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Understanding the role of mobility in the recorded levels of violent crimes during COVID-19 pandemic: a case study of Tamil Nadu, India

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Abstract

Purpose/Goal This research investigates the potential link between mobility and violent crimes in Tamil Nadu, India, using an empirical study centred on the COVID-19 pandemic waves (2020–2022). The goal is to understand how these events influenced crime, employing a counterfactual approach.

Methods The study employs the XGBoost algorithm to forecast counterfactual events across different timeframes with varying levels of mobility. The mobility data sources include historical bus and passenger records spanning a decade, along with Google Community Mobility Reports added during the pandemic phases. The foundation for crime analysis is built upon the univariate time series of violent crimes reported as First Information Reports from 2010 to 2022.

Findings Results indicate a significant correlation between mobility and violent crimes when mobility drops below a specific threshold. However, no such correlation is observed when mobility is above this threshold during the non-pandemic periods. The COVID-19 pandemic had a major impact on people's and vehicular mobility, especially during the complete lockdown periods of the first two waves, and also affected crime rates.

Conclusions The decrease in recorded incidents could also be attributed to fewer criminal opportunities. Additionally, this could be due to unfavourable situational factors, such as victims' limited access to appropriate health and law enforcement agencies to report crimes. Furthermore, frontline services were busy with pandemic-related commitments, which could have contributed to a lack of crime registration even when crimes were committed.

Keywords Violent crimes, Counterfactual analysis, XGBoost, Mobility, Time series analysis, Pandemic

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Introduction

Mobility holds a pivotal role in shaping crime dynamics by influencing spatial crime distribution and victimisation risks (Browning et al., 2021). It impacts opportunities for crime, either by bringing together potential offenders and targets or by disrupting social controls and fostering anonymity (Felson & Cohen, 1980). This understanding is vital for crafting effective crime prevention strategies.

In Tamil Nadu, India, human mobility is influenced by a multitude of factors. Public health crises, such as the COVID-19 pandemic, have led to lockdowns and social distancing measures, markedly altering mobility patterns (Paramasivan et al., 2022). Natural disasters, including cyclones and floods, particularly in Chennai, necessitate evacuations and disrupt travel, as observed by Narayan (2017*)*. Economic drivers also play a role, with certain cities experiencing an influx of guest workers (Ramesh & Ramya, 2023). Political events, like the deaths of prominent leaders, have drawn millions to urban areas, drastically impacting mobility (*The Asian Age*, *2018*; *Times of Islamabad*, *2016*). Additionally, technological advancements have facilitated remote work, reducing the need for commuting (Mukherjee & Narang, 2023). Improved transportation infrastructure undoubtedly plays a role in influencing movement patterns. Overall even during non-pandemic times, there is considerable variation in the mobility pattern.

Extreme events like pandemics significantly disrupt mobility patterns, primarily due to imposed travel restrictions and social distancing measures. (de Palma et al., 2022). Such disruptions can cause disorientation and economic hardships, affecting people's ability to move (Onyeaka et al., 2021). Grasping these effects is crucial for responding to crises and curbing their impact on public safety.

To capture this dynamic mobility landscape, the study utilises two key data sources. First, it leverages passenger and operational data spanning a decade (Jan. 2010 – Dec. 2022) from one of the largest bus transport corporations in the region that is responsible for all the public transport in Tamil Nadu. Second, the study incorporates Google Mobility Community Reports for Tamil Nadu, encompassing pandemic and post-pandemic periods across six land-use categories. This comprehensive data approach will enable a nuanced understanding of human mobility patterns within Tamil Nadu.

The COVID-19 pandemic's unprecedented restrictions on movement offer a unique opportunity to examine the causal relationship between human mobility and violent crime rates. Taking advantage of a situation resembling a natural experiment, this study examines how changes in mobility patterns, especially during the three distinct pandemic waves with varying lockdown strictness, affect violent crime rates in Tamil Nadu (TN), India.

Directly comparing crime rates during the pandemic to pre-pandemic periods can be misleading due to factors like existing trends, seasonal variations, and holiday effects. To overcome this challenge, this research utilises a counterfactual approach that quantifies the impact of the pandemic on violent crime. The study employs a robust machine learning model, XGBoost, to perform a counterfactual prediction. This analysis estimates the crime rate that would have likely occurred in the absence of the pandemic. By comparing the actual reported crime rate with the predicted counterfactual rate, we can isolate the causal impact of the pandemic on crime.

To further elucidate the relationship between mobility and crime, the study replicates the counterfactual analysis using mobility data, specifically focusing on passenger volume and the number of buses operating. Although the primary emphasis is on the pandemic period and its induced mobility patterns in Tamil Nadu, the research spans nearly a decade, providing a broader context for understanding the dynamics between mobility and violent crime. This extensive approach enables a comprehensive assessment of how variations in mobility influence violent crime rates in Tamil Nadu, extending beyond the pandemic period alone.

Literature review and theoretical framework

Human mobility and crime

Browning and colleagues (2021*)* highlight the growing importance of human mobility in understanding crime patterns. They propose three key perspectives: place and neighborhood approaches, which analyze how the concentration of potential offenders, victims, and guardians in specific areas influences crime rates; person-centered approaches, which focus on individual movements and interactions with places to assess personal crime risk; and ecological network approaches, which examine broader systems of connections based on shared activity locations to understand how these connections impact crime variations at both individual and spatial levels. These perspectives collectively underscore the increasing theoretical significance of mobility within the field of criminology. Studies have demonstrated that increased human mobility often correlates with higher property crime rates in large cities. This suggests that previous research on population size and crime rates might have been skewed by the presence of "floating populations" (e.g., tourists, temporary workers) rather than solely focusing on resident populations (Caminha et al., 2017). Furthermore, research indicates that the interconnectedness of human mobility networks plays a crucial role in predicting violent crime, even more so than geographical proximity alone. Neighborhoods experiencing significant changes in mobility patterns often see a rise in violent incidents, highlighting the importance of considering mobility dynamics in crime prevention strategies (Vachuska, 2022).Several studies have successfully used aggregated human mobility data from mobile networks, combined with demographic information, to accurately predict crime hotspots in cities like London (Bogomolov et al., 2014). Including mobility data in crime prediction models has demonstrably improved accuracy, with studies showing increases of up to 89% (Kadar & Pletikosa, 2018) and 70% (Wu et al., 2022).

It's important to note that the influence of human mobility on crime likely varies depending on the specific crime type. Crimes like cybercrime, domestic violence, child sexual abuse, institutional crimes (e.g., corruption), and certain white-collar crimes are often driven by unique opportunity structures and may be less influenced by location compared to violent crimes like homicide, assault, and rioting.

Impact of COVID-19 on violent crime worldwide

The COVID-19 pandemic has undoubtedly impacted the occurrence and reporting of violent crime worldwide. A complex interplay of factors, including mobility restrictions, media coverage, mental health impacts, resource availability, and emergency response efforts, has contributed to these changes. Research findings indicate that the pandemic's effects on crime varied significantly across countries and crime categories (Nivette et al., 2021).

As LeClerc and Wortley (2013) emphasise, it's crucial to avoid overgeneralizing crime patterns in criminology. Understanding the specific decision-making processes of offenders is essential for developing effective crime prevention strategies.

This emphasis on specificity is crucial, especially within crime types, to grasp the nuances of shifting crime patterns. It becomes even more critical during pandemics, where understanding subtle changes, like opportunity structures, is paramount. For instance, pandemic-induced alterations in daily routines can lead to decreased populations in non-residential areas and increased populations in residential zones (Stickle et al., 2020).

The opportunity structure for a particular form of crime is not always the same. Most property offences, for example, have greatly dropped, as have road traffic accidents (Paramasivan et al., 2022). Murder, assault, and rioting, on the other hand, increased in certain places in the USA (Kim, 2022; Meyer et al., 2022) while remaining stable (Campedelli et al., 2021) or dropping in others (Calderon-Anyosa & Kaufman, 2021).

Regarding the pandemic, a few research works predict a drastic to moderate reduction in all crimes, including violent crimes (Abrams, 2020; Cheung & Gunby, 2021; Halford et al., 2020; Nivette et al., 2021). On the other hand, there are contradictory patterns of increased violent crimes in many places around the world (Hilsenrath, 2020; Kourti et al., 2021; Krishnakumar et al., 2021; Maji et al., 2021; Piquero et al., 2021; Raghavan, 2021).

According to Abrams (2020*)*, the theoretical framework of opportunity theory posits that a decrease in interpersonal connection during the various pandemic phases is likely to result in a corresponding decline in opportunities for the commission of specific violent crimes, including assault, rape, and robbery. The potential impact of implementing or removing restrictions on mobility is expected to have an effect on the incidence of reported criminal activities, either registering an increase or decrease in crime rates. The authors suggest that this discovery provides empirical backing for routine activities/opportunity theory, as there is a positive correlation between the incidence of violent crime and the increased mobility of potential victims and offenders across temporal and spatial dimensions (Lopez & Rosenfeld, 2021).

