Infrastructure, Institutions, and the Conservation of Biodiversity in India

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January 30, 2024

Abstract

Anthropogenic land use change is the leading threat to biodiversity. This paper studies how forest encroachment by infrastructure degrades biodiversity and the role of local institutions in mitigating species loss. Combining new data from India on infrastructure-driven deforestation with one million birdwatching diaries, and using within-observer variation for identification, I document a sizeable infrastructure-biodiversity tradeoff. Forest encroachment by transport, irrigation, resettlement camps, and mining projects account for 20% of total species loss. Common and threatened species are particularly sensitive, and species diversity does not recover in the medium run. However, the extent of species loss is more than halved when local institutions enable marginalized communities, who are excluded from project planning, to mobilize around their interests. Informed consent between developers and tribal communities is a key mechanism, underscoring the importance of inclusive institutions for balancing development and conservation.

Keywords: sustainable development, economic development, infrastructure, biodiversity, conservation, institutions, political economy.
JEL Codes: Q01, Q56, Q57, Q20, O13.

*University of Minnesota, Department of Applied Economics. Email: rmadhok@umn.edu. For helpful comments, I thank Sumeet Gulati, Patrick Baylis, Frederik Noack, Siwan Anderson, Eyal Frank, Ryan Abman, Teevrat Garg, Meredith Fowlie, Sonja Kolstoe, Bianca Cecato, Tatiana Zarate, and the Wildlife and Conservation Economics Lab at UBC. I also thank seminar audiences at the World Bank, NBER Summer Institute (EEE), Vancouver School of Economics, Columbia IPWSD, CREEA, AERE, WEAI, PacDev, and Camp Resources. Veena Vinod provided excellent research assistance. I am grateful for the SSHRC CGS Doctoral Fellowship for generous funding. All errors are my own.

1 Introduction

Global infrastructure spending totalled $US 2.3 trillion in 2015 (Oxford Economics, 2017). Although crucial for economic growth, infrastructure expansion narrows the frontier between human activity and fragile ecosystems. The ecological threat from encroachment is especially acute in the tropics, home to two-thirds of Earth's biodiversity yet where over 60% of global infrastructure spending occurs (FAO and UNEP, 2020). This is exacerbated by the fact that millions of indigenous people—who have supported biodiversity for millennia—are displaced by, disaffected by, or excluded from project planning.

Economists have long sought how to reduce environmental costs of development (Grossman and Krueger, 1995; Dasgupta et al., 2002; Copeland and Taylor, 2004). Biodiversity receives little attention in this literature (Frank and Schlenker, 2016), let alone grassroots solutions for balancing development and conservation. Filling this gap thus requires not only estimates of the ecological threat from infrastructure, but also the role of local institutions for neutralizing it.

The first goal of this paper is to provide a deeper understanding of the extent to which infrastructure expansion drives biodiversity loss. I call this the infrastructure-biodiversity tradeoff. The second goal is to investigate the role of decentralized forest governance in mitigating the tradeoff. Better understanding these socio-ecological and institutional processes can assist countries in meeting the dual objectives of development and conservation.

The broad setting is the tropics, where over half of global deforestation occurs (Pacheco et al., 2021). India notably avoided widescale forest loss despite recording rapid economic growth (Forest Survey of India, 2019). It is unclear whether this was due to concerted tree-planting or changing definitions of forest cover. Even if development did leave forests unscathed, important inhabiting species may still become threatened and require policy attention. Elusive measurement of such species has led to biodiversity being overlooked in previous studies (Foster and Rosenzweig, 2003; Burgess et al., 2012).

The first part of this paper estimates the infrastructure-biodiversity tradeoff in India's forests between 2015-2020. This constitutes a valuable setting for three reasons. First, India is among the planet's most biodiverse countries, home to 8% of global biodiversity and 12% of bird diversity (Venkataraman and Sivaperuman, 2018; Jayadevan et al., 2016). Second, India's biodiversity is documented by active "citizen scientists" who upload sightings on species-specific (e.g. eBird) or general (e.g. iNaturalist) platforms. India boasts the highest eBird membership of any developing country. Their geocoded uploads serve as a new, high-resolution biodiversity repository unmatched in the literature. Third, India publicly reports forest encroachments by infrastructure. Deforestation for building roads, mines an other projects now account for 17% of yearly forest loss (authors calculation). The Forest Act (1980) mandates environmental review of such projects before construction. The review process underwent a transparency initiative in 2014, unlocking new administrative data for estimating threats to biodiversity.

To measure infrastructure development, I digitize the universe of deforestation permits awarded to firms that passed environmental review. This includes 7,000 permits scraped from a public portal and 2,000 digitized by hand. Each permit describes a forest patch diverted for construction and uniquely bundles infrastructure and deforestation into a single variable. For analysis, permits are aggregated into a cumulative measure of district-monthly forest area diverted for development. This new data improves on satellite measures because the latter overlooks the source of deforestation. Pixel values are also annual aggregates, which masks deforestation throughout the year. In contrast, my data directly measures infrastructure-driven deforestation and features sharp monthly landscape changes as projects roll out. I do, however, use satellite data to verify that *approved* projects trigger *actual* deforestation.

To measure biodiversity, I obtain one million geocoded birdwatching diaries from eBird, the world's largest crowd-sourced platform for wildlife sightings (Sullivan et al., 2009). Birds are a credible indicator species for ecosystem health, sensitive to environmental change, and documented with high precision

(Morrison, 1986; Fraixedas et al., 2020). Each diary reflects a unique birdwatching session—which I call a "trip"—and lists the date, time, GPS coordinates, and a taxonomy of species sightings. I count the number of species listed on diaries that best reflect the local species pool. This yields a representative biodiversity dataset with unparalleled spatiotemporal resolution, spanning 95% of districts from the Himalayas to the Western Ghats.

The matched panel permits a two-way fixed effects (TWFE) design, which I employ to estimate the impact of infrastructure development on bird species diversity (hereafter, species diversity) in a typical Indian district. The data allow me to characterize heterogeneity in a way that has eluded previous studies. I decompose estimates by project category, ownership (public/private), and shape (linear/nonlinear) to show which types of infrastructure are the least and most harmful. I also stratify districts by initial fragmentation level to reveal whether projects have differential effects in pristine or already-fragmented habitats. These results can help policy makers optimize the allocation of conservation budgets by choosing the location and infrastructure mix with minimal harm to local ecosystems.

Despite the promise of citizen science, its opportunistic nature yields more sample selection than typical administrative data. eBird users tend to visit more biodiverse locations, especially in the Western Ghats. There is also a Siberian bird migration to India in winter, and a lull in birdwatching activity during monsoons, which induces stark seasonality. Lastly, users possess a range of abilities, complicating inference from cross-user comparisons. I employ district fixed effects to address site choice, state-month fixed effects to address seasonality, and individual fixed effects to compare trips *within* the same user. Even after removing the ability bias, within-user residuals still trend upward due to learning. User-by-year fixed effects address this, and I show that this design outperforms previous studies.

Endogenous sorting of both birds and users is the main threat to identification, even with the fixed effects. If construction pushes birds into less-fragmented districts, then the control group is contaminated. Similarly, if users sort towards biodiverse districts, then estimates are upward biased. I address both issues with spatial lags. First, I show that species immigration into a district is uncorrelated with nearby development. Second, I show that the number of district users is unchanged when nearby districts become more developed. These tests are robust to different distance cutoffs, ruling out most concerns of endogenous mobility.

My analysis yields four key findings. The main result is that infrastructure development triggers substantial species loss. Ten square kilometres of infrastructure encroachments reduce species diversity by 4%, as observed by the average eBird user. In contrast, the portion of these projects falling on *non-forest* land has no impact on species diversity, suggesting that habitat loss is a key mechanism. In aggregate, approximately 20% of the observed decline in species diversity over the study period can be attributed to development in India's forests.

Second, nearly all project categories drive the infrastructure-biodiversity tradeoff. The top three most harmful are resettlement, transport, and irrigation projects. Resettlements are akin to camps for relocating displaced communities. The negative impact of mining is surprisingly small, which I show is due to low eBird activity in mining districts. The mining impact doubles when the sample is restricted to higher-activity districts.

Third, common and vulnerable species are the most sensitive to infrastructure-driven deforestation. I manually match bird taxonomies with their IUCN Red List status and count the number of times each user observes a common, vulnerable, or endangered species. Poisson regression estimates show a sharp decline in the abundance of common and vulnerable species following infrastructure expansion.

Lastly, species are more resilient to infrastructure development in intact forests. Heterogeneity by baseline forest cover shows that the infrastructure-biodiversity tradeoff is halved in districts with one standard deviation higher initial forest cover. This suggests that degraded landscapes should be earmarked for protection, advancing the debate about how to target conservation action (Betts et al., 2017).

The results are robust to a variety of stress tests and alternative samples. Estimates are stable when accounting for individual-level seasonality, sub-state seasonality, and more flexible specifications of learning. To show that results are not driven by a changing user base, I show that estimates are similar when restricting the sample to users who signed up in 2015. Estimates are also similar when dropping users' home districts, suggesting that estimates are not biased by different behaviour at home and away. I also test robustness to more intricate diversity indices. Estimates remain negative but become noisy due to low-quality bird counts. Lastly, to show that estimates are unbiased by the switch to "balcony birdwatching" during COVID-19, I document stable estimates when dropping the year 2020.

The infrastructure-biodiversity tradeoff is also apparent under an alternative, widely implemented, identification strategy based on close elections. Since winner identity in close elections is essentially determined by coin toss, I use the fraction of district constituencies where an incumbent won in close elections as an instrument for infrastructure. First stage estimates show less forest degradation from infrastructure in closely contested districts. The second stage, once again, shows that forest encroachment prompts species decline. One concern is that incumbents may affect local ecology through other types of public spending. While controlling for nightlights partially mitigates this, the exclusion restriction assumption remains strong. Moreover, these estimates do not generalize to non-competitive districts. I therefore view them as a validation of coefficient sign rather than a second set of main estimates.

The second part of the paper investigates which institutions minimize biodiversity loss. India is home to nearly 200 million members of forest-dependent indigenous tribes, who have been custodians of biodiversity on traditional forestland for millennia. Today, they are among the country's most economically vulnerable, politically excluded, and face livelihood loss as forests are handed over to commercial interests. I study whether inclusive local institutions that emphasize decentralized decision-making can mitigate the infrastructure-biodiversity tradeoff.

Data are from Banerjee and Iyer (2005) and indicate whether district institutions favour elites (extractive) or are more inclusive of the masses. The measure is based on whether historic tax collection was through a middleman or not. Banerjee and Iyer (2005) find that non-middleman districts feature higher income equality today and better ability of the disenfranchised to mobilize around their needs. If tribal groups are better able to protect their livelihoods—which hinges on protecting forests—in inclusive districts, then better conservation outcomes are expected there.

The infrastructure-biodiversity tradeoff estimated in the first part of the paper is significantly smaller in inclusive districts. Implied magnitudes are large; the tradeoff is 78% smaller in these districts, where disaffected groups can better engage in the development process. Results are independent of tribal population share, suggesting that heterogeneity reflects institutional, not population, differences. These results underscore the importance of inclusive forest governance in achieving sustainable development.

The paper concludes by probing the mechanisms through which inclusive institutions mitigate the infrastructure-biodiversity tradeoff. This helps answer *why* inclusive development fosters conservation. I extract unique data from project permits reporting whether indigenous tribes were consulted during the review process and whether a supplemental cost-benefit analysis was commissioned during project review. I find that projects approved in inclusive districts are associated with significantly higher rates of informed consent and environmental scrutiny compared to those approved in extractive districts. These results indicate that grassroots participation in project planning, along with higher environmental standards, are key features of inclusive institutions that balance development and conservation. These findings are crucial given India's prioritization of Northeastern states—which have the higher forest cover and largest tribal populations in the country—for industrialization (Nayak et al., 2020).

Literature Contributions: This paper contributes to three literatures. My main contribution is to provide the first country-wide evidence that infrastructure expansion triggers local species loss. Most

economics studies that quantify infrastructure externalities estimate pollution costs (Currie et al., 2015; Hanna and Oliva, 2015). A handful have estimated forest loss: Asher et al. (2020) and Garg and Shenoy (2021) find surprisingly little effect of infrastructure on forest cover in India, and Baehr et al. (2021) also find muted effects in Cambodia. While this suggests that ecosystems are resilient to infrastructure[1], my results indicate otherwise. Using detailed species-level data, I document the extent to which infrastructure development erodes biodiversity.

The most similar paper is Liang et al. (2021), who study GDP and biodiversity in the United States[2]. Biodiversity is compiled from hundreds of ecological studies covering many animals. Development is measured by state-level GDP, which subsumes many underlying mechanisms driving biodiversity loss. In contrast, my data captures infrastructure development at the forest frontier. Despite the differences, our results are consistent: development drives species loss.

The second contribution of this paper is to extend the ecology literature by expanding the spatiotemporal scope of data and integrating empirical techniques from economics. The ecology literature has long documented anthropogenic pressures on ecosystems. In these studies, field workers often count species in transects with different levels of human activity. This yields accurate data but limits analysis to cross-sectional comparisons (Reis et al., 2012; Stephens et al., 2004). Although citizen science dramatically improves data coverage, most interest in the ecology literature has been in identifying endogeneity i.e., from seasonality, site choice, and detection ability, rather than conducting quasi-experiments (Callaghan et al., 2019; Kelling et al., 2019). I advance this literature by accounting for documented as well as undocumented biases, especially within-user learning, to arrive at quasi-experimental estimates of the infrastructure-biodiversity tradeoff. These estimates can be generalized beyond existing cross-sectional estimates due to the national-scale panel nature of my data.

The third contribution of this paper is to extend research at the intersection of political economy and conservation. I do this by showing empirically that inclusive institutions matter for natural resource conservation. A seminal literature shows how historic institutions shape modern economic development (Nunn, 2009), yet few have considered biodiversity outcomes[3]. In contrast, the conservation literature acknowledges the importance of institutions in moderating economy-environment tradeoffs, yet few have tested the claim credibly (Börner et al., 2020). I advance this literature by credibly estimating of the role of institutions in reducing species loss.

I am also able to fill a gap in this literature by pinning down mechanisms. Duflo and Pande (2007) use the same institutional data to show that the poverty impact of dams is muted in inclusive districts, and argue that the poor are better able to obtain compensation in these districts. Lee (2019) confirm that inclusive districts have better contemporary state capacity. My results point to a mechanism with "teeth", namely, higher rates of informed consent in inclusive districts. My paper therefore ties together this literature and shows that grassroots institutions are crucial for successful sustainable development.

The rest of this paper is organized as follows. The next section provides background on infrastructure-driven deforestation in India. Section 3 introduces the construction permit and citizen science data. Section 4 presents stylized facts to motivate the research design, described in Section 5. Section 6 presents estimates of the impact of infrastructure expansion on biodiversity. Section 7 explores the role of institutions for mitigating the tradeoff. Section 8 concludes.

[1] Kaczan (2020) find that road building in India reduces tree cover in remote areas and increases tree cover in peri-urban areas. The net effect may explain the small effects found in previous studies.

[2] Related studies include Liang et al. (2020), Noack et al. (2021) and Noack et al. (2019). The first studies pollution effects on bird abundance, whereas I focus on effects of habitat loss. The second studies the impact of farm size on bird species diversity. The third studies the impact of plant species diversity on income fluctuations in the tropics.

[3] Prior work has studied institutions and water conservation (Libecap, 2011; Hagerty, 2021) and forest conservation (Börner et al., 2020; Lal et al., 2021). Tsuda et al. (2023) consider place-based infrastructure policies and resource depletion. Neither consider biodiversity per se. Most related is Noack et al. (2021), who show that different land institutions in historic East and West Germany led to differences in modern farm size which, in turn, impacts bird diversity.

2 Background

India's Forest Act (1980) Regulates Construction in Forests: India's Forest (Conservation) Act (1980) protects its forests from "conversion to non-forest uses" (MoEFCC, 1980). Infrastructure is among the main regulated activities because it fragments important habitats. For example, roads split contiguous forests into smaller patches, restricting wildlife movement and gene flow since many fauna avoid clearings as narrow as 30 metres (Riley et al., 2006; Benítez-López et al., 2010). Infrastructure also generates noise pollution, changes soil properties, and facilitates invasive species dispersal (Laurance et al., 2009).

When non-forest sites are unfeasible, the Act permits infrastructure encroachments pending a rigorous environmental review process. It also sets up a forest advisory committee (FAC) comprised of government officials and forestry experts to rule on construction proposals. Projects involving any amount of deforestation, on any land recorded as forest in government records irrespective of ownership (i.e. public/private forest), undergo this review process.

Despite the Act's intent, huge swathes of India's forests have been transferred to public and private firms. Between 1985-2014, approximately 4,000 km^2 of forest were clearcut for the construction of 23,000 infrastructure projects. Total deforestation during this period was 24,223 km^2 (Meiyappan et al., 2017)[4], implying that infrastructure intrusions accounted for 17% of India's deforestation during the three decades preceding this study.

Informed Consent Required Since 2006: Infrastructure-driven deforestation sanctioned by the Act is often at the expense of India's 200 million indigenous Scheduled Tribes. These tribes are mainly forest-dependent and conserve biodiversity through traditional knowledge. Yet, they have been excluded from development decisions because the Act historically gave powers only to state institutions.

In 2006, the landmark Forest Rights Act (FRA) democratized forest governance by granting tribes formal rights to manage village forests. These rights also prevent firms from diverting forests without informed consent from the concerned Gram Sabha (village council)[5]. While examples of successful implementation exist, the FRA has become diluted and is often flouted (Menon, 2016). Empirically, weak implementation provides variation to study the merits of such grassroots institutions (Section 7).

Project Approval is Granted via Forest Clearances: The journey of a project proposal is known as the Forest Clearance (FC) Process (MoEFCC, 2003). There are two stages: stage-I approval is granted after environmental review. Stage-II is granted after FRA compliance and payment into a tree-planting fund. As discussed below, these funds are rarely disbursed and pose little threat to my research design.

To receive stage-I approval, the firm first submits an application to the District Forest Office (DFO). The DFO may commission a site inspection report, which typically includes stipulations to change project size or location. The report is then forwarded to the State Forest Department, which can add more stipulations. At this point, approval is granted to small projects (0-5 ha., except mining). Medium projects (5-40 ha.) are forwarded to the Regional Office (RO) and large projects ($>$ 40 ha.) are forwarded to the Ministry of Environment Forests and Climate Change (MoEFCC). The FAC[6] then rules on stage-I, indicating that environmental review is complete.

To receive stage-II approval, firms pay a state-fixed rate into a compensatory afforestation fund. Despite potential to offset my findings, the fund is fraught with issues and tree-planting is rarely carried out. A recent audit found that just 7% of land secured for afforestation between 2006-12 had been planted in 2013 (MoEFCC, 2013). Other studies either find no impact of plantations on satellite forest cover (Coleman et al., 2021), or no existence of plantations whatsoever during field visits (World

[4]Forest loss was 18,000km^2 from 1985-2005 (Meiyappan et al., 2017), and 6223km^2 from 2006-14 (Global Forest Watch)

[5]FRA guildelines: http://forestsclearance.nic.in/writereaddata/public_display/schemes/981969732$3rdAugust2009.pdf

[6]The regional FAC consists of senior RO and DFO officers as well as non-government forestry experts.

Rainforest Movement, 2019). Sanctioned afforestation thus poses minimal threat to my research design.

Another stage-II requirement is for the DFO to verify ST rights and submit evidence of Gram Sabha consent to the MoEFCC. After fundraising and FRA compliance, the central FAC makes their decision and, if approved, the firm begins deforestation. My data consists of firms with stage-II approval.

Whether *approved* deforestation can be taken to mean *actual* deforestation is an empirical question. In Section 4.1 I verify that stage-II project approvals trigger satellite-observed deforestation. References to approved project area hereafter can thus be interpreted as actual area of forest diversion.

Projects Take Several Years to Complete: Projects take many years to complete after stage-II approval due to permitting and regulatory red tape across multiple agencies. Sixty percent of Indian infrastructure projects experience time overruns, with dispute settlement between project owners and construction contractors reported as the main delay (Salunkhe and Patil, 2014; Prasad et al., 2019). These disputes take around 6.5 years to resolve (Construction Federation of India, 2015). Given that my study period is 6 years, and that other construction delays likely take place, it is unlikely that projects in my sample will complete construction during the study period.

Project non-completion is an advantage from an inference standpoint since economic spillovers are minimized. It ensures that estimates capture species loss from forest encroachment during construction, not through agglomeration effects from operational infrastructure. To the extent that local economies anticipate infrastructure, I control for district nightlights and state-month fixed effects (Section 3.3).

The Forest Clearance Process was Fast-tracked and Digitized in 2014: In 2014, prime minister candidate Modi promised to speed up the FC process, which the Environment Minister referred to as a "roadblock to growth". Delivering on this after election, the annual rate of stage-I and II approvals jumped 60% compared to the previous 40 years (authors calculation). The share of rejected proposals also considerably declined post-2014. Faster approvals materialized through easing norms (e.g. diluting no development zones), exempting certain projects from FRA compliance, and changing project size thresholds for state versus central review. Another cornerstone of the fast-track initiative is the digitization of the FC process. An online portal automates much of the review process and reduces turnaround time. For research purposes, an added benefit is data availability and process standardization, which reduces variation from state-level bureaucratic differences.

3 Data

I estimate the infrastructure-biodiversity tradeoff by drawing on several new datasets. I use newly digitized FC permits to measure development in India's forests. Species diversity is from eBird, a popular e-notebook for birdwatchers. The final panel covers all of India from 2015 to 2020. This section describes the data and provides summary statistics.

