The Effects of Power Outages on Crime*

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Abstract

Power outages disrupt lighting, economic activity, and routine social behavior, yet little is known about their short-run effects on crime in developing-country contexts. This paper examines how unplanned power outages affect crime in Maharashtra, India. I assemble a novel daily dataset linking feeder-level outage records to police-station crime reports, enabling the measurement of crime outcomes within precise policing jurisdictions. To identify causal effects, I exploit quasi-experimental variation from isolated unplanned outages and compare treated stations to optimally matched nearby controls with no outages in the same event window. Using a stacked event–time difference-in-differences design, I trace dynamic crime responses before and after outages. Preliminary results from the $\pm$5-day window show no detectable short-run effect of one-day unplanned outages on total or property crimes, and no consistent patterns across urban and rural stations. The findings suggest that short-duration outages may be insufficient to alter criminal behavior, and that incorporating outage duration, nighttime timing, and multi-year data may be essential for detecting behavioral responses. The study provides new micro-level evidence on the relationship between electricity reliability and public safety in a major developing-country setting.

Keywords: electricity reliability; outages; crime; India

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1 Introduction

Frequent power outages remain a defining feature of electricity systems in many developing economies. In India, states such as Uttar Pradesh, Jharkhand, Assam, Bihar, and Haryana continue to experience substantial daily disruptions, with Maharashtra also reporting significant outages (Agrawal et al., 2020). While prior work has examined the socio-economic consequences of unreliable electricity, little is known about its impact on crime. Existing Indian studies have focused on power plant–level yearly panel data, estimating effects on manufacturing (Allcott, Collard-Wexler and O'Connell, 2016) and wholesale electricity demand (Jha, Preonas and Burlig, 2021), or have used household surveys to study electrification and reliability (Sedai, Nepal and Jamasb, 2022; Khandker, 2012). None have examined the crime outcomes. Evidence from other settings highlights the link between electricity reliability, lighting, and security. In Africa, outages have been tied to household welfare losses and increases in theft, robbery, and violent crime(Amadi, 2015; Imelda and Guo, Xiaoying, 2024). In the United States, studies show that extended daylight reduces robberies(Doleac and Sanders, 2015) and that streetlight outages shift crime to nearby areas, especially robberies and vehicle theft (Chalfin, Kaplan and LaForest, 2022).

This study analyzes the impact of power outages on crime rates in Maharashtra, leveraging a novel daily feeder-level outage data which documents reasons for outages. Unplanned outages generate plausibly exogenous variation in electricity supply that will be exploited to estimate causal effects on reported crimes. The Maharashtra State Electricity Distribution Company Limited (MSEDCL), which operates the world's second-largest distribution network ("Maharashtra State Electricity Distribution Company Limited," 2025), provides an exceptionally rich context for this analysis. The findings from this study would contribute to the literature on power outages and crimes by documenting a new channel through which electricity reliability affects these social outcomes.

The remainder of the paper is organized as follows. Section 2 describes the data sources and the construction of the police–substation linkage, and Section 3 presents preliminary descriptive insights. Section 4 outlines the methodology, including the matching procedure and stacked event-time design. Section 5 reports the preliminary causal estimates, and Section 6 discusses limitations and outlines next steps for extending the analysis.

2 Data

2.1 Outages

Power outage data were obtained from the official MSEDCL website, which provides daily feeder-level records from March 2024 to February 2025. The dataset includes reported reasons for each outage, allowing classification into planned, faulty, and unplanned events. Notably, approximately 80% of outages are attributed to emergency causes, shown in Table 2. These are collectively categorized as unplanned outages, and the preliminary analysis focuses on this subset. To enable spatial matching with police jurisdictions with their nearest substations, the data were subsequently aggregated to the substation level using geocoded substation names within each district.

2.2 Crimes

The FIR data was sourced from the publicly available Maharashtra Police – Services for Citizen portal, downloading records for the same period as the power outages dataset to ensure temporal alignment. The FIR data are available at the police station and daily level and include details on the relevant sections of crimes. Police station names were geocoded to their specific locations using their names and corresponding districts.

2.3 Police Station level aggregation

To link substations with their corresponding police jurisdictions, I use a nearest-neighbor matching approach to identify the substations located closest to each police station. The analysis reveals that most substations fall within a 39-kilometer radius of their nearest police station, see Figure 4. I adopt this 39-kilometer threshold as the baseline jurisdictional boundary but also conduct robustness checks using alternative thresholds of 13 and 26 kilometers to assess the sensitivity of the results. The spatial distribution of these matches is illustrated in the accompanying map, see Figure 4.

3 Preliminary Insights

The month-by-month scatter plots show a weak and noisy positive correlation between ln(unplanned outages) and ln(property crimes) across months in 2024–2025 (see Figure 5). In several months, the fitted linear trend suggests a slightly upward-sloping relationship, indicating that higher outages tend to correlate with higher property crimes. However, the variation is substantial and the magnitude of the trend is small, implying that any association is far from deterministic. Few months also show near-flat patterns, reflecting the large dispersion in both crime and outage intensity across police stations and time.

I use a log-log specification to stabilize variance, reduce the influence of extreme values, and interpret coefficients as elasticities, which is particularly useful given the skewed distribution of both outages and crime counts. This transformation also makes the linear fits in the scatterplots more comparable across months by compressing large values and highlighting proportional rather than absolute differences.

