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Ruling the roost: Avian species reclaim urban habitat during India's COVID-19 lockdown

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ABSTRACT

As we retreated to our dwellings in the "anthropause" of spring 2020, were the wildlife sightings in previously crowded spaces a reclamation of habitat, or a mere increase in detection? We leverage an increase in balcony birdwatching, a million eBird entries, and difference-in-difference techniques to test if urban avian species richness rose during India's COVID-19 lockdown. Controlling for effort, birdwatchers in the 20 most populous cities observed a 16% increase in the number of species during lockdown. While human activity stopped overnight, and noise and visual pollution decreased soon after, increased species diversity was observed 1–2 weeks later; evidence that gradual population recovery, not better detection, underlay our results. We find at-risk, and rare, species among those reclaiming cities, implying that reducing human disturbance in urban areas can protect threatened species. Increased species diversity likely derives from a reduction in noise and air pollution associated with the lockdown, implying that urban planners should consider conservation co-benefits of urban policies when designing sustainable cities.

1. Introduction

On March 27th, 2020, three days after India's abrupt cessation of human activity, a reporter posted a video on Twitter of a Sambar deer crossing a road in Chandigarh—among India's most population dense cities (Ghazali, 2020). Two days later, in the same city, a leopard was seen and tranquilized (Tribune News, 2020). Similar sightings were reported elsewhere; a Nilgai walked along a usually bustling street in a Delhi suburb, a critically endangered Malabar Civet wandered alongside traffic in Kozikhode, Kerala, and flamingos returned in unusually large numbers to the Mumbai wetlands (Guy and Gupta, 2020). These sightings were not unique to India. As countries reined in human activity to fight the spread of COVID-19, animals were reported in urban locations across the globe, including pumas in Santiago, Chile, dolphins in the Bosphorous, mountain goats in Wales, and deer in Nara, Japan, and Romford, UK. Were these chance sightings, or a systematic increase in animal presence in previously forbidding urban areas? The cascade of global COVID-19 lockdowns provides a unique opportunity to shed light on this (Bates et al., 2020; Rutz et al., 2020).

Here, we use citizen science data from before and during India's lockdown to evaluate how the "anthropause" (a term coined by Rutz et al. (2020)) affects urban avian diversity. We also investigate if changes in avian diversity derive from a change in abundance, or from improved detection. Finally, we employ a species level analysis to provide a deeper understanding of the avifauna repopulating the cities in our sample. Together, our findings have important management lessons for optimizing the design of sustainable cities.

We study birds because they are a known proxy for ecological health (Morrison, 1986; Xu et al., 2018), are easily observable, and are among the few animals documented with unparalleled spatiotemporal coverage. We use over one million bird sightings from eBird, the world's largest citizen science platform (Cornell Lab of Ornithology, 2020; Sullivan et al., 2009), to test whether observed species richness in India's 20 most populous cities rose during the COVID-19 lockdown. As wildlife surveys stalled under lockdown (Corlett et al., 2020), eBird usage soared (Hochachka et al., 2021). This allows us to present a robust and comprehensive analysis of our question.

India is among the best settings to learn about human-wildlife interactions. It juxtaposes a backdrop of unrivaled biodiversity, home to 12% of the world's bird species (Jayadevan et al., 2016), against dense urban centres that are particularly forbidding for wildlife. Indeed, 21 out of the world's 30 most polluted cities (IQAir, 2019), and 4 out of the 10

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most traffic congested cities are in India (TomTom International, 2020). These cities typically have noise levels deemed by the World Health Organization as unhealthy for humans (Dantewadia et al., 2020), and featured a deep and sudden reduction in human activity during spring 2020 (see section S1.1 in Supplementary Materials for timeline).

Our methodology addresses two main empirical challenges. First, we establish a credible counterfactual to ensure that eBird entries before and after March 25th 2020 are statistically similar except for the imposition of lockdown. The crux of this strategy is the use of the difference-in-difference (DD) technique (Angrist and Pischke, 2008), with the same 48-day period in 2019 as the basis for our counterfactual. Second, we ascertain if changes in observed species diversity represent changes in animal behaviour (abundance) or human behaviour (detection ability). Several studies discuss this in detail (Manenti et al., 2020; Simons et al., 2007; Williams et al., 2002), yet few show how to disentangle these competing mechanisms. Here, we introduce a way to separate the abundance and detection mechanisms by estimating impacts over time. As changes in human activity, and associated reductions in noise and pollution, occur almost immediately after lockdown, any sizeable lag suggests that changes in avian presence rather than improved detection underlie our results.