The researchers of the present work seek to explain the role of mobility in the recorded levels of violent crimes on the basis of Crime Pattern Theory (Brantingham et al., 2016), Routine Activity Theory (RAT) (Felson & Cohen, 1980) and Crime Opportunity Theory (Hannon, 2002). Crime Pattern Theory, which is based on environmental psychology, emphasises the relevance of people's habitual actions in raising awareness of criminal opportunities. First, offenders may be able to discover criminal opportunities more quickly and frequently near their points of activity, known as nodes. Qualitative research has established that the potential for crime opportunity awareness exists in the family, workplace, and other non-criminal settings (Curtis-Ham et al., 2023). Some quantitative research works (Brantingham & Brantingham, 1993; Menting et al., 2019; van Sleeuwen et al., 2021) suggest that offenders are more likely to commit crimes near their houses, the residences of close relatives, and the sites of previous offences than in other regions. On the other hand, because normal activities play a role in raising awareness of criminal chances, the likelihood of offending is highest near activity nodes and diminishes with distance. This decreasing distance pattern reflects the fact that people are more familiar with places closer to their activity locations than with areas farther away, and familiarity is a major component in crime location selection. All of this is also consistent with the concept of least effort: in theory, people will take the smallest distance possible to find a chance to commit a crime (Curtis-Ham et al., 2020). When mobility is severely hampered in the context of extraordinary circumstances such as a pandemic, there is a lower probability of crime occurrence due to fewer crime opportunities and a lower likelihood of committing offences near activity space where there is increased guardianship.

Building on the comprehensive discussion of human mobility's influence on crime and the pandemic's impact on crime rates, this literature review highlights a critical gap. While existing research explores these topics, there is a scarcity of studies examining the relationship between mobility and crime across an extended timeframe encompassing both pre-pandemic normalcy and the entire COVID-19 pandemic period (2020–2022).

This research aims to address this gap by investigating the potential link between mobility and violent crimes in Tamil Nadu, India, using an empirical study focused on the COVID-19 pandemic waves. This counterfactual approach will employ the XGBoost algorithm to forecast crime occurrences under hypothetical scenarios with varying levels of mobility.

The study employs counterfactual analysis using the rich datasets spanning a decade: historical bus and passenger records for mobility data and First Information Reports (FIRs) for crime data from 2010 to 2022. By analyzing these data in conjunction with Google Community Mobility Reports from the pandemic period, this research seeks to find the relationship between human mobility and violent crime.

Data and method

In response to the World Health Organization's (WHO) declaration of COVID-19 as a pandemic, the Government of Tamil Nadu, under the National Disaster Management Act, 2006, issued emergency orders through the Revenue and Disaster Management Department to contain the virus by restricting movement. Throughout 2020–2022, the department released a series of government orders (GOs) that prohibited, restricted, or relaxed activities for individuals, organisations, and agencies. These GOs, available on the official government website, document the lockdown measures implemented during Waves 1 and 2 (*Government of Tamil Nadu. (2020). Order: Wave 1*; *Government of Tamil Nadu. (2021). Order: Wave 2*). During Wave 3, although mandatory restrictions were not imposed, the government issued precautionary measures and advisories to encourage public safety.

The study investigates three pandemic waves that occurred from Mar. 23, 2020 to Aug. 31, 2020, Apr. 10, 2021 to Jun. 07, 2021 and Jan. 07, 2022 to Feb. 17, 2022, respectively, spanning 2020–2022. The region of analysis is Tamil Nadu, the sixth most populous state in India. Figure 1 illustrates the study's timeline across various windows corresponding to the pandemic waves. Criminality was evaluated using time-series data, primarily focusing on crimes against individuals documented through First Information Reports (FIRs) — formal reports of cognisable offences initiating investigations.

Lockdown severity fluctuated throughout the pandemic. Complete lockdown (CL) represented the most stringent measures, prohibiting all movement of people and vehicles. All institutions, markets, businesses, and shops, including those selling essential goods like alcohol, were completely shut down. People were mandated to stay indoors except for limited windows for purchasing medicines, essential groceries and vegetables. Social gatherings, including funerals and weddings, were heavily restricted. Exceptions were made for vehicles transporting essential goods and personnel involved in pandemic response, particularly healthcare, police, and local administration.

Partial lockdown (PL) introduced a gradual easing of these restrictions. Key industries and establishments reopened with limited staff and operating hours. Shops selling essential goods received extended opening times compared to CL. Alcohol sales were permitted for a limited daily window. Social gatherings of up to 50 people were allowed, but large venues like stadiums, theatres, malls, and major markets remained closed. Importantly, schools and colleges stayed shut, and private taxis and public transportation like buses, trains, and coaches remained non-operational.

The research relies on the First Information Reports (FIRs) registered in Tamil Nadu. Crimes are reported via FIRs in TN's 1356 police stations, primarily governed by the Indian Penal Code (IPC) Chapter XVI (Sects. 299–377) for crimes against the human body. The analysis

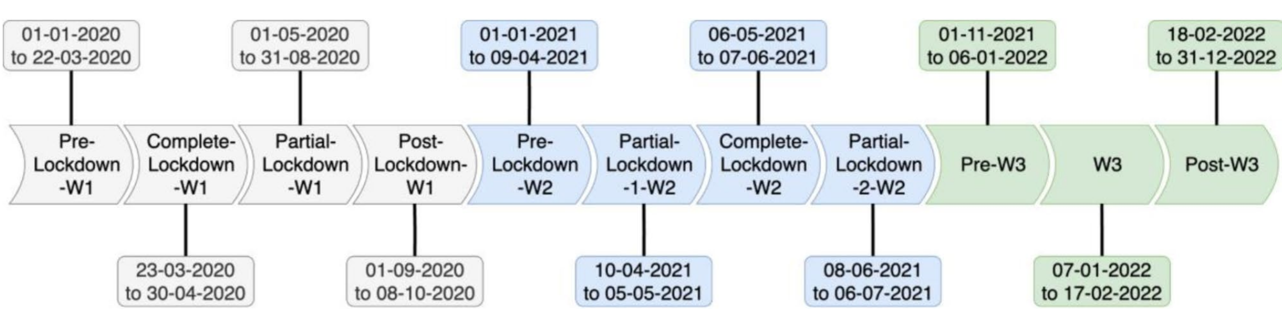

Fig. 1 The timeline for the different phases of lockdowns during the three pandemic waves (W1, W2, and W3) in 2020–2022

centres on frequently reported offenses within this category — including murder, attempted murder, aggravated assault, and rioting. The study employs univariate time series data of the state's daily crime count spanning Jan. 1, 2010, to Dec. 31, 2022, for counterfactual analysis.

This research leverages mobility data from two sources to provide a comprehensive picture of the movement of people and vehicles in Tamil Nadu. The first source, encompassing daily bus and passenger frequency data from the Tamil Nadu State Transport Corporation (TNSTC) between Jan. 1, 2010 and Dec. 31, 2022, offers over a decade of pre-pandemic and pandemic period information. The second source, the Google Community Mobility Report, provides data on movement trends across six land-use zones within TN during the pandemic and post-pandemic period. By combining these two datasets, the study gains a richer understanding of mobility patterns throughout the region.

Google Community Mobility Reports (GCMR) that utilise user data — especially from handheld devices — are used to assess mobility trends for the pandemic phases. GCMR categorises user presence and time spent in domains like 'retail and recreation', 'parks', 'groceries and pharmacies', 'workplaces', 'transit stations', and 'residential areas' to gauge mobility changes. For each domain (e.g., retail, grocery stores), it calculates the relative change in visits compared to a pre-pandemic baseline (median visits from Jan. 3, 2020, to Feb. 6, 2020). This change signifies mobility trends within that domain. For example, a -20% change in retail visits signifies a 20% decrease compared to the baseline, while a + 15% change in residential time indicates a 15% increase in time spent at home.

Table 1 XGBoost training, validation, and forecast periods for daily crime registration, bus operation, and passenger count prediction

Model Number	From	To
Model – 1		
Training Period	01/01/10	31/12/19
Validation Period	01/01/20	22/03/20
Forecast Periods		
Complete-Lockdown-W1	23/03/20	30/04/20
Partial-Lockdown-W1	01/05/20	08/06/20
Post-Lockdown-W1	01/09/20	08/10/20
Model – 2		
Training Period	01/01/10	31/12/20
Validation Period	01/01/21	31/03/21
Forecast Periods		
Partial-Lockdown-1-W2	10/04/21	05/05/21
Complete-Lockdown-W2	06/05/21	07/06/21
Partial-Lockdown-2-W2	08/06/21	06/07/21
Pre-W3	01/11/21	06/01/22
W3	07/01/22	17/02/22
Post-W3	18/02/22	31/12/22

The research starts with an exploratory analysis to determine if the pandemic caused significant changes in crime rates. Instead of merely comparing the mean or median of daily crime frequencies between pandemic and non-pandemic periods, it compares the distributions to identify any differential impacts. The Shapiro-Wilk Test is used to check for normality. Given that the population sizes differ between the periods, normality is likely violated, so the Mann-Whitney U test, a non-parametric test, is employed to check for statistical differences between the two distributions. To quantify the difference, Cliff's Delta, another non-parametric measure of effect size, is used (Hess et al., 2014).