Despite the noisy correlations, the fact that several months indicate a small positive association provides initial motivation to explore whether unplanned outages might actually increase property crime. Because these patterns are purely correlational and subject to confounding factors, they should not be interpreted as causal. To obtain a defensible estimate of the effect of outages on crime, we therefore proceed with a causal identification strategy that leverages quasi-experimental variation in unplanned outage timing across treatment-control police station pairs.

4 Methodology

4.1 Construction of Treatment-Control Pairs

To identify the causal effect of short, localized power outages on crime, I construct geographically matched micro treatment–control pairs of police stations across Maharashtra (N = 565 pairs). Stations are first assigned geographic coordinates and, within each district and urban or rural classification, optimally matched using a Hungarian assignment algorithm applied to the Euclidean distance matrix. This algorithm enforces a strict one-to-one, non-overlapping pairing structure, ensuring that each police station is matched to exactly one nearest neighbor and cannot serve as a control unit for multiple treated stations. This avoids the overlap and reuse problems that arise with simple greedy nearest-neighbor matching. See Figure 6 for visual inspection.

4.2 Stacked Event-Time Data Setup

Within each police station, I identify isolated one-day outage shocks, which serve as sub-experiments in the stacked difference-in-differences (DID) framework Wing et al. (2024). A day is classified as a valid outage event if (i) the treated station records a strictly positive outage duration on that day, (ii) the station has no other outages in the surrounding $\pm k$-day window ($k \in \{5, 10, 15\}$), and (iii) its matched control station experiences zero outages throughout the same window. These trimming rules ensure that each sub-experiment isolates a clean, localized treatment contrast and is not confounded by overlapping feeder failures or broader reliability disturbances.

For every valid outage shock a, I construct a balanced event-time panel containing all observations for the treated and control stations over the relative time interval $e \in [-k, +k]$, where e denotes calendar time measured relative to the outage event. Each sub-experiment therefore produces a unit $\times$ event-time dataset indexed by (s, a, e), where s is the station, a is the shock identifier, and e is the event-time index. A binary treatment indicator $D_{sa} = 1$

is assigned to the treated station within sub-experiment a and $D_{sa} = 0$ to its control station, following the notation in the stacked DID literature Wing et al. (2024).

These sub-experimental panels are then vertically concatenated to form a single "stacked" dataset. In this stacked structure, each row corresponds to a station–day–event observation, with an associated event identifier, treatment status, and event-time indicator. This construction aligns all shocks in event time while preserving their original matched-pair structure, enabling estimation of dynamic treatment effects that compare outcome trajectories between the treated and control stations within each sub-experiment without relying on comparisons across unrelated locations or calendar periods.

Table 4 summarizes the number of isolated outage shocks identified under different window widths among the 565 station pairs. The 5-day window yields 1,730 valid shocks across 389 pairs (mean of 4.45 shocks per pair), while the 10-day and 15-day windows produce 649 and 355 valid shocks, respectively. In the main analysis, I focus on the 5-day window, while retaining the 10-day and 15-day windows as robustness checks that impose stricter temporal isolation around each outage event.

4.3 Empirical Specification

Following the simple stacked DID regression framework of Wing et al. (2024) each isolated outage shock defines a separate sub-experiment in which a treated police station is compared to its matched control station over an event-time window $e \in [-k, +k]$. Let $Crimes_{sae}$ denote the total crime outcome (can be property or total crimes) for station s in sub-experiment a at event time e. Let D_{sa} be an indicator equal to one if station s is the treated unit in sub-experiment a, and zero otherwise. For each event time $e \neq -1$, let $L_{e,sae}$ be an indicator equal to one if the observation falls in event time e and zero otherwise, omitting $e = -1$ as the reference period.

The empirical model is:

$$Crimes_{sae} = \sum_{e \neq -1} \beta_e \big(L_{e,sae} \cdot D_{sa}\big) + \alpha_s + \lambda_{t(sa,e)} + \varepsilon_{sae}, \tag{1}$$

where α_s are station fixed effects and $\lambda_{t(sa,e)}$ are calendar-date fixed effects. The coefficients β_e trace out the dynamic treatment effect of an isolated outage e days from the shock, measured relative to the $e = -1$ period. Standard errors are clustered at the matched-pair.

5 Preliminary Results

Using the matched police-station pairs and the ±5-day stacked event-time design, I estimate dynamic treatment effects of isolated unplanned outages on crime outcomes. The specification uses an *unweighted* stacked DID, and includes event-time indicators for $f1$ and $f2$ to allow for delays in the registration of reported crimes. Table 5 presents estimates for total and disaggregated crimes, and Figure 7 displays the corresponding event-study coefficients for all, urban, and rural stations.

Across all stations, the estimated effects are small and centered tightly around zero at all event times. Pre-treatment coefficients (days -5 to -2) show no systematic trends and are statistically indistinguishable from zero, supporting the parallel-trends assumption within matched pairs. On the outage day ($e = 0$), the estimated change in total crimes is -0.04, and the post-outage coefficients ($e = 1, 2$) remain close to zero and statistically insignificant. Property crimes—trespass, robbery, and theft—exhibit similarly flat patterns with no discernible discontinuity at the outage.