2. Methods

2.1. Selecting a counterfactual

To estimate the causal impact of India's lockdown on avian diversity, we need to compare observed species richness during lockdown with a counterfactual when lockdown never occurred. The weeks prior to lockdown are inappropriate as the available species pool differed. Migratory species arrive during India's warm winter and depart in Spring, coinciding with the lockdown period (Veen et al., 2005). A simple pre-post comparison thus conflates lockdown with species migration.

We choose the same period in 2019 as our counterfactual. The assumption being, had lockdown not occurred, species richness would have evolved as it did during the same 48-day window in 2019 (the parallel trend assumption). The difference in species richness before and after the fourth Wednesday in March 2019 captures species migration, and we subtract this from the pre-post difference in 2020. Any remaining "difference in differences" (Angrist and Pischke, 2008) is devoid of the bias from migration (see S1.6 for a mathematical derivation).

For this method to work, we first need to establish that species diversity during March and April 2019 was not systematically different from other non-lockdown years. To verify the robustness of our counterfactual, we compare the daily mean species richness per trip on a given day in 2019 to the same day in 2018. Since there was no lockdown in either year, we expect no difference in daily species richness. Fig. S5B confirms this, showing no systematic difference between 2019 and 2018 and thereby validating the robustness of our choice of 2019 as the counterfactual period. See Section S1.7.2 for more details on this placebo check.

2.2. Mitigating selection bias

Whereas our counterfactual accounts for species migration, it does not account for the changing nature of birdwatching after March 25th 2020 (see Section S1.4). We use a DD design that eliminates biases from these contemporaneous changes by taking advantage of eBird's requirement to enter a trip protocol (e.g., stationary or travelling; Table S1) and other trip characteristics alongside a species checklist (see Section S1.2). Immediately following lockdown, there is a near-quadrupling of stationary users across India (Fig. 1A) and the number of trips they report (Fig. 1B), consistent with reports of surges in balcony birding in isolation (Fortin, 2020). Correspondingly, there is an unsurprising reduction in users taking travelling trips. To exclude new sign-ups, who likely have different characteristics than their pre-lockdown counterparts, we impose a participation constraint to compare checklists from a constant user base (Section S1.4, Table S3). In our preferred sample, only users recording at least two trips in the 24 days before and after lockdown—called consistent users—are selected.

Before lockdown, collective species richness was substantially higher on travelling trips compared to stationary ones, because users could venture deeper into bird habitats (Fig. 1C). After lockdown, this trend reverses as travelling becomes restricted, resulting in a species richness *decline* when protocols are pooled (Fig. S1). Within stationary trips, however, species richness generally *increases* post-lockdown. Thus, we make all pre-post comparisons within trips of the same type to remove the protocol bias.

Additional biases arise from the changing schedule of birdwatching during lockdown (Fig. 2) and rural-urban differences (discussed in Section S1.4). We use hour-of-day fixed effects to control for the former and restrict our analysis to the top 20 densest cities (Table S2) to control for the latter.

Lastly, we control for a range of climatic and behavioural variables—including weather and trip duration—that change during our study window and also impact species diversity (Section S1.5). For