In the next level, to gauge the impact of the pandemic specifically and only on the major violent crimes, including attempted murder, murder, aggravated assault and rioting, the study deploys counterfactual analysis as the simplistic aggregated comparison done might be erroneous as likely it would have missed the trend, seasonality and holiday effects of the time series of the past historical data. This study utilizes XGBoost, a machine learning algorithm for time series forecasting and counterfactual analysis, to make predictions during the pandemic period based on a decade of historical data. The historical data is used to create lag and rolling features, capturing trends and patterns for accurate predictions. The variables include daily crime counts. The research involves creating and fine-tuning models through training, validation, and forecasting stages, as detailed in Table 1.

During training, XGBoost sequentially trains decision trees, improving model accuracy by focusing on incorrectly predicted observations and predicting their residuals. The algorithm monitors performance on a validation set to avoid overfitting, using an early stopping criterion when validation performance stops improving.

The model's accuracy is evaluated using the weighted mean absolute percentage error (WMAPE) metric, which avoids infinite errors by addressing zero crime days. WMAPE is calculated as the summation of absolute differences between actual and predicted values divided by the summation of actual values over the time period t from 1 to n.

$$WMAPE = \frac{\sum_{\{t=1}}^{n} |actual_t - predicted_t|}{\sum_{\{t=1}}^{n} actual_t}$$

To gain a more comprehensive understanding of the pandemic's impact, the counterfactual analysis is replicated for mobility data. This analysis explores changes in both vehicular mobility (number of buses operated) and people's mobility (passenger travel).

Next, a deeper investigation assesses the pandemic's influence on four specific violent crimes. Utilising data

Table 2 Comparison of distributions of actual daily number of crimes during pandemic and non-pandemic periods – statistical difference test- effect size measured

	Pandemic				**Non-Pandemic**				**M-W U test**	**Cliffs Delta**	
Category of Crime	Mean	Median	Mode	Std. Dev.	Mean	Median	Mode	Std. Dev.	p value	Value	Confidence Interval
Aggravated Assault	70	69.5	69	35.6	80.7	78	76	24.5	**< 0.001**	-0.20	[-0.296, -0.108]
Attempted Murder	8.7	8	8	5.7	8.8	8	8	4.2	0.06	-0.08	[-0.17, 0.008]
Murder	4.4	4	1	3	5	5	4	2.6	**< 0.001**	-0.14	[-0.231, -0.056]
Rioting	5.8	4.5	4	4.3	7.5	7	4	5	**< 0.001**	-0.25	[-0.326, -0.166]
Domestic Violence	1.8	1	0	1.8	4.5	4	3	3.3	**< 0.001**	-0.53	[-0.583, -0.466]
Dacoity	0.4	0	0	0.7	0.5	0	0	0.8	0.08	-0.06	[-0.116, 0.006]
Dowry Prohibition Act	0.5	0	0	0.8	0.4	0	0	0.7	**0.01**	0.09	[0.021, 0.154]
Fatal Accident	32	33.5	34	15.1	43.3	43	40	11.6	**< 0.001**	-0.43	[-0.508, -0.348]
Grevious Injury	43.6	44	16	23	55.2	52	23	30.6	**< 0.001**	-0.21	[-0.274, -0.129]
Minor Injury	85.8	87.5	100	45.1	131.6	135	132	32	**< 0.001**	-0.57	[-0.644, -0.503]
Murder For Gain	0.1	0	0	0.3	0.4	0	0	0.7	**< 0.001**	-0.17	[-0.21, -0.131]
Pocso Act	12	12	13	6.4	5.8	4	0	6.2	**< 0.001**	0.54	[0.481, 0.592]
Rape	1.2	1	0	1.3	4.7	2	1	17.4	**< 0.001**	-0.23	[-0.303, -0.163]
Robbery	6.8	7	2	4.2	8.6	8	7	3.7	**< 0.001**	-0.25	[-0.331, -0.162]
Sexual Harassment	1.8	1	1	1.7	1.7	1	0	1.7	0.09	0.07	[-0.002, 0.14]
Burglary	11.3	11	13	6.2	14.7	14	15	5.6	**< 0.001**	-0.32	[-0.399, -0.235]
Non Injury	201.7	154.5	3	178.3	152.5	158	148	62.2	0.22	0.05	[-0.05, 0.156]
Theft	36.4	40	10	19.5	53.4	54	59	15.9	**< 0.001**	-0.53	[-0.596, -0.462]

M-W U test: Mann-Whitney U test for statistical difference between two distribution

Significance bold values: p-value less than 0.05

Table 3 Prediction error (WMAPE) for six time series — four violent crimes and mobility (bus and passenger) in the appropriate validation periods

	Aggravated Assault	**Attempt to Commit Murder**	**Murder**	**Rioting**	**Bus Mobility**	**Passenger Mobility**
Model-1 Pandemic Wave-1	0.158	0.27	0.103	0.229	0.02	0.09
Model-2 Pandemic Wave-2 and Wave-3	0.111	0.179	0.143	0.252	0.041	0.18

from the Google Community Mobility Report (GCMR), the analysis examines these crimes across six land-use categories. This detailed exploration considers data from three distinct pandemic waves, further divided into nine phases with varying mobility patterns.

Similar to the crime analysis, the researchers compare actual and predicted distributions for mobility and crime data using appropriate statistical tests. Finally, Cliff's Delta, a non-parametric effect size measure, is employed to quantify the magnitude of these effects.

In the last part of the investigation, the study evaluates Pearson's correlation coefficient between mobility metrics and four categories of violent crime for various phases in the pandemic period. The mobility metrics in the results include transportation data (buses operated and passengers traveled) as well as the percentage change in mobility provided by GCMR. The carefully examined relationship between these factors becomes one of the major findings of the research.

Results

Compared to non-pandemic periods, most crime categories – including violent crime, property offenses, and crimes against women and children – showed statistically significant declines during the pandemic. However, the decrease was negligible for these crimes. Road crashes, domestic violence, and theft saw substantial reductions with medium to large effect sizes. Notably, child sexual abuse cases exhibited a large effect size increase during the pandemic compared to non-pandemic times (see Table 2).

The counterfactual analysis performed using XGBoost prediction provided results within acceptable levels of accuracy for several time series forecasts (see Table 3). The investigation yielded two significant results. The first is about counterfactual analysis of the impact on crime and mobility during exceptional circumstances, and the second is about descriptive statistical analysis exploring the relationship between mobility and recorded levels of crime at all times.

Counterfactual daily counts of violent crimes represent incidents without an emergency. The observed/actual daily violent crime counts and predicted numbers in a non-emergency scenario were compared. The Wilcoxon test revealed no significant variations in distributions across violent crime categories throughout time frames, as highlighted in Table 4, except during the complete lockdown in Wave-1 when all violent crimes reported a significant drop in recorded levels. During this severely restricted movement period, the effect size for aggravated assault, attempted murder, murder, and rioting was −0.96, -0.4, -0.45, and −0.28 compared to the counterfactual (refer to Table 5). The most noticeable effect was on aggravated assault levels. This trend is visually illustrated in Fig. 2, which showcases a distinct decline in aggravated assault cases during Wave-1's lockdown. The counterfactual analysis was extended to measure people's mobility and vehicular mobility during the COVID-19 pandemic, and it revealed that only during Wave-1 of the pandemic was there a significant reduction in both mobilities, whereas during the non-pandemic period did not report any significant reduction as can be seen in the effect sizes which were negligible or small (See also Table 6**and** Table 7). These findings mirror the analysis of the Google Mobility Community Report (GMCR) in Table 8. The GMCR investigation, which is not a counterfactual analysis, is only applicable during the pandemic phases and compares pandemic mobility to pre-pandemic mobility.

The study analyses the correlation between registered crimes and mobility (transportation department data) using Pearson's correlation coefficient (r) based on daily crime counts and mobility data from Jan. 1, 2010, to Dec. 31, 2022. Table 9 indicates a negligible correlation between crimes and vehicular mobility, and the same for people's mobility, except for aggravated assault ($r=+0.456$) and child sexual abuse (r = -0.577), moderately correlated to people's mobility via passenger counts.