Urban and rural stations show broadly comparable dynamics. Rural stations, which have lower baseline crime levels, exhibit coefficients clustered around zero with no detectable post-outage movement. Urban stations display modest negative pre-event estimates in the trespassing category, and rural stations show mild pre-trend deviations in total crimes. Although these deviations are small, several are statistically distinguishable from zero, indicating slight departures from perfect parallel trends. However, these differences do not persist after the outage and do not form a coherent pattern.

One exception arises in the rural property-crime panel, where the coefficient at $e = 1$ is negative and statistically significant. This isolated deviation does not appear elsewhere in the data and does not alter the overall pattern. Figure 7 reinforces the main conclusion: dynamic treatment effects fluctuate narrowly around zero, and post-outage coefficients show no meaningful changes. The absence of anticipatory responses before $e = -1$ further supports the validity of the design.

A related feature of Table 5 concerns the coefficients for control group on the outage day (the row labeled as 0.treatcl0 dum). In several specifications, these coefficients are negative and statistically significant, implying that crime in control stations tends to fall slightly on days when the paired treated station experiences an outage. Because the DID estimator differences out these common shocks, this pattern does not threaten identification; instead, it suggests that district-level or temporal shocks unrelated to outages influence both stations concurrently, with somewhat larger declines recorded in the control station. The treatment effect remains near zero precisely because these shared movements cancel out in the DID contrast.

Overall, the $\pm$5-day event-study analysis reveals no detectable short-run effect of isolated unplanned outages on reported crime—whether in aggregate or within crime categories—and this result holds in both urban and rural jurisdictions. Given that the analysis relies on an unweighted stacked DID with geographically matched pairs and lacks demographic information to refine matching or weighting, alternative approaches may provide sharper identification. Matching treated stations to multiple nearby controls and estimating a weighted stacked DID, complemented by demographic covariates when available, may improve precision and better capture heterogeneity in subsequent extensions.

6 Discussion and Next Steps

The preliminary event–study results suggest that short, isolated unplanned outages do not generate detectable short-run changes in reported crime across Maharashtra's police jurisdictions. The dynamic treatment effects are small, statistically indistinguishable from zero, and show little meaningful variation across crime categories or urban–rural settings. While this null result may reflect the true absence of behavioral responses to short outages, several empirical and conceptual considerations merit further investigation.

First, the identifying variation used here is deliberately narrow: the design isolates one-day outages that occur without additional outages in the surrounding window. These shocks are typically short in duration and may not meaningfully reduce lighting, economic activity, or public presence in ways that would affect criminal opportunities. Crime responses may instead depend on outage duration, timing, or spatial spillovers—dimensions that the current binary treatment definition does not capture. Extending the analysis to incorporate outage duration or constructing a continuous treatment variable may uncover heterogeneity obscured by the present specification.

Second, the matched-pair design creates strong local comparability but may attenuate statistical power. Some matched pairs exhibit mild deviations from parallel trends, and the one-to-one matching rule prevents leveraging multiple nearby controls. A natural next step is to construct synthetic controls or inverse-distance weighted control groups, allowing treated stations to be compared to the weighted average of several nearby controls. Combined with a weighted stacked DID approach, this may yield more precise and robust estimates.

Third, the current study relies on one year of data. Because outages and crime vary substantially over seasonal cycles, expanding the dataset to multiple years (2017–2025) would greatly increase the number of isolated sub-experiments and permit richer designs. A longer panel would allow examination of (i) seasonal or monsoon-specific effects, (ii) district-by-year heterogeneity, (iii) changes in outage–crime relationships during periods of high grid stress, and (iv) the possibility that behavioral responses accumulate or differ in years with more severe outages.

Fourth, outages may influence crime at specific times of day rather than at the daily level. Many theoretical links—reduced lighting, lower surveillance, disrupted economic activity—operate primarily during evening or nighttime hours. If outages commonly occur during the day, the null effects may reflect misalignment between treatment timing and the periods when crime is most responsive. Incorporating time-of-day information for both outages and crimes is therefore a promising extension.

Finally, the present study lacks demographic and institutional covariates that could sharpen identification and explain heterogeneity. Incorporating local socio-economic measures, police staffing, CCTV coverage, and neighborhood characteristics would allow testing of mechanisms and exploring distributional effects across richer versus poorer areas.

Together, these extensions will strengthen the empirical framework and deepen our understanding of how electricity reliability shapes criminal behavior.

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Tables

Table 1: Distribution of Reasons for Power Interruptions- Feeder and Daily Level

Reason of Interruption	**Frequency**	**Percent**	**Cumulative (%)**
EHV Transformer Failure	118	0.01	0.01
Emergency Outage	864,770	81.63	81.64
Fault in EHV substation	1,925	0.18	81.82
Fault on Distribution Transformer	1,431	0.14	81.96
Fault on HT Line	146,768	13.85	95.81
Fault on HT line due to Heavy Rain	6,115	0.58	96.39
Fault on HT line due to Storm	2,251	0.21	96.60
Fault on LT Line	1,444	0.14	96.74
Planned Maintenance 22/11KV HT Line	4,941	0.47	97.20
Planned Maintenance 33KV HT Line	20,880	1.97	99.17
Planned Maintenance Distribution Transformer	542	0.05	99.22
Planned Maintenance LT Line	651	0.06	99.28
Planned Maintenance Substation/Equipment	4,449	0.42	99.70
Power supply switched off due to water supply work	739	0.07	99.77
Works–Commissioning/Testing of Equipment	135	0.01	99.79
Works–Line Shifting	613	0.06	99.85
Works–New Service Connection	147	0.01	99.86
Works–Project/Scheme	836	0.08	99.94
Works–Replacement of Equipment/PTF	656	0.06	100.00
Total	**1,059,411**	**100.00**	

