the crimes is shown in Figure 1.

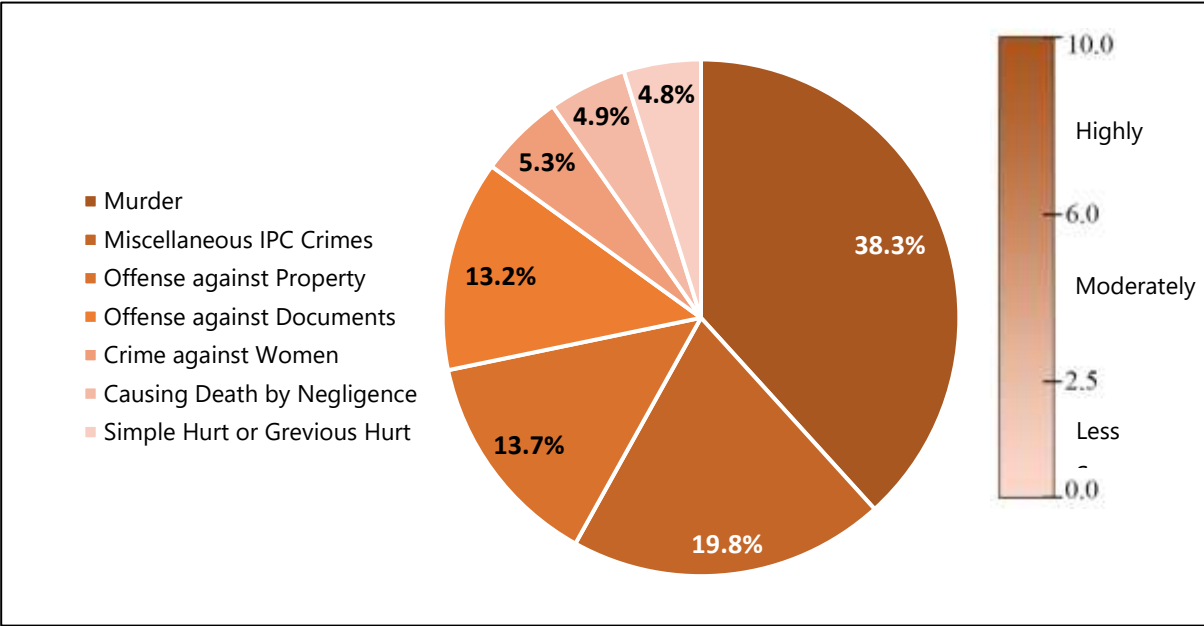


Figure 1. Final Standardized Weights Distribution and Classification of Severity. Source: Authors’ calculation.

The construction of the *Crime Severity Index (CSI)* needs to go through the final step of aggregation. Taking the sum of normalized crime scores (equation 1) assigned with their respective weightage (equation 5) ends up with the final district-level CSI scores. The aggregation process follows the equation (6),

$$CSI_{jt} = \sum_{i=1}^7 (C'_{ijt} \times W'_{c_i}) \dots\dots (6)$$

C'_{ij} = Normalized score for the i^{th} crime indicator for j^{th} district in t^{th} year.

W'_{c_i} = Estimated weights for the i^{th} crime.

One argument that may arise is why we need a separate crime index when we can compare the areas based on their crime rates. The explanation is as easy as rational, the crime rate merely indicates the frequency of occurrence of all crimes together in terms of per 1,00,000 people (just some raw fractions) and does not account for the severity of the crimes i.e. the likelihood and cruelty level of murder or rape is not the same as that of theft and larceny. Thus, the Crime Severity Index (CSI) is an effective approach to the crime rate since it includes both the severity and frequency of crimes simultaneously.

Spearman rank correlation coefficient has been estimated initially for five different years to check the correlation between seven selected crime categories.

To identify the factors affecting regional crime rates and the violence severity level two types of panel regressions are performed. First, we fitted the basic panel regression models with fixed and

random effects. The suitable model for the study is determined using the Hausman specification test. The panel regression model follows the equation (7),

$$y_{jt} = \alpha + \beta X_{jt} + \varepsilon_{jt} \dots\dots (7)$$

Where, y_{jt} is the dependent variable, X_{jt} is the vector of explanatory variables and ε_{jt} indicates the unexplained error terms associated with the model. The problem of multicollinearity among the explanatory variables is checked using the Variance Inflation Factor (VIF). Furthermore, robust standard error is used in all models to address the heteroscedasticity issue. The Hausman test suggests the fixed effect model would be an appropriate one for further investigation. Thus, we run the Least Square Dummy Variable (LSDV) model (equation 8) considering district-specific dummies to observe the regional impacts.

$$y_{jt} = \alpha + \beta X_{jt} + \sum_{j=1}^{18} \gamma_j D_j + \varepsilon_{jt} \dots\dots (8)$$

Where D_j represents the 18 regional dummies and γ_j are the respective dummy coefficient terms. To avoid the dummy variable trap 1 district is omitted from the model.

According to earlier studies, several employment and educational factors may affect criminal activities. In this study, we attempted to examine the impact of a few socioeconomic determinants such as male labor force participation rate (MLFPR), urbanization rate (URB), female education level (FGRAD), per capita income (PCGDDP), Population to Police Station ratio (PSPOP), etc. However, only a handful of literature tried to find the determinants of crime considering the space and time together. To fill that gap, we applied the spatial panel regression model (equation 9) taking crime rate and crime severity index as the dependent variable.

Methodology for Spatial Analysis

To identify the existence of spatial interdependency in the dependent variable we use the Global Moran’s I (GMI) statistics for the selected years. Following L. Anselins’s (1988, 1995) methodology, the Global Moran’s I coefficient can be calculated using the formula (9),

$$I = \frac{n}{W} \cdot \frac{\sum_{i=1}^n \sum_{j=1}^n w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^n (x_i - \bar{x})^2} \dots\dots (9)$$

Where, n is the number of spatial units (districts), $W = \sum_i \sum_j w_{ij}$ is the sum of spatial weights, w_{ij} shows the matrix of row standardized spatial weights. x_i and x_j are the values of the variable for i^{th} and j^{th} region respectively, $\bar{x}$ represents the mean of the variable. The value of Moran’s I coefficient lies between 0 to 1, where 0 indicates no spatial interdependency and 1 suggests the highest degree of spatial correlation. We used the Rook’s contiguity method to determine the spatial neighbourhoods (Anselin, 1988). The *Z-score* of GMI indicates the degree of spatial correlation, where, a high and positive *Z-score* represents a cluster of similar values and a negative *Z-score* is the indication of spatial dissimilarities. A perfect zero score suggests no geographical autocorrelation is present.

We performed two basic spatial panel regression models expressed in equations 10 and 11, Spatial Panel Autoregressive Model (SPAM):

$$y_{jt} = \rho \sum_{j=1}^N W_{ji} y_{jt} + X_{jt} \beta + \mu_j + \varepsilon_{jt} ; j = 1, 2, \dots, N; t = 1, 2, \dots, T \dots\dots (10)$$

and,
Spatial Panel Error Model (SPEM):

$$y_{jt} = X_{jt}\beta + \mu_j + \varphi_{jt},$$

where,

$$\varphi_{jt} = \lambda \sum_{j=1}^n W_{ji}\varphi_{it} + \varepsilon_{jt} \dots\dots (11)$$

Where in equation (10), $W_{ji}y_{jt}$ is the spatially lagged dependent variable vector for all units at time t ; X_{jt} shows $(1 \times K)$ matrix of independent variables at time t ; β stands for $(K \times 1)$ parameters; μ_i is the individual region-specific effect which is random in spatial models with zero mean and constant variance $i.i.d (0, \sigma^2)$; and, ε_{jt} indicates the vector of idiosyncratic error terms at time t . And for equation (11), λ is the spatial error coefficient of the error term; φ_{jt} spatially correlated error term at time t which is not captured in the SPAM model. The equations of the maximum likelihood function of these models are derived in Appendix A.

