The Social Costs of Keystone Species Collapse: Evidence From The Decline of Vultures in India

Online Appendix

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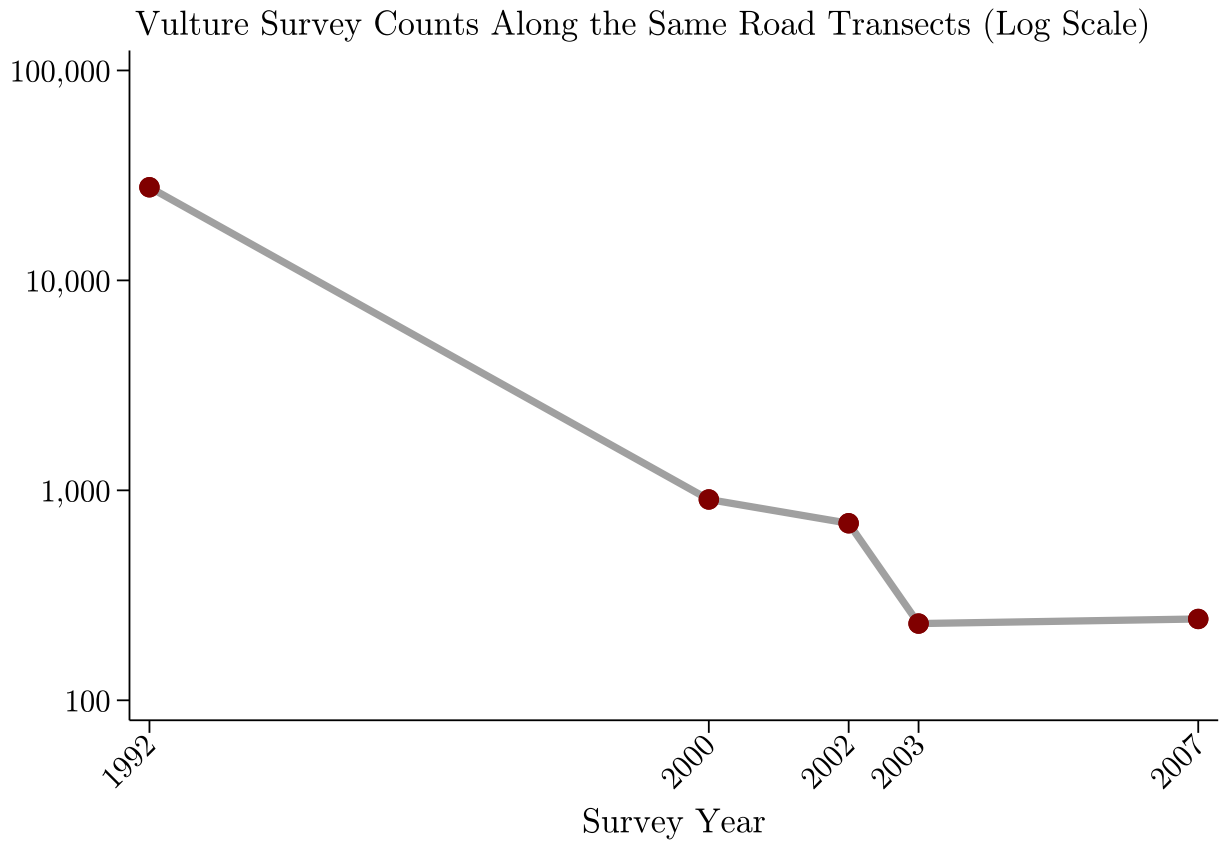
A Additional Results

A.1 Survey Results on Diclofenac-Affected-Vulture Populations

In the main text, we rely on bird observations at a national level to document a decline in vulture populations. However, the reported observations in the Global Biodiversity Information Facility (GBIF) database are likely upward biased as there was likely more attention given to documenting and reporting vultures after it became public knowledge that their populations were in decline. Unfortunately, there are no large-scale repeating surveys of vulture populations as they were always seen as too numerous to count. One exception is a repeating population survey that took place along 70 road transects during the years of 1992, 2000, 2002, 2003, and 2007. That data and survey methodology are reported in Prakash et al. (2007). While some survey years included additional road transects we only use the data from the 70 road transects that were repeatedly surveyed. In Figure A1, we plot the data from the repeated surveys as reported in Prakash et al. (2007), showing a large decline of three orders of magnitude from 1992 to 2007.

Figure A1: Vulture Counts From Repeated Surveys Along Road Transects



Notes: Each dot is the sum of surveyed vultures, in log scale, along the same 70 road transects for the three diclofenac-affected species. Data are reproduced from Prakash et al. (2007).

A.2 Validating Habitat Overlap Serves as a Population Level Proxy

In the analysis, we use the overlap of vulture habitats to define districts as high or low suitability, under the assumption that the degree of overlap captures meaningful information about the vulture population levels before they collapsed. To better support this interpretation of the habitat overlap as a meaningful baseline population proxy, we summarize here references from the ecological literature, as well as original data analysis. First, we present a short literature review regarding habitat suitability modeling—the underlying feature that generates the type of habitat maps used to construct the mean suitability score we use. Second, we combine data for hundreds of bird species on their habitat maps, and compare the habitat overlap to scientifically collected population-level data.

A.2.1 Previous Work on Habitat Suitability Modeling and Population Levels

We have reviewed the literature in the field of ecology that discusses the relationship between the habitat range a species can occupy, and as a result the number of sites a species occupies, to the population level of that species—their abundance. In analyzing 400 bird species across North America, Brown and Maurer (1987) write that the "area of the geographical range provides a measure of the breadth of tolerances and requirements of the individual units, and it characterizes the extent to which each species is able to use the total space available to the biota." While the literature discusses the heterogeneity in the strength of those relationships, it overwhelmingly concludes it is a positive relationship that is widely observed across taxonomic groups (Zuckerberg et al. 2009). Brown (1984) writes that "There appears to be a general relationship between abundance and distribution." Freckleton et al. (2006) state that "Positive abundance-occupancy relationships (a relationship between the number of sites a species occupies and the average density of individuals in occupied sites) are widespread through a range of taxa." Borregaard and Rahbek (2010) go as far as stating that "The positive relationship between a species' geographic distribution and its abundance is one of ecology's most well-documented patterns." Reviewing decades of papers on the topic, a meta-analysis by Weber et al. (2017) concludes that "In all cases we found a significantly positive relationship between abundance and suitability." In particular, the positive relationship between the size of the habitat and the abundance of a species has been observed in numerous studies for various bird populations (Järvinen and Sammalisto 1976; Hengeveld and Haeck 1982; Bock 1984; Lacy and Bock 1986; Brown and Maurer 1987).