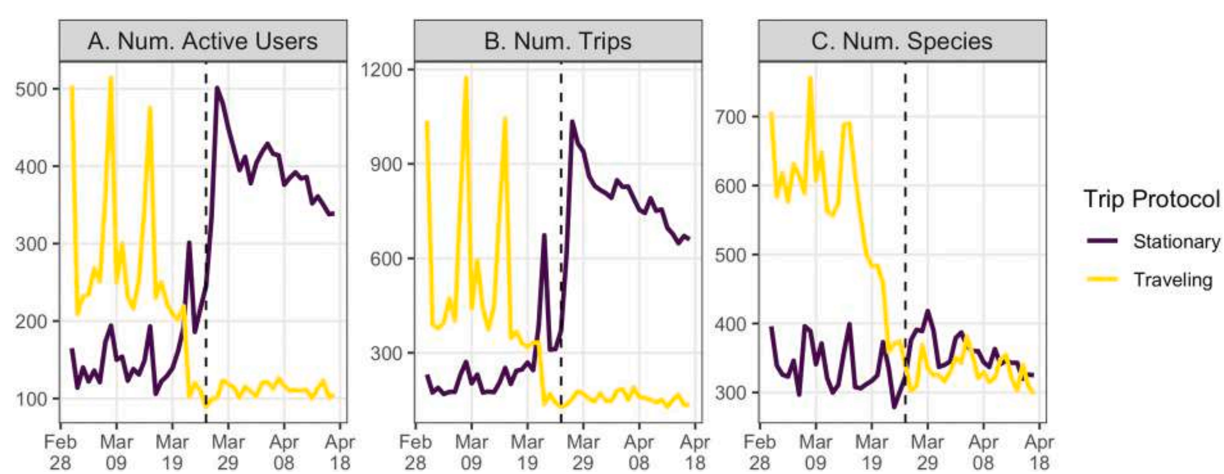

Fig. 1. Daily birdwatching activity in India from eBird trips reported between March 1st and April 17th, 2020. Data is pre-processed as described in Section S1.3. Panel A) plots the number of unique user ID's active each day; panel B) plots the total number of daily trips; panel C) plots collective, daily species richness. The vertical dashed line denotes lockdown (March 25th, 2020).

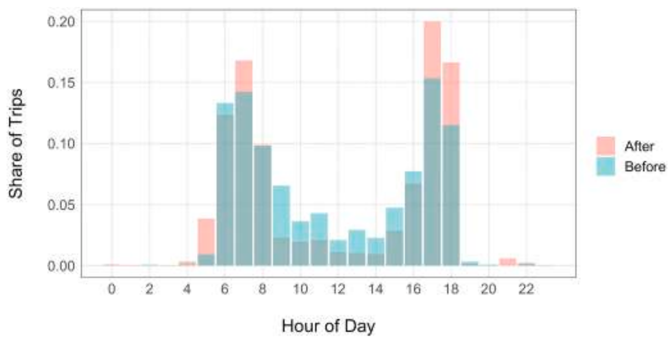

Fig. 2. Hour-of-day distribution of eBird trips reported in 2020 in the top 20 cities by population density. Data covers consistent users who recorded at least two trips in each of the 24 days before and after lockdown. Janta Curfew (March 22nd) is dropped.

example, mean temperature was 2° warmer during lockdown compared to the 24 days prior (Table S4B). Equivalent warming is also observed across the same period in 2019. In contrast, rainfall was 0.2 mm higher during lockdown compared to before, whereas in 2019 rainfall *decreased* over the same period. Our climatic controls account for such weather aberrations relative to the counterfactual so that species observations before and after March 25th 2020 are statistically similar except for the imposition of lockdown, delivering precise estimates of the ecological impact of lockdown in India's urban core.

2.3. Difference-in-difference model

Combining our counterfactual with the procedure for mitigating selection bias, we proceed to estimate the DD specification (Angrist and Pischke, 2008). The goal is to compare changes in outcomes in a treatment group before and after a policy date (the first difference) with changes in outcomes over the same period in a counterfactual where the policy was never implemented (second difference). We estimate:

$$SR_{ijdyt} = \alpha + \delta\left[Treatment_y \times T_t\right] + \gamma\left[Treatment_y\right] + \lambda[T_t] + X_{ijdyt} + \eta_p + \mu_d + \theta_t + \varepsilon_{ijdyt} \tag{1}$$

where SR_{ijdyt} is species richness observed by user i on trip j in district d during year y and day-of-year t. $Treatment_y$ is a dummy for 2020. T_t is a time dummy for the post period $t \in [Policy_t, Policy_t + 24]$, where $Policy_t$ is the 4th Wednesday of March—the "policy date". The pre-policy period in 2020 is March 1st until $Policy_t$, and the post-policy period spans 24 days afterwards. X_{ijdyt} is a vector of weather and trip covariates (Section S1.5). η_p is a protocol fixed effect that ensures all pre-post comparisons are made among trips of the same type. μ_d is a district fixed effect and ensures comparisons are made across trips within the same district (Table S2). θ_t is a set of temporal controls including hour-of-day fixed effects and weekend fixed effects. δ is our parameter of interest, denoting the causal impact of India's COVID-19 lockdown on species richness. Section S1.6 provides a detailed mathematical derivation.