The investigation distinguishes between crisis (pandemic lockdowns) and non-emergency periods, particularly during 2010–2022. Analysis within these emergency periods reveals a significant correlation between mobility and violent crimes during severe restrictions, importantly in complete lockdown phases of the first two pandemic waves. Particularly, aggravated assault cases displayed a significant correlation during restricted mobility windows in pandemic lockdowns of Wave-1 and Wave-2. Noticeably, all categories of violent crimes exhibited moderate correlation during both waves of complete lockdown. People's mobility and vehicular mobility showed no discernible difference concerning their relationship with registered violent crimes (Table 10).

The transportation department's mobility data validation using GMCR data confirmed the relationship between mobility and violent crime. Figure 3 visually depicts the direct correlation between mobility changes across public spaces and reported crimes in the first six time windows from Wave-1 to Post-Wave-2. The percentage variations in mobility in different time frames follow the same trend, with the exception of the residential zone, where mobility increased as people stayed indoors more during the lockdown stages. However, the magnitude of such change expectedly varied, with the maximum occurring in the retail and recreation zone and the minimum in the spatial domain of pharmacy and grocery. In the most recent two periods, Wave-3 and post-Wave-3, there is no such correlation, as the percentage change in mobility increased across all land-use categories during these periods.

Discussion

This section begins by highlighting the key findings presented in the previous section. Table 2 presents a straightforward comparative impact on general crimes, revealing a statistically significant difference between crime distributions during the pandemic and

Table 4 Results of wilcoxon test for actual vs. predicted distribution of violent crimes and mobility during pandemic periods

Timeline	Aggravated Assault	Attempted Murder	Murder	Rioting	Bus	Passenger
	p-value	p-value	p-value	p-value	p-value	p-value
Pre-Lockdown-W1	**0.034**	0.315	0.965	0.417	**0.013**	**< 0.001**
Complete-Lockdown-W1	**< 0.001**	**0.001**	**< 0.001**	**0.012**	**< 0.001**	**< 0.001**
Partial-Lockdown-W1	0.929	0.138	0.062	0.167	< 0.001	**< 0.001**
Post-Lockdown-W1	0.742	0.626	0.455	0.709	< 0.001	**< 0.001**
Pre-Lockdown-W2	0.010	0.233	0.593	0.472	**0.009**	**< 0.001**
Partial-Lockdown-1-W2	0.499	0.784	0.437	0.452	**0.024**	**0.001**
Complete-Lockdown-W2	**< 0.001**	0.572	0.396	0.672	**0.009**	**< 0.001**
Partial-Lockdown-2-W2	**0.046**	0.932	0.405	0.609	0.815	**0.016**
Pre-W3	0.631	0.476	0.306	0.694	< 0.001	**< 0.001**
W3	**0.022**	0.450	0.352	0.729	< 0.001	**< 0.001**
Post-W3	0.146	0.483	0.954	0.218	< 0.001	**< 0.001**

Significance bold values: p-value less than 0.05

Table 5 Violent crime change with counterfactual and effect size in emergency phases in TN

	Assault			Attempted Murder			Murder			Rioting		
	% Change	Cliff's Delta Confidence Interval	Cliff's Delta	% Change	Cliff's Delta Confidence Interval	Cliff's Delta	% Change	Cliff's Delta Confidence Interval	Cliff's Delta	% Change	Cliff's Delta Confidence Interval	Cliff's Delta
Wave – 1												
Pre-Lockdown-W1	-5.22	[-0.327, 0.037]	-0.15	7.42	[-0.136, 0.221]	0.04	1.95	[-0.17, 0.191]	0.01	3.39	[-0.175, 0.179]	0.00
Complete-Lockdown-W1	**-62.27**	**[-1.0, -0.809]**	**-0.96**	**-23.35**	**[-0.625, -0.098]**	**-0.40**	**-31.48**	**[-0.66, -0.16]**	**-0.45**	**-15.31**	**[-0.481, 0.045]**	**-0.23**
Partial-Lockdown-W1	4.39	[-0.207, 0.323]	0.06	12.77	[-0.215, 0.316]	0.06	-6.27	[-0.357, 0.157]	-0.10	-7.21	[-0.332, 0.187]	-0.07
Post-Lockdown-W1	-0.57	[-0.32, 0.226]	-0.05	-0.81	[-0.274, 0.256]	-0.01	-2.29	[-0.276, 0.245]	-0.02	0.47	[-0.271, 0.258]	-0.01
Wave-2												
Pre-Lockdown-W2	-4.16	[-0.265, 0.057]	-0.11	4.79	[-0.106, 0.207]	0.05	2.91	[-0.144, 0.183]	0.02	0.17	[-0.212, 0.116]	-0.05
Partial-Lockdown-1-W2	-2.87	[-0.364, 0.275]	-0.04	0.87	[-0.361, 0.308]	-0.03	-2.69	[-0.367, 0.266]	-0.05	1.45	[-0.402, 0.263]	-0.07
Complete-Lockdown-W2	**-16.40**	**[-0.691, -0.159]**	**-0.46**	-3.90	[-0.377, 0.188]	-0.10	-3.89	[-0.333, 0.26]	-0.04	-5.25	[-0.374, 0.218]	-0.09
Partial-Lockdown-2-W2	4.67	[-0.237, 0.377]	0.08	0.46	[-0.31, 0.298]	0.00	5.16	[-0.315, 0.298]	-0.01	-2.06	[-0.382, 0.225]	-0.08
Wave-3												
Pre-W3	-3.31	[-0.26, 0.151]	-0.06	-1.84	[-0.232, 0.158]	-0.04	-1.90	[-0.224, 0.173]	-0.03	-1.27	[-0.27, 0.131]	-0.07
W3	-4.29	[-0.381, 0.101]	-0.15	2.02	[-0.207, 0.293]	0.05	0.87	[-0.213, 0.287]	0.03	1.32	[-0.246, 0.26]	0.01
Post-W3	-0.97	[-0.127, 0.051]	-0.04	-1.00	[-0.115, 0.066]	-0.02	0.56	[-0.104, 0.077]	-0.01	1.08	[-0.105, 0.076]	-0.01

Significance bold values: p-value less than 0.05

non-pandemic periods. However, the effect size for violent crimes, such as attempted murder, murder, rioting, and aggravated assault, is negligible. A more detailed counterfactual comparison dividing the pandemic into nine phases (Table 4) shows a substantial drop in all violent crimes during the complete lockdown in Wave-1 when mobility was severely restricted.

When examining the correlation between mobility (using passenger and bus data) and violent crime, significant correlation coefficients were observed during the complete lockdown periods of both waves (Table 10). Further analysis across the entire pandemic period, relying on the standards of the range of Pearson's correlation coefficient (Ratner, 2009), found a moderate positive correlation between percentage changes or effect size metrics of mobility and violent crime (Table 11).

Unlike the transportation data, which does not categorise crime locations, the GCMR data provides percentage changes in mobility divided into six specific land-use categories, facilitating further analysis. The study reveals a high correlation between changes in mobility within these six land-use categories and four types of violent crimes, as shown in Fig. 3. Notably, during post-wave-2, wave-3, and post-wave-3 periods, when mobility levels remained stable, this correlation disappeared across all land-use zones and crime categories (Fig. 3).

In summary, there is generally no correlation between mobility and violent crimes at all times. However, if mobility falls below a certain threshold, a relationship emerges, with substantial reductions in mobility leading to significant decreases in violent crime.

Recorded levels of crime rates are affected by other situational factors such as victims' ability, willingness, and eagerness to report crimes (Stefanovska, 2019; Wittebrood & Junger, 2002) and law enforcement's proficiency and responsiveness (Boateng, 2016). The second wave of COVID-19 was more lethal than the first (Tendulkar et al., 2023); India Coronavirus: Worldometer, 2024), but violent crimes decreased despite a relative increase in mobility during the complete lockdown during the second wave. This decline may occur due to a clogged crime reporting system and overburdened hospitals and other frontline agencies. Deterioration of the medical infrastructure impedes crime reporting and victim assistance.

During the complete lockdown in wave-1 of the pandemic, the decline in aggravated assault, attempted murder and murder, as reported by Cliffs Delta, were −0.96, -0.4,-0.45, respectively. In the same period, mobility decreased most significantly in Retail and Recreation zones (-80.5%), followed by Workplace (-64.3%), Transit Stations (-62%), Grocery and Pharmacy (-51.2%), and Parks. Locations such as bars, recreational centers, street-side shops, and bus stations are particularly prone to the above violent crimes (Brantingham et al., 2016).