Note: Data Source- Maharashtra DISCOM

Table 2: Clubbed distribution of outage types

Outage Type	**Frequency**	**Percent**	**Cumulative (%)**
Faulty outages	160,052	15.11	15.11
Planned outages	34,589	3.26	18.37
Unplanned outages	864,770	81.63	100.00
Total	1,059,411	100.00	

Table 3: Summary statistics of outages and crimes at police station and daily level

Area Type	**Variable**	**N**	**Mean**	**p25**	**p50**	**p75**	**p90**
Rural area	total_hours_unplanned_outages	153,929	2.83	0.00	0.00	1.00	6.17
	total_crimes_all	153,929	1.77	1.00	1.00	2.00	4.00
	total_robbery_theft_tres	153,929	0.23	0.00	0.00	0.00	1.00
Urban area	total_hours_unplanned_outages	110,369	2.31	0.00	0.00	0.17	3.70
	total_crimes_all	110,369	2.12	1.00	2.00	3.00	4.00
	total_robbery_theft_tres	110,369	0.51	0.00	0.00	1.00	1.00
Total	total_hours_unplanned_outages	264,298	2.61	0.00	0.00	0.67	5.12
	total_crimes_all	264,298	1.91	1.00	1.00	2.00	4.00
	total_robbery_theft_tres	264,298	0.35	0.00	0.00	1.00	1.00

Note: Total robbery theft tres- Total of robbery, thefts and trespassing.

Table 4: Summary of identified outage shocks across event windows

Window Size	**Total Valid Shocks**	**Pairs with ≥1 Shock**	**Avg. Shocks per Treated Pair**
±5 days	1,730	389	4.447
±10 days	649	292	2.223
±15 days	355	219	1.621

Table 5: Dynamic Effects of Outages on Crime (Stacked DID, ±5 Days)