2.4. Dynamic difference in differences

The term δ in Eq. (1) captures an average impact over 24 days of lockdown. We decompose this to parameterize marginal effects over time in order to investigate whether our estimates represent actual changes in species presence, or whether birds are just easier to observe in the absence of human activity. A reduction in noise pollution associated with the reduction in human activity—as found by Mishra et al. (2021) during India's lockdown—may lead to an increase in species detection. Indeed, Simons et al. (2007) find that detection probability is 42% lower with 10 dB of white noise. Since human activity stopped overnight, a lag between lockdown and higher species diversity suggests a gradual recovery of species. We estimate:

$$SR_{ijdyt} = \alpha + \sum_{k=-4}^{K=4} \delta_k\left[Treatment_y \times T_k\right] + \gamma\left[Treatment_y\right] + \sum_{k=-4}^{K=4} \lambda_k[T_k] + X_{ijdyt} + \upsilon[d \times t] + \eta_p + \mu_d + \theta_t + \varepsilon_{ijdyt} \tag{2}$$

where δ_k is the DD estimate in time bin k. We use 8 bins with 6 days each so that every bin has the same number of days (48 days/8 bins = 6 days per bin). $k = (-6, 0]$ is omitted so that all estimates are relative to the six days before (and including the day of) lockdown. We also include a district level time trend, $d \times t$, to control for a linear district-specific trend in species richness that may be observed even in the absence of lockdown. All other parameters are defined and interpreted in the same way as Eq. (1).

2.5. Marginal species identification

SR_{ijdyt} measures changes in the *number* of species, but not *which* ones are seen more or less often during lockdown. Thus, we conduct a species-level analysis to complement our DD estimates. We use the same sample used in our DD regression and calculate frequency distributions for individual species in 2019 and 2020 in Bangalore and Delhi—two cities with the most eBird activity. We then identify 28 "marginal" species (out of 211 total) in Bangalore and 30 (out of 147) in Delhi according to three criteria: a) the average daily proportion of checklists reporting the species after the policy date is higher in 2020 than 2019; b) the average daily proportion of checklists reporting the species pre-lockdown in 2020 is no more than in 2019, thus excluding species consistently more common in 2020; c) the species is observed on at least seven days in the post-lockdown period in 2020.

Having established which species are observed more often during lockdown, we classify the rarity of these marginal species at a global and local level. For the global classification, we list the IUCN Red List category. Since this may misrepresent the local threat level, we classify a species as locally rare if their 2019 reporting frequency is in the bottom 25th percentile, a common threshold in the literature (Gaston, 1994).

Note that δ in Eq. (1) reveals the *net* change in species diversity during lockdown. Whereas the marginal species analysis identifies those observed more often, there may also be species that retreated away during lockdown. For completeness, we investigate this opposing scenario by reversing the criteria above. This procedure identifies species observed *less* frequently during India's lockdown, which we call retreating species.

3. Results

3.1. Lockdown increases species diversity in cities

Before turning to the formal regression results, we first illustrate our research design, without controls or fixed effects. Fig. 3 shows mean species richness per trip on a given day in 2020 relative to that on the same day in 2019. Species richness on travelling trips drops after the fourth Wednesday in March (the policy date), but gradually increases among stationary trips, compared to 2019. This corroborates a story of recovering species abundances (or diversity, see Discussion in Section 4). Importantly, in the absence of lockdown (left of vertical dashed line), there was no systematic difference in species richness between 2020 and 2019, bolstering our choice of 2019 as the counterfactual. Fig. S2 shows the same illustration for number of users and trips. Stationary activity spikes and travelling activity drops after the 2020 policy date compared to 2019 due to mobility restrictions in the former but not latter.

The formal DD estimates (Eq. (1)) show robust evidence that a reduction in human activity increases observed avian diversity (Fig. 4A).