3.1 Forest Clearances

Forests cover 22% of India (Figure 1A)(Forest Survey of India, 2019). This paper studies how encroachment of these forests by infrastructure impacts biodiversity. Administrative data on infrastructure-driven deforestation rarely exist, and previous work mainly relies on remote sensing. However, satellites have difficulty distinguishing anthropogenic intrusions from natural sources (e.g. forest fires). Moreover, the best satellite data report annual aggregates, which mask within-year encroachments that may have important local ecosystem impacts.

I construct a dataset of monthly infrastructure encroachments using newly digitized FC proposals approved between 2015-2020. All proposals submitted post-digitization and approved during the study

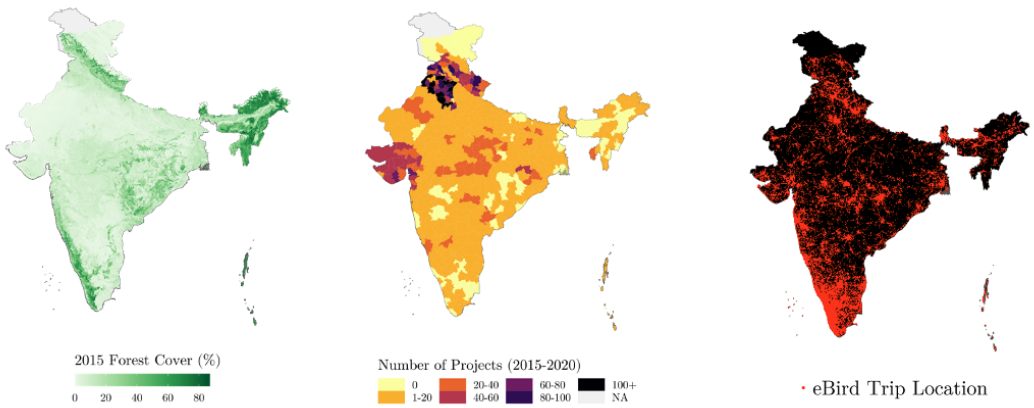

Figure 1: Infrastructure Encroachments and eBird Activity

Note: Panel A shows a heat map of 2015 forest cover from Townshend et al. (2017). Pixels are shaded by percent forest cover. Panel B maps the number of forest infrastructure projects that were approved for construction between 2015-2020. Panel C shows GPS coordinates of all birdwatching trips recorded through eBird during the study period.

period were scraped from the web portal ($N = 6,597$)[7]. I call this the digital subsample. Another 1,732 proposals submitted pre-digitization, but approved during the study period, were digitized by hand. I call these the manual subsample. These 8,329 projects, called the full sample, comprise the universe of industrial forest encroachments in India. Figure 1B shows the spatial distribution of projects. Figure A1 shows an approval letter authorizing 185 ha. of deforestation for an irrigation project in Rajasthan.

Both the digital and manual subsamples report approved deforestation (in ha.) and project category (road, mine, etc), the most important variables for the analysis. District-wise deforestation is provided for multi-district projects (e.g. transmission lines). Digital applications additionally report: non-forest land diversion, ownership (public, private, neither[8]), and shape (linear, nonlinear). Linear projects are contiguous in terms of land displaced, such as roads and railways. Nonlinear projects are non-contiguous, such as mines, power plants, and dams. Digital applications also report whether a cost-benefit analysis was commissioned, and whether informed consent was obtained from tribal land claimants. The latter enables analysis of how local institutions mediate ecosystem impacts (Section 7), a subject overlooked in prior studies. Appendix B1 provides additional data details.

Project data are aggregated to the district and year-month level, both overall and category-wise (e.g. total deforestation in January 2018 for electricity projects in Delhi). For multi-district projects ($< 4\%$ of sample) such as roads, the section falling into each district is listed as a separate row, and thus aggregation is over project *patches* in a district-year-month (Appendix B1). Aggregation is at the district level, firstly, because the district is the only consistent location identifier. Second, districts are the administrative unit immediately below the Indian state (similar to a United States county) and forms a natural unit for local policy implementation. The panel is balanced by zero-filling project approvals in districts not in the full sample (see cream color in Figure 1B). This is reasonable since all projects undergo the FC process, and the full sample contains the universe of approvals.

3.2 eBird

eBird entered the Indian market in 2014 and only requires a smartphone. Each birdwatching session (hereafter, "trip") is GPS-tracked, and users enter a taxonomy of sightings called a checklist. Checklists are vetted by ornithologists on each upload (Sullivan et al., 2009). eBird is revolutionary for research

[7]Data are publicly available at `www.parivesh.nic.in/`

[8]"Neither" are mainly joint public-private partnerships.

because it documents both species observations and the observation process. The latter includes: trip date, duration, protocol (e.g. stationary or travelling), and whether all observed species were recorded, called a complete checklist. These data help identify checklists reflecting actual species diversity.

Sample Selection and Representativity: My sample frame is the eBird Basic Dataset for India (eBird Basic Dataset, 2019), which includes all trips between 2015-2020. To identify representative checklists, I start with stationary and traveling protocols, which characterize 99% of trips. Next, I keep complete lists collected in < 5 hours and with group size ≤ 10. This produces the "gold standard for analysis", according to the eBird manual (Strimas-Mackey et al., 2020). Lastly, I link trip coordinates to 2011 district borders, which provides a matching key and reveals off-coast boating trips, which are dropped. This leaves 1,049,930 trips by 17,634 users across 628 districts (out of 640). Figure 1C plots all locations where eBird lists were uploaded.

The resulting user base records data that largely reflects the local species pool: birdwatchers collectively traverse 20% of district area for birdwatching in a typical district-month. They cover half of district area during the full study period (see Summary Statistics for details). Although there are no ground-truthing studies in India, several studies use a similar sample selection procedure to show that eBird data mirrors observations from nearby bird census sites in North America (Horns et al., 2018; Munson et al., 2010) and Australia (Callaghan et al., 2018). Ground-truthing the sample selection procedure, paired with wide spatial coverage of Indian eBird users, builds confidence that eBird data can deliver reliable statistical inferences about factors affecting biodiversity.

Final Sample: Outcomes and Aggregation: My main outcome measure is species richness, the number of unique species observed on a trip. Richness indicates conservation value, proxies the number and stability of ecosystem services, and is a widely used biodiversity metric (Fleishman et al., 2006). I also compute abundance metrics that count species according to their conservation importance. To do this, I manually code individual taxa reported in eBird with their corresponding IUCN Red List status: least concern, near-threatened, vulnerable, endangered, or critically endangered[9].

Despite having 1 million trips, the final panel aggregates users' trips in each district-year-month, which keeps relevant variation and reduces noise. Otherwise there would be no variation in development across trips in the same month and location since deforestation is district-monthly. Aggregation retains information from all 17,634 users but reduces the effective sample to 161,896, where each observation is at the user-district-month level. The outcome thus becomes mean species richness across users' trips in a district-year-month. I count of the number of trips underlying the mean, truncate at the 99th percentile to exclude outliers[10], and use these as regression weights in the robustness checks.

One concern is that aggregating over users trips' in a district masks within-district sorting, which can bias estimates. I design a test for this in Section 5.3.3 and show that users do not shuffle within districts following project approvals. This suggests that they do not birdwatch near construction sites in the first place, although I am unable to verify this since projects are not geocoded.

During aggregation, I also compute the *number of times* that each user recorded species in each IUCN category in a district and year-month. This enables me to assess whether changes in species diversity are being driven by common, vulnerable, or endangered species.

Who uses eBird? To estimate the infrastructure-biodiversity tradeoff, it is more important that eBird users collect representative data rather than themselves be representative of the population. The latter is implausible since users have smartphones and the privilege to engage in nature recreation. Yet citizen

[9] Dataset of taxa names of IUCN status obtained from: `https://datazone.birdlife.org/home`.

[10] As an example of one outlier, the maximum is 3779 trips in a district-month by a single user. This amounts to approximately 126 birdwatching trips *per day*.

science is becoming the chosen data source in studies on the economic drivers of biodiversity loss. Thus, it is important to frame a deeper discussion about who these citizen scientists are.

Since eBird does not record demographics, I characterize users by matching their approximate home locations to the nationally representative Demographic and Health (DHS) survey. This method, first proposed by Blanchard et al. (2023), reveals how residents of users' home locations compare to the typical Indian. Perhaps unsurprisingly, I find that users are from more urban and better-off places. Yet despite statistical differences, they are not atypical along either of these dimensions. Appendix B2 elaborates and provides supporting results (Figures B1-B2, Table B2).

3.3 Covariates

Environmental Covariates: The first set of covariates are environmental and include temperature and rainfall. Controlling for weather is important because it affects species detection. Monthly temperature (°C) is from the ERA5 product on a $0.125° \times 0.125°$ grid (Hoffmann et al., 2019). Monthly rainfall (mm) is from the NASA GPM Level 3 product on a $0.1° \times 0.1°$ grid (Huffman et al., 2019). To compute the covariates, I extract means over cells within a district, weighted by cell overlap fraction.

Observer Effort: The second set of covariates captures effort and includes: trip distance and duration, protocol, group size, and spatial coverage. Duration (minutes) and distance (km) are recorded by eBird. Protocol equals one if the user is moving and zero if stationary. Group size is the birdwatching party size[11]. Spatial coverage accounts for projects opening inaccessible forest patches (e.g., through supply roads), which may draw users to new sites and upward bias estimates. It also enables me to characterize the representativity of eBird species lists (see Fact 4 below). I measure spatial coverage by overlaying trip coordinates on a 10km grid and computing the fraction of district cells traversed by users.

Economic Spillovers: The third set of covariates captures general equilibrium spillovers. This helps disentangle the effect of infrastructure-driven habitat loss from broader changes to market structure prompted by the projects. This bias from market spillovers should be minimal in any case since projects are unlikely to complete construction during the study period (Section 2). Even otherwise, market spillovers "help" the research design as they reflect alternate channels threatening species diversity, including noise and air pollution (Liang et al., 2020).

In the absence of official district GDP statistics, I control for nightlight radiance, a common GDP proxy (Henderson et al., 2012). Data are obtained from the VIIRS satellite at 500m resolution and aggregated to the district-month (Elvidge et al., 2017). I show in Section 6.1 that the infrastructure-biodiversity relationship is unchanged when controlling for nightlights.

3.4 Summary Statistics

Figure 1 visualizes the main variables. Both sparse and dense forests (Panel A) have been fragmented by infrastructure (Panel B). The dense forests of Northern India suffered the most encroachment. These regions are also popular eBird destinations (Panel C), providing needed variation for the analysis. Users are also particularly active in Southern and Central India.

Table 1 shows that infrastructure triggered 122,000 ha. of deforestation between 2015-2020. The average encroachment is 14 ha., roughly 20 soccer pitches. Mines and resettlement projects are few in number but massive in size. Mines account for 3% of projects but 30% of total deforestation. Resettlements are least common and second-to-mines in size. Contrastingly, "other" projects are most common,

[11] If multiple eBird users birdwatching together, only one needs to record a checklist. This is shared at the end, and the others can edit it to include additional species they observed.

Table 1: Summary Statistics of Forest Infrastructure Projects (2015-2020)

	Num. Projects	Mean Size (ha.)	SD (ha.)	Total Area (ha.)
Electricity	882	27.5	228.4	24,274.5
Irrigation	430	57.5	252.5	24,731.1
Mining	229	148.2	253.7	33,927.6
Other	4,448	2.4	34.5	10,486.4
Resettlement	44	71.5	92.9	3,147.2
Transportation	2,296	10.9	32.5	24,986.0
Total	8,329	14.6	110.6	121,552.9

Note: Data are arranged at the project level for 8,329 approved projects, prior to aggregating to the district level. Total area (ha.) is the summed deforestation area of all projects in the sample for the particular category.

but mainly reflect small patches. Projects not fitting into any of the listed categories fall under "other" (see Appendix B1 for details)[12]. Transportation is the only category that is both numerous and accounts for a large (20%) share of total deforestation.

Table A1 shows summary statistics by ownership and shape. Over 70% of projects are publicly owned (Panel A). These are about five times larger than non-public projects. Grouped by shape, only 10% of projects are nonlinear, but these are five times larger than linear projects (Panel B). Table A2 shows the project distribution by ownership, shape, and category. Public projects are largest because resettlement and irrigation—the second and third largest category—are almost all publicly owned (column 1). Mining and "other" feature a more even public-private split than any other category. Nonlinear projects are largest because nearly all mining and resettlement projects are non-linear (column 5).

Table A3 summarizes eBird activity. Over 1,600 trips by 100 users are recorded in the average district during the study period. Users are quite active: the typical birdwatcher records in four districts, two states, and six periods. This within-user variation is the cornerstone of my identification strategy (Section 5). About 23 species are recorded during the average trip. These species are observed while traversing a wide area: birdwatchers cover 20% of district area in a typical month. Across the study period, they cover over half of district area. Wide spatial coverage increases representativity of their species lists and is important for delivering reliable estimates (see discussion in Section 3.2).

4 Empirical Patterns

This section presents four stylized facts that make the data ideal for studying the infrastructure-biodiversity tradeoff in India. The first fact verifies that project approvals trigger real deforestation. The second and third illustrate shortcomings of citizen science for causal inference as well as remedies. The fourth fact is that users are highly mobile, providing a source of spatial variation for identification. These facts motivate the empirical strategy in section 5.

4.1 Fact 1: Approved deforestation triggers actual deforestation

This paper uses newly digitized infrastructure permits to study infrastructure-driven deforestation. Using this data to estimate biodiversity impacts requires a crucial assumption: that authorized deforestation equates to actual deforestation. I validate this using forest cover observed from outer space. Annual forest cover (% of a pixel) is from the VCF satellite product and converted to km^2 (Townshend

[12]The most common "other" projects are approach roads (driveways) and fibre optic lines.

Table 2: Correlation between approved and actual deforestation

	Linear	Weighted	Log
	(1)	(2)	(3)
Forest Infrastructure	-1.048	-2.590*	-0.024***
	(0.941)	(1.433)	(0.009)
Controls	Yes	Yes	Yes
District FEs	✓	✓	✓
Year FEs	✓	✓	✓
Observations	4480	2568	4480
R^2	0.973	0.962	0.978

Note: * $p < .1$, ** $p < .05$, *** $p < .01$. Data are aggregated district-yearly. The outcome is km^2 of forest cover in a district. Approved deforestation is cumulative up to the year end. Column 1 is a linear specification, with both outcome and explanatory variable in km^2. Column 2 weights the regression by mean size of approved projects, and observations report *effective* sample size. Column 3 is a log-log specification using log(x+1) to account for zero values. All specifications include controls for nightlights as well as district and year fixed effects. Standard errors clustered by district.

et al., 2017)[13]. Since validation data is annual, I estimate the following equation on aggregated data:

$$ForestCover_{dsy} = \alpha + \beta_1[Infrastructure]_{dsy} + \beta_2[X]_{dsy} + \gamma_d + \theta_t + \epsilon_{dsy} \tag{1}$$

$ForestCover_{dsy}$ is *actual* forest cover in district d of state s in year y. $Infrastructure_{dsy}$ is *approved* deforestation, the cumulative area of approved encroachments in year y in the same district. X_{dsy} is a control for nightlight intensity, which helps disentangle infrastructure encroachment from other anthropogenic drivers of forest loss. γ_d and θ_y are district and time fixed effects, respectively. $\beta_1 < 0$ tests whether approved deforestation translates into actual deforestation.

Forest cover declines as districts approve more projects (Table 2). The linear specification in column 1 suggests a one-to-one relationship between sanctioned and actual deforestation. Low precision may arise from the fact that $Infrastructure_{dsy}$ is a district aggregate of differently sized underlying projects. Small project patches in particular may not be captured by the satellite. Column 2 therefore weights Equation 1 by underlying project size[14] in the district to upweight observations more likely to be captured by the satellite. Precision improves and coefficient magnitude increases, suggesting that forest cover declines beyond the permitted amount[15]. The inverse association is also robust to a log-log specification (column 3). I use $log(1 + Infrastructure_{dst})$ since districts may have zero approvals in year t. A 1% increase in approved deforestation for infrastructure results in a much smaller percentage reduction in *total* forest cover since infrastructure is one of many sources of total deforestation.

4.2 Fact 2: eBird activity surges in winter and in more biodiverse districts

Citizen science is revolutionizing biodiversity monitoring through crowd-sourced data. Yet, loose restrictions on when, where, and by whom data are collected yields more endogeneity than typical administrative data. eBird records details about the observation process, helping mitigate such concerns.

Seasonality: The seasonality bias arises from the ability to record trips at any time. Figure 2A shows stark seasonality in collective species richness (left axis), with a peak in winter when Siberian birds migrate to India, and a trough during lulls in activity (right axis) during monsoons. I address seasonality by exploiting within-month variation so that all time-invariant differences across months, such

[13] I convert to km^2 by multiplying cell values (% forest cover) by pixel area and then summing over district boundaries.

[14] Project size = cumulative project area divided by cumulative number of projects plus one in a district-year.

[15] Table 2 Column 2 does not necessarily mean that developers illegally deforest beyond the permitted amount. It could be due to spillover activity alongside the project site that is not captured by nightlights.

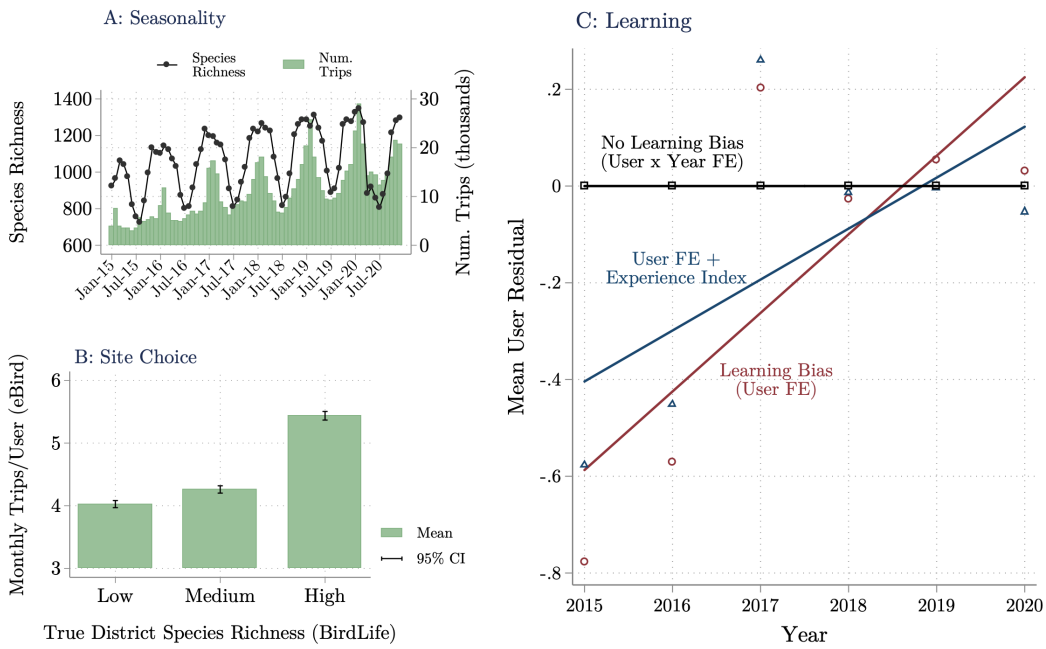

Figure 2: Biases in Citizen Science

Note: The left y-axis of Panel A shows total species richness across all users. The right y-axis shows total number of trips. Panel B shows mean number of trips per user-month in three quantiles of *true* species richness, obtained from historic range maps. In Panel C, red circles plot mean residuals per user from regressing species richness on user, district, state-month, and year fixed effects. Blue triangles control for experience. Black squares partial out user-year, district, and state-month fixed effects.

as seasonal species fluctuations, are eliminated. I do this separately by state since migratory patterns vary regionally. I also test cases where seasonality is assumed at the sub-state level. Neither approach addresses sub-state seasonality from climate-induced shifts in bird migration. This requires district-yearmonth fixed effects, which is the same level as the treatment. This issue is unlikely to bias my estimates, though, since climate adaptation occurs over time spans longer than my study period.

Site Selection: The site selection bias arises from the ability to record species from anywhere, triggering a convergence of activity in certain districts. Figure 2B shows that eBird users record more trips in districts with higher "true" species diversity, measured by intersecting historic bird range maps (BirdLife International, 2018). Species checklists will be longer in biodiverse districts since the species pool is larger. Previous studies account for this with a variety of fixed landscape covariates (Kelling et al., 2015), whereas I use district fixed effects to rule out site selection more confidently.

4.3 Fact 3: Learning is a crucial source of bias in citizen science

Besides seasonality and site selection, another bias arises from pooling users with heterogeneous abilities (Farmer et al., 2014; Fitzpatrick et al., 2009). I decompose this into a fixed and variable component, called innate ability and the learning curve, respectively. Low-ability users may misidentify species or overlook them, whereas the opposite is true for high-ability users. Volunteer training or ability scores are typically used to reduce inter-observer variability in previous studies. Kelling et al. (2015) construct a fixed ability score for eBird users based on predictions from a random effects model. For causal inference, this requires a strong orthogonality assumption between the score and other unobserved user attributes. I relax this assumption by comparing species richness across time and space *within the same user*, making the ability score superfluous.

Table 3: Variation in Species Richness Under Various Fixed Effects

	$1 - R^2$	σ_ϵ
	(1)	(2)
District FE	0.825	16.998
District + State-Month + Year FE	0.806	16.798
User + District + State-Month + Year FE	0.515	13.418
User-Year + District + State-Month FE	0.441	12.401

Note: This table summarizes regressions of species richness on various sets of fixed effects (rows). Data is at the user-district-month level. Column 1 reports $1 - R^2$ of the regression, indicating the fraction of variation not explained by the fixed effects. Column 2 is the standard deviation of the residuals (units = number of species).