	(1) Total	(2) Prop	(3) Tres.	(4) Rob.	(5) Theft	(6) Total_UR	(7) Prop_UR	(8) Tres_UR	(9) Rob_UR	(10) Theft_UR	(11) Total_RUR	(12) Prop_RUR	(13) Tres_RUR	(14) Rob_RUR	(15) Theft_RUR
Lead: 5 days before outage (l5_dum)															
0.treat × l5	-0.080*	-0.029**	-0.016***	-0.000	-0.013	-0.053	-0.072***	-0.023**	0.000	-0.049***	-0.097*	0.001	-0.010	-0.001	0.012
	(0.047)	(0.013)	(0.006)	(0.003)	(0.011)	(0.080)	(0.021)	(0.010)	(0.006)	(0.019)	(0.058)	(0.015)	(0.007)	(0.003)	(0.013)
1.treat × l5	-0.080*	-0.017	-0.002	-0.003	-0.012	-0.028	-0.036	0.001	0.001	-0.038*	-0.110*	-0.005	-0.005	-0.006**	0.006
	(0.047)	(0.015)	(0.007)	(0.003)	(0.013)	(0.075)	(0.024)	(0.011)	(0.007)	(0.021)	(0.065)	(0.018)	(0.008)	(0.003)	(0.015)
Lead: 4 days before outage (l4_dum)															
0.treat × l4	-0.007	-0.022	-0.002	0.000	-0.020*	0.037	-0.051**	-0.005	-0.004	-0.042**	-0.054	-0.004	-0.001	0.004	-0.006
	(0.055)	(0.014)	(0.007)	(0.003)	(0.012)	(0.075)	(0.023)	(0.011)	(0.006)	(0.020)	(0.084)	(0.016)	(0.008)	(0.004)	(0.014)
1.treat × l4	-0.085*	-0.015	-0.007	-0.001	-0.007	0.005	-0.012	-0.006	-0.001	-0.005	-0.162***	-0.020	-0.008	-0.001	-0.011
	(0.045)	(0.015)	(0.006)	(0.003)	(0.012)	(0.076)	(0.028)	(0.010)	(0.006)	(0.023)	(0.058)	(0.015)	(0.008)	(0.003)	(0.012)
Lead: 3 days before outage (l3_dum)															
0.treat × l3	-0.058	-0.017	-0.005	0.004	-0.015	-0.008	-0.032	-0.014	0.005	-0.023	-0.087	-0.007	0.004	0.003	-0.014
	(0.040)	(0.013)	(0.006)	(0.003)	(0.011)	(0.066)	(0.025)	(0.011)	(0.006)	(0.022)	(0.054)	(0.014)	(0.008)	(0.003)	(0.012)
1.treat × l3	-0.027	-0.025*	-0.008	-0.002	-0.015	0.108	-0.025	-0.010	0.001	-0.016	-0.117*	-0.026*	-0.005	-0.003	-0.018
	(0.047)	(0.013)	(0.006)	(0.003)	(0.011)	(0.074)	(0.022)	(0.011)	(0.006)	(0.020)	(0.061)	(0.016)	(0.008)	(0.004)	(0.013)
Lead: 2 days before outage (l2_dum)															
0.treat × l2	-0.078*	-0.015	-0.006	0.004	-0.013	0.010	-0.006	-0.001	0.009	-0.014	-0.143**	-0.019	-0.009	0.001	-0.011
	(0.042)	(0.013)	(0.006)	(0.004)	(0.012)	(0.064)	(0.022)	(0.010)	(0.007)	(0.019)	(0.056)	(0.016)	(0.007)	(0.003)	(0.014)
1.treat × l2	-0.057	-0.014	-0.001	-0.002	-0.012	0.059	-0.044*	-0.022**	-0.004	-0.018	-0.135**	0.013	0.017*	0.000	-0.004
	(0.050)	(0.015)	(0.007)	(0.004)	(0.013)	(0.086)	(0.025)	(0.010)	(0.007)	(0.023)	(0.059)	(0.018)	(0.010)	(0.004)	(0.014)
Event time 0 (day of outage)															
0.treat × l0	-0.040	-0.042***	-0.009	0.006	-0.039***	0.007	-0.060***	-0.017	0.015*	-0.058***	-0.070	-0.030**	-0.003	-0.000	-0.027**
	(0.044)	(0.013)	(0.006)	(0.004)	(0.011)	(0.073)	(0.022)	(0.010)	(0.008)	(0.018)	(0.055)	(0.014)	(0.008)	(0.003)	(0.013)
1.treat × l0	-0.041	0.003	-0.008	0.001	0.009	0.121	-0.010	-0.022**	-0.001	0.013	-0.154***	0.012	0.003	0.004	0.005
	(0.048)	(0.015)	(0.007)	(0.003)	(0.013)	(0.088)	(0.026)	(0.010)	(0.005)	(0.023)	(0.053)	(0.017)	(0.009)	(0.004)	(0.014)
Lag 1 (f1_dum)															
0.treat × f1	-0.013	0.013	0.000	0.003	0.009	0.040	0.003	-0.009	0.003	0.009	-0.046	0.016	0.007	0.003	0.006
	(0.047)	(0.013)	(0.006)	(0.003)	(0.012)	(0.082)	(0.023)	(0.010)	(0.006)	(0.020)	(0.056)	(0.015)	(0.008)	(0.003)	(0.013)
1.treat × f1	-0.068	-0.023	-0.010*	0.000	-0.012	0.071	-0.013	-0.013	0.004	-0.005	-0.163***	-0.034**	-0.010	-0.004	-0.021
	(0.045)	(0.014)	(0.006)	(0.003)	(0.013)	(0.068)	(0.026)	(0.010)	(0.007)	(0.025)	(0.061)	(0.014)	(0.007)	(0.003)	(0.013)
Lag 2 (f2_dum)															
0.treat × f2	-0.031	-0.005	-0.002	0.004	-0.007	0.021	0.017	0.004	0.007	0.006	-0.069	-0.023	-0.006	0.002	-0.018
	(0.045)	(0.015)	(0.007)	(0.003)	(0.013)	(0.073)	(0.026)	(0.013)	(0.006)	(0.025)	(0.060)	(0.015)	(0.007)	(0.004)	(0.013)
1.treat × f2	-0.027	-0.013	0.000	-0.006**	-0.007	0.025	-0.033	-0.008	-0.008	-0.017	-0.059	0.002	0.007	-0.005	-0.000
	(0.047)	(0.015)	(0.007)	(0.003)	(0.014)	(0.068)	(0.029)	(0.011)	(0.006)	(0.027)	(0.063)	(0.016)	(0.009)	(0.003)	(0.014)
_cons	1.286***	0.223***	0.048***	0.010***	0.165***	1.451***	0.320***	0.059***	0.015***	0.246***	1.150***	0.148***	0.039***	0.006***	0.103***
	(0.024)	(0.008)	(0.004)	(0.002)	(0.007)	(0.038)	(0.013)	(0.006)	(0.004)	(0.012)	(0.032)	(0.009)	(0.004)	(0.002)	(0.008)
N	27316	27316	27316	27316	27316	12060	12060	12060	12060	12060	15256	15256	15256	15256	15256

Notes: Table reports stacked difference-in-differences estimates from event-study specification around isolated outage shocks (±5 days). Each column corresponds to a crime category and subsample (all, urban, rural). Standard errors clustered at matched-pair level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figures