These spatial panel models can help us to understand the spatial neighbourhood dependency (*Rho* and *Lambda* coefficient) of crime rate and the severity level. The coefficients of explanatory variables can explain the direct impact of neighbouring socio-economic determinants on regional crimes.

Data Sources

This research is based on the secondary data available openly in public repositories. The district-level crime data are collected from the National Crime Records Bureau (NCRB), Government of India. Explanatory variable data on Education, employment, and police stations are estimated from several Primary Census Abstracts (2001 and 2011), District Reports, and various NSSO Survey Rounds (55th, 61st, 66th, 73rd & 78th Rounds).

Our structure of panel data comprises five time points i.e., 2000, 2005, 2010, 2015, and 2020 for 19 districts in West Bengal. The number of districts has changed over the years as new districts are formed bifurcating the other districts (a total of 19 districts were there in the year 2000; by 2020 some of them were bifurcated and the number of districts increased to 23). As the data not available of those bifurcated districts for the earlier time points, we merged those regions with their pre-partition district. Also, as the census reports are available in 10-year gaps (2001 and 2011), we used an appropriate interpolation technique to generate the mid-year records of 2005 from census data.

Results and Discussion

The summary statistics in Table 4 reveal a considerable variation in crimes and other socio-economic factors in West Bengal. The crime rate (CR) is widespread, indicating significant differences in crime levels across districts. The crime severity index (CSI) also varies notably, with a minimum of 0.089 and a maximum of 5.482, reflecting the diversity in the degree of violence across areas. The pattern of different crimes in West Bengal over the five time points is shown graphically in Appendix B.1 (Figure 4).

Table 4. Descriptive Statistics of Crime and Selected Explanatory Variables.

Variable (Notation)	Obs.	Mean	SD	Min	Max
Crime Rate (CR)	95	143.99	94.506	31.314	558.55
Crime Severity Index (CSI)	95	1.619	1.176	0.089	5.482
Urbanization Rate (URB)	95	36.126	27.068	7.322	100.00
Male Labour Force Participation Rate (MLFPR)	95	81.534	8.968	53.268	95.660
21+ Age Female Graduate (FGRAD)	95	11.494	7.390	0.580	36.306
Per Capita District Domestic Product (PCDDP)	95	49,479	36,118	7,774	1,80,026
Police Stations Per 1 Lakh Population (PS)	95	0.623	0.358	0.281	1.979

Source: Author’s calculation based on the mentioned data sources.

Socio-economic variables exhibit substantial disparities as well. The maximum and minimum values of the urbanization rate (URB) suggest differing levels of urban development among districts. Similarly, the male labor force participation rate (MLFPR), and female education levels (FGRAD) also vary. Income levels, represented by the per capita district domestic product, also display wide variation, signaling inequality in economic resources (PCDDP) across districts. Lastly, the police stations per 1 lakh population (PSPOP) indicates an uneven distribution of police infrastructure, potentially impacting law enforcement capacity. Our topic of interest is how these variations may impact criminal activities in West Bengal. A graphical representation of the changes over the years in these explanatory variables is produced in Appendix B.1 (Figure 5).

District-wise Overall Crime Rate and Severity Index Scores

From the above summary statistics in Table 5, it has been noticed that crime weaves in West Bengal in a tapestry of diverse landscapes and communities. The metropolis of Kolkata stands out with its bustling streets and dense population, creating an environment where crime is more prevalent. Similarly, the hills of Darjeeling, known for their tourism, experience unique localized challenges that contribute to higher crime rates. Moving to the urbanized areas of Howrah and the expansive regions of North and South 24 Parganas, a balanced mix of frequent but less severe crimes reflects the complexities of the urban side. However, Murshidabad, positioned near the international border of Bangladesh, grapples with more serious and impactful crimes, highlighting the influence of its geographic location. Throughout West Bengal, there is a clear connection between how often crimes occur and how severe they are, especially in areas facing urban pressures and economic disparities. This intricate interplay between the frequency and severity of crimes with West Bengal’s socio-economic condition needs to be studied in depth.

Table 5. District-Specific Average Crime Rate and CSI Score.

Districts	Crime Rate	Rank	Crime Severity Index	Rank
Kolkata	394.25	1	2.837	2
Darjeeling	246.32	2	2.513	3
Howrah	188.80	3	1.716	9
North 24 Parganas	175.37	4	1.860	6
South 24 Parganas	168.08	5	1.203	14
Uttar Dinajpur	154.91	6	2.038	5
Nadia	153.68	7	1.764	7
Murshidabad	149.53	8	2.877	1
Grand Total	144.00	9	1.619	11
Jalpaiguri	143.72	10	1.735	8
Maldah	124.40	11	2.222	4
Cooch Behar	117.62	12	1.478	12
Dakshin Dinajpur	115.68	13	1.667	10
Bardhaman	115.57	14	1.120	16
Hooghly	99.04	15	0.907	17
Paschim Medinipur	88.45	16	1.121	15
Purba Medinipur	87.53	17	0.848	18
Birbhum	82.45	18	1.348	13
Puruliya	68.65	19	0.769	19
Bankura	61.93	20	0.743	20
Spearman’s Rank Correlation Coefficient			0.794	

Source: Author’s calculation.

Correlation Statistics of Different Crimes

Over the years, the Spearman rank correlation among various types of crimes shows notable shifts (Table 6). Initially, a high correlation is observed between crimes like theft and miscellaneous offenses, as well as assault on women and murder, suggesting overlapping socio-economic factors influencing these crimes. But by 2005, the correlations have intensified, particularly between theft, miscellaneous, and fraud, indicating possible co-occurrence or mutual escalation across regions. Over the recent past crime patterns in West Bengal have been significantly concentrated on assault on women, theft, negligence, and breach of trust. This evolving pattern may suggest a complex interaction between economic factors, urbanization, and enforcement disparities across regions.

Table 6. Spearman Rank Correlation Between Different Types of Crime.

Year: 2000	Murder	Assault	Theft	Negligen ce	Fraud	Miscellaneo us	Hur t
Murder	1						
Assault	0.755*	1					
Theft	0.785*	0.562*	1				
Negligence	0.045	0.062	0.022	1			
Fraud	0.508*	0.245	0.525*	0.251	1		
Miscellaneous	0.803*	0.736	0.896*	0.115	0.451*	1	
Hurt	0.229	0.248	0.333	0.751*	0.208	0.150	1
Year: 2005							
Murder	1						
Assault	0.816*	1					
Theft	0.761*	0.653*	1				
Negligence	0.220	0.134	0.442	1			
Fraud	0.627*	0.563*	0.794*	0.447*	1		
Miscellaneous	0.809*	0.781*	0.849*	0.304	0.838*	1	
Hurt	0.296	0.247	0.549*	0.791*	0.374	0.275	1
Year: 2010							
Murder	1						
Assault	0.795*	1					
Theft	0.410	0.548*	1				
Negligence	0.052	0.081	0.448*	1			
Fraud	0.474*	0.601*	0.855*	0.629*	1		
Miscellaneous	0.636*	0.815*	0.819*	0.292	0.816*	1	
Hurt	0.277	0.535*	0.314	0.141	0.347	0.220	1
Year: 2015							
Murder	1						
Assault	0.423	1					
Theft	0.249	0.733*	1				
Negligence	0.659*	0.668*	0.597*	1			
Fraud	0.426	0.724*	0.770*	0.724*	1		
Miscellaneous	0.291	0.638*	0.800*	0.705*	0.924*	1	
Hurt	0.632*	0.300	0.312	0.160	0.377	0.216	1
Year: 2020							

Murder	1						
Assault	0.481*	1					
Theft	0.217	0.716*	1				
Negligence	0.182	0.677*	0.909*	1			
Fraud	0.320	0.483*	0.789*	0.669*	1		
Miscellaneous	0.275	0.705*	0.754*	0.719*	0.719*	1	
Hurt	0.384	0.607*	0.621*	0.484*	0.534*	0.349	1

Source: Author’s calculation based on the mentioned data sources. Significance parentheses: **p* < 0.05.