Red circles in Figure 2C show species richness residualized on user, state-month, and district fixed effects. A steep upward trend remains, illustrating the learning curve. Blue triangles show the same with a control for experience, in line with Kelling et al. (2015). The experience index increments with each trip and assumes constant returns. The learning curve flattens, but is not fully absorbed. This is evidence that learning is driven not only by short term experience, but also by longer-term unobservables (see gradual upward trend in Figure 2A). For example, a novice may detect the same common species month-to-month, gradually listing rarer species over longer time spans after learning their songs.

My solution hinges on restricting variation from within-user to within-user-by-year. This has three advantages. First, user-specific annual trends are removed, including accumulated trips, number of months per year of activity, and other longer-term learning indicators. Second, it is agnostic about the shape of the learning curve. A line of best fit (Figure 2C) is one possibility, but the true shape is unknown. Lastly, it allows for differential learning rates between users. Partialling out user-by-year fixed effects mechanically flattens the trend (black line), implying that residual variation has been stripped of the learning bias. This is the variation that I use to estimate the impact of infrastructure encroachment on biodiversity in Section 5.

4.4 Fact 4: Users are highly mobile across space and time

One concern with high-dimensional fixed effects is that they might absorb too much useful variation. District and state-month fixed effects leaves monthly within-state deviations from district means, e.g. the amount by which a district in Kerala is more species diverse than normal in a given month compared to its neighbour. User fixed effects subtracts additional variation by restricting district comparisons to those traversed by individual users. This is less of a problem if users are sufficiently mobile.

Summary statistics showed that the average user visits multiple districts and states (section 3.4). Figure A2 shows distributions of within-user mobility. About 90% of users visit between 1 to 4 states. Over 40% of users are active in multiple months over the study period.

Table 3 presents the identifying variation more formally. It summarizes regressions of species richness on different fixed effects and reports the amount of residual variation (column 1) and the standard deviation of residual variation (column 2). One-fifth of the variation in species richness is explained by seasonality and site choice (second row). About half is explained when user heterogeneity and learning is also accounted for (third and fourth row). Overall, substantial identifying variation remains——driven by users traveling across space and time—even after removing important biases in citizen science data. The residual standard deviation is 12-13 species in the most saturated specifications, providing a wide margin for identification. These findings underscore the richness of crowd-sourced data.

5 Empirical Strategy

My analysis leverages panel fixed effects to quantify the infrastructure-biodiversity tradeoff. Development projects fragment district forests throughout the study period. eBird users venture to these districts to record birds. My specifications compare species diversity *within* a user's trips as they travel for birdwatching. This identification strategy exploits rich cross-sectional and time-series variation, giving rise to plausible control groups within users: their recorded species diversity in districts and time periods with different levels of encroachment.

5.1 Main Specification

I estimate the following equation to reveal the infrastructure-biodiversity tradeoff:

$$SR_{idsym} = \alpha + \beta_1[Infrastructure]_{dsym} + \beta_2[X]_{idsym} + \phi_{iy} + \gamma_d + \theta_{sm} + \epsilon_{idsym} \tag{2}$$

where SR_{idsym} is mean species richness observed by user i across their trips in district d of state s during year y and month m. I also estimate specifications where the outcome is a count of common, vulnerable, and endangered species observed by user i. $Infrastructure_{dsym}$ is the cumulative area of infrastructure encroachments in the same district and time period. X_{idsym} is a vector of weather and effort covariates described in Section 3. It includes spatial coverage, which accounts for projects opening up inaccessible parts of the forest. It also includes nightlights, which controls for market spillovers within the district. User-by-year fixed effects, ϕ_{iy}, absorb cross-user differences in ability and account for individual-specific learning. District fixed effects, γ_d, absorb mean checklist length and other other fixed district attributes. State-by-month fixed effects, θ_{sm}, control for state-specific seasonality.

Identifying Variation: User-year fixed effects require that user i visit at least one district in two months of the year to qualify for the estimation sample. In this case, only time-series variation is exploited. Users active for just one month are also included as long as they visit two or more districts, in which case cross-sectional comparisons are the basis for identification. In general, users are more active than these limiting cases (Figure A2) and both temporal and spatial variation across user i's trips to different districts over months of the year are used for identification.

Conditional on covariates and fixed effects, β_1 identifies the impact of infrastructure on species diversity. It captures the impact of infrastructure-driven forest loss, not general equilibrium effects of infrastructure, because nightlights are a covariate and because projects are unlikely to complete construction during the study period. If species relocate within the district, then they may be spotted by user i on another trip or by other users, leaving species diversity unchanged[16]. $\beta_1 < 0$ is thus even more striking as it implies the species and its ecosystem services are displaced from the district altogether.

Estimator and Counterfactuals: Since Equation 2 includes group (district) and time (state-month) fixed effects, estimation of β_1 falls under the umbrella of TWFE estimators. Recent developments in this literature apply to binary treatments (Roth et al., 2022), whereas my setting features a continuous treatment (area deforested). I therefore use a standard panel TWFE estimator with high dimenstional fixed effects.

Callaway et al. (2021) provide a theoretical decomposition of TWFE estimators with continuous treatment. They show that, in my setting, β_1 represents the weighted average change in outcomes from incremental changes in infrastructure development across and within periods. Identification thus requires that the parallel trends assumption holds at every level of infrastructure development. I expand on this and other identification assumptions in Section 5.3.

[16]The fact that 10 users are active in the typical district-month, together covering 20% of district area (Table A3), helps ensure that the local species pool is reported, even if one user misses a species.

Clustering: Standard error clustering is an experimental design issue in this analysis, which leaves the choice of cluster somewhat subjective (Abadie et al., 2017). I cluster at the biome level in the main analysis. From an ecological view, this is the most appropriate cluster because biomes delineate biological communities with shared eco-climatic characteristics that are unobserved in my model. These characteristics may generate arbitrary correlation of ϵ_{idsym} across time and space within a biome. Maps of India's 12 biomes are obtained from the Nature Conservancy[17] and plotted in Figure A3. For districts spanned by multiple biomes, I select the one with the largest overlapping area as the cluster.

From an econometric view, clustering by district is more appropriate since deforestation varies at the district level. Although unobserved ecological components of biodiversity are unlikely to adhere to political boundaries, I report estimates clustered by district in the robustness checks. I also cluster by state and report Conley standard errors as a compromise between biome and district clustering.

5.2 Additional Specifications

Decomposed Specification: I decompose $Infrastructure_{dysm}$ in Equation 2 into six separate categories: electricity, transportation, mining, resettlement, irrigation, and other. This not only reveals particularly harmful categories, but also those with negligible, or even positive, impacts on species diversity. I estimate the following specification:

$$SR_{idsym} = \alpha + \sum_{k=1}^{6} \beta_{1k}[Infrastructure]_{kdsym} + \beta_2[X]_{idsym} + \phi_{iy} + \gamma_d + \theta_{sm} + \epsilon_{idsym} \tag{3}$$

where the term under summation is cumulative forest area diverted for projects of category k in district d. Remaining terms and subscripts are defined as in Equation 2. β_{1k} represents the conditional impact of infrastructure category k on species richness.

I use the same approach to estimate species diversity impacts by project ownership (public, private) and shape (linear, nonlinear). Together, these decomposed estimates reveal useful information for policymakers tasked with allocating the right mix of projects that balance development and conservation.

Treatment Heterogeneity: There is debate among conservation practitioners about whether biodiversity is better conserved by protecting intact or already-fragmented landscapes. While both approaches are valuable, some species may be resilient to landscape modifications in certain habitats. I help resolve this debate by investigating whether the same infrastructure intrusion has differential effects by baseline ecosystem quality. I estimate heterogeneous treatment effects with the following specification:

$$\begin{aligned} SR_{idsym} = \alpha &+ \beta_1[Infrastructure]_{dsym} + \beta_2[Infrastructure_{dsym} \times EQ_d] \\ &+ \sum_{k=1}^{6} \beta_{2k}[Share]_{kdysm} + \beta_2[X]_{idsym} + \phi_{iy} + \gamma_d + \theta_{sm} + \epsilon_{idsym} \end{aligned} \tag{4}$$

where EQ_d is a fixed measure of ecosystem quality in district d. It is measured in two ways: 1) with forest cover in 2014, the year before my study period, and 2) with actual bird diversity from historic range maps (see Section 4.2). I also estimate specifications controlling for the share of approved projects in category k, which disentangles area effects from category effects. This important since some project categories may dominate certain landscapes (e.g., mines are usually sited in remote, intact forests). β_2 reveals whether the infrastructure-biodiversity tradeoff is accentuated or muted in more pristine landscapes, independent of project type.

[17] I use the "Terrestrial Ecoregion" files accessed from https://worldmap.maps.arcgis.com

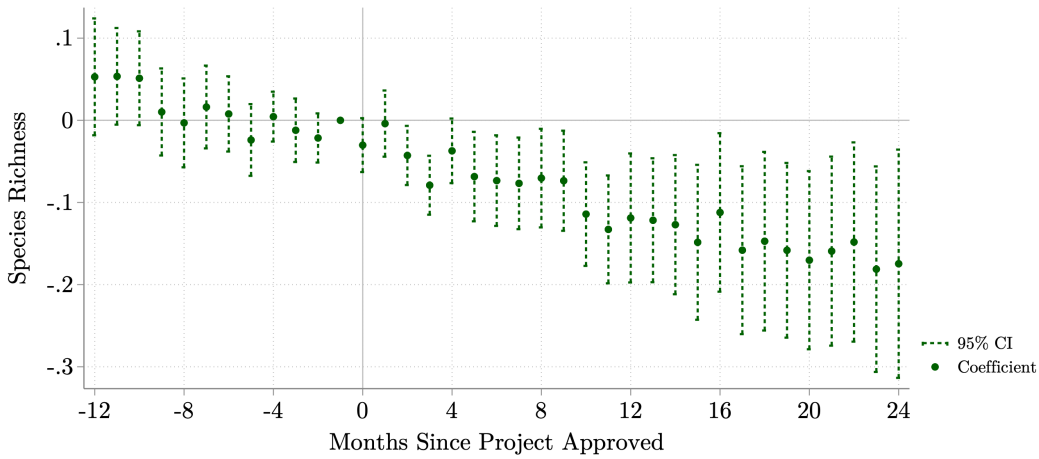

Figure 3: Event Study Results

Note: Dark green circles are coefficients from an event study regression at the project level (Equation 5).The outcome is log of mean species richness observed by users in a district-month. x-axis is the number of months since project approval in a district. The omitted period is -1. Dotted lines are 95% confidence intervals. All regressions include project, district, state-month, and year fixed effects as well as district-level controls for: temperature, rainfall, traveling trips, log nightlights, log duration, log distance, log group size, and log spatial coverage. Standard errors clustered by district.

5.3 Identifying Assumptions

5.3.1 Assumption I: Parallel Trends

Identification requires the parallel trends assumption: in the absence of treatment, species diversity in districts that received an additional km^2 of projects must be on the same outcome path as districts that never received the increment. Two challenges arise in testing for parallel trends. First, treatment is continuous (km^2) and comprises multiple events (project approvals) in a district. Second, treatment is cumulative i.e., the post-period of one project in a district is the pre-period of the next approved project. I address these challenges by stacking project data into a balanced project-district-month panel, which enables estimation of the following event study:

$$Log(SR_{dsym}) = \sum_{\tau=-12}^{24} \beta_{1\tau} \mathbb{1}[t - e_{pdsym} = \tau] + \beta_2 [X]_{dsym} + \alpha_p + \gamma_d + \theta_{sm} + \eta_y + \epsilon_{pdsym} \tag{5}$$

where p indexes projects, d indexes districts, s indexes states, and ym indexes year-months. The outcome is mean species richness observed by users in a district-year-month. e_{pdsym} is the date that project p was approved in district d. $\tau = -1$ is the reference period. $[X]_{dsym}$ are the same covariates from Equation 2 at the district level. Each $\beta_{1\tau}$ captures mean species richness τ months relative to the date of project approval. Non-existence of pre-trends is indicated by $\beta_{1\tau} = 0 \; \forall \, \tau < 0$.

Figure 3 displays coefficient estimates from Equation 5. Lack of pre-trends help support the parallel trends assumption and suggests that project placement is generally unpredictable. For example, if projects were selectively approved in high-growth districts, then species diversity would trend downwards even prior to project approval. Thus, while the FAC may approve projects based on certain district characteristics, these characteristics appear unrelated to changes in local species diversity around the time of approval. After project approval, coefficients turn negative and remain that way for two years. Section 6.5 discusses the persistence of species loss in more detail.

Beyond parallel trends, identification also requires that districts be otherwise similar without the marginal encroachment at every base level, which boils down to a no-selection-bias condition (Callaway et al., 2021). While the event study rule out many types of selection, I investigate two cases more closely.

5.3.2 Assumption II: No Spatial Spillovers

β_1 in Equation 2 is unbiased assuming no interference between units, known as the stable-unit treatment value assumption (SUTVA) (Imbens and Rubin, 2015). This requires that potential species richness in district d depend on infrastructure in district d only. SUTVA is violated in my context since habitat loss triggers species dislocation to other districts, introducing spatial links unmodeled in Equation 2.

The severity of the SUTVA violation is ex-ante unclear. The bias is zero if species relocation is random, since spillovers would be orthogonal to infrastructure development. It becomes positive (negative) if development causes species dislocation to less (more) fragmented districts. Bias magnitude is determined by marginal species; positive bias converges to zero if dislocated species are already found in destination districts, even though the spillover is non-random.

I address SUTVA by explicitly modelling spatial spillovers with a spatial matrix, $\mathbf{W}$. This transforms $Infrastructure_{dsym}$ into a "spatial lag of X" (SLX) (Elhorst and Vega, 2015) as follows:

$$SLX_{dsym} = (I_T \otimes \mathbf{W}_D)[Infrastructure]_{dsym} \tag{6}$$

where $\mathbf{W}_D$ is a symmetric $D \times D$ matrix where D is the number of districts in India. I_T is a $T \times T$ identity matrix where T is the number of year-months in the study period. The kronecker product signifies that $\mathbf{W}_D$ is applied to the infrastructure variable in each period and then stacked into a panel of spatially lagged infrastructure development.

I assume displaced birds relocate to other districts *within the same biome*, but less so to further away districts. This is modelled by setting $w_{dj} \in \mathbf{W}_D = \frac{1}{distance_{dj}}$, where $distance_{dj}$ is distance between centroids of district d and j if they are in the same biome and zero otherwise. Alternative spatial dependencies are modelled in the robustness checks. Finally, I add SLX_{dsym} to Equation 2. The coefficient captures changes to species diversity in district d when other districts j in the biome become relatively more fragmented. Conditional on this term, β_1 is purged of the spillover bias.

5.3.3 Assumption III: No Sorting of eBird Users Across or Within Districts

Another threat to identification in Equations 2-4 is endogenous user sorting. Since mobility is a key source of variation, estimates of the infrastructure-biodiversity tradeoff are unbiased only if unobserved determinants of species diversity are conditionally uncorrelated with site choice. The research design allows selection on time-varying observables and fixed unobservables. Suppose experience increases species detection and the probability of visiting pristine locations. This will not bias my estimates since I observe user experience. Similarly, citizen scientists may exhibit fixed, unobserved, heterogeneous preferences over nature (e.g. enjoying hiking). These preferences do not bias my estimates insofar as they affect site choice because they are absorbed by user fixed effects.

The orthogonality assumption is only violated if mobility reflects systematic *changes* in unobserved preferences. Suppose deforestation causes sorting towards more pristine districts. District fixed effects account for overall biodiversity, user fixed effects account for static preferences, but neither accounts for deviations from within-user species diversity as they sort across districts. These deviations are non-random if sorting correlates with project development.

I test for *cross-district* sorting as follows on data aggregated at the district-year-month level:

$$NumUsers_{dsym} = \alpha + \beta_1[Infrastructure]_{dsym} + \beta_2[X]_{dsym} + \beta_3[SLX]_{dsym} + \gamma_d + \theta_{sm} + \mu_y + \epsilon_{dsym} \tag{7}$$

where $NumUsers_{dsym}$ are the number of users active in district d during year-month ym. These are the same sample of users that identified species loss in Equation 2. The fourth term is the spatial lag defined

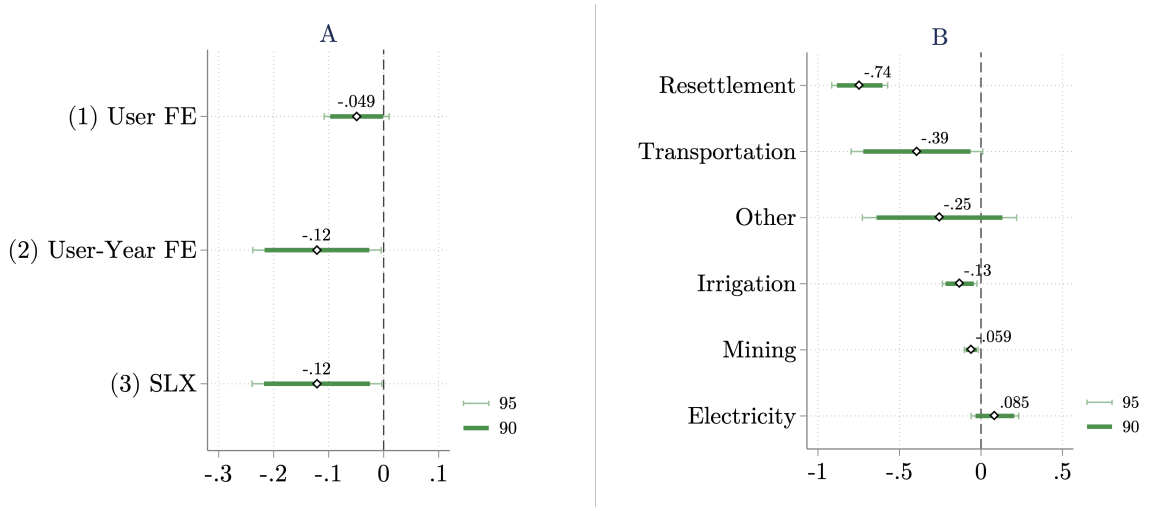

Figure 4: Estimates of the Infrastructure-Biodiversity Tradeoff in India

Note: The outcome in all specifications is mean species richness across users' trips in a district-month. Panel A shows coefficients on cumulative area of infrastructure encroachments in a district-month. Specification (1) includes fixed effects for user, district, state-month, and year. Specification (2) includes user-by-year, district, and state-month fixed effects. Specification (3) controls for spatial spillovers within the biome (see Section 5.3.2). Panel B is a single regression with deforestation decomposed into project categories. Shaded bars denote confidence intervals. All regressions control for: temperature, rainfall, traveling trips, log nightlights, log duration, log distance, log group size, and log spatial coverage. Standard errors clustered by biome.

in Equation 6, except $w_{dj} = \frac{1}{distance_{dj}}$ varies across the full support of $\mathbf{W}_D$ (instead of only within-biome). This model choice enable users to sort anywhere in India following project construction in district d, but with lower probability towards further destinations. I also test specifications that assign zero sorting probabilities to districts beyond 100km, 200km, and 500km. Remaining terms are as in Equation 2. $\beta_3 > 0$ implies that users sort into district d when other districts become relatively more fragmented.

I test for *within-district* sorting by estimating Equation 7 without the spatial lag term and with the outcome measured as the spatial coverage of district d. Spatial coverage is the percent of district grid cells (10km resolution) "birdwatched" by the average user in district d at time ym. If infrastructure development pushes users into new parts (grid cells) of the district, then spatial coverage will increase and $\beta_1 > 0$. As discussed in the next section, I find no evidence of cross- or within-district sorting, corroborating the orthogonality assumption and improving confidence in my research design.

6 Main Results

This section presents evidence on the impact of infrastructure expansion on biodiversity in India. Species diversity is significantly threatened by infrastructure development, driven by lower abundance of common and vulnerable species. Resettlement, transport, irrigation, and mining projects are particularly harmful. Lastly, species diversity does not rebound in the medium run.

6.1 Estimates of the Infrastructure-Biodiversity Tradeoff

Main Estimates: Figure 4A illustrates the infrastructure-biodiversity tradeoff (see Table A4 for tabulated estimates). Specifications (1) and (2) estimate Equation 2 with and without the learning curve, respectively. The main coefficient (β_1) is negative in both specifications, indicating that infrastructure intrusions reduce local species diversity. The upward learning curve counteracts species declines in specification (1), yielding a small coefficient with low precision. Removing this counterbalancing pressure with user-by-year fixed effects in specification (2) yields a steep decline in species richness.

An additional km^2 of forest infrastructure in a district causes users to observe 0.12 fewer species, equivalent to 0.5% of the average bird list. To put this in perspective, eBird users observed 0.8 fewer species at the end of the study period compared to the start. The average district had 1.14 km^2 of forest *newly* occupied by infrastructure during this time, implying a loss of $1.14 \times -0.12 = 0.14$ species. Thus, infrastructure accounted for $0.14/0.80 \approx 17.5\%$ of species loss across India between 2015-2020.

Sensitivity: Spatial Spillovers: Biases from spatial spillovers are minimal. Specification (3) of Figure 4A shows that species loss is unchanged when accounting for species displacement within the biome. Column 3 of Table A4 shows that, conditional on the direct effect, the spillover coefficient is positive but insignificant. Table A5 tests robustness to allowing spillovers to materialize over different distances, ranging from 100km to nationwide. In all cases, estimates of species loss remain stable, significant, and virtually equivalent to the main estimate. Spillovers similarly remain positive but noisy. This increases confidence that the lack of spillovers is pervasive, not an artifact of the within-biome assumption. These results do not mean species do not relocate following habitat loss. It means they do so in a way that is uncorrelated with local infrastructure development.