A.2.2 Comparing Bird Habitat Overlap With Bird Breeding Survey Data

One of the primary limitations that habitat suitability models are used to resolve is the lack of wildlife population data. Often, such populations are not monitored, and if they are, records might be available across a small geographic range, and measurement is conducted either once or over long (decadal) time periods. As in our setting, prior to vultures declining, there was no population census that would allow us to establish baseline vulture abundance.

A key exception to this scarcity of data is the Breeding Bird Survey (BBS) conducted by the United States Geological Survey (USGS) (Ziolkowski et al. 2022). Since 1966, the USGS (in partnership with Environment Canada's Canadian Wildlife Service) has been collecting

data on the presence and abundance of bird species in North America. Unlike other wildlife population data products such as eBird, the BBS relies on the repeated use of sampling protocols along the same road transects, and sampling is conducted by individuals who received training. In 1999, the coverage of the sampling area was greatly expanded. This data product allows us to test the key assumption regarding the correlation between habitat overlap and population levels.

We collect the habitat range maps data from BirdLife International (BLI)—the same source of habitat range maps as we use for the vulture species. We focus on the habitats that intersect with the contiguous US. For each county in the US, we calculate its overlap with the habitat of each bird species, for the species in the BLI repository that have a non-zero overlap with the contiguous US. Then, we use the geocoded data from the BBS to construct the mean count of birds for each species by county over the time period of 1999 to 2019.[31] We were able to match bird counts to habitat overlap scores for 524 species. Of those, we keep in the sample bird species that overlap with at least 30 counties, resulting in a total of 376 unique bird species, and 1,907 unique counties.

There is a clear increasing relationship between bird abundance and habitat overlap. We document this both descriptively, as well as in a cross-sectional regression. In Figure A2, we plot the local polynomial fit over all 376 bird species, across 1,907 counties, documenting the positive relationship between the counts of bird species and their habitat overlap. We fit the local polynomial over all the data, as well as sub-samples that exclude county-species pairs where the overlap is either above 95% or 90%—recovering an almost identical pattern over the overlapping ranges.

We further test the magnitude and precision of this abundance-habitat correlation using a simple cross-sectional regression. We regress the mean log of mean abundance on the continuous measure of overlap share (in percent), as well as quantiles of the overlap measure. In Table A1, we summarize these results for both the full sample, and the sub-sample which excludes overlap values above 95%. For a one percentage point increase in habitat overlap, mean abundance is associated with an increase of 0.68 percent in the full sample (column 1), or of 0.49 in the sub-sample (column 4). We split the habitat overlap score into terciles separately for each species.[32] Locations with high (third tercile) and medium (second tercile) habitat overlap values are associated with a 42% and 28.4% higher mean abundance relative to the first tercile (column 2). These correlations are precisely estimated, allowing us to reject the null hypothesis of no difference between the high and medium terciles. This pattern holds in the sub-sample as well, albeit with smaller coefficients (column 5). Finally, we use the same definition as the one in the paper, where we classify the high and medium terciles as the high suitability locations. We estimate that high suitability locations are precisely associated with 33.3% higher mean abundance in the full sample (column 3), and 19.7% in the sub-sample (column 6). In conclusion, the regression analysis recovers large differences in baseline populations, as reflected in the mean abundance values, across the gradient of habitat overlap.

[31] We exclude data from 2020 to 2021 because bird presence and counts might have responded to the lockdowns during the COVID-19 pandemic. Such responses have been documented in India by Madhok and Gulati (2022).

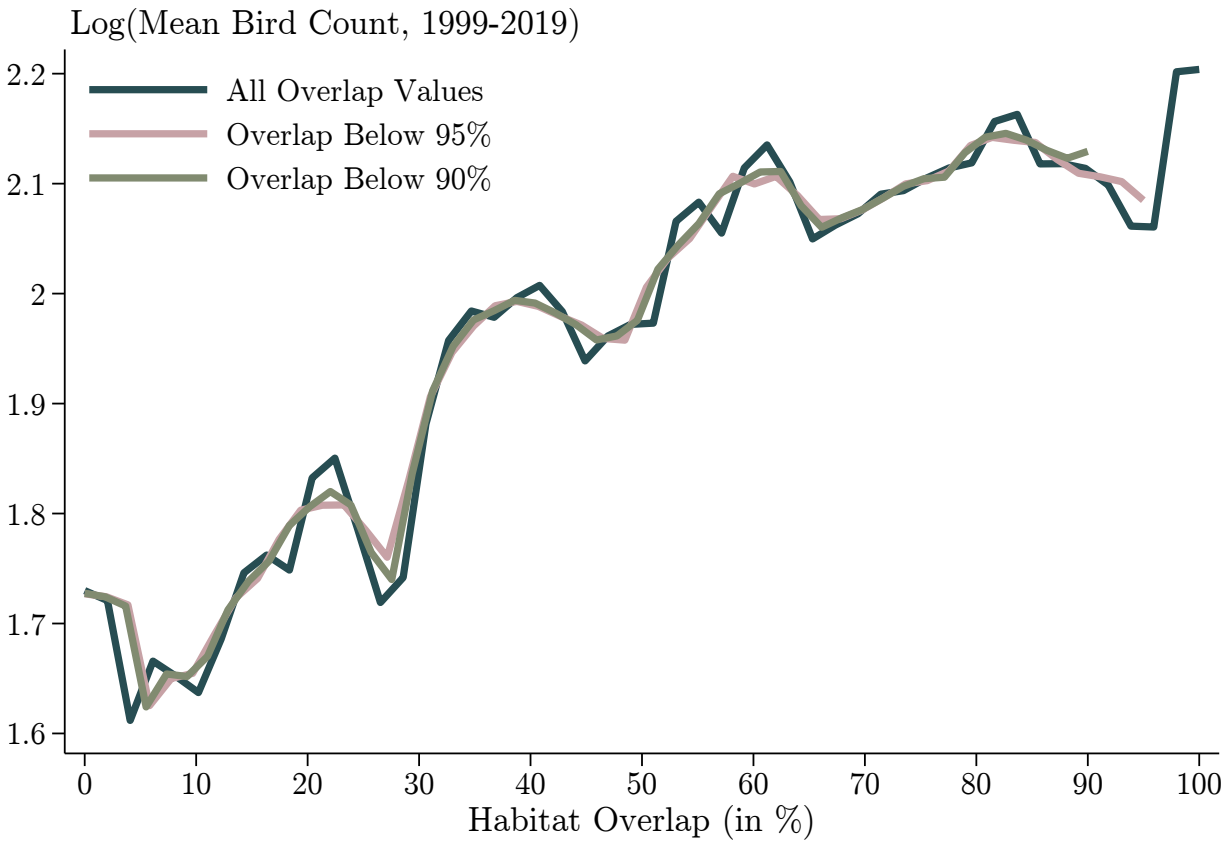
[32] We calculate the terciles over the species-specific distribution instead of the global, all-species, distribution.

