The Effects of Power Outages on Crime*

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Abstract

This study examines how unplanned power outages affect property crimes in Maharashtra, India. I assemble a novel daily dataset that links substation-level outage records with police-station crime reports, allowing crime outcomes to be measured within police station jurisdictional boundaries. To identify causal effects, I exploit exogenous variation from unplanned outages and compare treated stations to optimally matched control stations that experience no outages in the same event window. Using stacked event-time windows around each shock, a stacked difference-in-differences design will trace dynamic crime responses before and after outages. The findings will contribute to the literature on electricity reliability and public safety by uncovering a previously undocumented mechanism through which infrastructure disruptions shape criminal behavior.

Keywords: electricity reliability; outages; crime; India

JEL Codes: K42; O18; Q41

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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.

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 Results

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 Next Steps

With the matched station pairs and stacked event-time dataset in place, the next step is to estimate the causal impact of short, localized outages on crime using the dynamic stacked difference-in-differences framework described above. The primary specification will rely on the ± 5-day window, with the ± 10 and ± 15 windows serving as robustness checks that impose stricter isolation around each outage event. I will examine heterogeneous effects across crime categories and between urban and rural settings, taking advantage of the district-level classifications and the tightly matched station pairs. While the current analysis is based on one year of data, substantially longer panels can be constructed: daily feeder-level outage data and station-level crime reports are publicly available through the Maharashtra DISCOM portal and the FIR reporting system dating back to 2017. Expanding the dataset will enable richer identification, improved statistical precision, and additional assessments of year-to-year variation in reliability and crime dynamics.

As the project develops, the empirical strategy will be extended to several methodological dimensions. These include modeling multi-day outages and defining treatment–control contrasts when both stations experience outages of varying lengths; incorporating a continuous treatment-intensity design where outage duration replaces the binary shock indicator; and estimating count-data models (e.g. Poisson) that better reflect the discrete nature of crime and outage measures. I also plan to incorporate additional complexities, such as distinguishing between day and night outages, accounting for cloudy days, and integrating demographic and institutional controls to further strengthen the empirical design and mitigate potential confounding. Together, these extensions will yield a flexible and rigorous framework for understanding short-term behavioral responses to unreliability of electricity.

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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

Figures

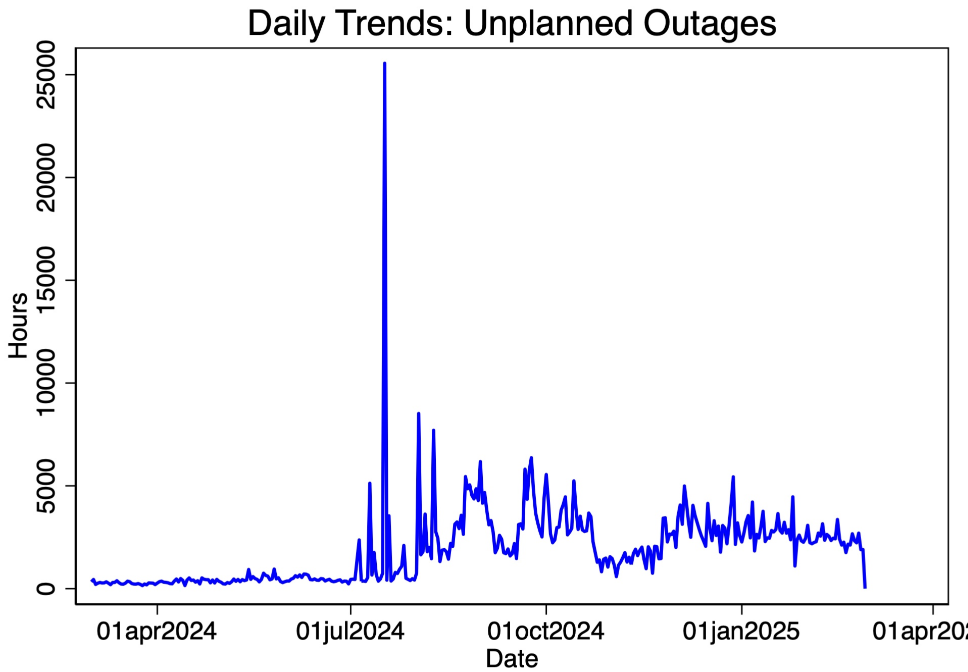

Figure 1: Daily total of unplanned outages in MH.