Sensitivity: Controlling for Observables: Columns 4-6 of Table A4 probe sensitivity by successively adding controls. When observer behaviour and nightlights are removed (column 4), the coefficient remains negative but loses precision. When behaviour is added back, the tradeoff reappears (column 5), suggesting that behaviour is a key source of bias. The coefficient is equivalent to the main specification, which also controls for nightlights (column 3). Equal point estimates with or without nightlights implies that species loss is driven by habitat loss, not economic spillovers. This is unsurprising given that developers have begun logging, but projects themselves remain incomplete during the study period.

Column 6 adds diversion of *non-forest* land for the same projects as a covariate. It has no impact on species diversity, underscoring habitat loss as the key mechanism driving species loss as opposed to other infrastructure-driven disturbances such as pollution. It also implies that reorganizing economic activity away from forests can blunt biodiversity decline. Note that non-forest diversion is reported only in digital project proposals (80% of the full sample).

Additional robustness tests are in Section 6.6. These include: controlling for alternative forms of seasonality, accounting for a changing user base, testing differential user behaviour at home and away, and alternative species diversity metrics. I also investigate spatial correlation more systematically.

Ruling out Sorting Across and Within Districts: The main estimates do not appear to be driven by cross-district or within-district sorting. Table A6 tests for cross-district sorting by estimating Equation 7 on the same user sample that identified species impacts in Figure 4A. The outcome is log number of users. Infrastructure measures are standardized for comparability between direct and spillover effects. Users do not sort into district d when other districts j within 100km become relatively more fragmented (column 1, second row). Neither does development in d itself push users elsewhere (first row). Lack of spillovers are also visible under distance cutoffs up to 500km (columns 2-3). These results suggest eBird users are highly mobile (Fact 4, Section 4.4), but not because of infrastructure development.

Column 4 tests for within-district sorting by dropping the spatial lag term and using the percent of "birdwatched" grid cells in a district as the outcome in Equation 7. The coefficient is negative and insignificant, suggesting that eBird users continue visiting the same sites as districts undergo development. This is an indication that they rarely birdwatch near construction sites, although I am unable to verify this since exact project coordinates are unavailable. Taken together, the lack of sorting across and within districts supports causal interpretation of the main estimates.

6.2 Estimates by Project Category, Ownership, and Shape

Estimates by Category: Figure 4B presents TWFE estimates of Equation 3 by project category. Coefficients describe the impact of a marginal encroachment by projects of that category, conditional on that by other categories. Five out of six categories trigger species diversity loss. Four of them—resettlement, transport, irrigation, and mining—do so with statistical precision.

Resettlements threaten species the most. An example is the diversion of 2.85 km^2 of forest in Betul district, Madhya Pradesh for relocating a village previously located in a nearby Tiger Reserve[18]. These projects are not infrastructure per se, but rather a package of infrastructure including access roads and shelters that together resemble a settlement camp. The coefficient is largest likely because it reflects a sum of coefficients on other categories. Another possible reason is that it is the only category directly connected to human activity. To the extent that $1km^2$ of habitat loss for building resettlements is associated with spillover economic activity *not captured by nightlights*, it will result in more species loss than from $1km^2$ of other projects. In the absence of project GPS coordinates or details on what is inside each resettlement, I am unable to formally test these hypotheses.

The negative impact of "other" projects is imprecise. These are the smallest projects on average, but feature a standard deviation 17 times greater than the mean, the largest ratio of any category (Table 1). When aggregated to the district, a marginal encroachment thus comprises many underlying patch sizes. The coefficient magnitude is likely driven by the large projects, where marginal encroachments comprise a single patch, and the noise by the smaller projects, each too small to affect species diversity with statistical precision. The same logic may explain the noisy impact of electricity projects, which have the second highest noise-to-signal ratio. The largest electricity projects are dams, which may explain the positive coefficient. Dams create reservoirs, which may attract previously unseen waterbirds.

Although mining appears to threaten species minimally, the coefficient is likely attenuated since mines are often sited in remote areas where few eBird users travel. Half of sample mines are in Odisha, Madhya Pradesh, and Chhattisgarh, with 27% in Odisha alone. The median number of users and trips in Odishi mining districts is under half of the national median. The few users who travel there may be a selected sample that miscount the species pool, despite my attempts to prevent this (section 3.2).

Table A7 probes sensitivity of the estimates and further investigates the mining effect. Similar to the overall tradeoff, category-wise tradeoffs materialize when observer behaviour is accounted for (column 2) and remain stable when controlling for economic activity (column 3). To test the conjecture about the small mining effect, I estimate Equation 3 in districts with high eBird activity: above-median numbers of users recording above-median trips per user. If the bias is mining-specific, then the sample restriction should only accentuate the mining coefficient. Indeed, mining projects are twice as harmful in the high-activity sample whereas coefficients on other categories remain virtually unchanged (column 4). This implies that non-mining projects are sited in districts with sufficient eBird activity to begin with.

Estimates by Ownership and Shape: Table A8 groups estimates by project ownership and shape. Public projects are the main threat to biodiversity (Panel A), mainly because resettlement, transport, and irrigation projects—the three most harmful categories—are almost all publicly owned (Table A2). In contrast, the effect of private projects is noisy, likely because "other" projects are largely privately owned (Figure 4B). Similar logic helps interpret the estimates by project shape (Panel B). Nonlinear projects have a robust negative impact on species diversity. The magnitude is a combination of the small mining and large resettlement coefficients in Figure 4B, which are almost entirely nonlinear (Table A2). The tradeoff for linear projects is weaker but the magnitude is twice as large. The large magnitude is a combination of the transportation, electricity, and irrigation coefficients, which are predominantly linear

[18]The project was approved in April 2017 and includes housing, playgrounds, and roads. Site inspection report: http://forestsclearance.nic.in/writereaddata/SIR/06022017561SBScan_02-06-2017_1501.pdf.

Table 4: Estimates by IUCN Threat Status

	Least Concern		Vulnerable		Endangered	
	(1) Level	(2) Poisson	(3) Level	(4) Poisson	(5) Level	(6) Poisson
Infrastructure (km^2)	-0.961***	-0.012***	-0.007*	-0.009***	0.002	0.006
	(0.280)	(0.003)	(0.004)	(0.003)	(0.002)	(0.008)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Outcome Mean	90.541	90.545	0.589	0.741	0.167	0.378
User x Year FEs	✓	✓	✓	✓	✓	✓
District FEs	✓	✓	✓	✓	✓	✓
State × Month FEs	✓	✓	✓	✓	✓	✓
Observations	161896	161889	161896	128511	161896	71284
R^2	0.517		0.395		0.377	

Note: * $p < .1$, ** $p < .05$, *** $p < .01$. The outcome is a frequency count for the number of times a user observed a species of each type during a district-year-month. Forest infrastructure is cumulative area of infrastructure encroachments in a district-month. Poisson regressions are estimated with a pseudo-maximum likelihood estimator. All specifications include user-year, district, and state-month fixed effects as well as controls for temperature, rainfall, traveling trips, log nightlights, log duration, log distance, log group size, and log spatial coverage. Standard errors clustered by biome.

(Table A2). Wide standard errors likely come from "other" projects, which are also mostly linear.

6.3 Estimates by IUCN Threat Status

Having established that infrastructure drives species loss, I now investigate which species are under threat. Table 4 shows estimates of Equation 2 with the dependent variable measured as counts of common, vulnerable, and endangered species observed by user i in a district-year-month[19]. These estimates should be interpreted in terms of abundance and not diversity.

Low-concern and vulnerable species are under threat from infrastructure expansion. The coefficient in columns 1 and 3, where outcomes are in levels, is negative and statistically significant. Magnitudes relative to the mean imply that an additional unit of infrastructure causes users to observe 1% fewer low-concern and vulnerable species. Since the outcome is a count, columns 2, 4 and 6 report Poisson estimates. I use the pseudo-maximum likelihood estimator to adjust standard errors (Wooldridge, 1999). Again, lower species abundance is detected for low-concern and vulnerable species. Since observing endangered species is rare, there is insufficient variation to detect effects in columns 5 and 6.

These results suggest that the decline in species *diversity* in the main estimates (Figure 4A) is driven by lower *abundance* of common and vulnerable species. The negative estimates in columns 3 and 4 are particularly concerning since these species are already vulnerable according to the IUCN. Given that site monitoring is required during project review (Section 2), my findings highlight the need to monitor vulnerable taxa in particular in order to prevent these species from being further down-listed.

6.4 Heterogeneity: Species are More Resilient in Intact Forests

I next investigate whether conservation should focus more on intact or fragmented landscapes. This question is especially important in India, home to some of the most biodiverse, but also most degraded, places in the world. Table 5 presents estimates of Equation 4, which tests for heterogeneity by baseline ecosystem quality. Columns describe heterogeneous treatment effects using two different measures of ecosystem quality. Both are standardized so that a one-unit change can be compared.

Species are more resilient to infrastructure development in pristine districts. Column 1 shows that the adverse impact of infrastructure on species diversity is halved in districts with one standard devia-

[19]IUCN lists species as: least concern, near threatened, vulnerable, endangered, and critically endangered. To reduce the number of categories, I combine least concern and near threatened as well as endangered and critically endangered.

Table 5: Treatment Effects by Baseline Forest Intactness

	(1)	(2)	(3)	(4)
Infrastructure (km^2)	-0.130***	-0.148***	-0.133***	-0.151***
	(0.019)	(0.020)	(0.024)	(0.026)
Infrastructure (km^2) × Baseline Forest Cover	0.065*	0.073**		
	(0.030)	(0.030)		
Infrastructure (km^2) × Baseline Species Richness			0.052**	0.056**
			(0.020)	(0.023)
Controls	Yes	Yes	Yes	Yes
Category Shares	No	Yes	No	Yes
User x Year FEs	✓	✓	✓	✓
District FEs	✓	✓	✓	✓
State × Month FEs	✓	✓	✓	✓
Observations	161896	161896	161896	161896
R^2	0.690	0.690	0.690	0.690

Note: * $p < .1$, ** $p < .05$, *** $p < .01$. The outcome is mean species richness across users' trips in a district-month. Forest infrastructure is cumulative area of infrastructure encroachments in a district-month. Columns 1 and 2 include an interaction with baseline forest cover in 2015 (% of district area). Columns 3 and 4 show interactions with baseline species richness obtained from overlapping species range maps. All specifications include user-year, district, and state-month fixed effects as well as controls for temperature, rainfall, traveling trips, log nightlights, log duration, log distance, log group size, and log spatial coverage. Columns 2 and 4 additionally control for the share of approved projects in each category. Standard errors clustered by biome.

tion higher initial forest cover[20]. To account for potential selection of sustainable projects into pristine districts, column 2 controls for the district share of projects in each category. This ensures that the interaction term reveals heterogeneous impacts of 1 km^2 of habitat loss independent of project type. The results are very similar. Remaining columns explore sensitivity to measuring baseline species richness from BirdLife range maps. The tradeoff reduces by a similar amount without (column 3) and with (column 4) controls for category shares. These results support stronger protections for degraded landscapes, where the infrastructure-biodiversity tradeoff is the largest.

This finding corroborates existing theory from ecology (Hanski, 1998) and is among the first empirical tests. An exception is Betts et al. (2017), who find that species are more threatened in intact landscapes. They interact time-varying forest loss with an indicator for baseline forest cover above 90%, whereas I use a continuous measure of baseline forest cover that exploits substantially more variation.

6.5 Dynamics: Species Diversity Loss is Persistent in the Medium Run

My estimates reflect *instantaneous* responses of species to habitat loss. Scientists view biodiversity as only partially determined by current habitat, and the rest by legacies of landscape change (Odum, 1969). The infrastructure-biodiversity tradeoff may thus feature a lag as species diversity equilibrates. Lagged effects may also arise from delays between project approval and initiation of logging. To separate these channels, I investigate dynamics up to two years. Since logging begins with the year (Table 2), lagged effects beyond one year is suggestive of delayed species responses.

Figure 5 presents estimates of Equation 2 with monthly lags of $Infrastructure_{dsym}$ up to two years. White diamonds are the sum of baseline and lagged coefficients, which measures *net impacts* of infrastructure several periods later. First, species declines are triggered in the month of project approval and persist thereafter. The cumulative impact three months later ("Sum L0-L3") is nearly equal to the baseline effect, with stable point estimates up to six months. Second, a slight lagged effect is observed after one year and persists through the second year. This suggests delayed species responses as opposed

[20]Forest cover (% of a pixel) is from the VCF satellite product on a 250×250m grid (Townshend et al., 2017)

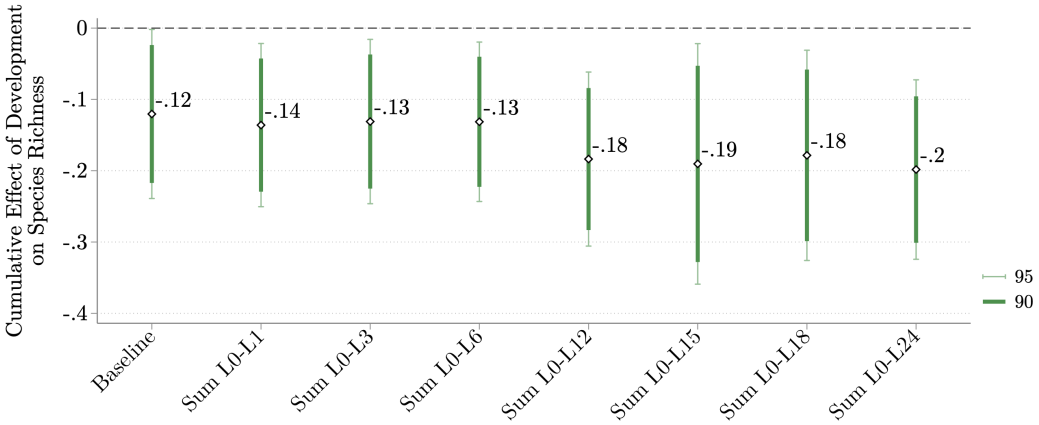

Figure 5: Cumulative Dynamic Lag Results

Note: "Baseline" repeats the main result with user-year, district, and state-month fixed effects. "Sum L0-L1" adds the first lag of forest diversion to the main specification and reports the sum of coefficients on the first lag and baseline effect. "Sum L0-L3" sums up to the third lag, and so on. Shaded bars are confidence intervals. All regressions control for: temperature, rainfall, traveling trips, log nightlights, log duration, log distance, log group size, and log spatial coverage. Standard errors clustered by biome.

to construction lags, since logging typically begins within the year of project approval (Table 2). Note that this evidence is very weak since confidence intervals overlap point estimates across all periods, in which case we cannot reject the null that second-year coefficients are the same as the first year.

The main takeaway is that species loss is persistent and does not recover in the medium run. This has two implications. First, it provides further evidence that my estimates capture responses to permanent habitat loss. If species were responding to temporary disturbances, such as noise or air pollution, then Figure 5 would feature an inverted U-shape as species return after the disturbance dies down. However, in this context, once the forest patch is displaced for infrastructure, the habitat is lost permanently. Second, the dynamic results also highlight the ineffectiveness of compensatory afforestation requirements. Compensatory afforestation would also be indicated by an inverted U-shape. However, as described in Section 2, tree-planting rarely takes place, posing minimal threat to the research design.

6.6 Additional Robustness Checks

This section demonstrates robustness of the estimates to: alternative forms of seasonality (Table A9), different estimation samples, different diversity metrics (Table A10) and spatial clustering (Table A11). The next section shows robustness to an alternative research design.

Alternative Fixed Effects: Seasonality, Skill, and Location: Table A9 tests robustness to alternative fixed effects. Columns 1-3 specify alternative forms of seasonality. Column 1 includes user-by-month fixed effects, a demanding specification relying on comparisons across districts and years within a user-month. This accounts for seasonality possibly exhibiting an individual component (i.e. winter migratory species mainly reported by experts) (Johnston et al., 2018). Columns 2 and 3 include district-month fixed effects, which accounts for sub-state seasonality[21]. All three estimates are strikingly similar to the main effect, suggesting that biases from individual and within-state seasonality are negligible.

Columns 4 and 5 test alternate ways of accounting for skill heterogeneity. User-year fixed effects in the main analysis do not account for different within-year learning rates across users. They also overlook learning among users active for less than one year. To address this, column 4 adds fixed

[21]Column 2 of Table A9 uses user-year and district-month fixed effects. This specification is likely too saturated to yield precise estimates. Column 3 includes user and district-month fixed effects as a compromise.

effects for cumulative number of trips, which more flexibly captures learning. Column 5 includes time-of-day fixed effects to account for differential species availability and user activity throughout the day[22]. Estimates are virtually unchanged from the baseline finding.

Column 6 tests robustness to sorting by dropping the user fixed effect and adding a fine-grained location fixed effect. Throughout the paper, user fixed effects remove biases from user heterogeneity, but requires a no-sorting assumption for identification. The reverse is to track species diversity in a fixed location as it develops, which obviates this assumption, but then pools checklists from heterogeneous users. I implement this with $10km^2$ cell fixed effects, which guards against sorting even within districts. Raw eBird data are aggregated to the user-cell-month level. Species loss is still observed, but estimates are noisy. This is likely from pooling heterogenous users within cells. Although effort covariates remove some heterogeneity, differences in fixed unobservables (e.g. ability) inflate the error. My chosen design, with user fixed effects, solves this issue and, coupled with evidence of minimal sorting (see Section 6.1), delivers credible estimates of the infrastructure-biodiversity tradeoff.

Sample Restrictions: Fixed user base, home vs. away, and non-COVID years: Table A10 columns 1-4 show estimates from alternative samples. Whereas the main specification accounts for within-user behaviour changes over time, it does not account for the changing user base itself. Column 1 does this by fixing the sample to users who signed up in 2015 (N=2,938 users). The estimate is virtually unchanged, suggesting that users who joined later are similar to the veterans.

Column 2 drops users' home districts (see Section B2 for computation). Since the main specification does not have a user-district fixed effect, this tests whether users have different recording practices at home and away. The point estimate is very similar, suggesting that they do not. Column 3 drops districts with low eBird activity, measured as districts with below-median number of users. Remaining users recording below-median trips per user are also dropped. Again, the coefficient is remarkably similar, suggesting that my estimates are not biased by peculiarities in places with sparse eBird usage.

Lastly, column 4 drops the year 2020, when COVID-19 swept the globe. India faced one of the world's toughest lockdowns. In the wake of this tragedy, "balcony birdwatching" was popularized and eBird sign-ups quadrupled (Madhok and Gulati, 2022). Estimates from the non-COVID sample are very similar, implying that my estimates are robust to the shock. This is unsurprising since year fixed effects absorb macro-shocks, state-month fixed effects absorb state-level project approval rates, and the protocol covariate controls for the shift indoors.

Outliers: Dropping mega-projects and IHS: I transform the sample in two ways to test robustness to removing outliers. In column 5, before aggregating, I drop India's top three "mega-projects": 1) the world's largest lift irrigation[23] project, located in Telangana and requiring 3,168 ha. of deforestation, 2) a 4,000 MW coal plant, also in Telangana, that requires 4,334 ha. of deforestation, and 3) the world's largest concrete dam, located in Arunachal Pradesh, that requires 5,056 ha. of deforestation. The coefficient size doubles but still aligns with the lower bound of the baseline estimate. The larger magnitude is likely from the two irrigation mega-projects, which may create water habitat that attract new species. Dropping these releases this offsetting pressure on the coefficient, leading to greater species loss.

In column 6, instead of dropping mega-projects, I apply the inverse hyperbolic sine (arcsinh) transformation[24] to $Infrastructure_{dsym}$. Small changes in $arcsinh(x)$ reflect proportional changes in x and can be interpreted similar to a log-transform (Bellemare and Wichman, 2020). There are two advantages: first, $arcsinh(x)$ is defined at $x = 0$, which is common in districts with no forest or no projects

[22]Time-of-day categorizes mean hour-of-day for user trips in a district-month. Categories are: morning: 6am-12pm; afternoon: 12pm-6pm; evening: 6pm-12am; night: 12am-6am.

[23]Lift irrigation is a method whereby water is transported by pumps rather than by exploiting natural flow.

[24]This uses the function $arcsinh(x) = ln(x + (x^2 + 1)^{1/2})$.

(Figure 1B). Second, since it mimics the natural log, $arcsinh(x)$ reduces the influence of outliers. The coefficient implies that a 1% increase in infrastructure leads to a loss of 0.006 species. For comparison, 1% of $Infrastructure_{dysm}$ evaluated at the mean is 0.0114 km^2. Applying this to the baseline coefficient yields $0.0114 \times -0.12 \approx -0.0014$ species. The discrepancy likely arises from different functional assumptions: IHS assumes diminishing marginal effects of habitat loss whereas the baseline does not.

Alternative Diversity Measures: Shannon and Simpson Index: Species richness has been criticized for its simplicity. Somewhere with one pigeon and 99 crows, and another with fifty of each, both have a richness of two despite the latter being more even. I compute two metrics that account for evenness:

$$SH_j = -\sum_{s=1}^{S} p_{sj} ln(p_{sj}) \qquad\qquad SI_j = 1/\sum_{s=1}^{S} p_{sj}^2$$

where p_{sj} is the proportion of all observations on eBird checklist j belonging to species s. The Shannon Index (left) increases in diversity. The Simpson Index (right) reflects the probability that two randomly drawn birds belong to the same species (Magurran, 2013). I use $1 - SI_j$ so that it also increases in diversity. A limitation of implementing these indices is that bird counts are notoriously imprecise given difficulties with recording quickly moving flocks. About 90% of counts in my sample are approximated to the nearest tenth, and 10% of checklists have missing counts.