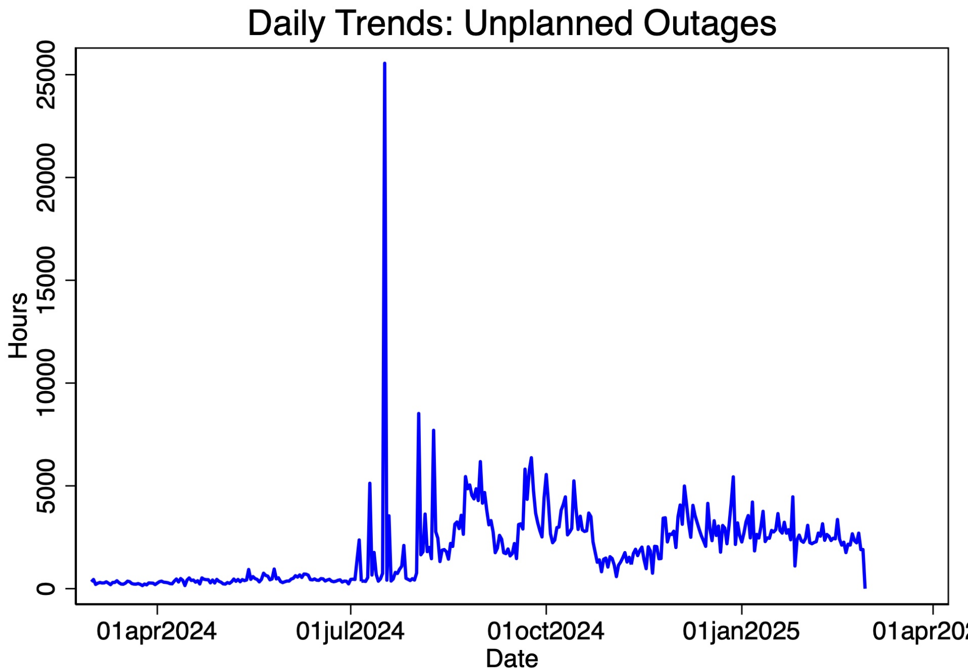


Figure 1: Daily total of unplanned outages in MH.

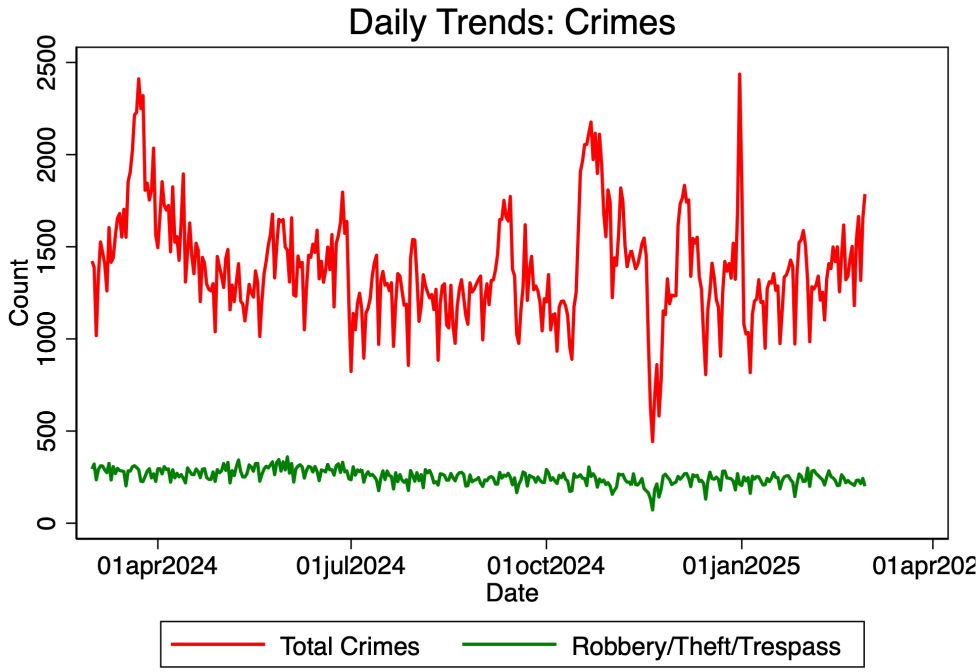


Figure 2: Daily total crimes in MH.

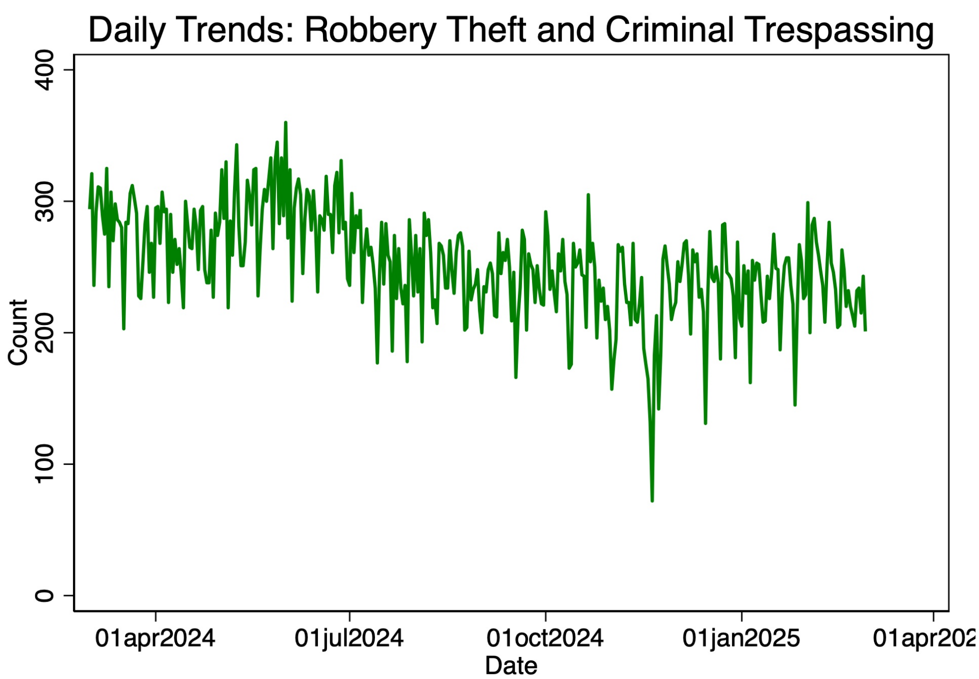


Figure 3: Daily total robbery, thefts and criminal trespassing in MH.