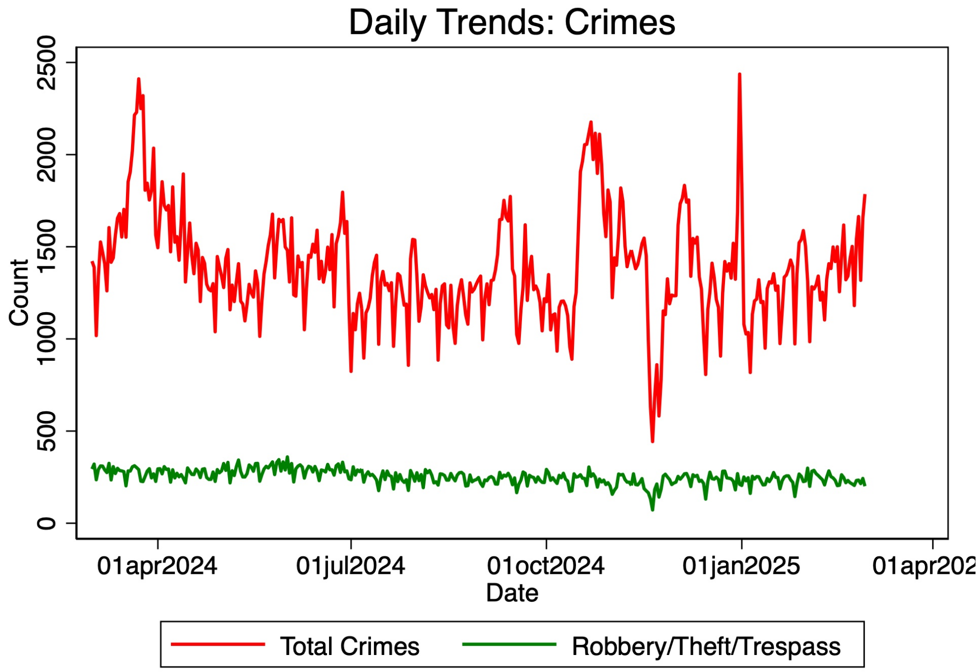

Figure 2: Daily total crimes in MH.

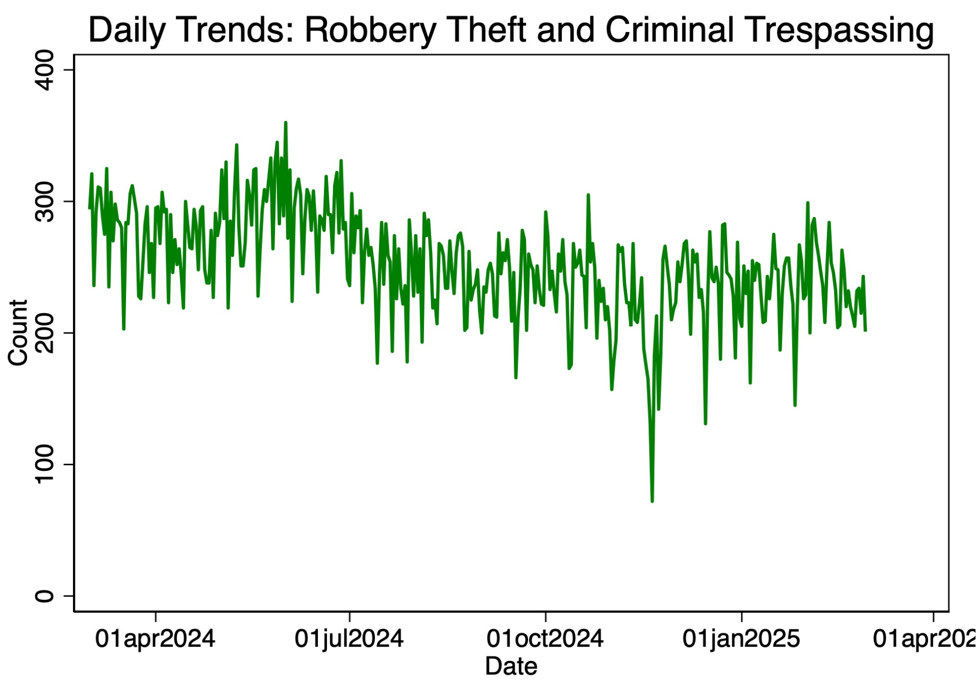

Figure 3: Daily total robbery, thefts and criminal trespassing in MH.