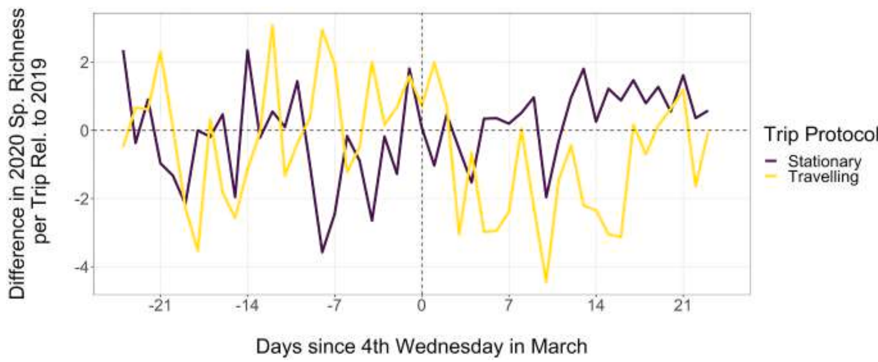

Fig. 3. Daily species richness in 2020 relative to 2019 in India. Selected users meet 2-trip participation constraint in both years. The policy date (dashed vertical line) is the 4th Wednesday of March, the date of lockdown announcement in 2020. Solid lines describe mean species richness per trip across users on a given day in 2020 minus the value from the same day in 2019.

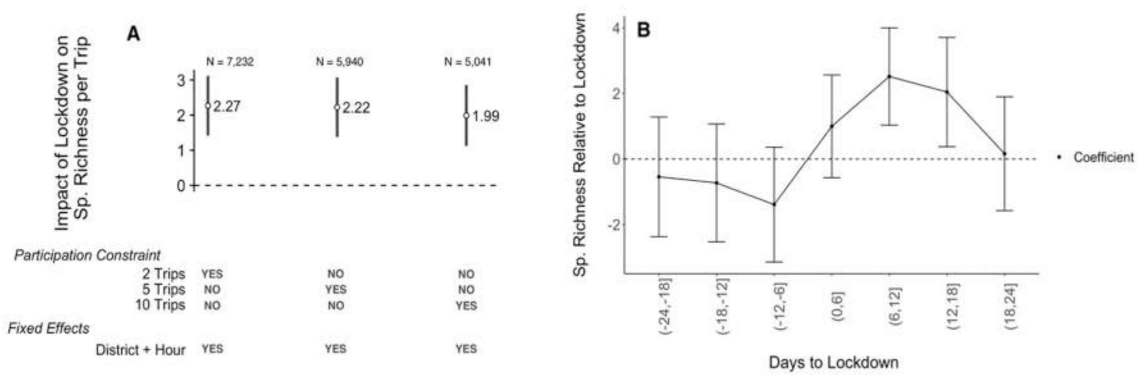

Fig. 4. Difference in difference results. White circles in panel A) describe the main DD estimate from Eq. (1). Panel B) shows the dynamic estimates from Eq. (2). The x-axis denotes 6-day time bins and negative values denote days before lockdown. In both panels, bars show 95% confidence intervals, the estimation sample is pre-processed, covers the top 20 cities, and data from March 22nd, 2020 (the Janta Curfew) are dropped. All regressions include district, hour-of-day, and protocol fixed effects as well as controls for trip duration, rain, temperature, number of observers, distance to nearest birding hotspot, and a weekend dummy. Standard errors are robust to heteroskedasticity.

The first coefficient—our preferred specification—shows that India's COVID-19 lockdown increases species richness by 2.27 species per trip ($p < 0.01$) in the top 20 cities, equivalent to 16% of the pre-lockdown mean. The other two coefficients show that tightening the participation constraint to five and ten trips yields point estimates of 2.22 (16% increase) and 1.99 (14% increase), respectively. Since more experienced users are selected when the participation constraint tightens, the number of selected users drops and sample size reduces each time.

Next, we decompose the DD estimates into weekly bins (Eq. (2)) to investigate whether our estimates represent changes in animal or human behaviour. The increase in species richness is detected after a one-week lag ($p < 0.01$), and persists through the second week of lockdown (Fig. 4B). The district-time trend in Eq. (2) ensures that these weekly estimates reflect deviations from a linear trend, thereby identifying the impact of lockdown and not a trend in species richness that would have occurred regardless. Pre-lockdown, there is no statistical difference in week-to-week species richness between 2020 and 2019, providing formal support for the parallel trend assumption.