Table A1.
Relationship Between Log(Mean Bird Counts, 1999-2019) & Habitat Overlap

	All Overlap Values			Overlap Values $\leq 95\%$		
	(1)	(2)	(3)	(4)	(5)	(6)
Habitat Overlap Share	0.68			0.49		
	(0.05)			(0.04)		
Habitat Overlap Tercile (M)		0.25			0.17	
		(0.02)			(0.04)	
Habitat Overlap Tercile (H)		0.35			0.27	
		(0.03)			(0.07)	
High Suitability (Terciles M or H)			0.29			0.18
			(0.02)			(0.04)
R^2	0.440	0.434	0.434	0.452	0.444	0.444
N	174,267	174,267	174,267	33,062	33,062	33,062
County Clusters	1,907	1,907	1,907	1,818	1,818	1,818
Bird Clusters	376	376	376	371	371	371

Notes: We use data for the contiguous United States on mean bird population counts from 1999 to 2019 (USGS Breeding Bird Survey), which we aggregate by county. We match each county to the habitat overlap of that county to each species, using data from BirdLife International. North America provides a setting where scientific measurement of bird populations has been carried out for a long period of time, allowing us to validate the assumption that habitat overlap provides a useful proxy for baseline wildlife bird populations. Each regression includes county and bird species fixed effects. Standard errors are clustered at both the county and bird species levels.

Figure A2: Local Polynomial Fit for Mean Bird Abundance & Habitat Overlap



Notes: Summarizing the relationship between the mean bird counts (in log points) and the habitat overlap (in percent), for all counties and bird species in the sample (see text for more details).

A.3 Vulture Habitat Overlap & Treatment Assignment

Here we provide more details about the distribution of the mean habitat overlap for the three vulture species—the suitability score—and report results for different choices of assigning treatment status based on the suitability score. In Section A.12, we also consider an alternative approach to constructing the suitability score using the BIOCLIM habitat suitability model.

A.3.1 Distribution of Suitability Score and the Number of Species

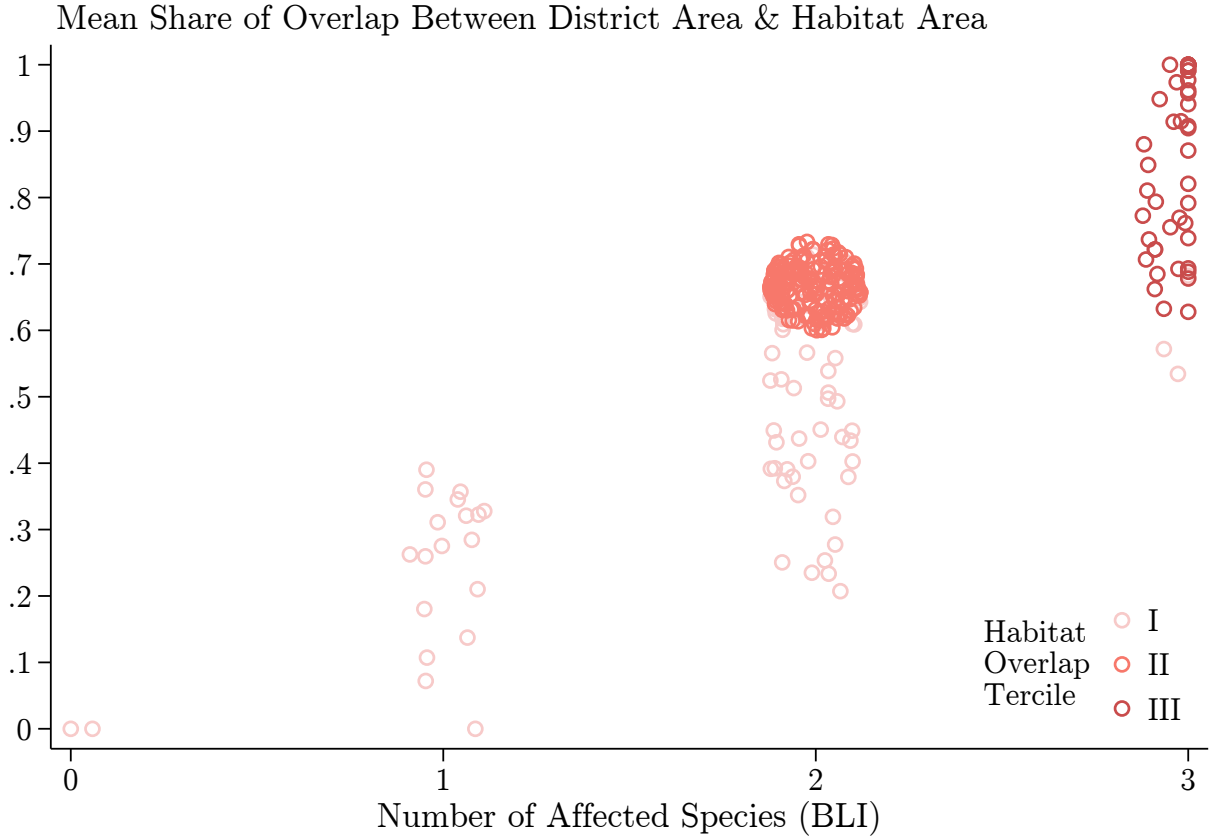
In Figure A3, we plot the relationship between the mean overlap of the district area and the three affected species, relative to the number of affected species that have a non-zero overlap with the district. Each dot is the suitability score (the mean overlap of the habitat area and the district area) for a specific district. To allow for easier visual inspection, the dots are jittered. We color each dot according to its habitat overlap tercile.

The highest tercile is composed of districts that overlap with all three species, and have mean area overlap between the habitats and the district of 66% and higher. The second

tercile is largely composed of districts that overlap almost entirely with two species (hence the bunching around 66%), and two districts that overlap partially with all three districts. Finally, the lowest tercile is composed of districts that overlap with either two, one, or none of the species. The lowest tercile covers the range of zero overlap up to approximately 60% overlap.

In the full sample, for all mainland districts, 111 districts are in the first (lowest) tercile, 184 districts are in the second tercile, and 45 districts are in the third (highest) tercile. In the main sample we use in the analysis, where we restrict the sample to a balanced sample with respect to the all-cause death rate, those numbers are 78, 71, and 4, respectively. In other words, for the main sample, our classification of high and low vulture suitability assigns 75 districts as high, and 78 districts as low suitability.

Figure A3: Mean Habitat Overlap VS. Number of Species



Notes: Summarizing the mean overlap of the habitat area and the district area for each district, relative to the number of species that have their habitats intersect with the district. Each dot is a separate district. Dots are jittered to allow for easier visual inspection.