Panel Regression Analysis of Crime Rate and Crime Severity Index

We used the natural log transform values of our dependent variables (i.e., crime rate and crime severity index) as well as the explanatory variables (URB, MLFPR, FGRAD, and, PCDDP) for the regression analysis. In comparison between fixed effect and random models, our Hausman test statistics suggested the fixed effect model would be a suitable one for both the dependent variables in further analysis.

The panel data regression result (Table 7) reveals several important socio-economic influences on crime rates and severity. Though urbanization cannot significantly explain the relation to crime rate in fixed effect but a strong positive association with the severity level, suggesting that as areas become more densely populated, crime may increase due to factors like anonymity, population stress, and local economic disparities. An inverted-U shaped relationship between male workforce participation and crime is established. Initially, male workforce participation (MLFPR) also has a positive impact on crime due to increased interactions in the workplace, commercial transactions, and general movement of people and resources, which can create more opportunities for crimes like theft, fraud, and conflicts. Though this influence weakens after a certain level of higher participation rate, implying that more economic activity and stable labor markets could later contribute to social order. Female graduation rates (FGRAD) are positively related to both crime rate and severity, possibly indicating shifts in social dynamics or greater empowerment among women, which might influence the likelihood of reporting crimes or alter social interactions. Inverted-U shaped relation between income level and crime rate is also suggested in the result. Per capita income (PCDDP) initially raises crime rates, perhaps due to income disparities or more appealing targets, but as income reaches a positive level, it seems to stabilize or even reduce crime, suggesting that economic stability may help in lowering criminal mindset. Finally, while an increase in police presence does not significantly change overall crime rates, it appears to reduce the severity of crimes, highlighting the potential of law enforcement to mitigate serious offenses. These findings emphasize the complexity of crime determinants and suggest that economic and social enforcement factors interact in many ways, shaping both the frequency and severity of crime within the state.

Table 7. Determinants of Crime Rate and Severity Index: Panel Regression Analysis.

Dep. Var Exp. Var	Crime Rate		Crime Severity Index	
	FE	RE	FE	RE
lnURB	0.1183 (1.31)	0.3317*** (4.80)	0.2276*** (1.78)	0.2693* (2.72)
lnMLFPR	72.909** (3.60)	11.5241 (0.72)	51.6406*** (1.81)	-12.1109 (-0.52)
(lnMLFPR) ²	-8.834*** (-3.66)	-1.2823 (-0.68)	-6.3223*** (-1.86)	1.4806 (0.55)
lnFGRAD	0.5342 (1.08)	0.1068* (2.13)	0.1391** (1.99)	0.1643* (2.13)

InPCDDP	2.0422*	0.7800	-0.5954	-1.0042
	(2.07)	(0.75)	(-0.43)	(-0.63)
(InPCDDP) ²	-0907***	-0.0268	0.04809	0.0730
	(-1.92)	(-0.54)	(0.72)	(0.95)
InPS	0.4738	0.1469	-1.3243*	-0.0711
	(1.22)	(0.94)	(-2.43)	(-0.39)
Constant	-157.059**	-27.533	-105.455***	25.9553
	(-3.61)	(-0.79)	(-1.72)	(0.51)
N	95	95	95	95
R ² W	0.75	0.68	0.81	0.77
R ² B	0.56	0.69	0.40	0.23
R ²	0.01	0.68	0.09	0.58
Hausman	21.71 (p = 0.001)		-5.64 (p=0.001)	

Source: Author’s calculation based on the mentioned data sources Significance parentheses: *p < 0.05; **p<0.01; ***p<0.10.

District-Specific Impact: LSDV Regression Analysis

Based on the Hausman test results, the Fixed Effects (FE) model is selected, leading us to apply the Least Squares Dummy Variable (LSDV) regression model (Table 8) with region-specific dummy variables in addition to the previously included explanatory variables. To avoid the dummy variable trap, the district of Puruliya is chosen as the reference category. This selection is intentional, as Puruliya’s location in the western part of the state places it at the longest distance from the Bangladesh border, making it an ideal baseline for examining the impact of cross-border dynamics on crime in districts closer to the national boundary. Thus, using Puruliya as the reference group allows us for a meaningful comparison of crime impacts in border districts, as illustrated in Appendix C (Figure 8).

Table 8. District-specific Impact on Crime Rate and Crime Severity: LSDV Model.

Dep. Var	Crime Rate		Crime Severity Index	
Exp. Var	Coef.	t stat	Coef.	t stat
InURB	0.1182	1.31	0.227***	1.78
InMLFPR	72.909**	3.60	51.64***	1.81
(InMLFPR) ²	-8.834**	-3.66	-6.322***	-1.86
InFGRAD	0.5342	1.08	0.1391	1.99
InPCDDP	0.0422*	2.07	-0.595	-0.43
(InPCDDP) ²	-0.907***	1.92	0.048	0.72
InPS	-0.473	-1.22	-1.324*	-2.43
D _{Bankura}	0.0614	0.31	0.0635	0.22
D _{Bardhaman}	0.7746*	2.30	0.2062	0.43
D _{Birbhum}	0.4902*	2.15	0.7723*	2.40
D _{Cooch Behar}	1.1715*	2.59	0.6555	1.03
D _{Dakshin Dinajpur}	1.0437**	2.63	0.7362	1.31
D _{Darjiling}	1.8694**	5.16	1.6842**	3.30
D _{Hooghly}	0.6910	1.42	-0.347	-0.51
D _{Howrah}	1.4584**	2.90	0.5069	0.71
D _{Jalpaiguri}	1.1911**	3.11	-0.929***	-1.71
D _{Kolkata}	3.1849**	5.18	2.9307**	3.38
D _{Maldah}	0.6130	1.56	0.3584	0.65
D _{Murshidabad}	1.0520*	2.48	0.8799	1.47
D _{Nadia}	0.6574	1.41	1.1636***	1.79
D _{North 24 Parganas}	1.4807**	2.70	0.4569	0.59
D _{Paschim Medinipur}	0.0009	0.00	-0.692	-1.31

DPurba Medinipur	-1.3160	-0.38	-1.327**	-2.70
DSouth 24 Parganas	0.8260**	2.77	0.0373	0.09
DUttar Dinajpur	1.3354**	3.14	0.9709	1.62
Constant	-158.0**	-3.63	-105.9***	-1.73
F stat (25, 69)	21.35		18.61	
N	95		95	
R ²	0.88		0.87	

Source: Authors’ estimation. **Significance parentheses:** **p* < 0.05; ***p*<0.01; ****p*<0.10. **Note:** The districts sharing a border with Bangladesh are highlighted in grey shades (see, Figure 8, Appendix C).

The district-specific result of LSDV regression shows that districts like Birbhum, Bardhaman, Cooch Behar, Dakshin Dinajpur, Jalpaiguri, Kolkata, Maldah, Murshidabad, Nadia, both Parganas and Uttar Dinajpur are significant in high crime rate compared to Puruliya. However, only the districts like Birbhum, Darjeeling, Kolkata, Nadia, and Purba Medinipur are significant in severity level. Among these high-crime regions, it is identified that most of them are located in the border area of Bangladesh except for the district of Jalpaiguri where the crime severity is significantly lower than the reference region. So, there should be some cross-border influence on crime and severity in the state.

Spatial Autocorrelation: Global Moran’s I

A positive and statistically significant Global Moran’s I indicate the presence of spatial correlation in the dependent variable. Table 9 demonstrates that the crime rate exhibits a positive spatial correlation across all selected time points, suggesting that crime rates in one region are influenced by those in neighboring areas. And, the severity of violence shows a significant spatial correlation at three of the time points, with an increasing trend over time.

Table 9. Global Moran’s I score of Crime Rate and Crime Severity Index.