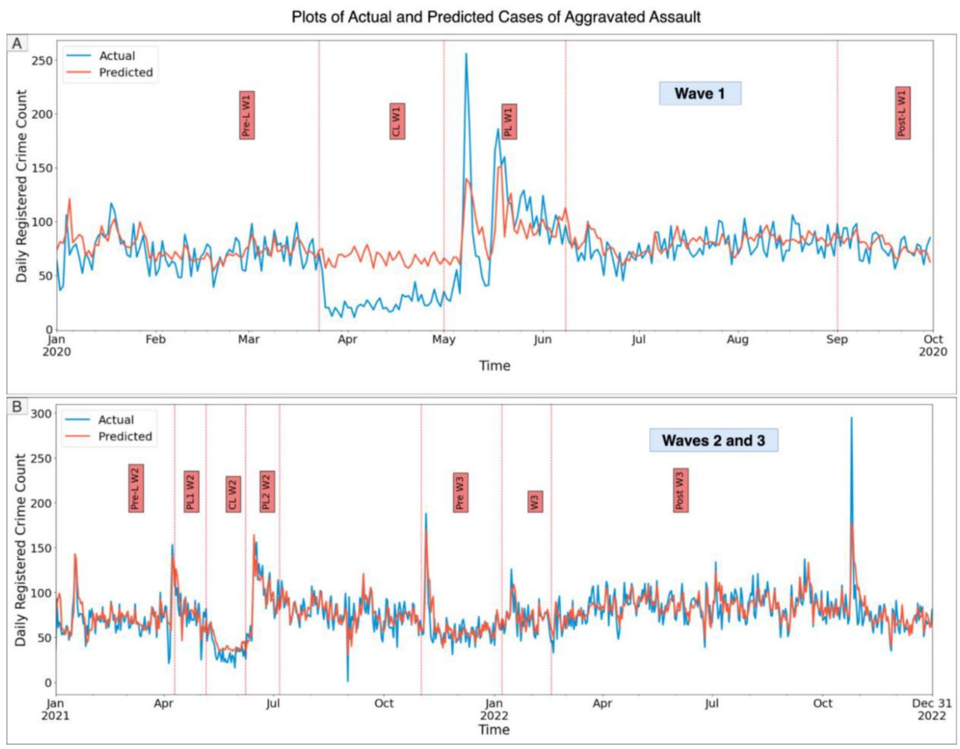

Fig. 2 **A**,**B** Plot of actual and predicted daily aggravated assault cases in TN during pandemic waves 1, 2, and 3

Table 6 Mobility measured through the number of buses operated during the COVID-19 lockdown (ES-Effect size cliffs Delta)

PERIOD	FROM	TO	ACTUAL	PREDICTED	PREDICTED RANGE	ES	ES RANGE	ES CATEGORY
WAVE – 1								
Pre-Lockdown-W1	01/01/20	22/03/20	18,457	18657.4	(18506.4, 18808.4)	-0.14	[-0.319, 0.032]	negligible
Complete-Lockdown-W1	23/03/20	30/04/20	3654	16058.74	(15706.2, 16411.2)	-0.99	[-1.0, -0.953]	large
Partial-Lockdown-W1	01/05/20	08/06/20	4167	16327.71	(16218.9, 16436.5)	-1.00	[-1.0, -1.0]	large
Post-Lockdown-W1	01/09/20	08/10/20	12,178	16546.64	(16374.9, 16718.4)	-1.00	[-1.0, -1.0]	large
WAVE-2								
Pre-Lockdown-W2	01/01/21	09/04/21	17,133	16983.11	(16827.9, 17138.2)	0.28	[0.102, 0.426]	small
Partial-Lockdown-1-W2	10/04/21	05/05/21	15,718	13429.73	(11723.2, 15136.2)	0.20	[-0.118, 0.5]	small
Complete-Lockdown-W2	06/05/21	07/06/21	5665	6675.807	(6012.9, 7338.7)	-0.70	[-0.884, -0.405]	large
Partial-Lockdown-2-W2	08/06/21	06/07/21	7180	7086.173	(6513.7, 7658.6)	-0.12	[-0.439, 0.208]	negligible
WAVE-3								
Pre-W3	01/11/21	06/01/22	17,344	17,140	(17041.6, 17238.4)	0.31	[0.107, 0.499]	small
W3	07/01/22	17/02/22	16,702	12,827	(11719.7, 13933.6)	0.76	[0.527, 0.889]	large
Post-W3	18/02/22	31/12/22	17,596	17,509	(17463.2, 17555.1)	0.23	[0.13, 0.313]	small

The substantial fall decline in mobility observed in retail and recreational, workplace, transit stations and parks may be attributable to a diminishing criminal opportunity for the offender due to limited activity space (Curtis-Ham et al., 2021). According to Brantingham and Brantingham (1993*)*, instances of crime arise when the awareness space of offenders, which refers to the areas they are cognizant of in proximity to their activity nodes, intersects with chances for criminal behaviour. The presence of potential targets and the absence of effective guardians create opportunities for criminal activity (Felson & Cohen, 1980), however, substantially reduced mobility during the strict stay-at-home orders did not pave the way for such circumstances for crime occurrences.

According to the researchers (Abrams, 2020), violent crimes, such as armed robbery, assault, rape, and murder, are declining because there are fewer possibilities for the crimes to occur. During the total lockdown, several locations were shut down. Bars, theatres, malls, restaurants, and concerts, which would ordinarily be locations where offenders would find targets to perpetrate crimes, were closed down. Similarly, there was an increase in mobility in the residential zone, implying enhanced guardianship

Table 7 Mobility measured through the daily number of passengers travelled during COVID-19 lockdowns 2020–2022 in TN — Effect size (ES) (Cliff's Delta)

PERIOD	FROM	TO	ACTUAL MEAN	PREDICTED MEAN	PREDICTED RANGE	ES	ES RANGE	ES CATEGORY
Pre-Lockdown-W1	01/01/20	22/03/20	138.11646	136.3904	(133.6672, 139.1136)	0.38	[0.21, 0.544]	medium
Complete-Lockdown-W1	23/03/20	30/04/20	11.660256	130.7308	(128.8616, 132.6)	-1.00	[-1.0, -1.0]	large
Partial-Lockdown-W1	01/05/20	08/06/20	11.185897	132.9777	(132.7349, 133.2205)	-1.00	[-1.0, -1.0]	large
Post-Lockdown-W1	01/09/20	08/10/20	51.825	132.9321	(132.7014, 133.1628)	-1.00	[-1.0, -1.0]	large
Pre-Lockdown-W2	01/01/21	09/04/21	95.73697	93.30566	(89.4601, 97.1512)	0.34	[0.18, 0.499]	medium
Partial-Lockdown-1-W2	10/04/21	05/05/21	77.568846	62.20838	(51.9114, 72.5054)	0.34	[0.015, 0.609]	medium
Complete-Lockdown-W2	06/05/21	07/06/21	32.08697	26.22012	(23.9024, 28.5378)	0.58	[0.286, 0.772]	large
Partial-Lockdown-2-W2	08/06/21	06/07/21	39.720345	36.79853	(31.2114, 42.3857)	0.23	[-0.092, 0.524]	small
Pre-W3	01/11/21	06/01/22	119.37657	108.616	(105.3691, 111.8629)	0.49	[0.294, 0.651]	large
WAVE-3	07/01/22	17/02/22	109.62167	62.53796	(55.3823, 69.6936)	0.80	[0.601, 0.918]	large
POST WAVE – 3	18/02/22	31/12/22	134.29795	130.1182	(128.4928, 131.7436)	0.05	[-0.045, 0.137]	negligible

and less opportunity for crime. The current study is predominantly in line with the work of Clarke (2012*)*, who suggests that rather than modifying offender propensity, situational factors facilitate or encourage the actual commission of criminal acts, explaining why some people are more likely to be delinquent or criminal (Clarke, 2012).

Whether considering the space-time convergence of routine activities or substantial changes in opportunities for committing crimes or place-based characteristics, these factors are affected only if mobility falls below a certain threshold. Similarly, situational factors that inhibit or impede the reporting and registration of complaints are impacted only when victims' mobility is severely restricted, as the physical presence of the complainant at the police station is required for investigation. During the complete lockdown, there was almost complete cessation of all modes of transport except a few permitted.

Building on routine activity theory's focus on the dynamics between offenders, victims, and guardians, research has highlighted the importance of spatial variations in crime at smaller scales, such as street segments and addresses (Eck & Weisburd, 2015; Hipp & Williams, 2020; McCord & Ratcliffe, 2007; Smith et al., 2000). Routine activities theory preconditions that a crime occurs when a motivated offender, a suitable target, and the absence of capable guardians converge in time and space. Offenders evaluate the costs and benefits of criminal acts based on immediate environmental conditions. This theory highlights the importance of mobility and the social composition of spaces in relation to offenders, guardians, and targets, leading to extensive research on place-based characteristics that inhibit or promote criminal opportunities (Wilcox & Cullen, 2018). It is important to discuss the corollary that during the same relevant time, the increase in mobility in residential zones was 32%. Increased mobility leads to a greater presence of capable guardians, such as parents, neighbors, and teachers, who monitor the area and deter potential offenders. Additionally, place managers who oversee the regular conditions of crime-prone sites are more likely to be present, further enhancing security (Eck, 2003; Weisburd et al., 2012). This present research empirically supports the exploration of mobility-related factors influencing crime at this "microplace" level.