Columns 7 and 8 show that an infrastructure-biodiversity tradeoff is still observed using these alternative measures, but coefficients are imprecise as expected. In terms of magnitude, effects on Shannon and Simpson diversity are 1.7% and 4.0% of their means, respectively.

Regression Weights: Species richness is a mean over users' trips in a district-month. Part of the error variance in Equation 2 may thus be explained by differences in the number of underlying trips. Figure A6 shows the cumulative distribution: 10% of observations are a mean over more than 10 trips (precisely measured) and 90% are over fewer than 10 trips (imprecisely measured). In column 9, I estimate the main equation with weighted least squares, with weights equal to the number of trips underlying each observation. This ensures that observations influence the coefficient in proportion to their measurement precision rather than be treated equally. The coefficient is virtually unchanged and remains significant at the 10-percent level.

Standard Error Clustering: Table A11 shows the baseline estimates adjusted for alternative clustering. Column 1 replicates the baseline, whereby unobservable biophysical determinants of species diversity are assumed to be correlated within biomes, even though treatment varies by district. Columns 2 and 3 show that estimates are quite similar when clustering by district or state, respectively. Clustering by state is a compromise between large biome clusters (Figure A3) and smaller districts. Columns 4-7 investigate spatial correlation more systematically by implementing Conley (1999) standard errors for several choices of the kernel cutoff distance. Reassuringly, precision remains similar, even when allowing for long distance spatial correlation up to 1000km.

Robustness by Project Category: Tables A12 and A13 report the same robustness checks with infrastructure decomposed by project category. Coefficients on most categories remain negative across the majority of stress tests. In particular, the negative effect of irrigation, transportation, mining, and resettlement projects is robust to alternative fixed effects and most other robustness tests. Electricity and Other projects continue to have no impact on species diversity.

6.7 Robustness: Instrumental Variable Estimates

Despite the robustness checks in the previous section, parallel trends, and no evidence of endogenous sorting, causal interpretability of estimates may still be in question since infrastructure is non-random. Next, I show that results are robust to a common IV design based on close races between incumbent and runner-up parties in State elections (see Appendix B3 for context and data details). I use the fraction of close-election constituencies in a district with incumbent winners as an instrument for project approvals. Since winners in close elections are essentially chosen through a coin toss, places where the incumbent just barely won and just barely lost should be statistically similar in terms of economic growth prospects and other confounders that were previously a concern.

One identification concern is that project approvals are a bundled treatment that capture two opposing first-stage forces: increased public spending on general infrastructure, and decreased approval of forest-encroaching infrastructure, to the extent that voters are pro-environment. I control for nightlights to address the first channel and rely on the identification assumption that district-level incumbent strength affects biodiversity only through influencing forest conversion for infrastructure. This assumption may be appropriate since the District Forest Office is charged with local conservation and the project review committee first meets at the district level (Section 2). A second concern with the close election IV strategy is that estimates do not generalize to non-competitive districts. For these two reasons, I view this design only as a check on coefficient sign rather than another set of main estimates.

I compare eBird observations within users travelling between districts where the incumbent just barely won and just barely lost with the following 2SLS specification:

$$\text{First Stage:} \quad Infrastructure_{dsym} = \mu_1 IC_{dsy} + \mu_2 C_{dsy} + \mu_3[f(M_{dsy}) \times I_{dsy}] + \mu_4 f(M_{dsy}) + \mu_5 I_{dsy} + \mu_6 E_{sy} + \mu_7 X_{idsym} + \phi_i + \gamma_d + \theta_{sm} + \nu_y + \epsilon_{idsym} \tag{8}$$

$$\text{Second Stage:} \quad SR_{idsym} = \beta_1 \widehat{Infrastructure}_{dsym} + \beta_2 C_{dsy} + \beta_3[f(M_{dsy}) \times I_{dsy}] + \beta_4 f(M_{dsy}) + \beta_5 I_{dsy} + \beta_6 E_{sy} + \beta_7 X_{idsym} + \phi_i + \gamma_d + \theta_{sm} + \nu_y + \epsilon_{idsym} \tag{9}$$

where $Infrastructure_{dsym}$, SR_{idsym}, subscripts, and fixed effects are denoted as in Equation 2. Infrastructure is instrumented with IC_{dsy}, the fraction of constituencies in district d of state s where the incumbent party won in a close race during the most recent election. Elections are close if the win margin is less than 2 percent. I control for C_{dsy}, the fraction of close-election district constituencies where the incumbent ran as well as a third-order polynomial, $f(M_{dsy})$, in the mean win margin (close or not), M_{dsy}, between incumbent and runner-up. I also interact $f(M_{dsy})$ with I_{dsy}, an indicator for whether incumbents ran anywhere in the district. Lastly, I control for election year, E_{sy}, and the same set of user- and district-level covariates, X_{idsym} as Equation 2. User-by-year fixed effects, which enabled identification in the main TWFE approach, are too demanding here since eBird users are unlikely to traverse many closely contested districts in a given year. I thus include user and year fixed effects separately.

Figure A4 graphically illustrates the first stage (Panel A) and reduced form (Panel B)[25]. A negative margin means that the incumbent lost. The first stage shows a sharp discontinuous decrease in forest encroachments when incumbents win in close elections. Unsurprisingly, this is accompanied by an increase in species richness at the discontinuity. Table A14 Column 1 presents 2SLS estimates of Equation 9. Columns 2-3 vary the bandwidth for close elections and Column 4 uses a 2nd-order polynomial in the vote margin. Coefficient estimates are negative and significant across the board and first-stage F-statistics are near rule-of-thumb levels; the infrastructure-biodiversity tradeoff is thus robust to this

[25] Appendix Figure A5 shows no evidence of manipulation around the cutoff. In particular, I fail to reject the null hypothesis of no difference in density at the boundary using the method proposed by Cattaneo et al. (2020).

alternative research design. When user- and year-fixed effects are interacted (column 5), coefficient sign and magnitude remain very similar but precision declines (p=0.11) due to the demanding specification.

Coefficient size implies a larger infrastructure-biodiversity tradeoff compared to the TWFE estimates. However, such a comparison cannot easily be made since the 2SLS and OLS estimates apply to different populations[26]. More important is that the two designs agree in terms of coefficient sign and statistical significance. This helps build confidence that my main findings capture a robust relationship between infrastructure development biodiversity loss.

7 The Political Economy of Conservation

Having established that infrastructure expansion degrades biodiversity, this section explores which institutions minimize the tradeoff. I estimate the tradeoff from the previous section as a function of whether districts have inclusive or extractive institutions. I find that the infrastructure-biodiversity tradeoff is smaller under inclusive institutions. I then explore mechanisms by documenting how project authorities interact with tribal groups under both institutional types. Informed consent between developers and tribes, as well as more stringent environmental review, is more common in inclusive districts.

7.1 Data: Measuring Institutional Quality

I start by categorizing districts as having inclusive or extractive institutions, broadly defined. Data on institutional quality is obtained from Banerjee and Iyer (2005) for 163 districts. They distinguish between two colonial institutions. In *zamindari* districts (N=64), landlords set land taxes, could dispossess peasants for nonpayment, and kept residuals after paying the British. In *raiyatwari* districts (N=99), cultivators paid taxes without a middleman. Perhaps unsurprisingly, *zamindari* districts perform worse today on several equality and development measures. Persistence of class-based inequality and lower ability of the disenfranchised to mobilize around their interests in *zamindari* districts are key mechanisms explaining the lack of convergence[27].

Building on this paper, I re-conceptualize *raiyatwari* and *zamindari* districts as inclusive and extractive, respectively. If disaffected groups are better able to engage in the development process and protect their livelihoods in inclusive districts, then the adverse environmental impacts of infrastructure development should be smaller in these districts. I provide evidence for this mechanism in Section 7.3.

7.2 Results: Inclusive Institutions Minimize Species Loss

Estimation: To investigate the role of institutions in mediating the infrastructure-biodiversity tradeoff, I estimate heterogenous treatment effects with the following equation:

$$\begin{aligned} SR_{idsym} = \alpha + \beta_1[Infrastructure]_{dsym} + \beta_2([Infrastructure]_{dsym} \times [Inclusive]_d) \\ + \beta_3[X]_{idsym} + \phi_{iy} + \gamma_d + \theta_{sm} + \epsilon_{idsym} \end{aligned} \tag{10}$$

where $Inclusive_d$ is a dummy for whether district d had a history of inclusive institutions. All other terms are as in Equation 2. Data are aggregated to 1991 census boundaries to match Banerjee and Iyer (2005). The coefficient of interest is β_1 and β_2, which captures the main infrastructure-biodiversity

[26] 2SLS measures the local average treatment effect (LATE) for the subsample that took up the treatment because of close elections (the "compliers"). OLS is an ATE for the compliers and the subsample that would have taken up the treatment regardless ("always-takers") and those who would have never taken up the treatment ("never-takers"). Since projects are not randomly assigned, I cannot distinguish these subsamples, in which case directly comparing LATE and ATE is misleading.

[27] In a follow up paper, Lee (2019) provide additional evidence that state capacity is indeed the most plausible mechanism driving the results in Banerjee and Iyer (2005).

Table 6: The Impact of Infrastructure on Biodiversity as a Function of Institutional Type

	(1)	(2)	(3)	(4)	(5)	(6)
Infrastructure (km^2)	-0.337***	-0.551***	-0.447***	-0.434***	-0.394***	-0.551**
	(0.042)	(0.067)	(0.051)	(0.073)	(0.082)	(0.214)
Infrastructure (km^2) × Inclusive (=1)	0.453**	0.434**	0.340*	0.315*	0.421**	0.434***
	(0.132)	(0.116)	(0.144)	(0.134)	(0.129)	(0.142)
Infrastructure (km^2) × Tribal Pop. Share	-0.148	-0.057	-0.039	0.030	-0.221	-0.057
	(0.227)	(0.290)	(0.306)	(0.175)	(0.296)	(0.402)
Baseline Forest Cover and Interactions	No	Yes	Yes	Yes	Yes	Yes
High-Activity eBird District and Interactions	No	No	No	No	Yes	No
User × Year FEs	✓	✓	✓	✓	✓	✓
District FEs	✓	✓	✓	✓	✓	✓
State x Month FEs	✓	✓	✓	✓	✓	✓
Spillovers			✓			
Weighted				✓		
Clustering	Biome	Biome	Biome	Biome	Biome	District
Observations	58760	58760	58760	58760	58760	58760
R^2	0.704	0.704	0.704	0.784	0.704	0.704

Note: * $p < .1$, ** $p < .05$, *** $p < .01$. The outcome is mean species richness across users' trips in a district-month. Inclusive (=1) means the district has historically inclusive institutions. Sample restricted to 163 districts in Banerjee and Iyer (2005) and aggregated to 1991 boundaries. Tribal share is the fraction of district population belonging to a tribal group as measured in 2011. All specifications include user-year, district, and state-month fixed effects as well as controls for temperature, rainfall, traveling trips, log nightlights, log duration, log distance, log group size, and log spatial coverage. Sensitivity checks described in footer.

tradeoff, and any moderation of the tradeoff depending on the type of local institution. I focus on the hypothesis that $\beta_2 > 0$, i.e., biodiversity is conserved in districts with better institutions.

Threats to Identification: The main identification concern is endogenous institutions (Aghion et al., 2004). This is less of an issue in my context because *zamindar* status was based on British politics and not local characteristics (Banerjee and Iyer, 2005). Moreover, time-invariant differences in the ecology of inclusive and extractive districts are absorbed by district fixed effects. The remaining concern is that infrastructure may exhibit heterogeneous effects along dimensions correlated with institutional type, in which case β_2 is biased. Although the first point protects against this, I test sensitivity to interactions between $Infrastructure_{dsym}$ and various district characteristics as a safeguard.

Results and Robustness: Estimates of Equation 10 are in Table 6. All specifications control for interactions between infrastructure and baseline tribal population share (from the 2011 Census) to separate heterogeneity through population effects from that through institutions. Column 1 shows that infrastructure-driven species loss is more than offset in inclusive districts. The offset is potentially upward biased if inclusive districts are more densely forested today, in which case β_2 also picks up higher species resilience in these districts (Section 6.4, Table 5). Column 2 reports estimates controlling for the interaction of infrastructure with baseline forest cover. Although the counterbalancing force weakens, 78% of species loss is still erased in inclusive districts.

The mitigating effect of inclusive institutions is robust to a range of sensitivity checks. Estimates are very similar when controlling for spatial spillovers within the biome (column 3), weighting by number of eBird trips underlying SR_{idsym} (column 4), and controlling for the interaction between infrastructure and a district dummy for high eBird activity (column 5). The latter is defined in Section 6.6 and accounts for β_2 potentially confounding differences in eBird usage across institution types. Lastly, the mitigating effect remains statistically significant under district clustering (column 6). The moderating role of institutions is independent of tribal population in all specifications, suggesting that institutions empowering disaffected people, not their population per se, determine the extent of sustainable development.

Table A15 conducts additional robustness tests performed in Section 6.6. Columns 1-4 show that

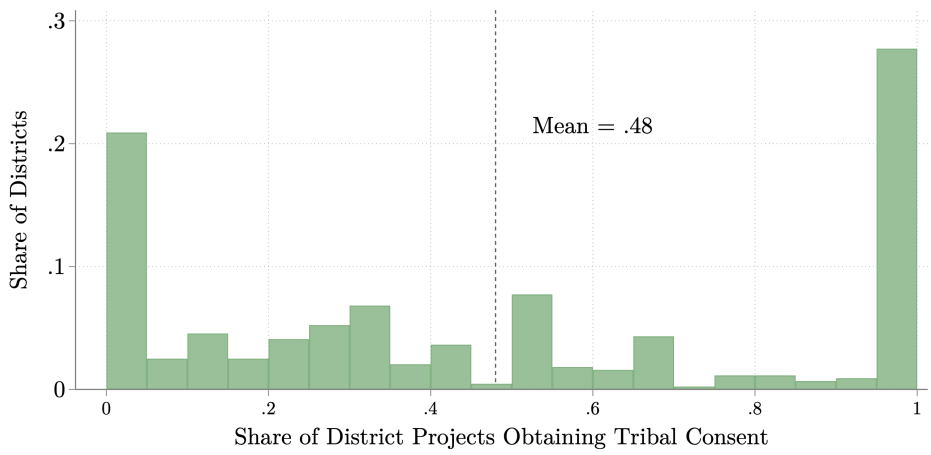

Figure 6: Enforcement of Forest Rights Act (2006)

Note: Data are the share of district projects approved with informed consent by the concerned Gram Sabha during the study period. Data represent an 80% subsample of projects that reported informed consent (the digital subsample).

estimates are generally robust to alternative fixed effects that account for sub-state seasonality and flexible learning rates. The interaction is noisy in column 1, likely due to demanding user-by-month fixed effects. To show that estimates are not driven by a changing user base, column 5 shows that treatment heterogeneity is very similar on the sample of users who signed up for eBird in 2015. The main effect becomes noisy, perhaps due to the stringent sample restriction. Column 6 shows stable estimates when accounting for the COVID shock. To account for outliers, columns 7 and 8 show that estimates are stable when dropping three mega-projects and when using the IHS transformation on the infrastructure variable, respectively. Lastly, estimates are robust to clustering by state (column 9).

The heterogeneity results highlight the importance of inclusive institutions in mitigating anthropogenic pressures on ecosystems. However, it is difficult to glean specific policy lessons since the muted tradeoff in inclusive institutions may operate through numerous channels. I turn to an investigation of mechanisms in the next section.

7.3 Policy Mechanisms: Tribal Rights and Informed Consent

Informed Consent between Developers and Tribes: Why are development projects more sustainable in districts with historically inclusive institutions? I provide evidence on two important mechanisms: project authorities are more likely to incorporate the voices of tribal people, and more likely to undergo more stringent environmental review, in inclusive districts.

Banerjee and Iyer (2005) argue that the absence of a landed gentry in inclusive districts left a legacy enabling "elites and the masses to act together in the collective interest" even today. Lee (2019) shows that more contact between the state and cultivators in inclusive districts created a legacy of better state capacity compared to extractive districts where the state was absent. This suggests that tribal groups can better mobilize around their interests in inclusive districts.

Permit Data: The simplest test is whether projects in inclusive districts are more likely to follow the FRA, which requires inclusion of indigenous tribes in the project approval process (Section 2). If the policy is binding, however, then there would be no variation. Recent reports indicate that FRA enforcement is weak, with exemptions made, non-recognition of land titles, and even bypassing consent altogether (Dubey et al., 2017). The permits that I collected report whether consent was obtained (Figure A7), enabling me to characterize variation.

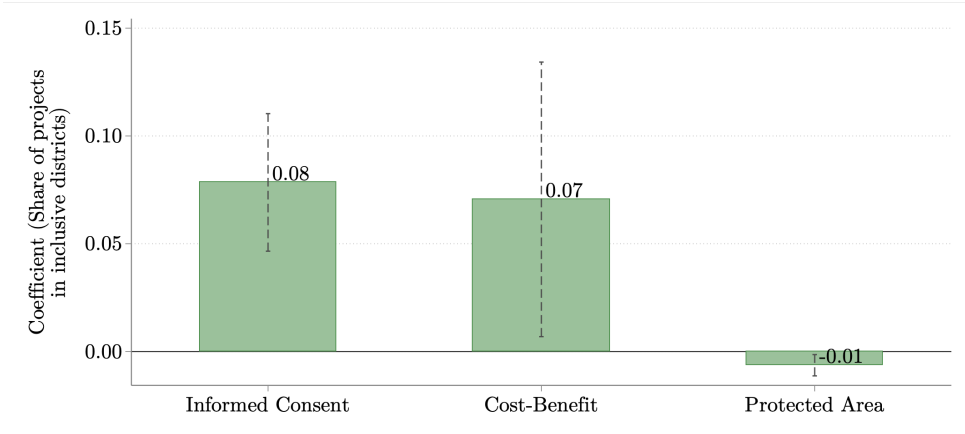

Figure 7: Mechanisms by which Institutions Mitigate the Infrastructure-Biodiversity Tradeoff

Note: Data are at the project level for the digital subsample. Bars represent coefficients from Equation (11) and describe the share of projects in inclusive districts compared to extractive ones. Sample is restricted to 163 districts in Banerjee and Iyer (2005) under British Rule. Informed consent indicates whether the Gram Sabha was consulted and the FRA followed. Cost-Benefit Analyses are reports commissioned during project review. Protected Area equals one if the project is sited in or near one. All specifications include controls for: project size, district population share belonging to a tribal group as measured in 2011, baseline forest cover, and district area. Grey bars represent 95% confidence intervals.

Figure 6 shows the distribution of projects obtaining Gram Sabha consent. The lack of right-tail bunching is evidence of imperfect compliance. There are districts where inclusive development is always, sometimes, and never observed. I exploit this weak implementation to study if inclusive institutions, as defined by Banerjee and Iyer (2005), are actually more inclusive.

Besides FRA compliance, two other variables from project permits highlight mechanisms. The first is whether a supplemental cost-benefit report was commissioned, beyond the standard site monitoring reports. This reflects the rigour of environmental review since commissioning is based on value judgement[28]. The second variable is whether the project is sited in a protected area buffer.

Estimation: I match project permits with the district level inclusive-extractive dummies and use pooled OLS to compare project characteristics under the two types of district institutions. Since institution type is time-invariant, I make cross-district comparisons within the same state and time-period:

$$Y_{pdsym} = \alpha + \beta_1 [Inclusive]_d + \beta_2 [X]_{pdsym} + \theta_{sm} + \epsilon_{pdsym} \tag{11}$$

where Y_{pdsym} is a dummy for whether project p approved in district d of state s in year y and month m received informed consent, completed a supplemental cost-benefit report, or was sited near a protected area. $Inclusive_d$ is the institutional dummy from Equation 10. X_{pdsym} is a set of covariates including project size, tribal population share, baseline forest cover, and district size. θ_{sm} are state-month fixed effects. β_1 reveals the proportion of projects with each feature in inclusive versus extractive districts.

Results: Projects in districts with inclusive institutions are more conservation friendly. Figure 7 shows coefficient estimates and 95% confidence intervals (see Table A16 for table). Projects in inclusive districts are 8% more likely to obtain informed consent from tribal groups and follow FRA provisions compared to projects approved in extractive districts in the same state. Forest officers in inclusive districts are also 7% more likely to commission supplemental cost-benefit reports during project review. Lastly, projects in inclusive districts are 1% less likely to be sited near a protected area. These results highlight three

[28] Value judgment is used for projects > 20 ha., which is more than 90% of my projects. Official guidelines here: http://forestsclearance.nic.in/writereaddata/Addinfo/0_0_7111512571261CostBenefitAnalysisGuidelinesforforestlanddiversion-2017.pdf

important mechanisms driving the smaller infrastructure-biodiversity tradeoff in Table 6.

The previous results do not appear to be driven by sorting of projects between inclusive and extractive districts. If sorting were present, the coefficients could reflect the fact that certain project categories are more conservation friendly, even if institutional type itself had no effect. To help rule this out, Table A17 shows a balance table for the project category distribution under each institutional type, using the same data as Equation 11. Values represent coefficients from a regression of an indicator for each category on $Inclusive_d$. In column 1 (no controls or fixed effects), the value in row 1 implies that the share of electricity projects in inclusive districts is lower by 1.6 percentage points compared to extractive districts, although the difference is statistically insignificant. Column 2 adds the covariate vector X_{pdsym} from Equation 11, while columns 3 and 4 add fixed effects. Overall, there are almost no significant differences in project category shares across institutional types. This supports the claim that inclusive institutions have "teeth", as observed through higher rates of informed consent (Figure 7) and a smaller ecological footprint by projects sited in these districts (Table 6).