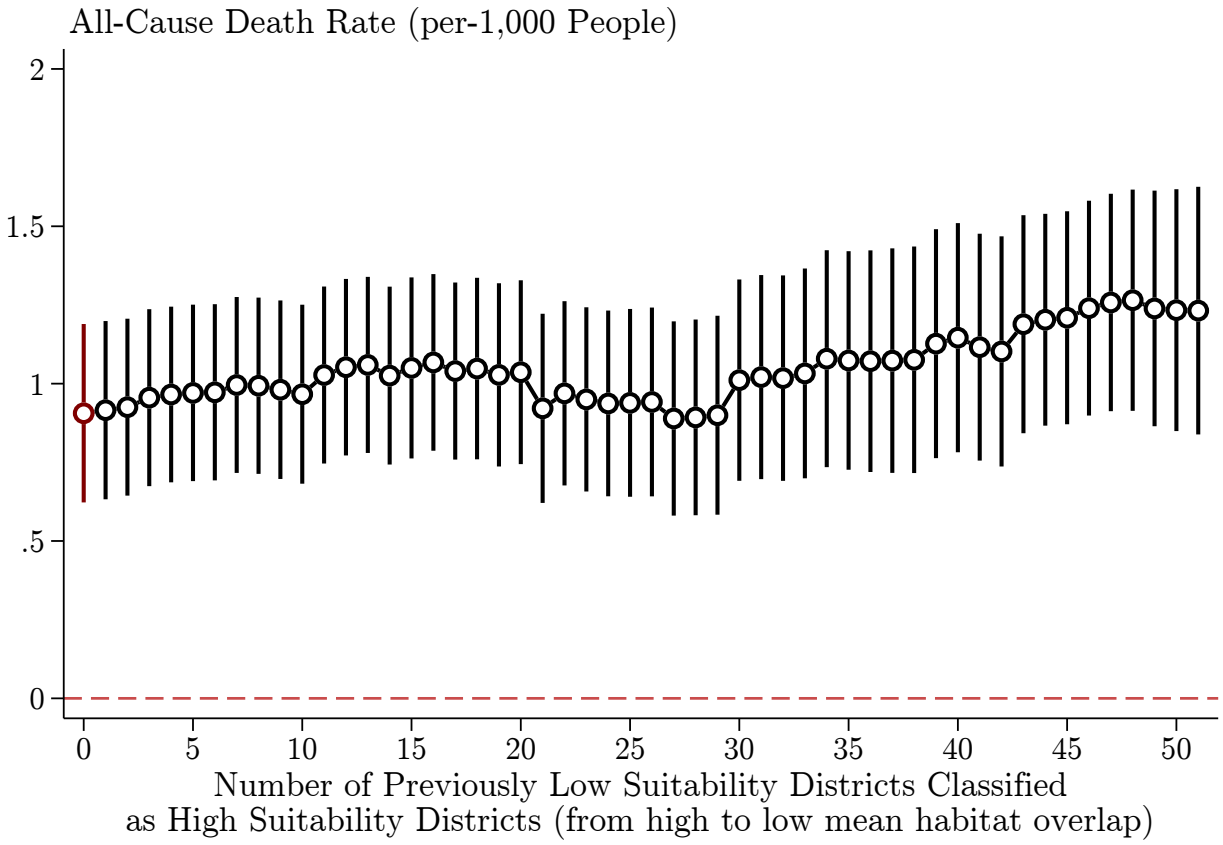
A.3.2 Sensitivity to Treatment Assignment Definition

Our main classification of treatment assigns districts in the second and third terciles as high vulture suitability districts. However, as seen in Figure A3, there are several districts that

have similar mean habitat overlap values, around 0.66. Here we report how sensitive the results are to changing the threshold that assigns treatment status. Explicitly, we use the ranking of the mean habitat overlap in the low vulture suitability group to incrementally shift more and more districts from the control to the treatment group. Each time we re-estimate the regression (that corresponds to the result in Table 2, Panel A, column 1).

The results are robust to shifting districts that were previously in the control group into the treatment group. In Figure A4, we report the coefficients and 95% CIs from repeatedly lowering the treatment assignment cutoff. Across all the results, we still recover a precisely estimated increase in the all-cause death rate. As more districts get reclassified from low to high vulture suitability, the effect size increases slightly, but remains within the confidence interval of the unmodified estimate. This result agrees with the interpretation that even some of the low vulture suitability districts are experiencing treatment, and by comparing high to low vulture suitability districts, we are recovering a lower bound of the effect.

Figure A4: Evaluating Sensitivity to Treatment Assignment of Districts



Notes: Repeating the estimation in Equation (2) but changing the treatment assignment such that more and more low vulture suitability districts are classified as treated. The result in maroon reflect the unmodified treatment assignment rule, which we use in the main text.

A.4 Pooled Estimation Results When Including State-Level Trends

In the main text, we report pooled results for the specification with the zonal council-by-year fixed effects, and then disentangle the pooled coefficient into two periods, 1994-1999 and 2000-2005, when including state-level trends. Here we report pooled results for the specifications with state-level trends.

The pooled estimation recovers large and meaningful increases in the all-cause death rate, even when we include state-linear trends, or state-by-year fixed effects. In Table A2, columns 2-3 and 5-6, we summarize the pooled results that correspond to the results in Table 2, Panel A, columns 3-4 and 7-8. To make comparison easier, we repeat the pooled result from the specification without state-level trends (columns 1 and 4). As expected, the coefficients in Table A2, columns 2-3 and 5-6, are higher than the 1994-1999 coefficients, but lower than the 2000-2005 coefficients. The estimated effect is larger in the census urban sample (columns 5 and 6), relative to the combined sample (columns 2 and 3).

Table A2.
Pooled Estimation Results
All-Cause Death Rate, per-1,000 People

	Combined Sample ($\overline{Y} = 10.2$)			Census Urban Sample ($\overline{Y} = 7.2$)		
	(1)	(2)	(3)	(4)	(5)	(6)
HVS×Post-1994	0.91	0.27	0.31	1.04	0.48	0.50
	(0.14)	(0.13)	(0.14)	(0.27)	(0.22)	(0.20)
R^2	0.74	0.77	0.80	0.67	0.70	0.76
N	2,754	2,754	2,700	2,808	2,808	2,754
Clusters	153	153	150	156	156	153
Zonal Council-by-Year FE	X			X		
State-Linear Trends		X			X	
State-by-Year FE			X			X