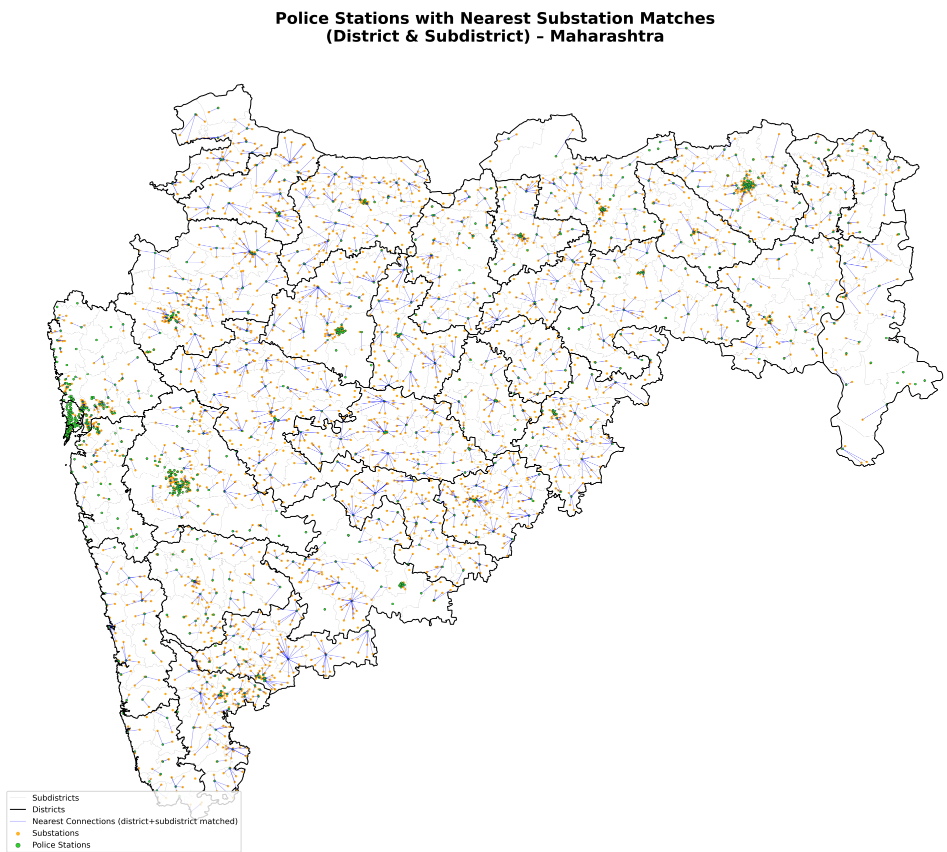

Figure 4: Police stations matched to their nearest substations, defining jurisdiction, ranging under 39 km.