The correlations in Figure 7 corroborate the logic of Banerjee and Iyer (2005) and other studies. Duflo and Pande (2007) use the same institutions classification to claim that populations affected by dams are more effective at demanding compensation in inclusive districts. Lal et al. (2021) show that inclusive governance in Indian districts increased tree cover. My results thus represent a test of mechanisms through which institutions drive conservation. They suggest that engaging forest-dependent communities in the development process, especially through informed consent and more stringent checks-and-balances during project approval, are vital for protecting biodiversity. Besides providing direct policy guidance, these results also add a procedural justice lens to the environment-development literature.

8 Conclusion

Infrastructure development in the tropics raises concern about harmful impacts that may percolate through our fragile ecosystems. This paper provides rigorous evidence on the impact of infrastructure expansion on biodiversity in a biodiverse developing nation. It also quantifies the role of inclusive institutions in mitigating the tradeoff. Between 2015-2020, development in India's forests accounted for nearly 20% of the decline in bird diversity, an important proxy for overall biodiversity. This decline is driven by lower abundances of IUCN-designated common and vulnerable species. Species loss does not rebound in the medium-run, and is accentuated in already-fragmented areas. This, however, is not a foregone result. The tradeoff is more than halved when local institutions emphasize community forest governance and amplify the voices of indigenous groups in the development planning process.

My results are especially relevant as emerging economies prioritize the types of infrastructure studied here. China's Belt and Road Initiative is the textbook example, envisioning enhanced regional connectivity across Asia and Africa. Surprisingly, studies from these regions find limited ecological costs of infrastructure development projects (Asher et al., 2020; Garg and Shenoy, 2021; Baehr et al., 2021). In the absence of biodiversity data, these studies use tree cover to measure ecosystem health, whereas I leverage several million verified species sightings. After accounting for observer biases and spatial spillovers, this novel data yields robust evidence of anthropogenic species decline, and can be used to inform infrastructure planning as economies expand throughout the 21st century.

Resettlement, transportation, irrigation, and mining projects are the main drivers of species loss. Village resettlements are particularly damaging. Several thousand communities await relocation from India's 600 protected areas, primarily due to human-wildlife conflict and forced evictions (Lasgorceix and Kothari, 2009). For example, Kerala's proposed Silver Line railway is set to divert forests and displace enroute communities. My results imply that species loss from such projects can be compounded

if displaced villages are resettled by fragmenting forests elsewhere.

These results are policy relevant at a broad and grassroots level. In places where institutions favour the economically advantaged, infrastructure development is associated with more biodiversity loss. This highlights the need for people-centred conservation policy. India has made strides with the FRA (2006), which promises forest rights to indigenous people and their inclusion in development decisions. Yet nearly two decades later, half of forest rights claims remain legally unrecognized and face other forms of weak enforcement (Ministry of Tribal Affairs, 2022). I find that upholding the FRA, and requiring informed consent during the infrastructure development process, helps neutralize the infrastructure-biodiversity tradeoff. In sum, inclusive institutions and procedural justice are critical for meeting the dual objectives of development and conservation.

This paper is not without limitations. First, species richness abstracts from notions of functional diversity, genetic diversity, and other dissimilarity indices (Weitzman, 1992, 1993). Second, with a six year study period, I am unable to study whether species diversity rebounds in the long-run. Lastly, without reliable species values, I am unable to benchmark the economic cost of infrastructure-driven species loss. Cost-benefit analyses are left for future work. Despite these limitations, this study provides powerful insights into the dynamics of biodiversity in human-modified landscapes and is relevant for decision-makers tasked with conserving local and global biodiversity.

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A Supplementary Tables and Figures

A1 Tables

Table A1: Summary Statistics of Projects by Ownership and Shape

	Num. Projects	Mean Size (ha.)	SD (ha.)	Total Area (ha.)
Panel A: Ownership				
Public	4,666	9.6	89.9	44,861.3
Private	1,549	1.9	15.2	2,910.6
Neither	382	2.7	24.9	1,019.8
Panel B: Shape				
Linear	5,768	4.8	28.2	27,472.6
Nonlinear	829	25.7	201.0	21,319.1

Note: Data are arranged at the project level for 6,597 approved projects that reported ownership, prior to aggregating to the district level. Panel A splits projects by ownership type. Panel B splits projects by shape. Total area (ha.) is the summed deforestation area of all projects in the sample for the particular project group.

Table A2: Percent of Projects in Each Category by Ownership and Shape

	Ownership (%)			Shape (%)	
	Public (1)	Private (2)	Neither (3)	Linear (4)	Nonlinear (5)
Electricity	81.48	15.86	2.67	86.03	13.97
Irrigation	95.34	2.48	2.17	72.05	27.95
Mining	49.15	35.59	15.25	0.00	100.00
Other	58.07	33.53	8.40	85.04	14.96
Resettlement	100.00	0.00	0.00	5.00	95.00
Transportation	88.41	9.54	2.05	99.03	0.97

Note: Data are arranged at the project level for 6,597 approved projects that reported ownership and shape, prior to aggregating to the district level. Cell values denote row percentages *within each group* (i.e. % of projects in each category falling under different ownership types). Thus, the row sum of columns 1-3 equals 100, and same for columns 4-5.

Table A3: eBird Summary Statistics (2015-2020)

	Mean	Std. Dev.	Obs.
District			
Num. Users	109.01	193.91	628
Num. Trips	1671.86	5497.55	628
Coverage (%)	52.88	32.26	628
User			
Num. Districts	3.99	7.45	16899
Num. States	1.93	2.21	16899
Num. Year-months	6.41	11.32	16899
User-District-Time			
Species Richness	23.39	18.72	173813
Duration (min)	85.51	70.70	173813
Distance (km)	3.06	6.02	173813
Coverage (%)	9.58	16.98	173813
District-Time			
Rainfall (mm)	0.34	0.82	21750
Temperature (° C)	23.30	7.22	21750
Nightlights (radiance)	2.61	7.28	21750
Coverage (%)	18.89	25.93	21750
Num. Users per District-Yearmonth	8.07	14.60	21750

Note: District variables reflect total eBird activity in a district during the study period. User variables describe number of locations and time-periods in which the user is active. Variables at the user-district-time level are means over users' trips in a district-month. Coverage is measured as the percentage of district cells traversed by a user on a 10km grid. Remaining covariate details are explained in section 3.

Table A4: Impact of Forest Infrastructure on Species Diversity

	Main Estimates			Sensitivity		
	(1)	(2)	(3)	(4)	(5)	(6)
Infrastructure (km^2)	-0.049*	-0.121**	-0.121**	-0.105	-0.120**	-0.110*
	(0.027)	(0.053)	(0.054)	(0.062)	(0.054)	(0.059)
Infrastructure (district j $\neq$ d)			0.232			
(Standard Deviations)			(0.251)			
Non-forest Land Diversion (km^2)						-0.046
						(0.056)
Weather Controls	Yes	Yes	Yes	Yes	Yes	Yes
Behaviour Controls	Yes	Yes	Yes	No	Yes	Yes
General Economic Trends	Yes	Yes	Yes	No	No	Yes
Outcome Mean	23.672	23.748	23.748	23.748	23.748	23.748
User FEs	✓					
User × Year FEs		✓	✓	✓	✓	✓
District FEs	✓	✓	✓	✓	✓	✓
State × Month FEs	✓	✓	✓	✓	✓	✓
Year FEs	✓					
Observations	167256	161896	161896	161896	161896	161896
R^2	0.635	0.690	0.690	0.559	0.690	0.690

Note: * $p < .1$, ** $p < .05$, *** $p < .01$. Columns 1-3 are the same as in Figure 4A. Columns 4-5 successively add controls. Weather controls include temperature and rainfall. Behaviour controls include: traveling trips, log duration, log distance, log group size, and log spatial coverage. General economic trends are measured by nightlights. Column 6 adds cumulative non-forest land diversion, which is available only the digital subsample of project proposals. Standard errors clustered by biome.

Table A5: Robustness—Spatial Spillovers

	(1)	(2)	(3)	(4)
Infrastructure (km^2)	-0.121**	-0.123**	-0.125**	-0.126**
	(0.053)	(0.055)	(0.054)	(0.056)
Forest Infrastructure (district j $\neq$ d)	0.025	0.081	0.399	0.441
(Standard Deviations)	(0.473)	(0.258)	(0.647)	(0.421)
Distance Cutoff	100km	200km	500km	None
User × Year FEs	✓	✓	✓	✓
District FEs	✓	✓	✓	✓
State × Month FEs	✓	✓	✓	✓
Observations	161896	161896	161896	161896
R^2	0.690	0.690	0.690	0.690

Note: * $p < .1$, ** $p < .05$, *** $p < .01$. The outcome is mean species richness across user's trips in a district-month. In column 1, forest infrastructure in other districts j describes cumulative encroachment area in other districts within 100km of the focal district d. In each time period, $Infrastructure_{dsym}$ is multiplied by a $N \times N$ (where N is the number of districts in India) dimensional weight matrix W with elements $w_{dj} = 1/distance_{dj}$ for districts j within 100km of d and zero otherwise. Columns 2 and 3 extend the distance cutoff to 200km and 500km, respectively. Column 4 applies the inverse distance weight to all districts. Section 5.3.2 elaborates the procedure. All regressions control for: temperature, rainfall, traveling trips, log nightlights, log duration, log distance, log group size, and log spatial coverage. Standard errors clustered by biome.

Table A6: Tests of Endogenous Sorting

	Across-District			Within-District
	(1) Num. Users	(2) Num. Users	(3) Num. Users	(4) % District Area
Infrastructure	0.010	0.010	0.008	-0.007
	(0.029)	(0.029)	(0.028)	(0.011)
Infrastructure (district $j \neq d$) (Standard Deviations)	-0.023	-0.017	-0.013	
	(0.020)	(0.024)	(0.029)	
Controls	Yes	Yes	Yes	Yes
Data Aggregation	District	District	District	District
Distance Cutoff	100km	200km	500km	
District FEs	✓	✓	✓	✓
State × Month FEs	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓
Observations	21256	21256	21256	21256
R^2	0.808	0.808	0.808	0.976

Note: * $p < .1$, ** $p < .05$, *** $p < .01$. Data are aggregated at the district-year-month level. The outcome in columns 1-3 is log number of users in a district. The outcome in column 4 is % of district grid cells traversed by the average user. Infrastructure is cumulative area of forest occupied by infrastructure in district d during a year-month. In column 1, infrastructure (district $j \neq d$) is inverse-distance weighted infrastructure in districts j within 100km of d. In columns 2 and 3, the distance cutoff is extended to 200km and 500km, respectively. Both infrastructure variables are standardized for comparability in column 1-3. Infrastructure is not standardized in column 4. Controls are the same as the main specification. Experience, duration, distance, group size, and % traveling trips are aggregated to district means and logged. Standard errors clustered by biome.

Table A7: Impact of Forest Infrastructure on Species Diversity by Category

	(1)	(2)	(3)	(4)
Electricity	0.088	0.090	0.085	0.091
	(0.066)	(0.066)	(0.066)	(0.066)
Irrigation	-0.105*	-0.130**	-0.131**	-0.121**
	(0.052)	(0.049)	(0.048)	(0.042)
Mining	-0.061	-0.059***	-0.059***	-0.111***
	(0.035)	(0.019)	(0.019)	(0.021)
Other	-0.165	-0.257	-0.254	-0.264
	(0.229)	(0.215)	(0.215)	(0.210)
Resettlement	-1.100***	-0.745***	-0.744***	-0.728***
	(0.062)	(0.080)	(0.078)	(0.088)
Transportation	-0.265	-0.392*	-0.393*	-0.444**
	(0.305)	(0.181)	(0.183)	(0.188)
Weather Controls	Yes	Yes	Yes	Yes
Behaviour Controls	No	Yes	Yes	Yes
General Economic Trends	No	No	Yes	Yes
Outcome Mean	23.748	23.748	23.748	23.983
Sample	Full	Full	Full	High-Activity
User x Year FEs	✓	✓	✓	✓
District FEs	✓	✓	✓	✓
State × Month FEs	✓	✓	✓	✓
Observations	161896	161896	161896	150011
R^2	0.559	0.690	0.690	0.687

Note: * $p < .1$, ** $p < .05$, *** $p < .01$. The outcome in all specifications is mean species richness across users' trips in a district-month. Rows denote cumulative area of infrastructure encroachments by a particular category in a district-month. Column 1-3 successively add controls. Weather controls include temperature and rainfall. Behaviour controls include: traveling trips, log duration, log distance, log group size, and log spatial coverage. General economic trends is measured by nightlights. Column 3 is the same as Figure 4B. Column 4 restricts the sample to districts with high eBird usage, measured as districts with above-median numbers of users, recording above-median trips per user. Standard errors clustered by biome.

Table A8: Impact of Forest Infrastructure on Species Diversity by Project Ownership and Shape

	(1)	(2)	(3)
Panel A: Ownership			
Public	-0.197***	-0.203***	-0.204***
	(0.047)	(0.048)	(0.048)
Private	-0.806	-0.299	-0.297
	(0.925)	(0.737)	(0.735)
Neither	2.911	0.852	0.851
	(1.854)	(0.667)	(0.669)
Panel B: Shape			
Linear	-0.260	-0.345*	-0.344*
	(0.193)	(0.168)	(0.168)
Nonlinear	-0.177***	-0.170***	-0.171***
	(0.043)	(0.036)	(0.035)
Weather Controls	Yes	Yes	Yes
Behaviour Controls	No	Yes	Yes
General Economic Trends	No	No	Yes
Outcome Mean	23.748	23.748	23.748
User x Year FEs	✓	✓	✓
District FEs	✓	✓	✓
State × Month FEs	✓	✓	✓
Observations	161896	161896	161896
R^2	0.559	0.690	0.690

Note: The outcome in all specifications is mean species richness across users' trips in a district-month. In Panel A, rows denote cumulative area of infrastructure encroachments by projects of a particular ownership type in a district-month. Panel B reports the same by project shape. Column 1-3 successively add controls. Weather controls include temperature and rainfall. Behaviour controls include: traveling trips, log duration, log distance, log group size, and log spatial coverage. General economic trends is measured by nightlights. Standard errors clustered by biome.

Table A9: Robustness—Alternative Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)
Forest Infrastructure	-0.125**	-0.114	-0.080**	-0.117*	-0.119**	-0.049
	(0.041)	(0.064)	(0.032)	(0.054)	(0.054)	(0.056)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
User x Year FEs		✓		✓	✓	
User × Month FEs	✓					
Experience FEs				✓		
District FEs	✓			✓	✓	
District × Month FEs		✓	✓			
Cell FEs						✓
State × Month FEs				✓	✓	✓
State × Year FEs	✓		✓			
Year FEs						✓
Time-of-Day FEs					✓	
Observations	143384	161029	166409	161557	161665	282427
R^2	0.702	0.706	0.654	0.694	0.690	0.542

Note: * $p < .1$, ** $p < .05$, *** $p < .01$. The outcome in all columns is mean species richness across users' trips in a district-month. The estimating equation is the same as Equation 2 with different fixed effects described in the footer. Experience fixed effects indicate cumulative number of trips taken by a user. Time-of-day fixed effects indicate whether users' trips in a district-month were recorded on average during morning, afternoon, evening, or night. In column 6, data are at the user-grid-cell level. Variation in observations across columns 1-5 is from dropping singletons. All regressions control for: temperature, rainfall, traveling trips, log nightlights, log duration, log distance, log group size, and log spatial coverage. Standard errors clustered by biome.

Table A10: Robustness—Other

	(1) SR	(2) SR	(3) SR	(4) SR	(5) SR	(6) SR	(7) Shannon	(8) Simpson	(9) SR
Infrastructure	-0.118**	-0.093*	-0.124**	-0.111***	-0.246**	-0.605***	-0.033	-0.036	-0.112*
(km^2)	(0.053)	(0.050)	(0.054)	(0.010)	(0.082)	(0.138)	(0.276)	(0.060)	(0.057)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Infrastructure Unit	km^2	km^2	km^2	km^2	km^2	IHS	km^2	km^2	km^2
Sample Restriction	2015 users	Away	Active	non-COVID	Truncate	None	None	None	None
User x Year FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓
District FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓
State x Month FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓
Weights	None	None	None	None	None	None	None	None	Trips
Observations	82339	123280	150011	123416	161896	161896	161896	157766	161896
R^2	0.684	0.685	0.687	0.690	0.690	0.690	0.645	0.445	0.762

Note: * $p < .1$, ** $p < .05$, *** $p < .01$. The outcome in all columns (except 7 and 8) is mean species richness (SR) across users' trips in a district-month. Column 1 is estimated on users who signed up for eBird in 2015. Column 2 drops observations in users' home districts. Column 3 restricts the sample to districts with above-median numbers of users who record an above-median number of trips per user. Column 4 drops the year 2020. Column 5 drops the three largest projects. Column 6 uses the inverse hyperbolic sine of the explanatory variable. Columns 7 and 8 show results with two alternative species diversity metrics. Column 9 weights the regression with number of trips underlying the outcome. All regressions control for: temperature, rainfall, traveling trips, log nightlights, log duration, log distance, log group size, and log spatial coverage. Standard errors clustered by biome.

Table A11: Robustness—Alternative Standard Errors

	Standard Error Boundary			Conley Spatial Error Cutoff			
	Biome	District	State	100km	200km	500km	1000km
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Infrastructure (km^2)	-0.122**	-0.122**	-0.122*	-0.122*	-0.122*	-0.122*	-0.122**
	(0.051)	(0.060)	(0.062)	(0.064)	(0.069)	(0.066)	(0.054)
User × Year	✓	✓	✓	✓	✓	✓	✓
District	✓	✓	✓	✓	✓	✓	✓
State × Month	✓	✓	✓	✓	✓	✓	✓
Observations	161,907	161,907	161,907	161,907	161,907	161,907	161,907
R^2	0.694	0.694	0.694	0.694	0.694	0.694	0.694

Note: * $p < .1$, ** $p < .05$, *** $p < .01$. Coefficient estimates and standard errors from baseline specification with alternative error clustering. Column 1 replicates the main estimate with clustering at the biome level. In columns 2-3, standard errors are clustered by district and state, respectively. Columns 4-7 implement Conley (1999) standard errors for four different values of the kernel cut off distance (in km). The R software was used to compute Conley errors; observations differ slightly from the main results due to differences in the way R drops singletons.

Table A12: Category-Wise Robustness—Alternative Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)
Electricity	-0.051	0.147*	0.036	0.095	0.090	0.037
	(0.090)	(0.071)	(0.098)	(0.066)	(0.065)	(0.051)
Irrigation	-0.026	-0.158**	-0.014	-0.127**	-0.126**	-0.062
	(0.046)	(0.064)	(0.046)	(0.050)	(0.051)	(0.109)
Mining	-0.205**	-0.051	-0.257***	-0.055**	-0.056**	-0.154
	(0.067)	(0.047)	(0.046)	(0.022)	(0.018)	(0.259)
Other	-0.236	-0.255	-0.152	-0.246	-0.256	-0.276
	(0.165)	(0.251)	(0.234)	(0.225)	(0.219)	(0.258)
Resettlement	-0.778***	-0.530***	-0.447***	-0.761***	-0.756***	-0.159***
	(0.166)	(0.065)	(0.060)	(0.084)	(0.077)	(0.036)
Transportation	-0.462	-0.431***	-0.513	-0.414**	-0.398*	0.159
	(0.284)	(0.136)	(0.299)	(0.167)	(0.186)	(0.233)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
User x Year FEs		✓		✓	✓	
User × Month FEs	✓					
Experience FEs				✓		
District FEs	✓			✓	✓	
District × Month FEs		✓	✓			
Cell FEs						✓
State × Month FEs				✓	✓	✓
State × Year FEs	✓		✓			
Year FEs						✓
Time-of-Day FEs					✓	
Observations	143384	161029	166409	161557	161665	282427
R^2	0.702	0.706	0.654	0.694	0.690	0.542

Note: * $p < .1$, ** $p < .05$, *** $p < .01$. The outcome in all columns is mean species richness across users' trips in a district-month. Coefficients describe the marginal impact of infrastructure encroachment by projects of a given category. The estimating equation is the same as Equation 3 with different fixed effects described in the footer. Experience fixed effects indicate cumulative number of trips taken by a user. Time-of-day fixed effects indicate whether users' typical trips in a district-month were recorded during morning, afternoon, evening, or night. In column 6, data are at the user-grid-cell level. Variation in observations across columns 1-5 is from dropping singletons. All regressions control for: temperature, rainfall, traveling trips, log nightlights, log duration, log distance, log group size, and log spatial coverage. Standard errors clustered by biome.