Our results are robust to a variety of alternative specifications (see Section S1.7). Including all cities in India, instead of only the top 20 most population dense ones, reduces the point estimate nearly three times. This is due to the inclusion of rural areas where human activity was less affected by the lockdown (Fig. S3, column 2). Despite the participation constraint and effort covariates, we also try a specification with user fixed effects to capture differences in ability between users. However, since very few users are observed during the pre- and post-period in both 2019 and 2020, we cannot add a user fixed effect directly in Eq. (1). Instead, we compute the pre-post difference in species richness in each year separately with a user fixed effect, and then manually subtract the coefficients (this is mechanically equivalent to our DD specification). We continue to find increased species richness during lockdown, but precision decreases because there is substantially less variation within a user and therefore larger standard errors (Fig. S3, columns 3 and 4).

We also estimate our dynamic specification under the five-trip participation constraint. The increase in species richness in the first and second week of lockdown is once again observed (Fig. S4). The magnitude and precision are similar to that in Fig. 4B, and there is also no pre-trend leading up to the policy date.

Lastly, our results are also robust to the level of aggregation (Section S1.7.3). We re-estimate our main specification at the city-level using mean species richness per trip across all trips recorded in a city-day, weighted by the number of trips in the day. The coefficients are largely similar to our main results at the trip level (Fig. S7). See Section S1.7 for more details as well as additional sensitivity checks.

3.2. *Both common and rare species repopulate cities*

Fig. 5 illustrates frequency distributions for four marginal species in Bangalore and Delhi (see Fig. S5 for full set). In Bangalore, the Black-rumped Flameback Woodpecker is never reported in 2019, and never reported in the pre-period of 2020, but we find several reports of the species 1–3 weeks into lockdown. In Delhi, the Black-rumped Flameback is reported by a larger proportion of checklists in the pre-period in both

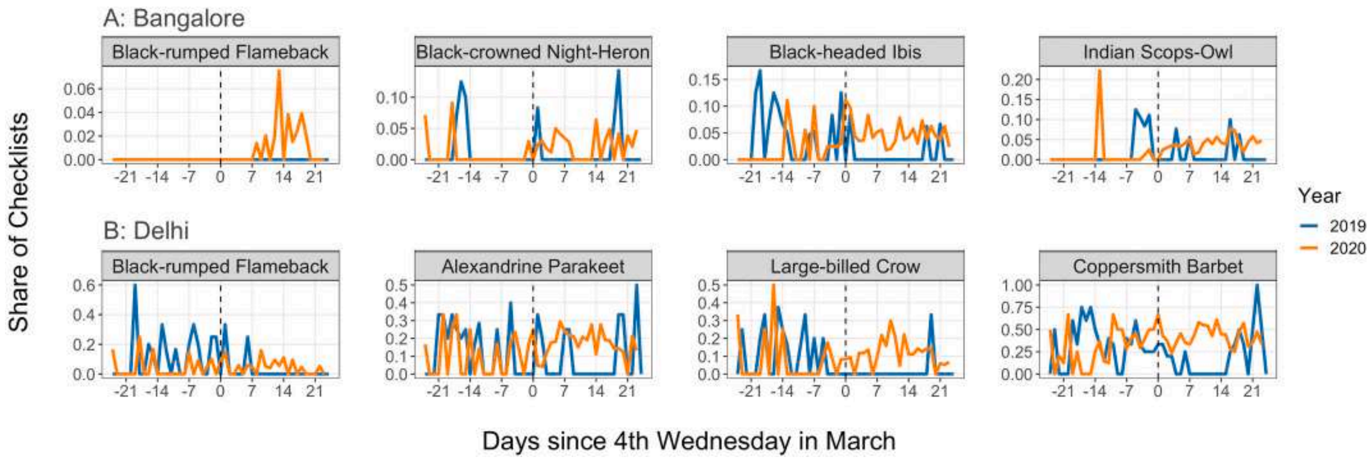

Fig. 5. Marginal species distributions of four example species in Delhi (panel A) and Bangalore (panel B). The x-axis is the number of days relative to the 4th Wednesday of March, the lockdown date in 2020. The y-axis is the share of checklists reporting the species on a given day. The sample of checklists consists of stationary trips from the main regression sample under the 2-trip participation constraint. Distributions for remaining marginal species are shown in Figs. S9 and S10 in the Supplementary materials.

years. In 2019, however, it is no longer observed during the post-period, but in 2020, continues to be reported throughout lockdown. A similar pattern is seen for the Large-billed Crow in Delhi: reported by a similar proportion of eBird checklists in the pre-period of 2019 and 2020, but mainly observed in the post period in 2020.