Dep. Variable	Crime Rate			Crime Severity Index		
Year	GMI	Z score	p-value	GMI	Z score	p-value
2000	0.109***	1.764	0.078	0.070	1.124	0.261
2005	0.223*	2.363	0.018	0.266*	2.275	0.023
2010	0.310**	2.648	0.008	0.189***	1.441	0.076
2015	0.262*	2.346	0.019	0.072	0.891	0.373
2020	0.187***	1.764	0.078	0.420**	3.202	0.001

Source: Authors’ estimation. **Significance parentheses:** **p* < 0.05; ***p*<0.01; ****p*<0.10.

Though spatial autocorrelation can be detected from the Moran’s I score but it fails to identify the zones clustered with high crime rates or severity. To recognize the regions with high (low) violence we used the Local Indicators for Spatial Autocorrelation (LISA) cluster maps or the Local Moran’s I (Figure 2). Local Moran’s I maps of the explanatory variables are shown in Figure 7 (Appendix B.2).

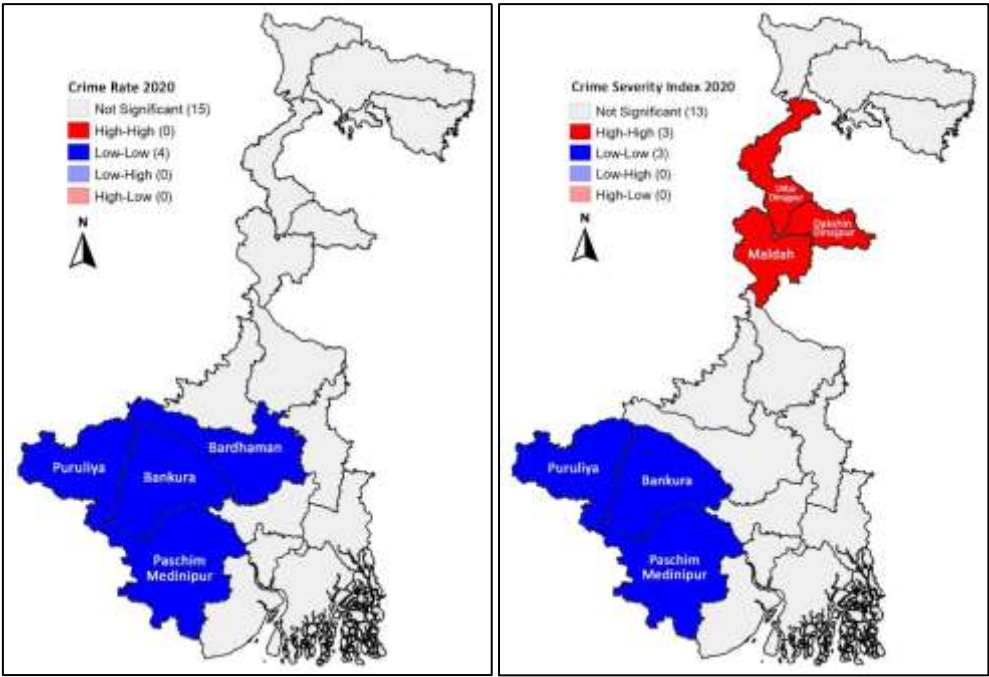


Figure 2. LISA Cluster Map of Crime Rate and Severity Index 2020. Source: All the maps are drawn by Authors.

Spatial Panel Regression Analysis: Using SPAM and SPEM

We previously confirmed the spatial interdependency of crimes from the Moran’s I score and LISA cluster maps but to identify the determinants of violence over space we proposed the two most popular spatial panel regression models – Spatial Panel Autoregressive Model (SPAM) and Spatial Panel Error Model (SPEM). The Rho (ρ) and Lambda (λ) coefficients of SPAM and SPEM respectively indicate the degree of the neighborhood(s) dependency in the dependent variable. From the result in Table 10, we found that the Rho coefficient ($-1.00 < 0.191 < 1.00$ and $-1.00 < 0.155 < 1.00$) is statistically significant for the dependent variables. So we can say that any changes in the dependent variable in one area have spillover effects on its neighborhoods. According to our results, increasing urban population (URB) in one district influence the crime incident not only in that region but also have a positive Spillover effect on its neighboring districts may be due to high population density creating opportunities for more severe criminal activities. The inverted-U shaped relationship between the male labor force participation rate (MLFPR) and crime rate suggests that more stable working opportunities for males can reduce the rate of violence within the state. According to the People’s Archive of Rural India (PARI) report of 2020 around 95% of violent crimes like murder, rape, and assault were committed by male offenders. NCRB’s report said that one woman is raped every 20 minutes in India but only a fraction of those cases are reported due to social stigma. So we took the FGRAD or percentage of 21+ age females who graduated (as a proxy of social awareness and women empowerment) to observe the impact on violence. A positive relation between FGRAD and crime rate is the indication of more number of reported crimes in the state. An increasing number of police stations (PS) can significantly reduce crimes in highly severe districts like Maldah, and Dinajpur regions. Hotspots of violence, crime-severe zones, and the explanatory variables in the latest year (2020) are shown in Figure 3. In addition to the above spatial regression models, we performed two more regression analyses of the Spatial Durbin Model (SDM) and Spatial Autoregressive model with Autoregressive disturbances (SARAR) to support our results (see, Table 11 in Appendix D).

Table 10. Spatial Regression Result of Crime Rate and Crime Severity Index.

Dep. Var	Crime Rate	Crime Severity Index
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Exp. Var	SPAM	SPEM	SPAM	SPEM
lnURB	0.119 (1.58)	0.118*** (1.68)	0.214*** (1.87)	0.224*** (1.87)
lnMLFPR	62.273** (4.62)	72.827** (4.62)	47.559 (1.55)	52.872 (1.60)
(lnMLFPR) ²	-7.516** (-4.68)	-8.824** (-4.69)	-5.792 (-1.60)	-6.469*** (-1.66)
lnFGRAD	-0.531 (1.45)	0.053*** (1.78)	0.133* (2.39)	0.140* (2.38)
lnPCDDP	1.534 (1.54)	2.037*** (1.81)	-0.557 (-0.51)	-0.558 (-0.55)
(lnPCDDP) ²	-0.068 (-1.44)	-0.090*** (-1.69)	0.042 (0.81)	0.046 (0.97)
lnPS	-0.613* (-2.05)	-0.474 (-1.56)	-1.436** (-3.73)	-1.335** (-3.18)
<i>Rho</i> (ρ)	0.191* (2.26)	-	0.155*** (1.80)	-
<i>Sigma</i> (σ)	0.038** (6.36)	0.039** (6.38)	0.076** (5.11)	0.078** (5.24)
<i>Lambda</i> (λ)	-	0.001 (0.01)	-	-0.031 (-0.24)
<i>N</i>	95	95	95	95

Source: Authors’ estimation. **Significance parentheses:** * $p < 0.05$; ** $p<0.01$; *** $p<0.10$. **Note:** SPAM stands for Spatial Panel Autoregressive Model; SPEM stands for Spatial Panel Error Model.