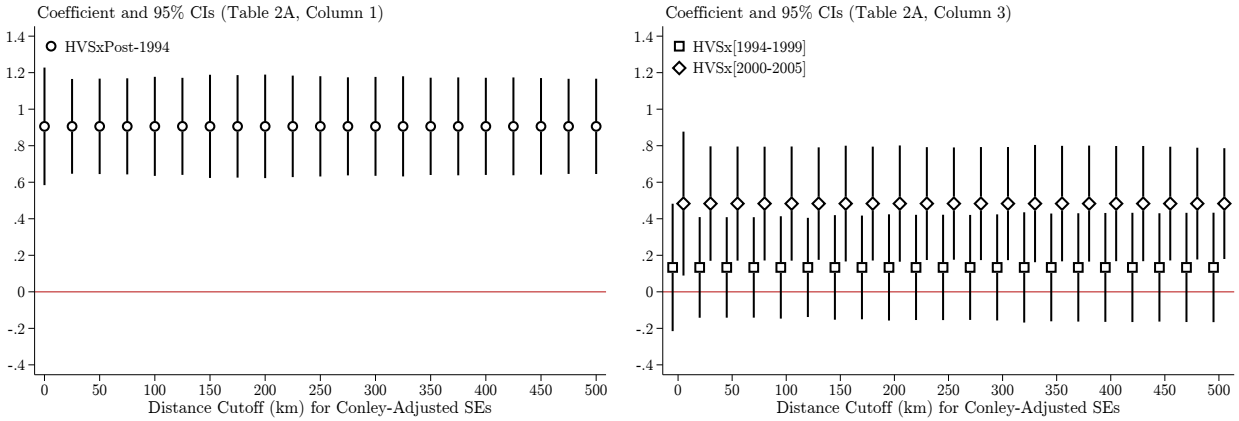
Notes: Estimation results for the specification in Equation (2). Comparing high-vulture-suitability (HVS) to low-vulture-suitability districts, after the collapse of the affected vulture populations. When we include state-by-year fixed effects (columns 4 and 8), three states get dropped as they have no district-level data. Reported means of 10.2 and 7.2 deaths per 1,000 people are for the pre-treatment period of 1988 to 1992. Sample includes balanced district-level data from 1988 to 2005. All regressions include district fixed effects. Observations are population-weighted. We report Conley standard errors that are serially correlated at the district level, and are allowed to be spatially correlated up to 200km.

A.5 Verifying Conley Standard Errors Are Not Sensitive to Bandwidth Choice

The precision of the estimates increases when we adjust for spatial correlation up to 200 km (Conley 1999; Hsiang 2010; Alan Bester et al. 2016). In the main text, as well as in the results reported in the Online Appendix, we report results that allow for spatial correlation up to 200 km. In Figure A5, we confirm that the choice of the bandwidth does not meaningfully change the precision once we adjust for spatial clustering.

Figure A5: Adjusting Standard Errors for Spatial Correlation

(a) Table 2A, Column 1 (b) Table 2A, Column 3



Notes: We report how the Conley standard errors change when we use different bandwidths for the spatial correlation. We narrow the attention to the two results that are the focus in the main text.

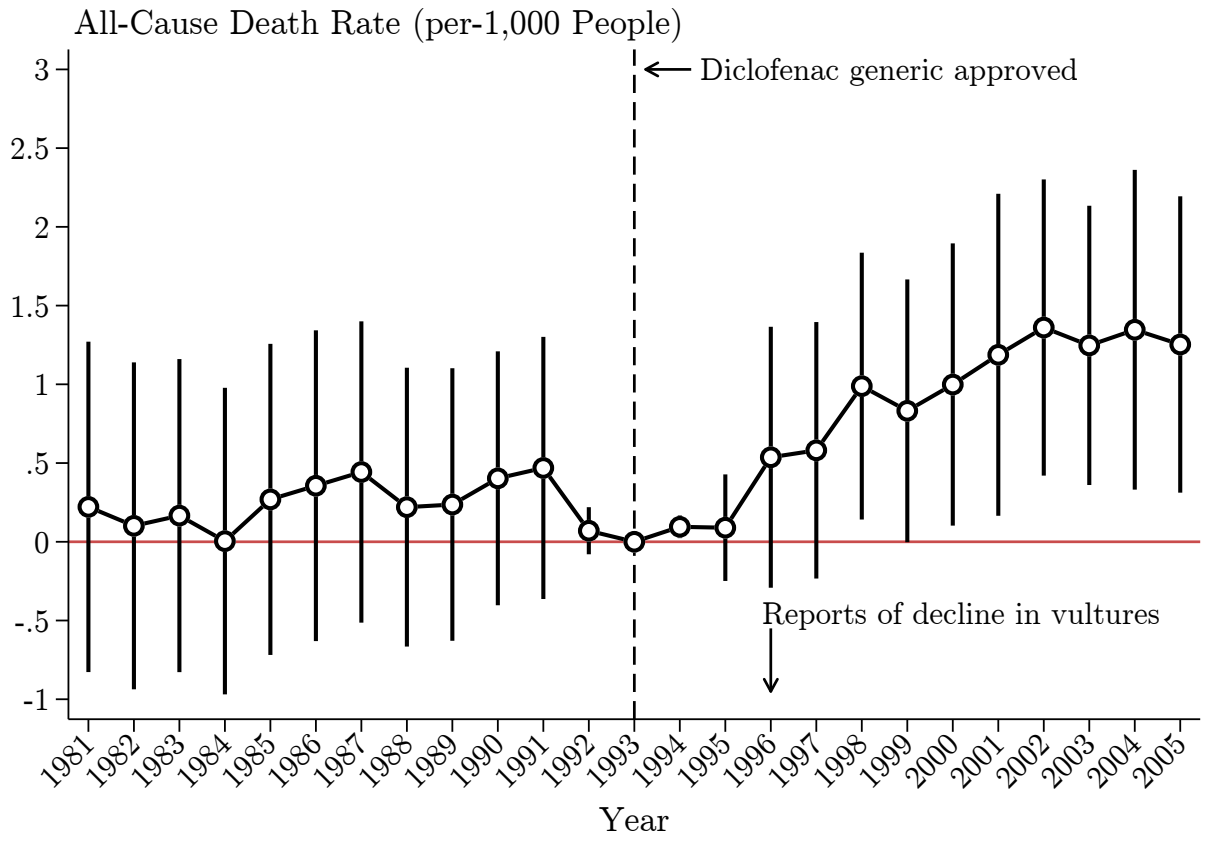
A.6 Extending the Panel to Cover 1981 to 2005

In the main text, we use the data from 1988 to 2005 for two main reasons. First, there was an abrupt shift in the reporting regime in 1988 when the vital statistics started reporting vital event counts instead of rates. We prefer to use data reported under the same regime, as this allows us to fully control the conversion to rates. Second, the number of districts that are fully balanced from 1988 to 2005 is 153, while there are only 104 balanced districts for the 1981 to 2005 period. When extending the panel to the full 1981 to 2005 period, and losing 33% percent of the districts, we recover similar results to those in the main text (Figure A6). Specifically, we do not observe a differential time trend in the years leading to the collapse in vulture populations, and find that death rates increase in the high-vulture-suitability areas only in the years after the collapse.