Table A13: Category-Wise Robustness—Other

	(1) SR	(2) SR	(3) SR	(4) SR	(5) SR	(6) SR	(7) Shannon	(8) Simpson	(9) SR
Electricity	-0.038	0.078	0.091	0.197	-0.224	0.132	-0.132	-0.099	0.026
	(0.145)	(0.076)	(0.066)	(0.438)	(0.854)	(0.926)	(0.287)	(0.076)	(0.029)
Irrigation	0.042	-0.049	-0.121**	-0.056*	-0.164	-0.580**	-0.034	-0.045	-0.175***
	(0.051)	(0.062)	(0.042)	(0.027)	(0.142)	(0.214)	(0.214)	(0.048)	(0.049)
Mining	-0.055	-0.023	-0.111***	-0.102***	-0.031	-0.332	-0.333*	0.028	0.077
	(0.046)	(0.091)	(0.021)	(0.027)	(0.031)	(0.403)	(0.178)	(0.088)	(0.132)
Other	-0.330	-0.230	-0.264	-0.209	-0.257	-0.646	0.024	-0.072	-0.323***
	(0.204)	(0.228)	(0.210)	(0.224)	(0.209)	(0.462)	(0.853)	(0.176)	(0.068)
Resettlement	-0.875***	-0.951***	-0.728***	-0.565***	-0.750***	-1.682***	2.362***	0.348**	-0.563***
	(0.097)	(0.125)	(0.088)	(0.095)	(0.084)	(0.307)	(0.162)	(0.124)	(0.066)
Transportation	-0.551***	-0.502**	-0.444**	-0.241	-0.381**	-0.882***	-0.783	0.073	-0.137
	(0.125)	(0.168)	(0.188)	(0.140)	(0.166)	(0.203)	(1.449)	(0.270)	(0.159)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Infrastructure Unit	km^2	km^2	km^2	km^2	km^2	IHS	km^2	km^2	km^2
Sample Restriction	2015 users	Away	Active	non-COVID	Truncate	None	None	None	None
User x Year FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓
District FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓
State x Month FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓
Weights	None	None	None	None	None	None	None	None	Trips
Observations	82339	123280	150011	123416	161896	161896	161896	157766	161896
R^2	0.684	0.685	0.687	0.690	0.690	0.690	0.645	0.445	0.762

Note: * $p < .1$, ** $p < .05$, *** $p < .01$. The outcome in all columns (except 7 and 8) is mean species richness (SR) across users' trips in a district-month. Coefficients show the marginal impact of infrastructure encroachment by projects of a given category. Column 1 is estimated on users who signed up for eBird in 2015. Column 2 drops observations in users' home districts. Column 3 restricts the sample to districts with above-median numbers of users who record an above-median number of trips per user. Column 4 drops the year 2020. Column 5 drops the three largest projects. Column 6 uses the inverse hyperbolic sine of the explanatory variable. Columns 7 and 8 show results with two alternative species diversity metrics. Column 9 weights the regression with number of trips underlying the outcome. All regressions control for: temperature, rainfall, traveling trips, log nightlights, log duration, log distance, log group size, and log spatial coverage. Standard errors clustered by biome.

Table A14: Robustness: Close Election Design

	(1)	(2)	(3)	(4)	(5)
Infrastructure (km^2)	-1.983**	-3.082*	-1.585*	-2.232**	-2.420
	(0.769)	(1.377)	(0.734)	(0.971)	(1.377)
Controls	Yes	Yes	Yes	Yes	Yes
First Stage F-Statistic	8.862	8.709	13.778	6.596	5.411
Bandwidth	2	3	5	2	2
Polynomial Order	3	3	3	2	3
User FEs	✓	✓	✓	✓	
User x Year FEs					✓
District FEs	✓	✓	✓	✓	✓
State × Month FEs	✓	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓	
Observations	134448	134448	134448	134448	129704

Note: * $p < .1$, ** $p < .05$, *** $p < .01$. Data are at the user-district-month level as in the main specifications. The outcome is mean species richness across user's trips in a district-month. Coefficients are 2SLS estimates as specified in Equation 9. Infrastructure is instrumented with the fraction of constituencies in a district where the incumbent won in a close race during the most recent state election. All regressions control for the same user- and district-level covariates as Equation 2 as well as the fraction of close-election district constituencies where the incumbent ran, election year, and the interaction of a third-order polynomial in the victory margin with an indicator for whether any incumbent ran in the district. Column 1 defines close election as a win margin of 2 percent. Columns 2-3 expand the win margin to 3 and 5 percent, respectively. Column 4 uses a second order polynomial in the win margin. Column 5 uses user-by-year fixed effects.

Table A15: Robustness: Treatment Heterogeneity by Institutional Type

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Infrastructure	-0.519**	-0.510***	-0.548***	-0.558***	-0.236	-0.607***	-0.551***	-1.227***	-0.551**
	(0.116)	(0.098)	(0.037)	(0.083)	(0.265)	(0.079)	(0.067)	(0.202)	(0.189)
Infrastructure	0.037	0.327***	0.435**	0.421**	0.377**	0.454*	0.434**	1.529***	0.434**
× Inclusive (=1)	(0.136)	(0.032)	(0.132)	(0.114)	(0.125)	(0.191)	(0.116)	(0.329)	(0.149)
Infrastructure	1.222	-0.240	-0.039	-0.014	-1.029	-0.290	-0.057	1.197	-0.057
× Tribal Pop. Share	(0.774)	(0.160)	(0.236)	(0.296)	(0.769)	(0.245)	(0.290)	(2.562)	(0.284)
Baseline Forest Cover + Interactions	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Infrastructure Unit	km^2	km^2	km^2	km^2	km^2	km^2	km^2	IHS	km^2
Sample Restriction	None	None	None	None	2015 users	Non-COVID	Truncate	None	None
User × Month FEs	✓								
User × Year FEs		✓	✓	✓	✓	✓	✓	✓	✓
District FEs	✓		✓	✓	✓	✓	✓	✓	✓
District × Month FEs		✓							
State x Month FEs			✓	✓	✓	✓	✓	✓	✓
State × Year Fes	✓								
Experience FEs			✓						
Time-of-day FEs				✓					
Clustering	Biome	Biome	Biome	Biome	Biome	Biome	Biome	Biome	State
Observations	47609	58587	58204	58678	29208	43788	58760	58760	58760
R^2	0.713	0.719	0.713	0.705	0.691	0.698	0.704	0.704	0.704

Note: * $p < .1$, ** $p < .05$, *** $p < .01$. The outcome in all specifications is mean species richness across users' trips in a district-month. Inclusive (=1) means the district has historically inclusive institutions. Sample restricted to 163 districts in Banerjee and Iyer (2005) and aggregated to 1991 boundaries. ST share is the fraction of district population belonging to a tribal group as measured in 2011. Experience fixed effects indicate cumulative number of trips taken by a user. Time-of-day fixed effects indicate whether users' typical trips in a district-month were recorded during morning, afternoon, evening, or night. Column 5 is estimated on users who signed up for eBird in 2015. Column 6 drops the year 2020. Column 7 drops the three largest projects. Column 8 uses the inverse hyperbolic sine of the explanatory variable. All regressions control for: temperature, rainfall, traveling trips, log nightlights, log duration, log distance, log group size, and log spatial coverage. Fixed effects and clustering described in the footer.

Table A16: Mechanisms by Which Institutions Mitigate the Infrastructure-Biodiversity Tradeoff

	(1) Informed Consent	(2) Cost-Benefit	(3) Protected Area
Inclusive (=1)	0.078***	0.071**	-0.006**
	(0.015)	(0.029)	(0.002)
Controls	Yes	Yes	Yes
Outcome Mean	0.234	0.156	0.007
State × Time FEs	✓	✓	✓
N	2275	2275	2270
R^2	0.541	0.510	0.237

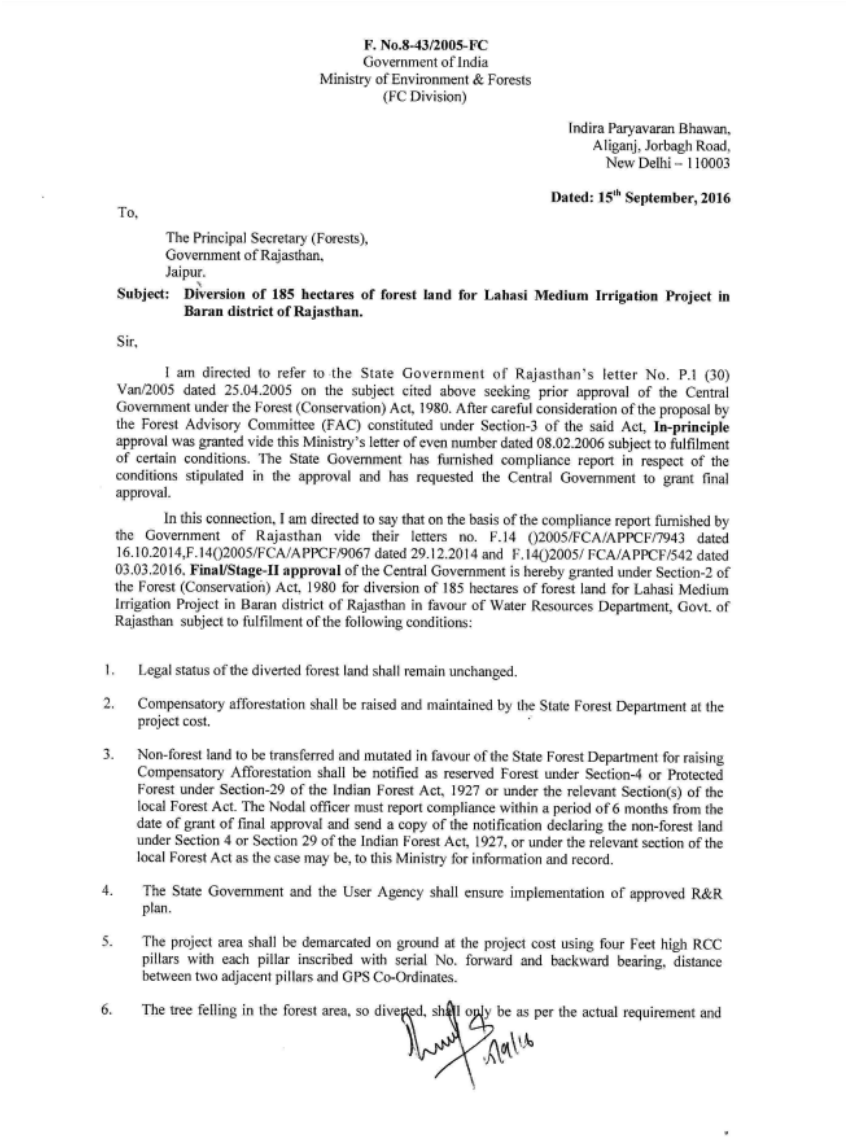
Note: * $p < .1$, ** $p < .05$, *** $p < .01$. Data are at the project level for the digital subsample. Inclusive (=1) means the district has historically inclusive institutions. Sample restricted to 163 districts in Banerjee and Iyer (2005) under British Rule. Informed consent indicates whether the Gram Sabha was consulted and the FRA followed. Cost-Benefit Analyses are reports commissioned during project review. Protected Area equals one if the project is sited in or near one. All specifications include controls for: project size, district population share belonging to a tribal group as measured in 2011, baseline forest cover, and district area.

Table A17: Balance of Project Category Distribution in Inclusive versus Extractive Districts

	(1) No Controls or FEs	(2) Controls	(3) State FEs	(4) State + Year FEs
Electricity	-0.016	0.039	0.066**	0.071**
	(0.023)	(0.038)	(0.029)	(0.029)
Irrigation	-0.049	-0.019	-0.012	-0.005
	0.034	0.032	0.020	0.020
Mining	-0.020	0.010	-0.018*	-0.017*
	0.015	0.011	0.010	0.010
Other	0.000	-0.081	-0.027	-0.028
	0.048	0.049	0.053	0.050
Resettlement	-0.020	-0.016	-0.001	-0.001
	0.012	0.010	0.008	0.008
Transportation	0.104*	0.067	-0.008	-0.019
	0.056	0.038	0.049	0.046

Note: * $p < .1$, ** $p < .05$, *** $p < .01$. Values describe the *difference* in project shares of each category between districts with inclusive and extractive institutions. For example, the first cell implies that inclusive districts have 1.6% more electricity projects than extractive districts. Values in each cell are from separate project-level regressions of an indicator for that category on an indicator for whether its district of approval is inclusive. Column 1 includes no other controls or fixed effects and describes the difference in mean project shares. Column 2 adds controls for: project size, district population share belonging to a tribal group as measured in 2011, baseline forest cover, and district area. Column 3 successively adds state fixed effects, and column 4 adds state and year fixed effects.

A2 Figures



F. No.8-43/2005-FC
Government of India
Ministry of Environment & Forests
(FC Division)

Indira Paryavaran Bhawan,
Aliganj, Jorbagh Road,
New Delhi – 110003

Dated: 15th September, 2016

To,

The Principal Secretary (Forests),
Government of Rajasthan,
Jaipur.

Subject: Diversion of 185 hectares of forest land for Lahasi Medium Irrigation Project in Baran district of Rajasthan.

Sir,

I am directed to refer to the State Government of Rajasthan's letter No. P.1 (30) Van/2005 dated 25.04.2005 on the subject cited above seeking prior approval of the Central Government under the Forest (Conservation) Act, 1980. After careful consideration of the proposal by the Forest Advisory Committee (FAC) constituted under Section-3 of the said Act, **In-principle** approval was granted vide this Ministry's letter of even number dated 08.02.2006 subject to fulfilment of certain conditions. The State Government has furnished compliance report in respect of the conditions stipulated in the approval and has requested the Central Government to grant final approval.

In this connection, I am directed to say that on the basis of the compliance report furnished by the Government of Rajasthan vide their letters no. F.14 ()2005/FCA/APPCF/7943 dated 16.10.2014,F.14()2005/FCA/APPCF/9067 dated 29.12.2014 and F.14()2005/ FCA/APPCF/542 dated 03.03.2016, **Final/Stage-II approval** of the Central Government is hereby granted under Section-2 of the Forest (Conservation) Act, 1980 for diversion of 185 hectares of forest land for Lahasi Medium Irrigation Project in Baran district of Rajasthan in favour of Water Resources Department, Govt. of Rajasthan subject to fulfilment of the following conditions:

1. Legal status of the diverted forest land shall remain unchanged.
2. Compensatory afforestation shall be raised and maintained by the State Forest Department at the project cost.
3. Non-forest land to be transferred and mutated in favour of the State Forest Department for raising Compensatory Afforestation shall be notified as reserved Forest under Section-4 or Protected Forest under Section-29 of the Indian Forest Act, 1927 or under the relevant Section(s) of the local Forest Act. The Nodal officer must report compliance within a period of 6 months from the date of grant of final approval and send a copy of the notification declaring the non-forest land under Section 4 or Section 29 of the Indian Forest Act, 1927, or under the relevant section of the local Forest Act as the case may be, to this Ministry for information and record.
4. The State Government and the User Agency shall ensure implementation of approved R&R plan.
5. The project area shall be demarcated on ground at the project cost using four Feet high RCC pillars with each pillar inscribed with serial No. forward and backward bearing, distance between two adjacent pillars and GPS Co-Ordinates.
6. The tree felling in the forest area, so diverted, shall only be as per the actual requirement and

Figure A1: Example Approval Letter

Note: Figure shows scanned letter from Principal Secretary of State Forest Ministry (Rajasthan) approving proposal for deforestation of 185 hectares for irrigation project. Encroachment area, district, and state are extracted for construction of manual sample. Additional fields from the actual proposal/application itself is only provided for the digital sample.

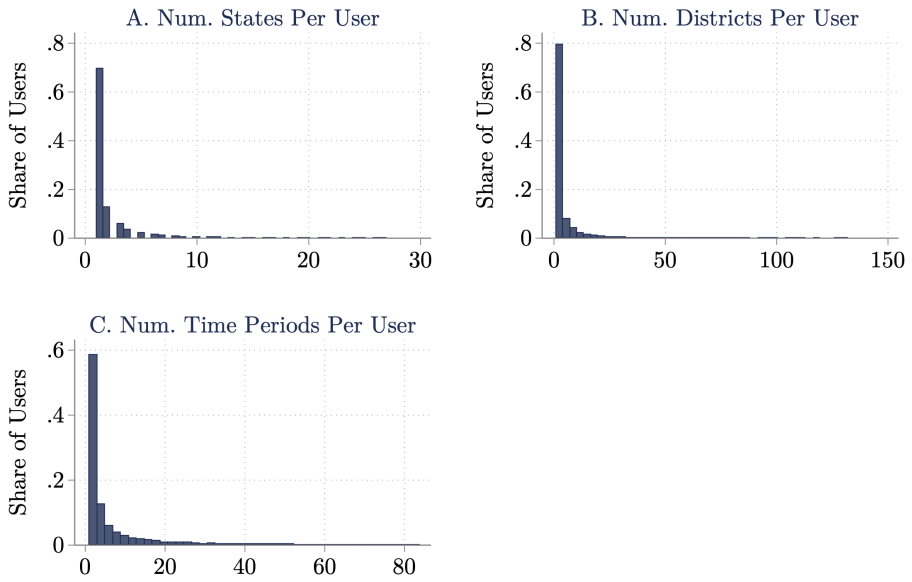


Figure A2: Within-User Distribution of Spatiotemporal Activity

Note: Distributions are based on aggregating eBird data (over all locations and time periods) to the user level (N=17,634 users). Panel A illustrates the distribution of total number of states traversed per user across all their trips during the study period. Panel B shows the same for total number of districts traversed per user. In Panel C, a time period is a year-month. There are 72 possible values (12 months*6 years). The distribution describes the number of periods in which a user recorded a trip.

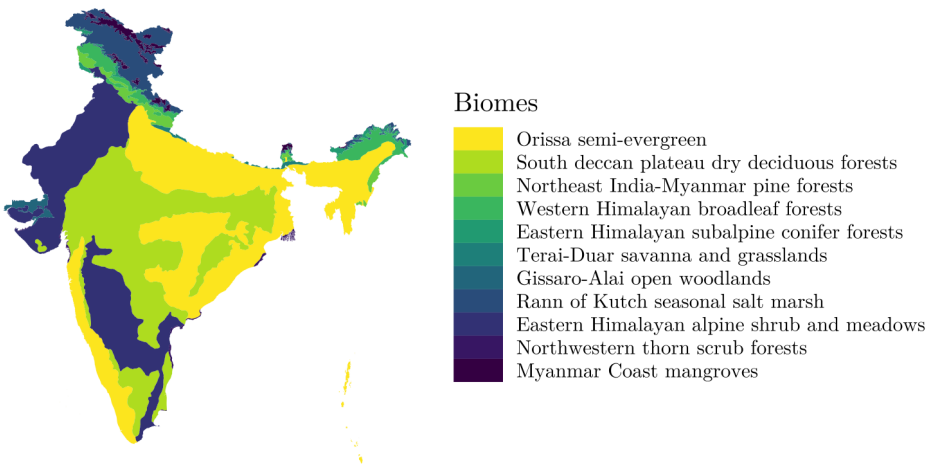


Figure A3: Biomes of India

Note: Data obtained from the Nature Conservancy Terrestrial Ecoregion shapefiles.

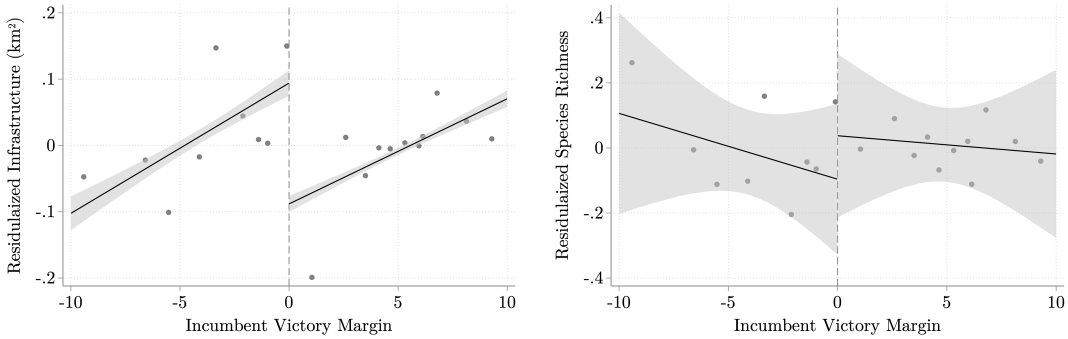


Figure A4: Margin of Victory, Infrastructure Project Approvals, and Species Richness

Note: Panel A (left) shows the first stage (Equation 8) and Panel B) right shows the reduced form. Each figure plots a binscatter of incumbent win margin in close elections (x-axis) against the outcome (y-axis) residualized on user, district, state-month and year fixed effects as well as the same set of user- and district-level covariates as the main TWFE specification. Points to the left of zero denote districts where incumbents lost in close elections. A linear fit is generated separately for each side of zero, with 95% confidence intervals displayed.

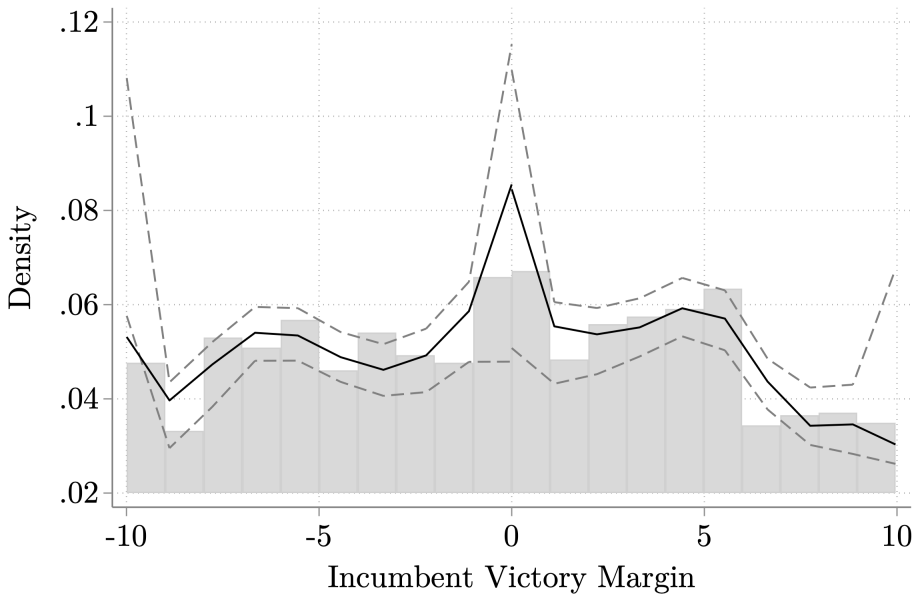


Figure A5: Density Discontinuity Test for Manipulation

Note: The figure plots a density test from Cattaneo et al. (2020). The black line traces the density of observations in each margin-of-victory bin. Dashed lines are 95% confidence intervals around the local linear density estimates. Grey bars are a histogram of victory margin.