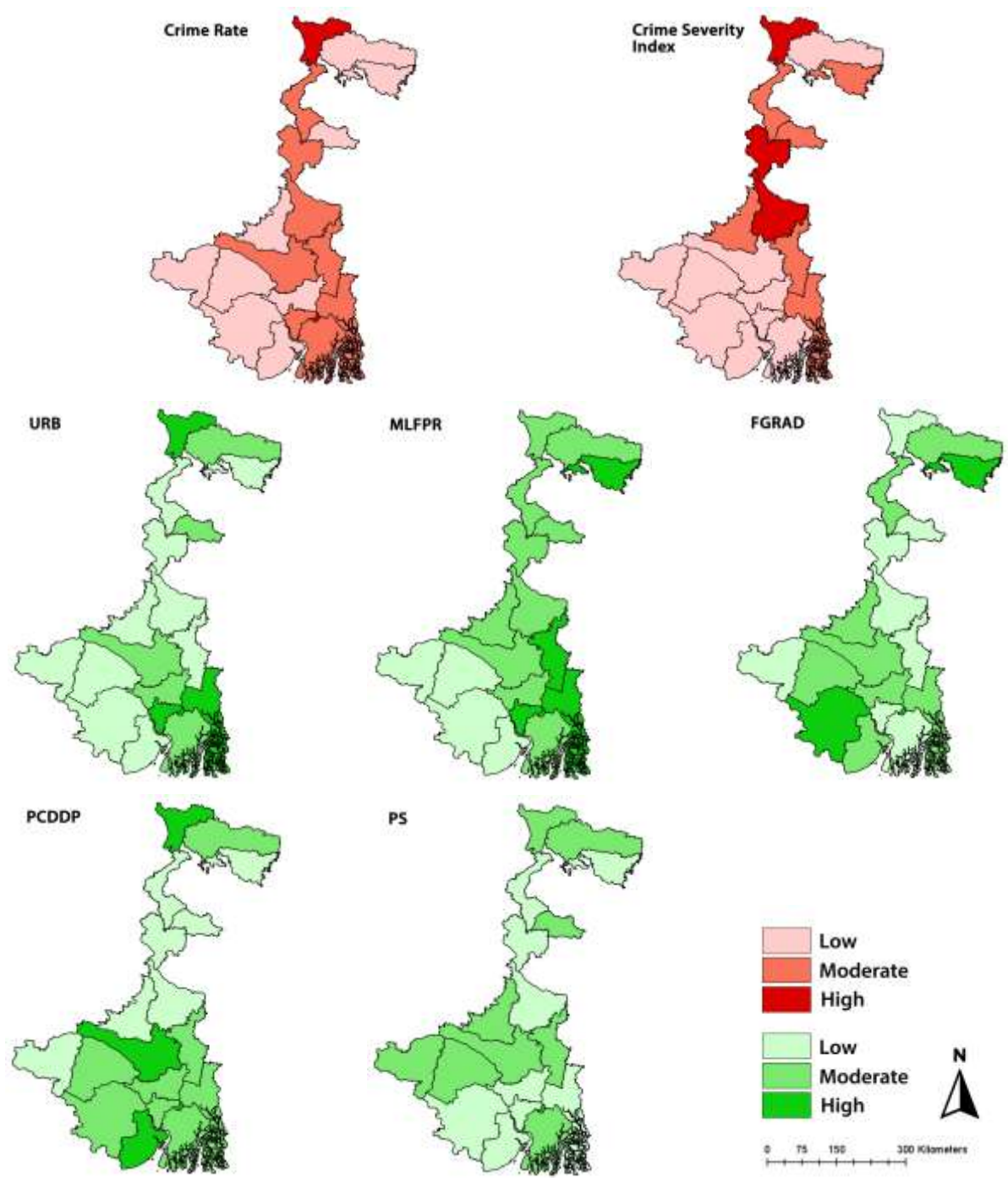


Figure 3. Hotspots of Violence, Severity, and Explanatory Variables in West Bengal, 2020. Source: All the maps are drawn by Authors.

Conclusion

The crime rate in West Bengal has increased over the years but the pattern of violence shifted drastically towards more severe crimes like murder, rape, and assault on women (see, Figure 6 in Appendix B.2). So, this study tried to conceptualize an index of crimes in terms of different severity levels called the Crime Severity Index (CSI) in West Bengal districts. Focusing on comprehending the dynamics of crime imposes a careful examination of socioeconomic variables as well as spatial interdependencies across the districts. Thus we used a spatiotemporal analysis forming a panel of 19 cross-sections for five time points which makes the investigation exceptional and more impactful.

Our initial findings from basic panel regression analysis identify the key socioeconomic factors influencing crime rates and crime severity in West Bengal. Specifically, male labor force participation rate and per capita income have a positive impact on crime at the early stage due to higher economic interaction but it reduces the crime incidents as rise further. Increasing educational attainment of females and the urbanization rate are found significant factors of violence and the degree of severity. Increasing the number of police stations could reduce more violent crimes in the state. West Bengal's crime patterns are intensely shaped by its economic structure, cultural diversity, and geographic position as a border state. The state's economy, with limited employment opportunities in certain regions, creates vulnerabilities to crime, as economic hardship can drive individuals toward illegal activities. This is compounded by its extensive border with Bangladesh, which facilitates trade but also enables cross-border crimes (Ghosh, 2011; Hasan, 2011; Jamwal, 2004). Socially, West Bengal's diverse population, spanning urban, rural, and tribal communities, fosters unique crime patterns. Traditional social structures influence certain crimes, particularly against women (Biswas, 2022; Roy, 2023; Pandit, et al., 2023), while urban areas experience distinct pressures from population density and resource competition (Mukherjee, 2020, Gupta & Kumar, 2020). So, we proposed a LSDV model to observe the district-specific impacts on crimes. The results suggest most of the districts that share a border with Bangladesh have higher average crime incidents and more severe crimes compared to the farthest-located region from the border.

However, we cannot capture the geographical impact of crime incidents from the prior discussion. So we proposed the spatial panel regression models to identify the determinants of crime considering neighborhoods' impact in the model. The Global Moran's I and LISA maps confirmed the spatial autocorrelation in violence and severity level. The spatial analysis suggests that determinants like urbanization, male labor force participation, and female educational attainment have noticeable spillover effects on nearby districts in addition to impacts on localized criminal incidents, indicating a complex and interconnected crime landscape influenced by regional socioeconomic structures. Notably, the Crime Severity Index (CSI), created specifically for this study, offers a more comprehensive view of crime by accounting for both frequency and severity and identifying geographically dependent clusters of high severity. The findings suggest that locations with high male employment rates initially suffer an increase in crime as a result of increased economic activity, but as labor markets stabilize with more workforce participation, crime rates fall all over the state showcasing an inverted-U curved relation. Female graduation rates, which serve as a proxy for awareness and women empowerment, show a positive correlation with reported crime rates, indicating that as women become more educated and aware of their rights, they are more likely to report crimes, altering crime statistics and emphasizing the importance of social awareness in crime reporting all over the state. The number of police stations also has a negative spillover effect on the severity of crime especially in trans-border districts like Maldah and Uttar Dinajpur.

Policy Implications

The Government of India has taken several initiatives in the past decade to prevent criminal offenses in the country. *The Criminal Law (Amendment) Acts* of 2013 and 2018, modified the punishments for sexual offences and expedited the investigation process. Furthermore, the *Emergency Response Support System* (i.e., dial 112) offers a centralized, pan-India emergency response structure that improves police response times. Major cities including Kolkata in West Bengal have started *Safe City Projects* to increase urban safety through police presence, street lights installation, and monitoring. Cybercrime reporting portals and the National Database on Sexual Offenders were developed with case monitoring and management, especially when it comes to women's protection. The West Bengal government has increased police recruitment and improved police infrastructure in the last few years to address local safety challenges. Acknowledging the initiatives taken by the central and state governments to prevent violence we suggest a few policies based on our research findings. The study's findings suggest a need for policies that address West Bengal's unique socio-economic and geographic crime drivers. Strengthening cross-border security and collaboration with

Bangladesh is crucial for managing the impacts of cross-border crime incidents; Promoting education and stable employment, particularly in severe districts, can help alleviate criminal activities; Expanding female education can also foster empowerment and encourage crime reporting. Given the sensitive crime severity in urban areas, personalized urban safety measures such as more police protection, surveillance, and social welfare programs are essential; Localized law enforcement resources are needed, especially in high-crime districts, through increased police presence and accessible police stations to deter crime more effectively; Finally, community-based crime awareness programs could enhance public safety, foster social consistency, and reduce criminal activity across both urban and rural regions within the state.