A.7 Accounting for State-Level Temporal Trends

To account for potential differential trends in the reporting of vital statistics data that systematically change by state, we repeat the estimation in Equation (1) and include either

Figure A6: All-Cause Death Rates DD Estimation Results With Earlier Years

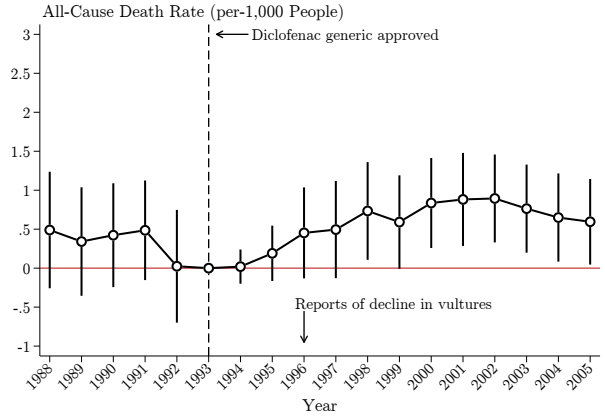


Notes: Estimation results from Equation (1). Comparing the third and second terciles to the first tercile of vulture habitat overlap. Expanding the sample to 1981, while still using a balanced sample, lowers the number of districts from 153 to 104. The regression includes district and zonal council-by-year fixed effects. Observations are population-weighted. We calculate Conley standard errors that are serially correlated at the district level, and are allowed to be spatially correlated up to 200km.

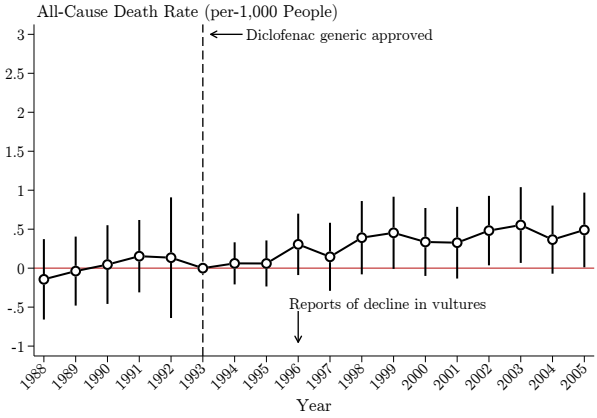
state-linear trends, in addition to the zonal council-by-year fixed effects, or include state-by-year fixed effects. The inclusion of state-level trends potentially absorbs a large share of the signal of interest as there is little sub-state variation in habitat suitability overlap. Even with the inclusion of flexible time trends that vary by state, we recover similar patterns in Figure A7 to those in Figure 4. The divergence in death rates only starts after the vulture populations collapse, yet the magnitude of the effect is smaller. By 2000, all-cause death rates were about 0.5 or 0.3 deaths per 1,000 people higher in the high-vulture-suitability districts when including state-linear trends, or state-by-year fixed effects, respectively.

Figure A7: All-Cause Death Rates DD Estimation Results With State-Level Trends

(a) State-Linear Time Trends



(b) State-by-Year Fixed Effects



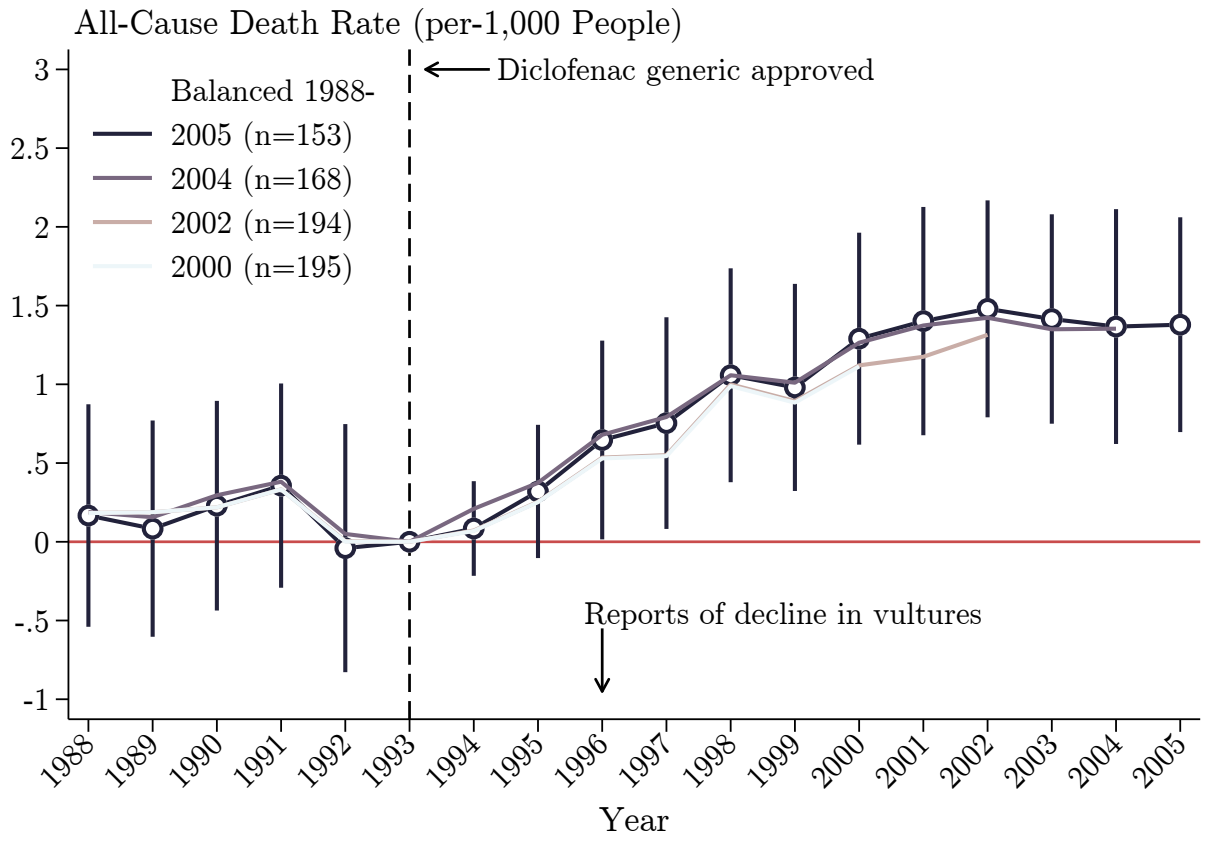
Notes: Estimation results from Equation (1). Comparing the third and second terciles to the first tercile of vulture habitat overlap. All regressions include district fixed effects. The regression in (a) includes zonal council-by-year fixed effects and state-level linear time trends, and the regression in (b) includes state-by-year fixed effects. Observations are population-weighted. We calculate Conley standard errors that are serially correlated at the district level, and are allowed to be spatially correlated up to 200km.