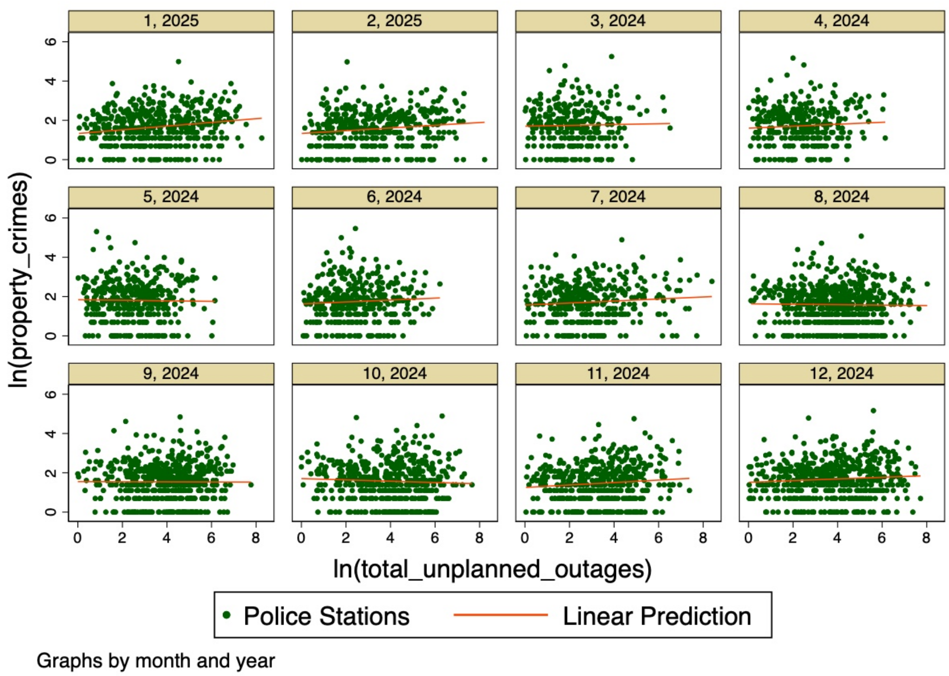

Figure 5: Scatter plot of property crimes and unplanned outages

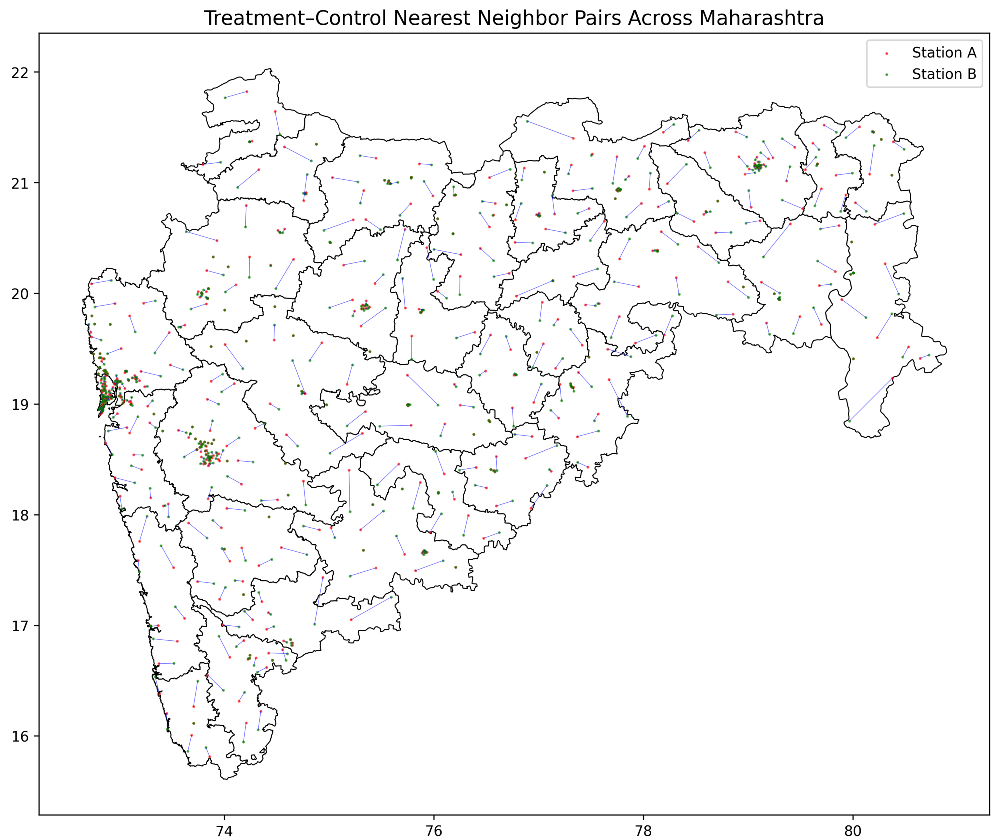

Figure 6: Treatment control neighboring police station pairs.