Certain types of crimes are differently impacted by human mobility, as their opportunity structures may differ or the location may have no significance. These crimes often involve circumstances or motivations less dependent on human mobility, whether involving the offender, victim, or guardian. Cybercrimes, including hacking, phishing, and online fraud, occur in the digital realm and are not reliant on physical human mobility. However, due to reduced human mobility during the pandemic, people were more present in the digital world, either working or on social networking sites or retailing, which caused an increase in these crimes (Hawdon et al., 2020).

It can also be said that intimate partner violence typically occurs within private residences and is influenced more by interpersonal conflicts due to jealousy, finances, women's gender role transgressions than by mobility patterns (Jewkes, 2002). Similarly, child sexual abuse often involves perpetrators known to the victim and typically occurs in environments such as homes or familiar settings, making it less influenced by general public mobility (Kaufman et al., 1998).

Human mobility will impact these offenses, such as intimate partner violence or child sexual abuse, differently. If mobility includes the presence of the offender for a longer duration, as increased mobility was during the pandemic stay-at-home orders, mobility indirectly impacts these occurrences. Regarding child sexual abuse, the prolonged closure of schools increased the possibility of abuse due to the opportunity for the offender to exploit the victim, while teachers, social workers, and others could not identify such cases and notify the appropriate agency for action (Paramasivan et al., 2023).

White-collar crimes, such as financial fraud, embezzlement, and insider trading, are usually conducted in the

Table 8 Percentage change in Community mobility based on GCMR during three pandemic waves compared to pre-pandemic period in TN

Wave-1-3	Retail and Recreation		Grocery and Pharmacy		Parks		Transit Stations		Workplace		Residential		All Zones Except Residential
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean
Complete Lockdown W1	-80.5	11.9	-51.2	17.7	-39.4	8.8	-62.0	9.3	-64.3	11.7	32.1	5.7	-59.5
Partial Lockdown W1	-61.9	13.2	-14.7	20.9	-41.8	6.1	-39.7	10.7	-35.0	10.2	20.0	4.8	-38.6
Post-Lockdown W1	-39.7	4.8	-0.6	7.9	-36.8	3.7	-22.7	3.8	-24.1	11.1	13.3	2.8	-24.8
Partial Lockdown 1 W2	-30.2	17.3	17.1	29.1	-21.0	12.0	-18.6	17.1	-22.7	15.2	14.6	5.2	-15.1
Complete Lockdown W2	-68.6	12.7	-27.8	30.7	-37.9	7.3	-53.8	16.2	-53.0	19.3	30.2	7.4	-48.2
Partial Lockdown – 2 W2	-42.9	11.4	10.5	12.5	-16.4	6.1	-30.5	9.6	-30.3	12.4	18.4	4.6	-21.9
W3	-2.0	21.8	51.8	33.4	19.6	15.2	6.6	19.3	-5.0	19.2	10.8	5.0	14.2
Post-W3	12.9	5.8	55.2	7.4	79.0	17.2	30.7	5.5	20.9	13.0	11.3	2.6	39.7

Table 9 Pearson's correlation coefficient between registered crime and mobility (buses operated and passengers carried) during Non-emergency Period (Jan. 1, 2010 – Dec. 31, 2022)

Type of Crime	Vehicular Mobility	People Mobility
Aggravated Assault	-0.014	0.456
Attempt To Commit Murder	0.166	-0.097
Burglary	0.268	-0.129
Cruelty By Husband and Relatives	0.273	0.222
Dacoity	0.016	0.003
Dowry Prohibition Act	0.029	-0.170
Murder	0.063	0.002
Murder For Gain	0.031	0.113
Child Sexual Abuse	-0.033	-0.577
Rape	-0.111	-0.216
Rioting	0.106	0.213
Robbery	0.088	-0.129
Sexual Harassment	0.168	-0.186
Theft	-0.057	0.000

immediate environment where crime opportunities are discovered and evaluated by potential offenders. They are not significantly affected by the broader mobility of people (Benson et al., 2009).

While general human mobility may not directly impact these crimes, changes in societal conditions, such as lockdowns, can still indirectly influence the incidence or reporting of these crimes. For instance, lockdowns may increase domestic violence due to prolonged proximity and stress (Kourti et al., 2021), or reduce the reporting of child abuse due to a lack of access to external observers like teachers (Baron et al., 2020). As the present study primarily concerns the specific violent crimes discussed, no detailed investigation has been done on whether these crimes are impacted by human mobility. This is identified as a future line of investigation.

Conclusions

The study makes an intriguing observation: when mobility falls below a certain threshold, a strong correlation between mobility and recorded violent crime levels emerges. Otherwise, the research found no relationship between mobility and recorded levels of crime. Stay-at-home orders in certain countries have led to a reduction in violent crimes. During Wave-1's complete lockdown in Tamil Nadu, both violent crime and mobility decreased, demonstrating a linear relationship.

The impact on vehicular and people's mobility during the pandemic period experienced a significant decrease in mobility, particularly during the complete lockdown stages of the initial two waves of the pandemic, having a discernible impact on recorded crime levels.

There was an exceptional drop in recorded levels of crime during the complete lockdown period of Wave-1,

Table 10 Pearson's correlation coefficient between mobility (buses operated and passengers carried) and Daily Count of registered crimes during emergency phases

Timeline	Correlation Timeline-wise							
	Aggravated Assault		Attempt to Commit Murder		Murder		Rioting	
	Vehicular Mobility	People's Mobility	Vehicular Mobility	People's Mobility	Vehicular Mobility	People's Mobility	Vehicular Mobility	People's Mobility
Pre-Lockdown-W1	0.162	0.099	-0.016	-0.185	0.121	0.166	0.107	0.073
Complete-Lockdown-W1	**0.735**	**0.735**	**0.510**	**0.506**	**0.270**	**0.276**	**-0.093**	**-0.098**
Partial-Lockdown-W1	-0.006	-0.029	-0.183	-0.191	0.120	0.128	-0.256	-0.210
Post-Lockdown-W1	-0.378	-0.334	-0.181	-0.152	-0.267	-0.235	-0.077	-0.050
Pre-Lockdown-W2	0.061	0.034	-0.018	-0.069	0.088	0.088	-0.048	-0.092
Partial-Lockdown-1-W2	0.508	0.478	0.184	0.176	0.174	0.194	0.058	0.103
Complete-Lockdown-W2	**0.662**	**0.692**	**0.560**	**0.539**	**0.660**	**0.703**	**0.227**	**0.208**
Partial-Lockdown-2-W2	-0.005	-0.007	-0.312	-0.320	-0.067	-0.053	-0.077	-0.078
Pre-W3	-0.253	-0.187	0.021	0.017	0.001	0.061	-0.259	-0.155
W3	0.059	-0.068	-0.003	-0.062	0.217	0.246	-0.088	-0.141

Significance bold values: p-value less than 0.05

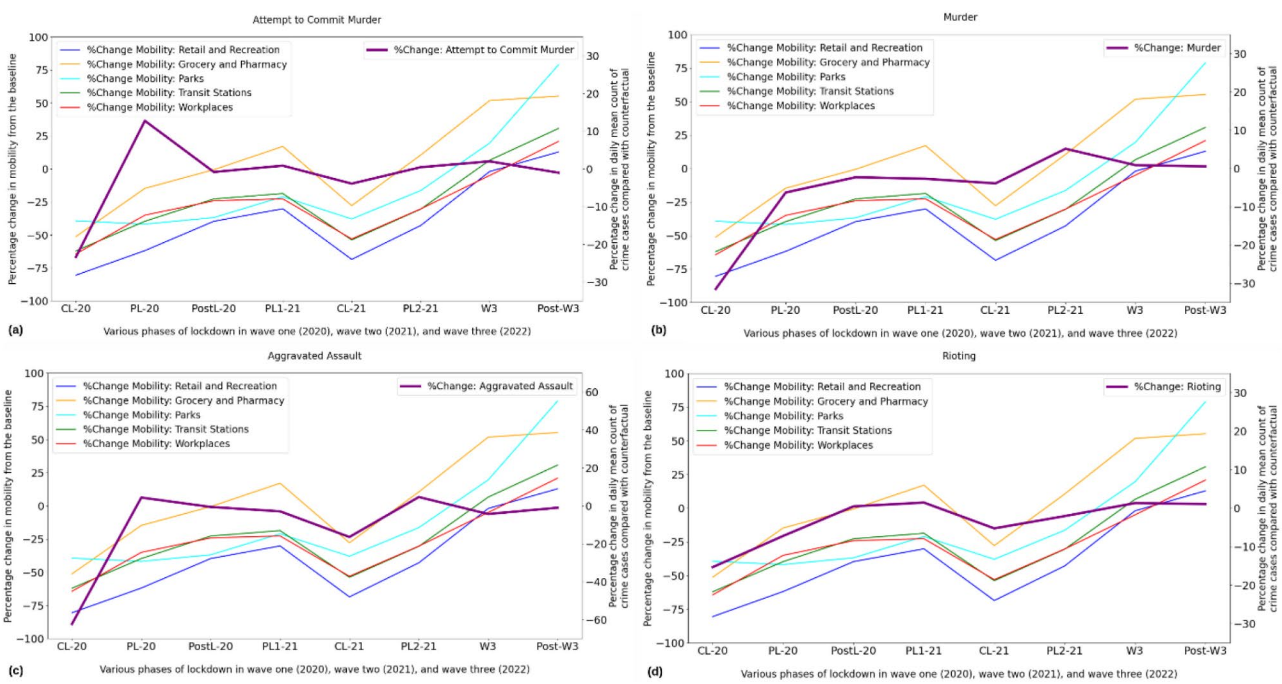

Fig. 3 Relationship between mobility change and reported violent crimes during pandemic waves in TN. The top panels show mobility vs. attempted murder and murder, while the bottom panels depict mobility vs. aggravated assault and rioting