Limitations of the Study

This present study has some limitations that need to be addressed properly. Reliance on secondary data sources, such as NCRB and census records, limits access to real-time or detailed crime data, while temporal gaps in data require interpolation techniques, potentially affecting trend accuracy. The district-level spatial aggregation may obscure the intra-district local impacts, especially in diverse areas of West Bengal. Additionally, certain cultural and social factors influencing crime such as social stigma and political dynamics are challenging to quantify and not taken into account. Lastly, the study focuses primarily on socioeconomic factors like employment, education, and urbanization, leaving out other relevant variables due to data constraints, such as human behavior, socially lagged population, political influence health, and housing conditions, that could provide robust findings. These limitations suggest cautious interpretation and point to areas for future research to develop a more detailed understanding of crime determinants.

Funding Statement: No financial support or funding was received for conducting this study. The research was self-initiated and carried out without any sponsorship from institutions, organizations, or individuals.

Human Ethics and Consent to Participate: This study does not involve human participants, biological materials, or data. Therefore, ethical approval and consent to participate are not applicable.

Appendix A (Maximum Likelihood Functions)

Following Griffith (1989), Lesage & Pace (2009), and Anselin (2013) we have used and derived the spatial econometrics models here. We have N number of cross-sections for T time points, which is a balanced panel model.

Rewriting the SAR model (equation 10) in vector form we get,

$$y = \rho W y + X\beta + \mu + \varepsilon ; i.i.d. \varepsilon \sim N(0, \sigma^2, I_{NT})$$

$$(I_{NT} - \rho W)y = X\beta + \mu + \varepsilon$$

$$y = (I_{NT} - \rho W)^{-1}(X\beta + \mu + \varepsilon)$$

Now, the log-likelihood function of the SPAM model can be formulated as,

$$L(\beta, \rho, \sigma^2) = -\frac{NT}{2} (\ln(2\pi \cdot \sigma^2)) + \ln|\Omega| - \frac{1}{2\sigma^2} (y - X\beta)^T \Omega^{-1} (y - X\beta)$$

$$\text{Given, } \Omega = (I_{NT} - \rho W)$$

This is the log-likelihood function that can be used to estimate the parameters β , ρ , and σ^2 in the Spatial Panel Autoregressive Model by maximizing it.

Rewriting the error term of the SEM model (equation 11) in vector form we get,

$$\varphi = (I - \lambda W)^{-1} \varepsilon ; i.i.d. \varepsilon \sim N(0, \sigma^2, I_{NT})$$

Since ε is normally distributed, φ is also normally distributed with,

$$\varphi \sim N[0, \sigma^2 ((I - \lambda W)(I - \lambda W)^T)^{-1}]$$

Substituting φ in the original model equation we get,

$$y_{jt} = X_{jt}\beta + \mu_j + (I - \lambda W)^{-1} \varepsilon_{jt}$$

Now, the log-likelihood function of the SPEM model can be expressed as,

$$L(\beta, \lambda, \sigma^2) = -\frac{NT}{2} (\ln(2\pi \cdot \sigma^2)) + T \ln |\Omega| - \frac{1}{2\sigma^2} \sum_{t=1}^T (y_t - X_t \beta - \mu)^T \Omega^T \cdot \Omega \cdot (y_t - X_t \beta - \mu)$$

Given, $\Omega = (I_{NT} - \lambda W)$

Where, $\ln|I_{NT} - \lambda W|$ term indicates the spatial dependence in the error term.

and, $\sum_{t=1}^T (y_t - X_t \beta - \mu)^T \Omega^T \cdot \Omega \cdot (y_t - X_t \beta - \mu)$ captures the spatially adjusted residual sum of squares.

By maximizing this log-likelihood function we can obtain the maximum likelihood estimates for the parameters of β, λ , and σ^2 .

Appendix B.1 (Pattern of Different Crimes in West Bengal)

See Figure 4.

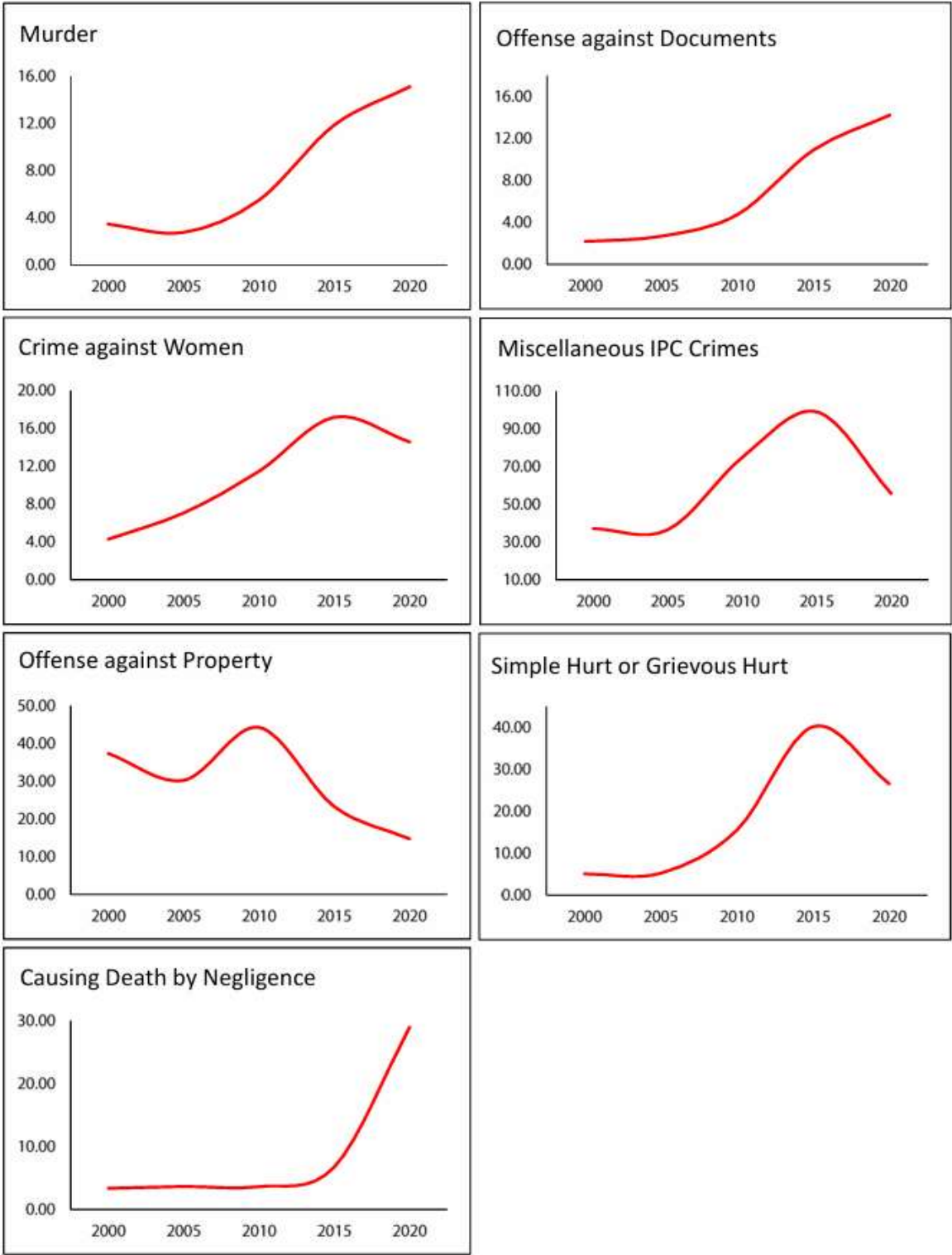


Figure 4. Different Types of Crime in West Bengal over the Years (Average per 1 lakh population) Source: Authors' estimation.

See Figure 5.