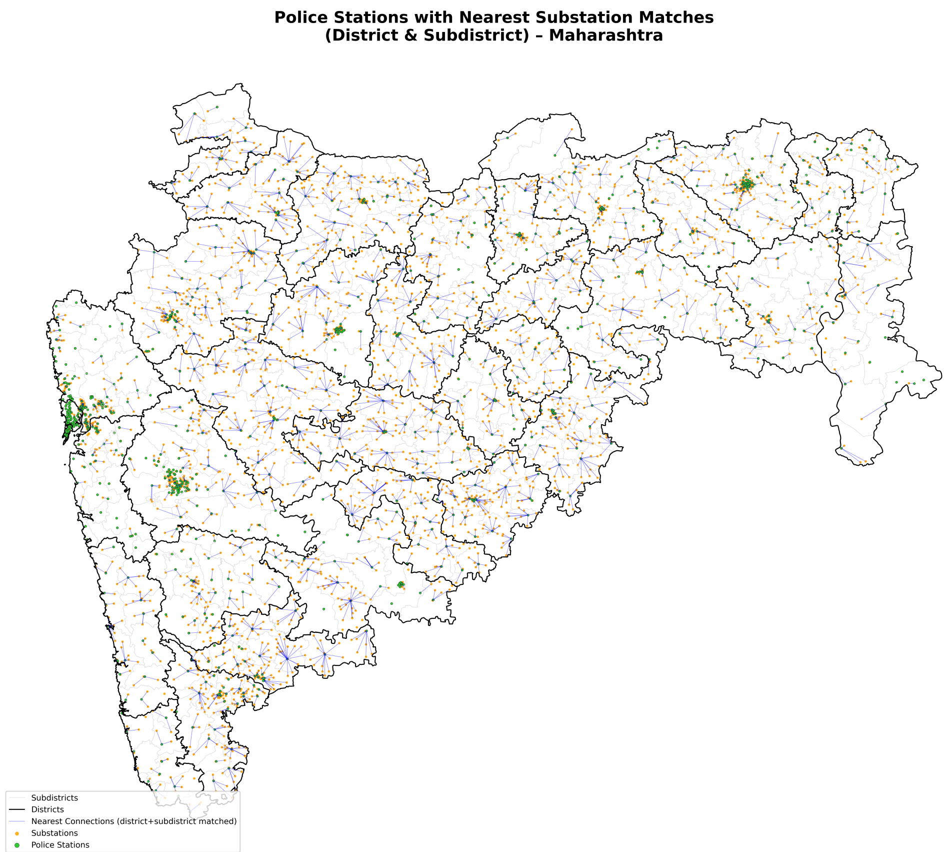


Figure 4: Police stations matched to their nearest substations, defining jurisdiction, ranging under 39 km.