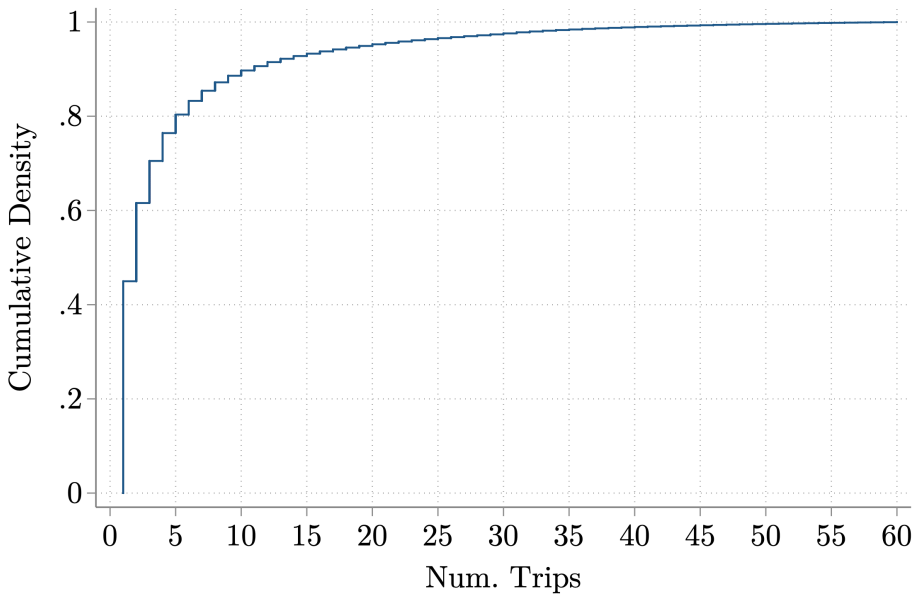
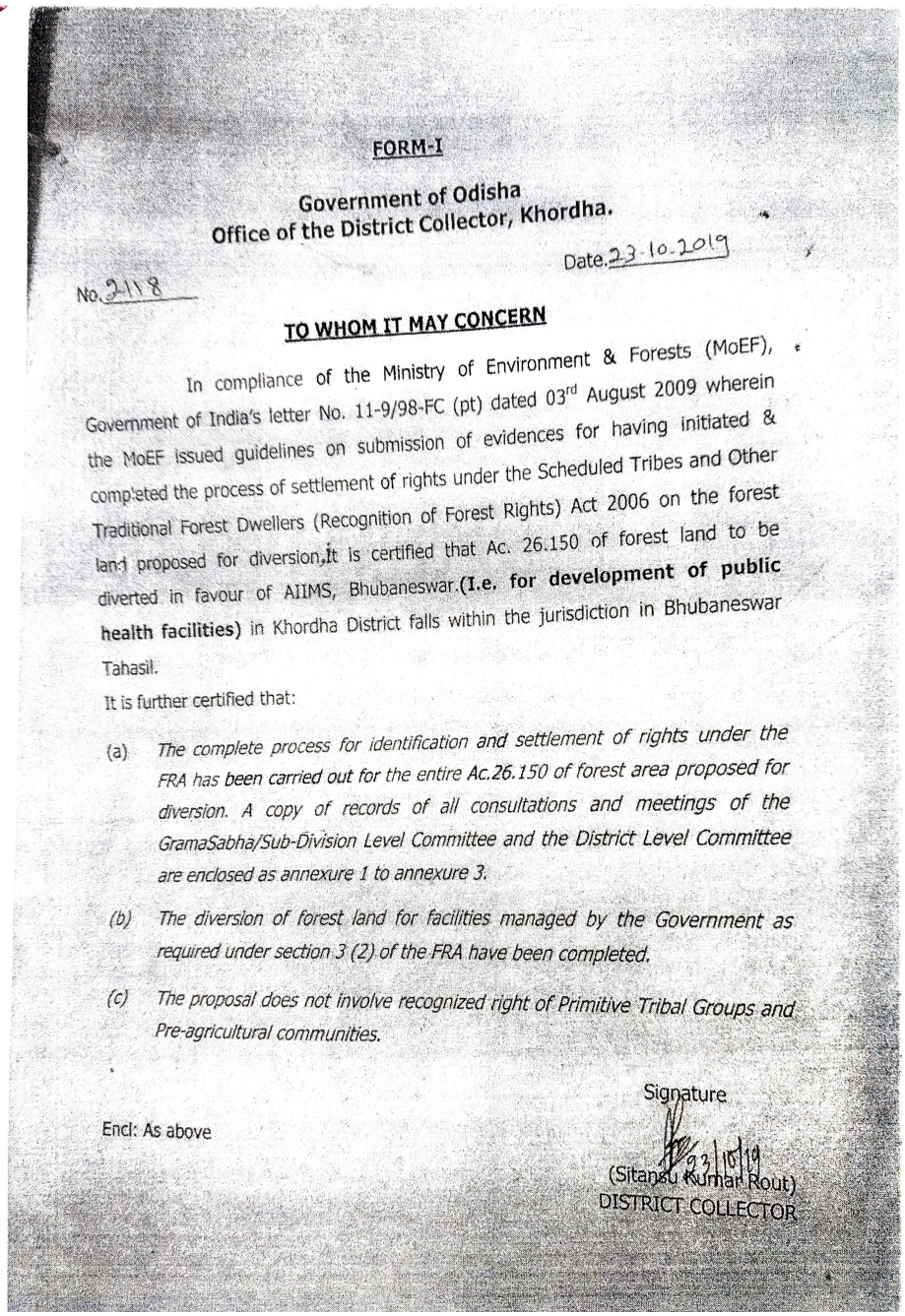


Figure A6: Cumulative Distribution of Weighting Variable

Note: The x-axis measures the total number of birdwatching trips taken by a user in a district-time period. Data are truncated at the 95th percentile to remove outliers. The y-axis is the percentage of observations with values less than the x-axis value.



FORM-I

Government of Odisha
Office of the District Collector, Khordha.

Date. 23-10-2019

No. 2118

TO WHOM IT MAY CONCERN

In compliance of the Ministry of Environment & Forests (MoEF), Government of India's letter No. 11-9/98-FC (pt) dated 03rd August 2009 wherein the MoEF issued guidelines on submission of evidences for having initiated & completed the process of settlement of rights under the Scheduled Tribes and Other Traditional Forest Dwellers (Recognition of Forest Rights) Act 2006 on the forest land proposed for diversion, it is certified that Ac. 26.150 of forest land to be diverted in favour of AIIMS, Bhubaneswar. **(I.e. for development of public health facilities)** in Khordha District falls within the jurisdiction in Bhubaneswar Tahasil.

It is further certified that:

(a) *The complete process for identification and settlement of rights under the FRA has been carried out for the entire Ac.26.150 of forest area proposed for diversion. A copy of records of all consultations and meetings of the GramaSabha/Sub-Division Level Committee and the District Level Committee are enclosed as annexure 1 to annexure 3.*

(b) *The diversion of forest land for facilities managed by the Government as required under section 3 (2) of the FRA have been completed.*

(c) *The proposal does not involve recognized right of Primitive Tribal Groups and Pre-agricultural communities.*

Signature

Encl: As above

23/10/19
(Sitanshu Kumar Rout)
DISTRICT COLLECTOR

Figure A7: Example Letter of Informed Consent

Note: Figure shows scanned letter from Principal Secretary of State Forest Ministry (Rajasthan) approving proposal for deforestation of 185 hectares for irrigation project. Encroachment area, district, and state are extracted for construction of manual sample. Additional fields from the actual proposal/application itself is only provided for the digital sample.

B Online Appendix

B1 Infrastructure Sample Construction

Table B1: Procedure for Project Categorization

Raw Entry	Recategorized Entry
hydel, sub station, thermal, transmission line, village electricity, wind power, solar power	Electricity
road, railway	Transportation
canal, irrigation, drinking water	Irrigation
forest village conversion, rehabilitation	Resettlement
mining, quarrying, borehole prospecting	Mining
Everything else	Other

Note: The left column is the verbatim project categories as entered in application by the firm. The right column describes the synthesized categories for the purpose of simplifying project types.

Sample Construction and Digitization. The project sample consists of projects approved between 2015-2020. Applications submitted after 2014 (N=6,597) were scraped from the online portal (the digital subsample). Applications submitted before 2014 but approved afterwards (N=1,732) were manually digitized (the manual subsample). The application itself was not available for the manual subsample, but a PDF of the approval letter listing project size, location etc., along with other bureaucratic documents, was available in the portal.

The manual subsample was digitized as follows. First, a PDF of each approval letter was downloaded. The district of each project was extracted from the subject header (see Figure A1) and cross-checked online. If only the village was given, the district was identified on Google. Second, project size (hectares approved for forest diversion) was also extracted from the letter. For projects that span multiple districts (e.g. roads), a separate document called "Form A" (also available in the portal) was downloaded to identify hectares per district. 26 multi-district projects did not specify a district-wise breakdown, in which case total project size was divided equally across districts. Lastly, project category was extracted from the letter. In some cases it was taken from the Form A document which includes a detailed project description[29] .

Project Categorization. Verbatim project categories often refer to the same type of project. To simplify the analysis, I re-categorize projects according to Table B1[30]. Because of inconsistencies in raw data entry by firms, I manually examine and reassign projects mistakenly categorized as "other". "Other" project descriptions with the word "power", "substation", and "kv" are placed in the Electricity category. "Other" projects with the word "resettle", "relocate", and "pattayam"[31] are placed in the Resettlement category.

District Splitting. I address the problem of district splitting and name changes. In the application, district name is an unstructured string with many spelling inconsistencies. To form a consistent matching key, I link the official district names and codes from the 2011 Census. To do this, I first manually rename district names to their original 2011 census name if there was a name change after 2011. Second, in the case of a district split after 2011, I rename the "child" districts to the name of the 2011 "parent" district.

[29] The category of each project in the manual subsample was available digitally, and scraped, but the majority were listed as "Other". I thus opted to categorize them based on the subject header text (see Figure A1)

[30] There are 89 projects categorized as "industry" which together make $< 0.1\%$ of total area cleared during the study period. For this reason, I include industrial projects in the "other" category.

[31] *Pattayam* means land deed and refers to a scheme for providing land to the landless, typically tribal families.

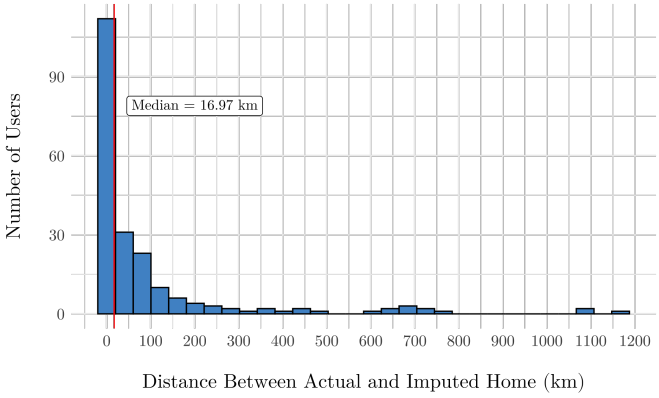


Figure B1: Distance between real and imputed home locations

Note: Data are from 210 eBird users who volunteered their actual home locations. Distance is the straight-line distance between their actual home and the gravitational centre of their trips, accounting for outliers (imputed home).

These two steps produce a single geographical unit that can be tracked consistently across years. Third, I perform a fuzzy match between district names in the application and the 2011 key using the Levensthein distance between the district strings. This algorithm identifies the official census code for 98% of districts in the application sample. The remaining 2% (8 districts) represent districts with more complex redrawing procedures and are dropped.

Panel Aggregation. I transform project-level data into a district-monthly panel in three steps. First, since each project can span multiple districts (e.g. roads), I reshape the data from project to project-district level. Each row contains the project component area falling into a specific district. The sum of rows for a single project equals total project size. Second, I aggregate to the total forest area diverted in each district and year-month, overall and category-wise (e.g. total deforestation in January 2018 for electricity projects in Delhi). Third, I balance the panel by assuming districts and time periods not in the portal had zero stage-II approvals.

B2 User Demographics

eBird does not release data on user demographics. This appendix describes a method for inferring demographics when official data is unavailable. First, I impute user home locations as the gravitational centre of their trips. Second, I compare the distribution of user home locations to the general population to see whether they are rural or urban. Lastly, I characterize users more precisely by studying respondents from a large household survey who live near eBird users. The last two steps are inspired by Blanchard et al. (2023).

User Home Locations. Home is defined as the gravitational centre of users' trips. I start with the full sample frame (all protocols) and find the centroid of users' trips. Since trips far away from the main cluster (e.g. trips during vacation) warp the centroid, I drop outliers and then re-compute the home. Outliers are identified by computing the straight-line distance from home to each trip destination, and then dropping those with distances below Q1-1.5*IQR or above Q3+1.5*IQR, where Q1 and Q3 are the first and third quartiles, respectively.

This method produces a fairly accurate approximation of home location. 210 users volunteered their real home locations, which I use for corroboration. I compute the straight-line distance (in km) between their real and imputed home. Figure B1 shows the distribution of offsets. The median difference is only 17km, which suggests considerable accuracy of the imputation.

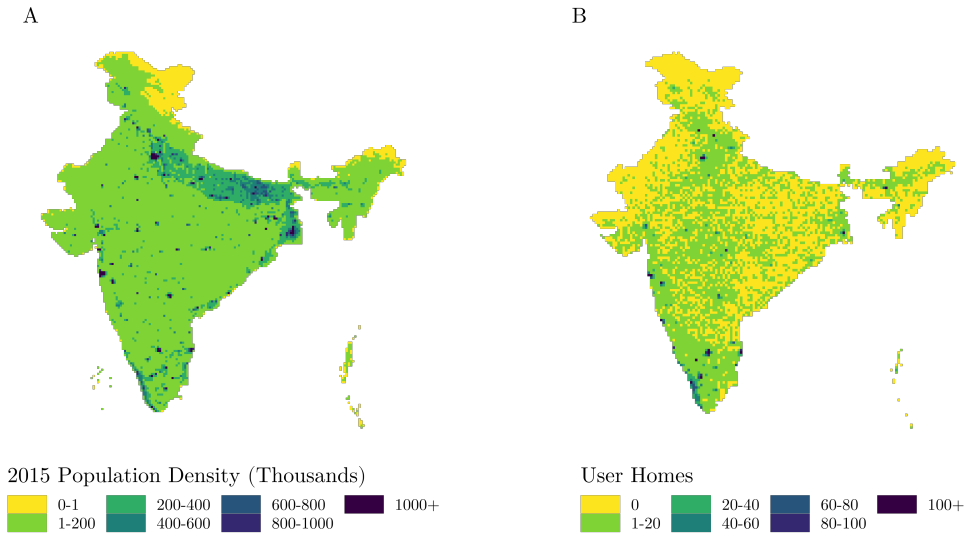


Figure B2: Population density of overall population and eBird users

Note: Both maps are at 20km resolution. Panel A) is the total population count in a cell from WorldPop. The method used for calculating population counts is described in the manual: https://www.worldpop.org/methods/top_down_constrained_vs_unconstrained. Panel B) shows the count of eBird user home locations in each cell.

I acknowledge this check is based on a selected sample. However, a similar imputation is applied for estimating eBird travel costs by Kolstoe and Cameron (2017), who received special access to eBird member profiles (including home address) for a much larger sample. Their results are robust to using imputed and real home locations.

Where Do Users Live? To visualize how representative users are in terms of where they live, I map the imputed homes of all 17,634 users in my analysis against gridded population density data for India. User density is mapped by constructing a 20 $\times$ 20km resolution grid and counting the number of user homes in each cell. Population density for 2015 is obtained from WorldPop[32]. Data are at 1km resolution and aggregated to 20km for consistency.

The dark hotspots in panel A of Figure B2 are India's largest cities. Many of these cities are also home to the highest density of eBird users (Panel B). While it may be unsurprising that eBird users live in big cities, Panel B also shows many remote eBird users (green).

To assess representativity, I compare the fraction of users living in "mega-cities" with more than 1 million population to that of the overall population. City polygons are obtained from the Global Rural-Urban Mapping Project (GRUMP), and I add a 3km buffer to include suburbs. Overlapping boundaries are dissolved into a single region. Extracting WorldPop counts over these polygons reveals that 27% of the Indian population live in megacities. The equivalent number for eBird users is 43%.

Location Profiles from the DHS 2015-16 Survey. As a last step to characterize eBird users, I draw on the DHS, a nationally representative household survey of 600,000 households. Households are grouped into georeferenced clusters, usually a village or town. There are 28,395 clusters with available coordinates. My goal is to identify clusters comparable to where eBird users live. The main challenge is that DHS geocodes are displaced to ensure confidentiality. Urban and rural clusters are displaced by up to 2 and 10 kilometres, respectively.

I start by defining eBird users as urban if they live in cities and rural if not. Cities are defined by GRUMP polygons (see above). Next, I identify DHS clusters within 5km of urban user homes and 10km of rural user homes to account for displacements. This may generate mismatched pairs if, for example,

[32]Data accessed from: https://www.worldpop.org/. I use the 1km resolution unconstrained mosaic.

Table B2: T-test for equality of means between matched eBird and DHS samples

Variable	All	Urban	Rural
HH Size	-0.375***	-0.193***	-0.341***
Cellphone (=1)	0.053***	0.013***	0.040***
Fridge (=1)	0.253***	0.089***	0.181***
Car (=1)	0.089***	0.056***	0.067***
Sep. Kitchen (=1)	0.139***	0.035***	0.190***
Colour TV (=1)	0.212***	0.045***	0.190***
Internet (=1)	0.110***	0.062***	0.041***
Washing Machine (=1)	0.191***	0.109***	0.101***
Flush Toilet (=1)	0.271***	0.053***	0.216***

Note: * $p < .1$, ** $p < .05$, *** $p < .01$. Difference in characteristics between DHS respondents living in similar locations as eBird users compared to the overall DHS survey. The former dataset is weighted by the number of users to which each cluster is matched and the latter uses DHS survey weights. Robust standard errors are bootstrapped.

a user living in a Delhi suburb is matched to a nearby rural cluster as well as urban clusters inside Delhi. Therefore, I only keep matches if the population density of the DHS cluster is within 25% of that in the user's home location, both calculated over a 5km buffer. This method matches 61% of users with at least one comparable DHS cluster. Note that the same cluster can match to several nearby users, resulting in duplicates. This is equivalent to a weighted dataset of unique DHS respondents with weights equal to the number of users to which the cluster is matched (Blanchard et al., 2023). I call this the "matched eBird" sample.

This procedure presents a new way to assess whether eBird users live in locations that are statistically similar to the average population. As such, the citizen scientists of India can be characterized in a data-poor context. I compare users along several wealth indicators reported in DHS, including: household size and ownership of various physical assets. T-tests for equality of means are conducted between the matched eBird sample and the overall DHS sample, with bootstrapped standard errors robust to heteroskedasticity. Survey weights are used for the overall sample and the number of matched users for the matched eBird sample.

Table B2 shows the results. Overall, there are statistically significant differences in wealth between the matched and overall sample, indicating that eBird users live in non-representative locations. Compared to the overall population, eBird users live in places with smaller household sizes and better access to amenities such as a fridge, car, separate kitchen, and flush toilets. These differences persist even within rural and urban subsamples. Put differently, the urban locations where eBird users live are wealthier than the average urban location. Yet it should also be noted that these wealth differences are quantitatively small. Thus, while eBird users live in places that are not nationally representative, these places are not markedly atypical either.

B3 Close Election Design: Context and Data

Section 6.7 of the main text tests robustness of the infrastructure-biodiversity tradeoff to an instrumental variables strategy based on close elections between incumbents and runner ups. The fraction of constituencies in a district where the incumbent won in close elections is used as an instrument for infrastructure approvals. Identification is based on comparisons of eBird observations among users travelling between places where incumbents just barely won to those where they just barely lost. This appendix outlines the political context and data construction details.

Context: India has a federal structure with national and state assemblies. States are partitioned into ad-

ministrative districts, which are politically significant units since States appoint several officials at this level, including a District Forest Officer. Districts are further split into single-member State Assembly constituencies with a leader elected through a simple majority (first-past-the-post) voting rule. The constitution requires state elections every five years, although elections are not synchronized across states. One limitation is that my 6-year panel is shorter than ideal for estimating the impact of elections on infrastructure and biodiversity. However, this drawback is partially mitigated by the staggered nature of state elections. There are 32 statewide elections across 30 states during the study period.

Data: Election data are from the Trivedi Center for Political Data and distributed through the Socioeconomic High-Resolution Rural-Urban Geographic Dataset on India (SHRUG) (Asher et al., 2021). Both winner-level and candidate-level data are available at the constituency level. The main data include candidate party, election year, and vote share. First, in each election year, I use the winner-level data to identify the winner party in the previous election. Next, I use the candidate-level data to identify incumbent candidates based on whether their party is the same as the previous election winner. 94% of constituencies had an incumbent go up for re-election. Lastly, I compute the win margin as the difference in vote shares between the winning candidate (highest vote share) and runner up (second highest vote share). Elections are quite competitive: half of elections in my sample were decided by margins $<$ 10%. In the main analysis, I classify "close" elections as those decided by margins within 2 percent.

Election data are at the constituency-year level whereas the eBird panel is at the user-district-month level. I use the crosswalk provided in the SHRUG to link constituencies to districts. There are an average of 6 constituencies in a district. I aggregate win margins and close-election dummies to the district level. The latter creates measures of "winning party strength" i.e., the fraction of constituencies with close elections and with incumbent winners. This strategy follows on previous studies that have studied electoral impacts by aggregating over constituencies (Anukriti et al., 2022; Cole, 2009; Clots-Figueras, 2012)