A.8 Increasing the Number of Balanced Districts in the DD Estimation

In the main text, we present results from three different estimation approaches: differences-in-differences (DD), long-differences (LD), and triple-differences (DDD). The DD and DDD estimations use a balanced sample from 1988 to 2005. Because many districts are missing all-cause death rate data at either the end of the sample period, or in the middle of the sample period, our balanced DD sample, for example, covers 153 of the 342 districts (held at 1981 borders). In the paper, we address this gap in coverage by relaxing the requirement for districts to have fully balanced data. Instead, we require districts to have at least one year of non-missing data before 1995 (including), and one year of non-missing data after 2000 (including). We use this sample in a long-differences estimation.

To verify that our results in the DD estimation are not sensitive to the composition of the sample, we run additional analysis where we truncate the sample earlier to allow for more districts to qualify as having balanced data. In Figure A8, we plot the DD estimation results from the main DD sample (same as in Figure 4), along with the event-study estimates of three new samples. In each new sample, we truncate the sample at 2004, 2002, or 2000. This increases the number of balanced districts from 153 to 168, 194, or 195, respectively. The results from each of these new samples track the main results very closely, and are all well within the 95% CIs.

Figure A8: All-Cause Death Rates DD With Different Terminal Years



Notes: Estimation results from the sample used for the DD analysis in the main text (as in Figure 4), with lines showing the event-study estimates of the same specification but balancing the data up to 2004, 2002, and 2000, instead of 2005, with the number of balanced districts of 168, 194, and 195, instead of 153, respectively

A.9 Decomposing the Triple-Differences Estimation

In the main text, we report results from a triple-differences approach, which uses livestock to test whether the mortality response is more pronounced in areas with both high-vulture-suitability and high levels of livestock at baseline. Another way to undertake the comparison embedded in the triple-differences is to separately evaluate two diff-in-diff components. In Table A3, we split the sample into high- and low-vulture-suitability districts. We then carry out a diff-in-diff exercise comparing districts with high vs low levels of baseline livestock, before and after the veterinary use of diclofenac.

This decomposition reveals that it is only in high-vulture-suitability districts that baseline levels of livestock are associated with elevated death rates in the post period (compare Table A3, columns 1 and 2 in Panels A and B). In areas where vultures were expected to be absent or less abundant, there is no differential change in mortality between low and high livestock districts. This is true even when restricting attention to urban portions of districts—here the difference is even more marked (Table A3, columns 3 and 4).

This decomposition analysis also alleviates concerns regarding possible spatial clustering of the vulture suitability as it offers an alternative research design. The diff-in-diff results in Table A3, Panel A, only rely on districts in the more central parts of India, where environmental conditions are similar in terms of vulture habitats. This alleviates concerns that coastal or mountainous districts might drive our results.

A.10 Back of the Envelope Calculation on Annual Cow Removal by Vultures at Baseline

In the main text, we highlight that we are comparing districts that suffered a large loss of vultures to districts that likely experienced a smaller loss of vultures. Here we provide a back-of-the-envelope calculation to better interpret the differences between districts in the treatment and control groups. Each vulture consumes four to six kg of meat each week (Ishwar et al. 2016). In our calculations below, we assume each vulture consumes five kg of meat a week, and therefore 260 kg of meat annually. Scientists have estimated there were between 30 to 50 million vultures before their population levels collapsed (Subramanian 2011). We choose the middle number of 40 million vultures as a baseline population level—resulting in an estimated annual meat consumption of 10.4 billion kg.

The mean weight of the Indian Gir cow is 385 kg (Felius 1995) implying that this amount of meat is the equivalent of removing 27,012,987 cows each year. This number strongly agrees with a separate report that estimates that vultures in India removed 25 million carcasses each year (Ishwar et al. 2016).

Our next step is to disaggregate this national-level approach to the district level. To do so, we first need to assign a baseline vulture population level to each district, and then use the above values to calculate the amount of cow-equivalent carrion removed each year. First, we calculate the total habitat area across all three affected species in each district. Second, we sum up all of the habitat areas across all the affected species and all districts. We then divide the first measure by the second to arrive at a set of district weights that sum up to one. A district will have a higher weight the more area it has that is suitable for vultures.[33] We multiply each weight by the baseline population estimate of 40 million vultures. Then, we multiply this estimated number of vultures in each district by the mean amount of meat (denoted in cow-equivalent carcasses) they remove each year: $\frac{385}{5} \times 52$. Finally, we sum the number of estimated cows removed each year by mean habitat overlap tercile (see Figure A3), and normalize it by geographic area, or by population density.

We summarize the back-of-the-envelope calculations in Table A4. In our treatment group, the sum of estimated removed cow-equivalent carcasses by vultures (the row that sums up the high and middle terciles) is about three times larger than the value in the lowest tercile (columns 1 and 3), or 50% larger than the lowest tercile (column 2). While this is a crude quantification of the removal of carrion by vultures, it highlights that the differences between the treatment and control groups are not trivial, and are in fact quite large and meaningful.

[33] Note that habitat areas can overlap, resulting in the total habitat area in a district being larger than the area of the district. This is not an issue because we normalize by the sum of all habitat areas across the country, which accounts for this potential habitat overlap.

Table A3.
Decomposing the DDD Results by Districts' Vulture Suitability

Panel A. High Vulture Suitability Subsample

	Combined Sample ($\overline{Y} = 10.2$)		Census Urban Sample ($\overline{Y} = 7.2$)	
	(1)	(2)	(3)	(4)
Livestock×Post-1994	0.62	0.57	1.07	1.05
	(0.19)	(0.19)	(0.30)	(0.28)
R^2	0.83	0.83	0.76	0.77
N	1,350	1,350	1,386	1,386
Clusters	75	75	77	77

Panel B. Low Vulture Suitability Subsample

	(1)	(2)	(3)	(4)
Livestock×Post-1994	0.08	0.11	-0.07	-0.12
	(0.21)	(0.21)	(0.48)	(0.48)
R^2	0.68	0.69	0.60	0.61
N	1,404	1,404	1,404	1,404
Clusters	78	78	78	78
Weather Controls		X		X

Notes: Estimation results for a specification similar to Equation (2). The estimation is comparing districts with high to low livestock agriculture at baseline, after the collapse of the affected vulture populations. We repeat the analysis in two subsamples: The districts with high vulture suitability where we expect high baseline livestock to affect health (Panel A), and low vulture suitability where we do not expect baseline livestock to affect health (Panel B). Sample includes balanced district-level data from 1988 to 2005. Reported means of 10.2 and 7.2 deaths per 1,000 people are for the pre-treatment period of 1988 to 1992. All regressions include district and zonal council-by-year fixed effects. Observations are population-weighted. We report Conley standard errors that are serially correlated at the district level, and are allowed to be spatially correlated up to 200km.