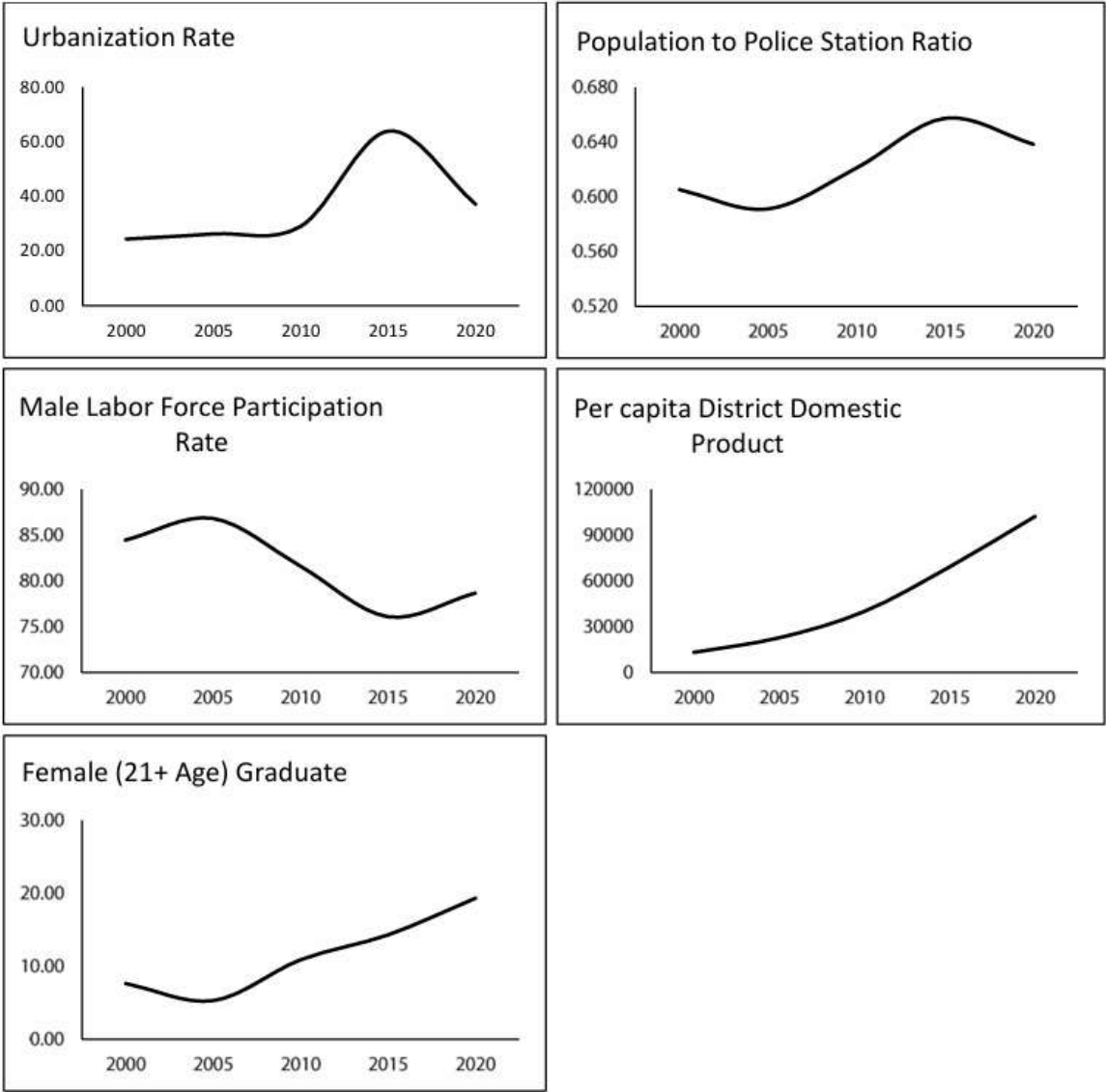


Figure 5. Change in Selected Explanatory Variable over the Years. Source: Authors’ estimation.

Appendix B.2 (Pattern of Crime Rate & Severity Index)

See Figure 6.

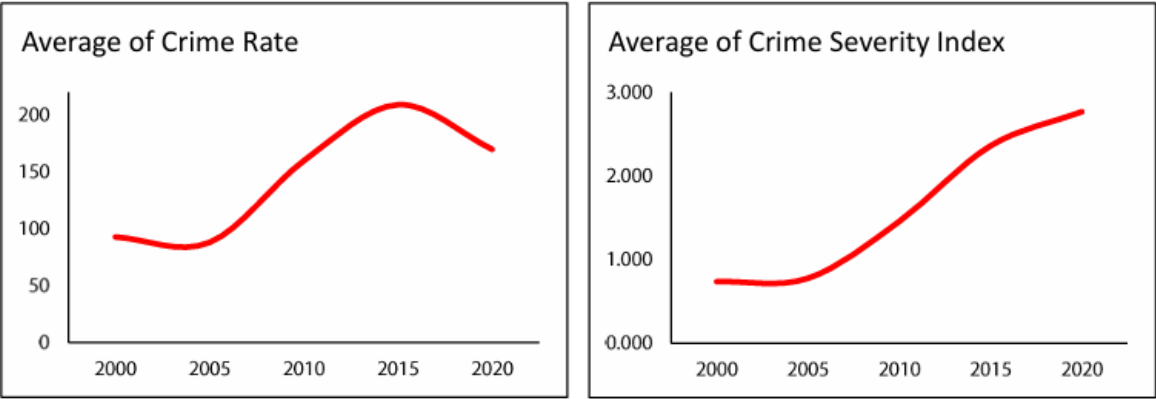


Figure 6. Change in Crime Rate and Severity Index Over the Years. Source: All the maps are drawn by Authors.

See Figure 7.

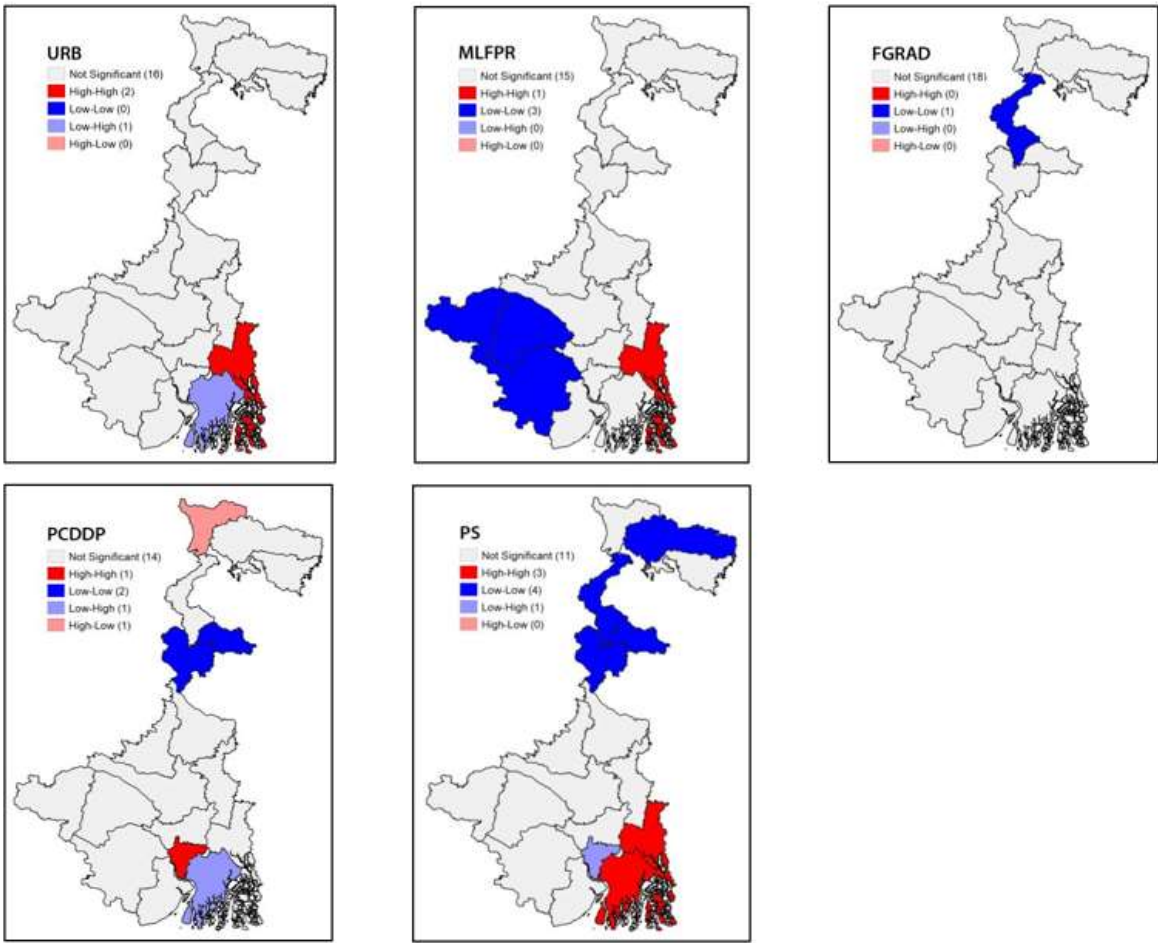


Figure 7. Local Moran’s I (LISA maps) of Selected Explanatory Variables in 2020. Source: All the maps are drawn by Authors.