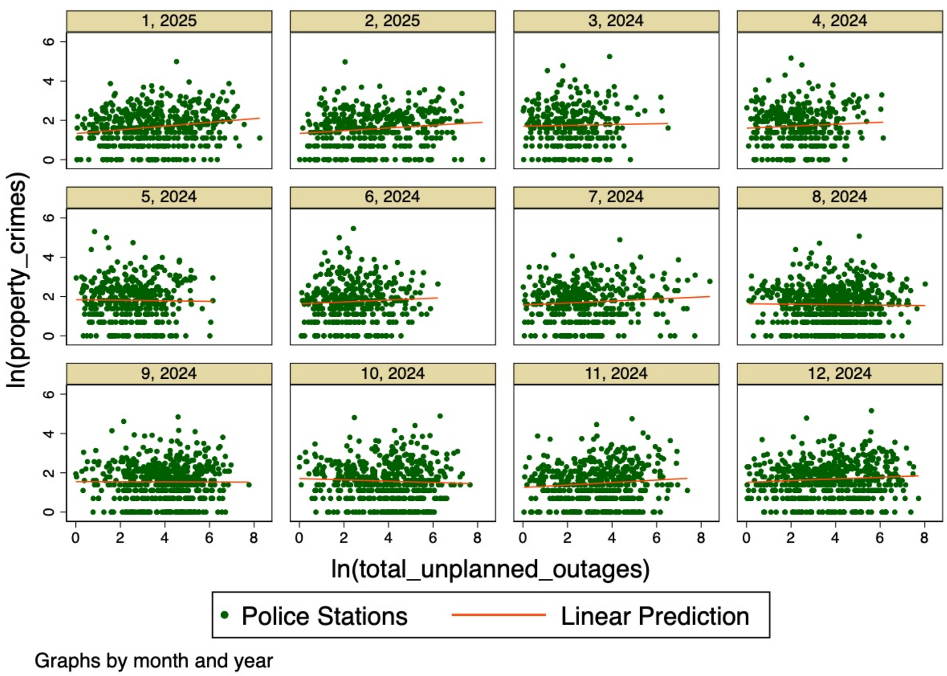


Figure 5: Scatter plot of property crimes and unplanned outages

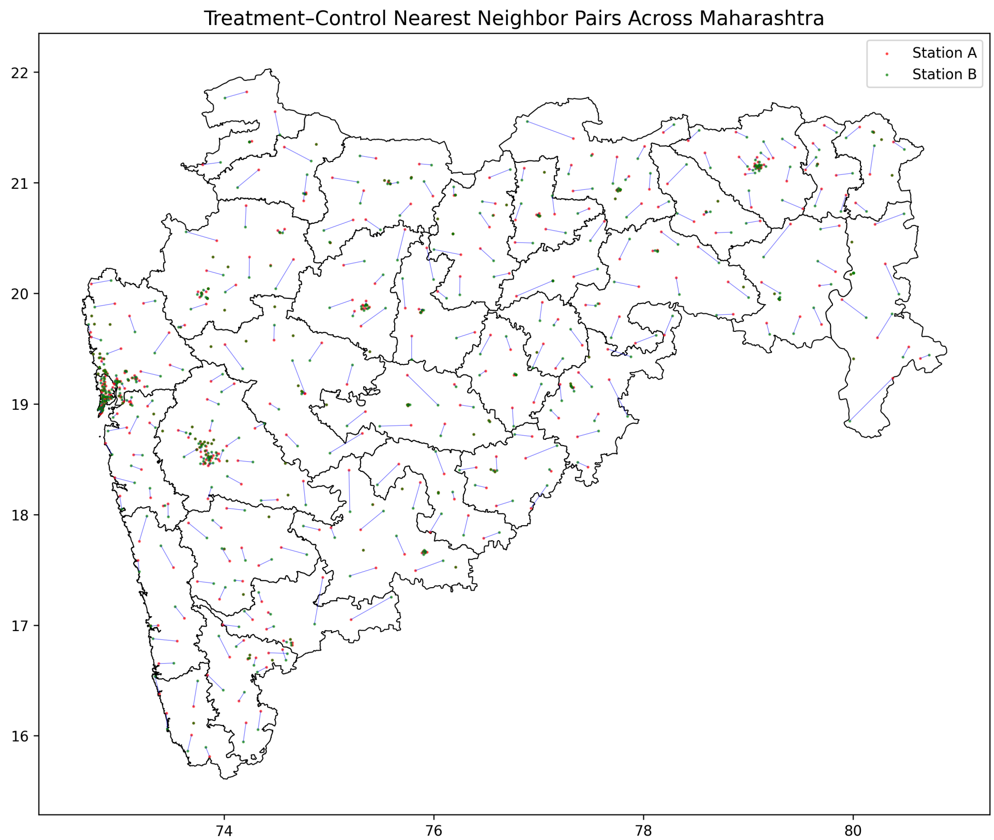
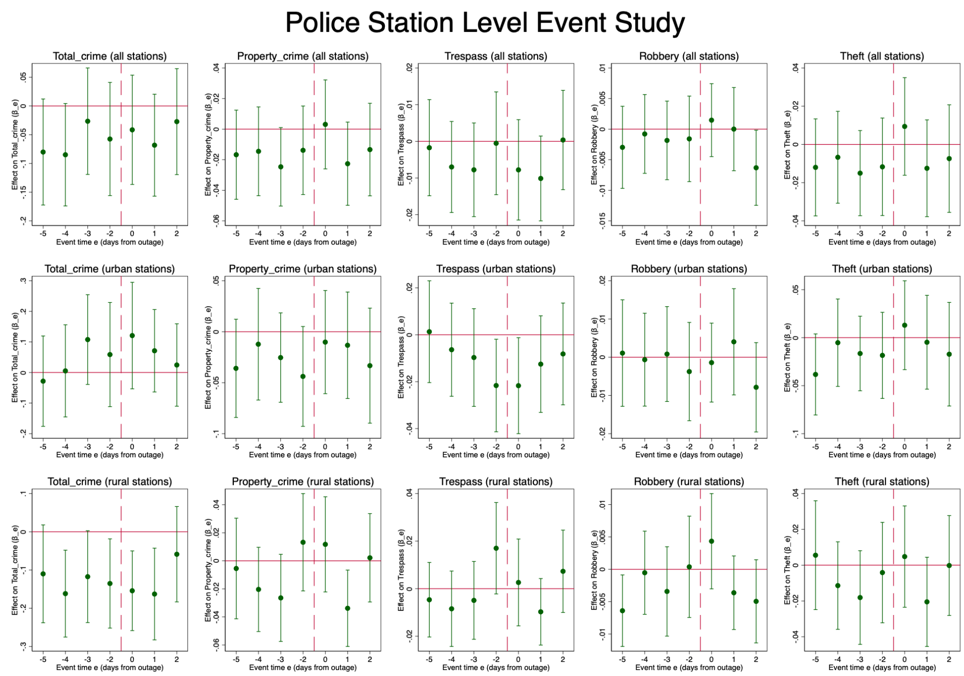


Figure 6: Treatment control neighboring police station pairs.



Note: Total crimes include all IPC and BNS crimes. Property crimes include trespassing, robbery, and theft.

Figure 7: Event Study Plots