Table 11 Pearson's correlation coefficient between change in mobility and change in Crime (Mean percentage change and effect size) during pandemic

Type of Correlation	Impacted Variable	PANDEMIC			
		Assault	Attempted Murder	Murder	Rioting
Crime- Vehicular Mobility	% Change	0.526	0.314	0.743	0.838
Crime-People's Mobility	% Change	0.386	0.232	0.629	0.659
Crime- Vehicular Mobility	Cliff's Delta	0.390	0.441	0.567	0.465
Crime-People's Mobility	Cliff's Delta	0.226	0.305	0.530	0.308

when mobility across all land-use categories (except residential zones) declined phenomenally. The decline in reported incidents may also be attributable to diminished criminal opportunities. Additionally, this could be due to unfavourable situational factors, such as victims' limited access to appropriate health and law enforcement agencies to report crimes. In addition, frontline agencies were preoccupied with pandemic-related responsibilities, which may have contributed to a lack of crime registration despite the fact that crimes were committed.

The significant decrease in crime during the lockdown, despite a potential increase in criminal motivation due to the pandemic, aligns with RAT principles. With drastically reduced mobility, offenders had fewer opportunities to encounter suitable targets and evade guardians. Additionally, the increased residential mobility suggests more potential guardians were present at home, further deterring crime. This empirical evidence from the lockdown strengthens the argument that opportunity, not social disorganization, played a major role in the observed crime decline.

Author contributions

Kandaswamy Paramasivan: Conceptualization, Methodology, Formal Analysis, Writing Original Draft. Saish Jaiswal: Methodology, Software, Formal Analysis, Investigation, Visualization. Rahul Subburaj: Methodology, Software, Formal Analysis, Investigation, Visualization. Nandan Sudarsanam: Writing- Reviewing and Editing, Refinement of core ideas and inferences. The first draft of the manuscript was written by Kandaswamy Paramasivan and all authors have edited and reviewed the manuscript.

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Data availability

The authors do not have permission to share the data publicly in view of the confidential agreement between the authors and the departments of Government of India. However data will be made available upon reasonable request from the corresponding author.

Declarations

Ethics approval and consent to participate

The authors declare that ethics approval was not required for this work as it involved only anonymized data from official sources and did not involve direct human participation.

Consent for publication

Not applicable.

Competing interests

The corresponding author certifies, on behalf of all authors, that there have been no involvements that could raise questions of bias in the work reported or in the stated conclusions, implications, or opinions.

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References

Abrams, D. S. (2020). COVID and crime: An early empirical look. Retrieved from https://ssrn.com/abstract=3674032. [Accessed 17 April 2023].

Baron, E. J., Goldstein, E. G., & Wallace, C. T. (2020). Suffering in silence: How COVID-19 school closures inhibit the reporting of child maltreatment. *Journal of Public Economics*, *190*, 104258.

Benson, M., Madensen, T., & Eck, J. (2009). White-collar crime from an opportunity perspective. In The oxford handbook of crime and public policy. https://doi.org/10.1007/978-0-387-09502-8_9

Boateng, F. (2016). Crime reporting behavior: Do attitudes toward the police matter? *Journal of Interpersonal Violence*, *33*. https://doi.org/10.1177/0886260516632356

Bogomolov, A., Lepri, B., Staiano, J., Oliver, N., Pianesi, F., & Pentland, A. (2014). Once upon a crime: Towards crime prediction from demographics and mobile data. In Proceedings of the 16th International Conference on Multimodal Interaction (pp. 427–434). https://doi.org/10.1145/2663204.2663254

Brantingham, P. L., & Brantingham, P. J. (1993). Nodes, paths and edges: Considerations on the complexity of crime and the physical environment. *Journal of Environmental Psychology*, *13*(1), 3–28. https://doi.org/10.1016/S0272-4944(05)80212-9

Brantingham, P. J., Brantingham, P. L., & Andresen, M. A. (2016). The geometry of crime and crime pattern theory. In Environmental criminology and crime analysis (pp. 1–20). https://doi.org/10.4324/9781315709826

Browning, C. R., Pinchak, N. P., & Calder, C. A. (2021). Human mobility and crime: Theoretical approaches and novel data collection strategies. *Annual Review of Criminology*, *4*, 99–123. https://doi.org/10.1146/annurev-criminol-061020-021551

Calderon-Anyosa, R. J. C., & Kaufman, J. S. (2021). Impact of COVID-19 lockdown policy on homicide, suicide, and motor vehicle deaths in Peru. *Preventive Medicine*, *143*, 106331. https://doi.org/10.1016/j.ypmed.2020.106331

Caminha, C., Furtado, V., Pequeno, T. H. C., Ponte, C., Melo, H. P. M., Oliveira, E. A., et al. (2017). Human mobility in large cities as a proxy for crime. *Plos One*, *12*(2), e0171609. https://doi.org/10.1371/journal.pone.0171609

Campedelli, G. M., Aziani, A., & Favarin, S. (2021). Exploring the immediate effects of COVID-19 containment policies on crime: An empirical analysis of the short-term aftermath in Los Angeles. *American Journal of Criminal Justice*, *46*(5), 704–727. https://doi.org/10.1007/s12103-020-09578-6

Cheung, L., & Gunby, P. (2021). Crime and mobility during the COVID-19 lockdown: A preliminary empirical exploration. *New Zealand Economic Papers*, 1–16. https://doi.org/10.1080/00779954.2020.1870535

Clarke, R. V. (2012). Opportunity makes the thief. Really? And so what? *Crime Science*, *1*(3). https://doi.org/10.1186/2193-7680-1-3

Curtis-Ham, S., Bernasco, W., Medvedev, O. N., et al. (2020). A framework for estimating crime location choice based on awareness space. *Crime Science*, *9*, 23. https://doi.org/10.1186/s40163-020-00132-7

Curtis-Ham, S., Bernasco, W., Medvedev, O. N., & Polaschek, D. (2021). A national examination of the spatial extent and similarity of offenders' activity spaces using police data. *ISPRS International Journal of Geo-Information*, *10*, 47. https://doi.org/10.3390/ijgi10020047

Curtis-Ham, S., Bernasco, W., Medvedev, O. N., et al. (2023). Relationships between offenders' crime locations and different prior activity locations as recorded in police data. *Journal of Police and Criminal Psychology*, *38*, 172–185. https://doi.org/10.1007/s11896-022-09540-8

de Palma, A., Vosough, S., & Liao, F. (2022). An overview of effects of COVID-19 on mobility and lifestyle: 18 months since the outbreak. *Transportation Research Part A: Policy and Practice*, *159*, 372–397. https://doi.org/10.1016/j.tra.2022.03.024

Eck, J. (2003). Police problems: The complexity of problem theory, research and evaluation. *Crime Prevention Studies*, *15*, 79–114.

Eck, J., & Weisburd, D. L. (2015). Crime places in crime theory. *Crime and Place: Crime Prevention Studies*, *4*, 1–33.

Felson, M., & Cohen, L. E. (1980). Human ecology and crime: A routine activity approach. *Human Ecology*, *8*(4), 389–406.

Government of Tamil Nadu (2020). Order: Wave 1. https://cms.tn.gov.in/sites/default/files/go/revenue_e_172_2020.pdf. [Accessed 18 May 2024].

Government of Tamil Nadu (2021). Order: Wave 2. https://cms.tn.gov.in/sites/default/files/go/revenue_e_342_2021.pdf. [Accessed 18 May 2024].

Halford, E., Dixon, A., Farrell, G., Malleson, N., & Tilley, N. (2020). Crime and coronavirus: Social distancing, lockdown, and the mobility elasticity of crime. *Crime Science*, *9*(1), 1–12. https://doi.org/10.1186/s40163-020-00121-w

Hannon, L. (2002). Criminal opportunity theory and the relationship between poverty and property crime. *Sociological Spectrum*, *22*(3), 363–381.