Appendix C (Identification of Borderline Districts)

See Figure 8.

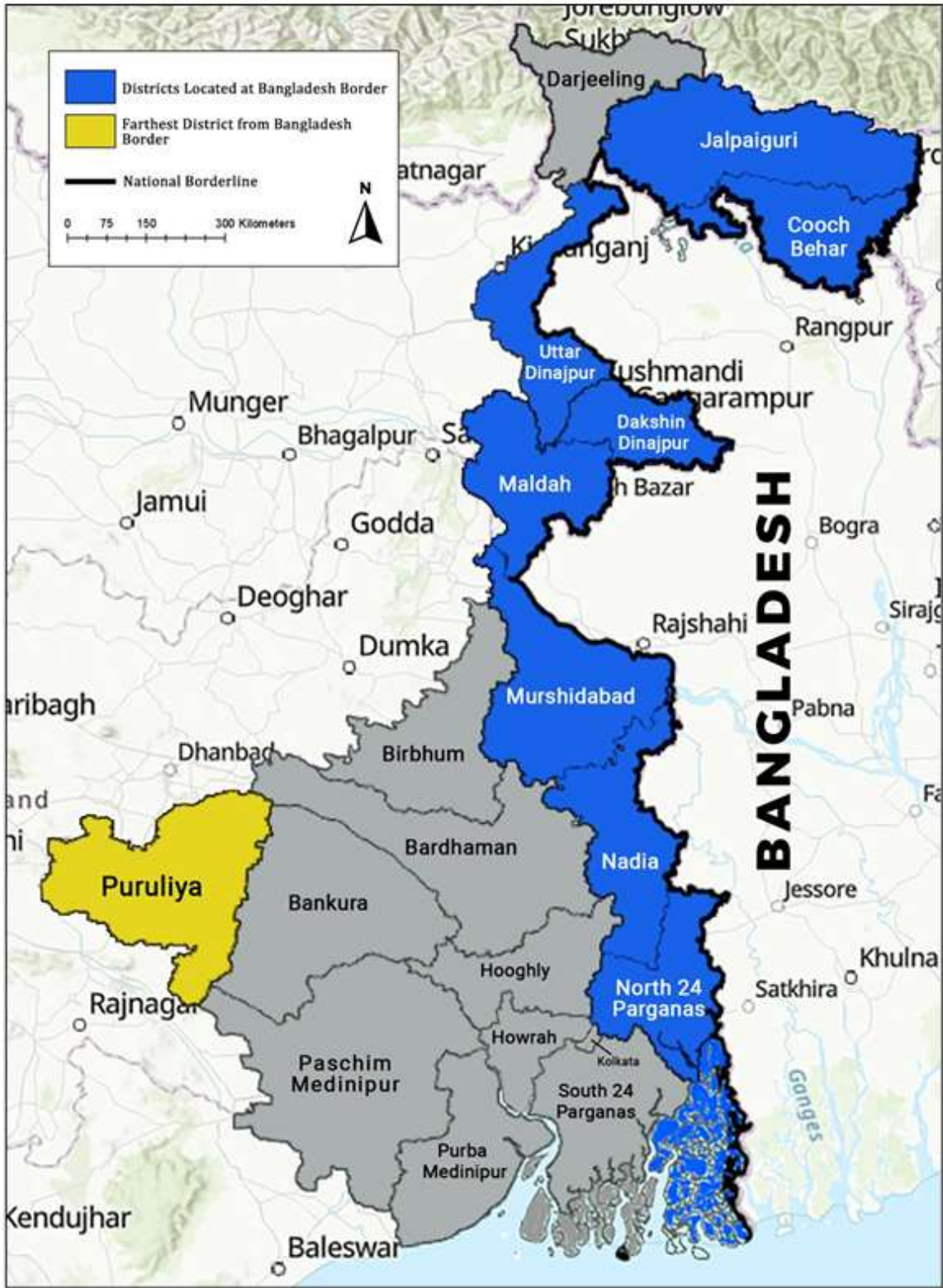


Figure 8. Districts in West Bengal Sharing a Common Boundary with Bangladesh. Source: All the maps are drawn by Authors.

Appendix D (Result of SPDM and SARAR Model)

Table 11. Spatial Regression Result of SDM and SARAR Models.

Effect	Dep. Var	Crime Rate	Crime Severity Index
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	Exp. Var	SDM	SARAR	SDM	SARAR
Main	lnURB	0.2695** (3.31)	0.0581 (1.26)	0.2684* (2.23)	0.1658* (1.99)
	lnMLFPR	-4.335 (-0.31)	49.485** (3.78)	-19.16 (-1.02)	49.897*** (1.70)
	(lnMLFPR) ²	0.5813 (0.35)	-5.933** (-3.77)	2.2920 (1.04)	-6.001*** (-1.72)
	lnFGRAD	0.0632 (1.26)	0.0461*** (1.75)	0.0810 (1.12)	0.1284* (2.55)
	lnPCDDP	-1.639 (-0.99)	1.3020* (2.29)	-1.6778 (-0.81)	-0.0857 (-0.10)
	(lnPCDDP) ²	0.0871 (1.10)	-0.060* (-2.23)	0.0892 (0.91)	0.0148 (0.36)
	lnPS	0.1438 (1.22)	-0.589* (-2.21)	-0.1436 (-0.69)	-1.559** (-4.09)
	Cons.	-3.460 (-0.04)	-	11.957 (0.09)	-
	lnURB	-0.001 (-0.02)	-	-0.0310 (-0.16)	-
	lnMLFPR	0.2541 (0.01)	-	11.672 (0.21)	-
Wx	(lnMLFPR) ²	0.0362 (0.01)	-	-1.333 (-0.20)	-
	lnFGRAD	0.1697** (3.14)	-	0.1591*** (1.76)	-
	lnPCDDP	3.7570* (2.15)	-	1.5247 (0.79)	-
	(lnPCDDP) ²	-0.1840 (-2.16)	-	-0.6521 (-0.69)	-
	lnPS	-0.0493 (-0.17)	-	-0.1917 (-0.34)	-
	<i>Rho</i> (ρ)	0.2917** (3.52)	0.5780** (5.52)	0.2460** (2.87)	0.4133** (4.58)
	<i>Sigma</i> (σ)	0.0517** (6.48)	0.0332** (7.84)	0.1062** (4.59)	0.0808 (6.41)
<i>Lambda</i> (λ)		-	-0.631** (-4.11)	-	-0.446** (-4.39)
<i>R</i> ² <i>W</i>		0.72	0.79	0.78	0.82
<i>R</i> ² <i>B</i>		0.78	0.25	0.62	0.33
<i>R</i> ²		0.75	0.61	0.00	0.08
<i>N</i>		95	95	95	95

Source: Authors’ estimation. **Significance parentheses:** **p* < 0.05; ***p*<0.01; ****p*<0.10. **Note:** SDM stands for Spatial Durbin Model; SARAR stands for Spatial-Autoregressive Model with Spatial Autoregressive Disturbances.

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