Among marginal species in Delhi and Bangalore, a handful are rare and the majority are common species detected more frequently. The IUCN classification yields two globally near-threatened species: the Black-headed Ibis in Bangalore and the Alexandrine Parakeet in Delhi (distributions in Fig. 5). The remaining marginal species in both cities are Least Concern. Our local rarity criteria classify seven (out of 28) marginal species in Bangalore (Table S5) as locally rare and six (out of 30) in Delhi (Table S6).

In stark contrast to the 28 marginal species in Bangalore and 30 in Delhi, we find five retreating species in Bangalore and only one in Delhi. This indicates that the increase in abundance and diversity of species during lockdown more than compensates for the few species simultaneously exiting urban spaces. Figs. S9 and S10 show frequency distributions for these species in Bangalore and Delhi, respectively. In Delhi, the Rosy Starling is never reported in the pre-period of 2019 or 2020. In the post-period, however, it is observed less frequently on average in 2020 compared to 2019. In Bangalore, most retreating species are observed at similar daily frequencies in both years, but slightly less often in the 2020 post-period. Unlike "true" marginal species—such as the Black-rumped Flameback in Bangalore—there is no equivalent for retreating species in either city (always seen in 2019 and only seen in 2020 pre-period). In terms of rarity, all six species are listed as Least Concern by the IUCN (Table S7).

4. Discussion

Our analysis presents a measurable change in the *viewing* of avian species. The cessation in human activity on March 25th 2020 was abrupt and strongly enforced. If the additional 2.27 species from our DD estimate were always present, but undetected because of distractions from human activity, then users should detect additional species immediately following lockdown (when human activity ceased). We find that balcony bird-watching soars the next day (Fig. 1A, B), but the fact that it takes up to two weeks to detect additional species suggests that the abundance of incumbent species, or the emergence of species previously absent, gradually grew until the probability of detection was high enough two weeks after lockdown (Fig. 4B). On the other hand, the viewing of these additional species seems to return to pre-lockdown levels by the end of the last week of lockdown. We do not have a verifiable hypothesis for why this occurs.

Our species-level analysis confirms that our findings are indeed based on both an increase in the abundance of incumbent species as well as the emergence of previously absent species (Fig. 5). Some species are seen frequently in Delhi and Bangalore before and after the 4th Wednesday of March in both years, but a greater proportion of checklists report them in the post lockdown period in 2020. Some are never seen in 2019 altogether, and only seen in 2020 during lockdown, exhibiting a "true" marginal observation.

Among the marginal species, the Black-headed Ibis in Bangalore, and the Alexandrine Parakeet in Delhi, are globally near-threatened according to the IUCN. At a local level, we classify 25% and 20% of species seen more frequently during lockdown as locally rare in Bangalore and Delhi, respectively. Rare species face greater extinction risk and are more sensitive to environmental changes (Gaston, 1994), making our study useful for allocating scarce conservation budgets. Our results suggest that investment in making our cities more wildlife friendly can also protect some at-risk species, not just the urban specialists.

At least two environmental mechanisms can explain the increase in avian diversity and abundance found in this study. The first is related to noise pollution. The abundance and occupancy of avian species are negatively impacted by noise pollution (McClure et al., 2013; Shannon et al., 2016). Specifically, elevated noise levels mask mating signals and defense mechanisms (Slabbekoorn, 2013). A February 2020 report in LiveMint, an e-paper in India, reports that average noise levels recorded by monitors in residential areas of Mumbai, Delhi, Bengaluru, Kolkata, Chennai and Hyderabad were 10 dB higher than the maximum recommended by the Central Pollution Control Board. For the city of Kanpur, Uttar Pradesh, Mishra et al. (2021) find average sound levels in the range of 42–87 dB before lockdown, and a reduction to 38–66 dB during lockdown (Dantewadia et al., 2020). Since the lockdown reduced traffic and other anthropogenic noise, certain species may reoccupy the landscape in larger numbers. However, lower noise pollution also increases the ability of observers to hear bird calls, but our dynamic DD results (Fig. 4B) show evidence ruling out this alternative explanation.