Hawdon, J., Parti, K., & Dearden, T. E. (2020). Cybercrime in America amid COVID-19: The initial results from a natural experiment. *American Journal of Criminal Justice*, *45*(4), 546–562.
Hess, M., & Kromrey, J. (2004). Robust confidence intervals for effect sizes: A comparative study of Cohen's d and Cliff's delta under non-normality and heterogeneous variances. Paper presented at the Annual Meeting of the American Educational Research Association.
Hilsenrath, J. (2020). Homicide spike hits most large U.S. cities. Wall Street Journal. Retrieved from https://www.wsj.com/articles/homicide-spike-cities-chicago-newyork-detroit-us-crime-police-lockdown-coronavirus-protests-11596395181
Hipp, J. R., & Williams, S. A. (2020). Advances in spatial criminology: The spatial scale of crime. *Annual Review of Criminology*, *3*, 75–97.
India coronavirus, & Worldometers (2024). Retrieved from https://www.worldometers.info/coronavirus/country/india/#google_vignette
Jewkes, R. (2002). Intimate partner violence: Causes and prevention. *The Lancet*, *359*(9315), 1423–1429. https://doi.org/10.1016/S0140-6736(02)08357-5
Kadar, C., & Pletikosa, I. (2018). Mining large-scale human mobility data for long-term crime prediction. *EPJ Data Science*, 7, 26. https://doi.org/10.1140/epjds/s13688-018-0150-z.
Kaufman, K. L., Holmberg, J. K., Orts, K. A., McCrady, F. E., Rotzien, A. L., Daleiden, E. L., & Hilliker, D. R. (1998). Factors influencing sexual offenders' modus operandi: An examination of victim-offender relatedness and age. *Child Maltreatment*, *3*(4), 349–361. https://doi.org/10.1177/1077559598003004007
Kim, D. Y. (2022). The COVID-19 pandemic, stay-at-home orders, and gun violence: A story of two cities. *Criminal Justice Policy Review*, *33*(7), 711–731. https://doi.org/10.1177/08874034221088742
Kourti, A., Stavridou, A., Panagouli, E., Psaltopoulou, T., Spiliopoulou, C., Tsolia, M., Sergentanis, T. N., & Tsitsika, A. (2021). Domestic violence during the COVID-19 pandemic: A systematic review. *Trauma Violence & Abuse*, *24*(2), 719–745. https://doi.org/10.1177/15248380211038690
Krishnakumar, A., & Verma, S. (2021). Understanding domestic violence in India during COVID-19: A routine activity approach. *Asian Journal of Criminology*, *16*, 19–35. https://doi.org/10.1007/s11417-020-09340-1
LeClerc, B., & Wortley, R. (Eds.). (2013). Cognition and crime: Offender decision making and script analyses.
Lopez, E., & Rosenfeld, R. (2021). Crime, quarantine, and the U.S. coronavirus pandemic. *Criminology & Public Policy*, *20*(3), 401–422. https://doi.org/10.1111/1745-9133.12557
Maji, S., Bansod, S., & Singh, T. (2021). Domestic violence during COVID-19 pandemic: The case for Indian women. *Journal of Community & Applied Social Psychology*. https://doi.org/10.1002/casp.2501. [Accessed 17 April 2023].
McCord, E. S., & Ratcliffe, J. H. (2007). A micro-spatial analysis of the demographic and criminogenic environment of drug markets in Philadelphia. *Australian & New Zealand Journal of Criminology*, *40*(1), 43–63.
Menting, B., Lammers, M., Ruiter, S., & Bernasco, W. (2019). The influence of activity space and visiting frequency on crime location choice: Findings from an online self-report survey. *The British Journal of Criminology*, *60*. https://doi.org/10.1093/bjc/azz044
Meyer, M., Hassafy, A., Lewis, G., Shrestha, P., Haviland, A. M., & Nagin, D. S. (2022). Changes in crime rates during the COVID-19 pandemic. *Statistics and Public Policy*, *9*(1), 97–109. https://doi.org/10.1080/2330443X.2022.2071369
Mukherjee, S., & Narang, D. (2023). Digital economy and work-from-home: The rise of home offices amidst the COVID-19 outbreak in India. *Journal of the Knowledge Economy*, *14*(2), 924–945.
Narayan, P. (2017). Displacement as disaster relief: Environmental gentrification and state informality in developing Chennai. In W. Curran, & T. Hamilton (Eds.), *Just Green Enough* (pp. 139–150). Routledge.
Nivette, A. E., Zahnow, R., Aguilar, R., et al. (2021). A global analysis of the impact of COVID-19 stay-at-home restrictions on crime. *Nature Human Behaviour*, *5*, 868–877. https://doi.org/10.1038/s41562-021-01139-z
Onyeaka, H., Anumudu, C. K., Al-Sharify, Z. T., Egele-Godswill, E., & Mbaegbu, P. (2021). COVID-19 pandemic: A review of the global lockdown and its far-reaching effects. *Science Progress*, *104*(2). https://doi.org/10.1177/00368504211019854
Paramasivan, K., Subburaj, R., Sharma, V. M., & Sudarsanam, N. (2022). Relationship between mobility and road traffic injuries during COVID-19 pandemic - the role of attendant factors. *Plos One*, *17*(5), e0268190. https://doi.org/10.1371/journal.pone.0268190
Paramasivan, K., Raj, B., Sudarasanam, N., & Subburaj, R. (2023). Prolonged school closure during the pandemic time in successive waves of COVID-19: Vulnerability of children to sexual abuses - a case study in Tamil Nadu, India. *Heliyon*, *9*(7), e17865. https://doi.org/10.1016/j.heliyon.2023.e17865
Piquero, A. R., Jennings, W. G., Jemison, E., Kaukinen, C., & Knaul, F. M. (2021). Domestic violence during the COVID-19 pandemic-evidence from a systematic review and meta-analysis. *Journal of Criminal Justice*, *74*, 101806.
Raghavan, V. (2021). Prisons and the pandemic: The panopticon plays out. *Journal of Social and Economic Development*, *23*(Suppl 2), 388–397. https://doi.org/10.1007/s40847-020-00127-9
Ramesh, G., & Ramya, V. (2023). A study on the causes and consequences of inter-state migration and reverse migration in Tamil Nadu, India. *South Asian Journal of Social Studies and Economics*, *18*(4), 64–72.
Ratner, B. (2009). The correlation coefficient: Its values range between + 1/−1, or do they? *Journal of Targeting Measurement and Analysis for Marketing*, *17*, 139–142. https://doi.org/10.1057/jt.2009.5
Smith, W. R., Frazee, S. G., & Davison, E. L. (2000). Furthering the integration of routine activity and social disorganization theories: Small units of analysis and the study of street robbery as a diffusion process. *Criminology*, *38*, 489–524.
Stefanovska, V. (2019). Real or false image of police recorded crime. *Kriminologija & Socijalna Integracija*, *27*(2), 221–234.
Stickle, B., & Felson, M. (2020). Crime rates in a pandemic: The largest criminological experiment in history. *American Journal of Criminal Justice*, *45*. https://doi.org/10.1007/s12103-020-09546-0
Tendulkar, P., Pandey, P., Panda, P. K., Bhadoria, A. S., Kulshreshtha, P., Mishra, M., & Saxena, G. (2023). Comparative study between the first and second wave of COVID-19 deaths in India: A single center study. *Cureus*, *15*(4), e37472. https://doi.org/10.7759/cureus.37472
The Asian Age (2018, August 9). Millions march for Karunanidhi, four die in stampede. Retrieved July 29, 2020, from https://www.asianage.com
Times of Islamabad (2016, December 6). CM Jayalalitha funeral attended by over 1 million Indians. Retrieved February 25, 2021, from https://www.timesofislamabad.com
Vachuska, K. (2022). Comparing mobility and spatial pathways in the hourly prediction of violent crime. *Urban Science*, *6*(4), 74. https://doi.org/10.3390/urbansci6040074
van Sleeuwen, S. E. M., Ruiter, S., & Steenbeek, W. (2021). Right place, right time? Making crime pattern theory time-specific. *Crime Science*, *10*(2). https://doi.org/10.1186/s40163-021-00139-8
Weisburd, D., Groff, E. R., & Yang, S. M. (2012). *The criminology of place: Street segments and our understanding of the crime problem*. Oxford University Press.
Wilcox, P., & Cullen, F. T. (2018). Situational opportunity theories of crime. *Annual Review of Criminology*, *1*, 123–148.
Wittebrood, K., & Junger, M. (2002). Trends in violent crime: A comparison between police statistics and victimization surveys. *Social Indicators Research*, *59*(2), 153–173.
Wu, J., Abrar, S. M., Awasthi, N., et al. (2022). Enhancing short-term crime prediction with human mobility flows and deep learning architectures. *EPJ Data Science*, *11*, 53. https://doi.org/10.1140/epjds/s13688-022-00366-2

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