The second possibility is a drop in air pollution. 21 of the 30 most polluted global cities are in India (IQAir, 2019). This includes 9 cities in our sample. During lockdown, these cities experienced unprecedented reductions in PM2.5 and other pollutants (Mahato et al., 2020; Sharma et al., 2020). Exposure to particulates can reduce species diversity (Liang et al., 2020; Sanderfoot and Holloway, 2017). Therefore, air quality improvements may underlie the higher species diversity we observe. However, lower air pollution, especially particulate pollution, also improves visibility, another important factor for species detection. Again, our dynamic results rule out this mechanism.

Taken together, this paper makes three important contributions to our understanding of anthropogenic pressures on avian diversity. First, we estimate the causal impact of reducing human activity on avian diversity in urban settings (Fig. 4A). We share this contribution with a nascent literature studying the impact of COVID-19 lockdowns on wildlife elsewhere (Vardi et al., 2021). Studies based on pre-COVID data typically evaluate species diversity along an urban gradient (see Chace and Walsh (2006) for a review). Such analyses confound changes in human activity with changes in habitat (Verma and Murmu, 2015; Xu et al., 2018). Instead, we compare species diversity as human activity varies within the same urban habitat.

Second, we present a method separating abundance from detection in observational surveys, something particularly important for studies analyzing avian populations. While technology-based methods capture animal *presence*, observational surveys typically capture species *detection*. Terrestrial species are increasingly monitored with autonomous cameras (Silveira et al., 2003), GPS collars, and radio collars (Cagnacci et al., 2010). In avian surveys, however, human observation remains the primary method to collect data, whether via systematic surveys or citizen science. Despite this, only 5% of 224 ornithology papers reviewed by Rosenstock et al. (2002) address the issue of abundance vs. observation. We formally investigate whether changes in species diversity represent changes in presence, or mere improvements in observer cognition from reduced noise and visual pollution.

Third, we present robust estimates derived from a very large sample collected over a geographically and culturally diverse region, extending external validity to other developing countries where urbanization is accelerating and large swathes of species are imperiled (Jenkins et al., 2013; Myers et al., 2000; Newbold et al., 2016). Many studies estimating the impact of COVID-19 lockdowns on animal presence or behaviour use small samples in distinct study sites in developed countries. For example, Manenti et al. (2020) survey water birds at an artificial lake during Italy's COVID-19 lockdown and find higher species richness compared to 2019. Derryberry et al. (2020) find that birds increase their acoustic distance during San Francisco's lockdown, and possibly improve breeding success (Manenti et al., 2020). In contrast, our estimates represent a statistically robust average impact of reduced human activity on avian diversity for 20 large cities across India.

In addition to the empirical contributions, our results also have important conservation policy implications. Our findings imply that policies influencing human activity, and consequently noise and air pollution, in urban centres also have conservation co-benefits. The most prominent examples of such policies are those managing traffic: congestion pricing, odd-even license plate restrictions, road closures, etc. However, most research evaluating urban traffic policies focus on congestion, air pollution, and human health effects (Farda and Balijepalli, 2018; Kumar et al., 2017; Simeonova et al., 2019; Zhou et al., 2010). Our results imply that researchers and policymakers should also consider their effect on avian (and other species) diversity. By not including these impacts they are likely underestimating policy benefits.

It is also important to note that there are important benefits from bird watching and engaging with nature in its own right (Bratman et al., 2019; Maldonado et al., 2018; Shanahan et al., 2016). A change in the viewing of birds documented in this paper (Fig. 1) represents a change in the well-being for bird-watchers during an unprecedented time. However, it behooves us to recognize that only those with the ability and resources to engage in leisure, in the face of the economic and humanitarian crisis precipitated by the pandemic, may be able to engage in this possibility.

CRediT authorship contribution statement

Raahil Madhok: Conceptualization, methodology, software, formal analysis, data curation, writing original draft, reviewing and editing draft, visualization. **Sumeet Gulati**: Methodology, resources, writing original draft, reviewing and editing draft, supervision, project administration.

Data and materials availability

Further details on data supporting the findings of this study are available in the Supplementary Materials. Raw datasets and code for reproducing summary tables, figures, and empirical estimates are deposited in a github repository: https://github.com/rmadhok/ebird-lockdown.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary material for this article can be found online at https://doi.org/10.1016/j.biocon.2022.109597.

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