Table A4.
Back-of-the-Envelope Calculation on
Annual Cow Removal by Vultures

Tercile	(1)	(2)	(3)
L	7.3	6.4	1,787.2
M	16.7	9.3	3,784.7
H	3.1	11.8	1,904.3
H+M	19.8	9.7	5,471
Total, Unadjusted	X		
Normalized by Area		X	
Normalized by Population/Area			X

Notes: In column 1, units are millions of cows. In column 2, units are cows per squared km. In column 3, units are millions of person-cows per squared km. In column 1, the fourth row simply sums the second and third rows, but in columns 2 and 3, we first sum the removed cows in M and H districts, and then divided by the area or population/area in M and H districts. See text in the Online Appendix for details on calculations and assumptions.

A.11 Examining Heterogeneity Between Census Urban & Rural District Areas

In Table A5, we explore the degree to which death rates respond differently to the collapse in vulture populations in either census urban or census rural areas. Because census urban areas have larger populations, are denser, and are more likely to have an animal landfill site at their outskirts, we expect that a larger portion of the average effect is driven by the census urban areas. When we use the district-level data reported by census urban or census rural areas, we find a higher average treatment effect in census urban relative to census rural areas, but the effects are not statistically different from each other.

A.12 Using Habitat Suitability Model to Define Treated Districts

In the main analysis, we rely on the habitat range maps, as produced by BirdLife International (BLI), to classify districts as either high or low suitability for the diclofenac-affected vultures. One concern is that the maps heavily rely on biased samples and local knowledge which places more weight on populated areas. To alleviate these concerns, and to examine the sensitivity of the classification to the maps by BLI, we estimate our own version of a habitat suitability model (HSM). In general, habitat suitability modeling uses data on the presence records of species along with a range of environmental variables in order to characterize the environmental niche that a species can occupy. An HSM will use observations of polar bears and conclude that cold tundras are a more likely habitat than tropical forests, or that mountain goats are more likely to be found in high-elevation areas than in flat plains.

Table A5.
All-Cause Death Rate, per-1,000 People

Panel A. Census Urban Sample ($\overline{Y} = 7.2$)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
HVS×Post-1994	1.04			0.48			0.50		
	(0.27)			(0.22)			(0.20)		
HVS×[1994, 1999]		0.68	0.72		0.35	0.40		0.34	0.32
		(0.30)	(0.29)		(0.26)	(0.26)		(0.22)	(0.22)
HVS×[2000, 2005]		1.34	1.32		0.68	0.67		0.63	0.64
		(0.30)	(0.25)		(0.23)	(0.22)		(0.24)	(0.25)
R^2	0.67	0.68	0.69	0.70	0.70	0.71	0.76	0.76	0.76
N	2,808	2,808	2,808	2,808	2,808	2,808	2,754	2,754	2,754
Clusters	156	156	156	156	156	156	153	153	153

Panel B. Census Rural Sample ($\overline{Y} = 11$)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
HVS×Post-1994	0.79			0.11			0.22		
	(0.17)			(0.16)			(0.16)		
HVS×[1994, 1999]		0.35	0.32		-0.06	-0.02		0.13	0.12
		(0.17)	(0.17)		(0.17)	(0.18)		(0.17)	(0.18)
HVS×[2000, 2005]		1.21	1.08		0.40	0.35		0.30	0.27
		(0.23)	(0.22)		(0.19)	(0.19)		(0.18)	(0.19)
R^2	0.73	0.73	0.74	0.75	0.76	0.76	0.80	0.80	0.80
N	2,916	2,916	2,916	2,916	2,916	2,916	2,862	2,862	2,862
Clusters	162	162	162	162	162	162	159	159	159

Zonal Council-by-Year FE	X	X	X						
State-Linear Trends				X	X	X			
State-by-Year FE							X	X	X
Weather Controls			X			X			X

Notes: Estimation results for the specification in Equation (2). Comparing high-vulture-suitability (HVS) to low-vulture-suitability districts, after the collapse of the affected vulture populations. When we include state-by-year fixed effects (columns 7 to 9), three states get dropped as they have no district-level data. Reported means of 7.2 and 11 deaths per 1,000 people are for the pre-treatment period of 1988 to 1992. Sample includes balanced district-level data from 1988 to 2005. All regressions include district fixed effects. Observations are population-weighted. We report Conley standard errors that are serially correlated at the district level, and are allowed to be spatially correlated up to 200km.

We use the well-known BIOCLIM HSM that was first developed in 1984 (Booth et al. 2014). The model uses data on the presence of a species, and links those records to local bioclimatic variables such as the elevation, temperature, and precipitation. The model uses weather data from several seasons on the mean, max, and min values. Overall, the standard application uses 19 such variables. Combining the data on the bioclimatic variables and presence records, the model constructs the convex hull of environmental conditions that appear to be beneficial for the presence of the species. Using that classification, the model then projects that convex hull back into geographic space to construct suitability scores. The higher the score, the more likely the area is a suitable niche for the species.

We use observation records from eBird and from the Global Biodiversity Information Facility (GBIF) to construct the BIOCLIM suitability scores. We then take the mean level of the suitability scores across all three affected species, and use it to define high and low suitability dummy variables. We either split the suitability score into terciles, defining high suitability as the third and second terciles, or we define the high suitability dummy as being above the median suitability score.

Using these alternative definitions of the treated districts, we re-estimate the specifications in Equations (1), (2), and (3). We report the maps showing the classification of districts, along with the event-study results in Figure A9, and the average treatment effects in Table A7. Across the two alternative treatment classification schemes, we recover similar magnitudes for the change in all-cause human death rates following the collapse in vulture populations. This helps us to reject that our analysis is extremely sensitive to the exact classification of districts in either treatment or control status.

A.13 Long-Differences Results With Time-Varying Controls

In the main text, we report results for the long-differences model in Table 3. This allows us to include additional districts even if they do not have fully balanced data. In Figure A12, we report a series of precisely estimated zero differences for a variety of outcomes between the high and low vulture suitability districts, before and after the collapse of the vulture populations. Here we combine the two and use the time-varying variables we use in Figure A12 with the long-differences model.

We recover similarly meaningful and precisely estimated increases in the all-cause death rate for the high vulture suitability districts after the collapse. In Table A6, we report the estimation results of the long-differences model when including each set of time-varying controls, as well as when we include all the time-varying controls in the same regression. The estimation results are fairly insensitive to the included controls.

A.14 Additional Water Quality Parameters

Here we report additional results on water quality for biological and chemical oxygen demands (BOD and COD), as well as turbidity. In general, as the demand for oxygen in the water system increases with more substances that react with it, we see dissolved oxygen levels decline (as seen in Table 5), as well as increasing levels of BOD and COD. Because BOD only captures biological uses of oxygen, it will be below the COD level which captures

Table A6.
Long Differences Results With Controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
HVS×Post-1994	0.40	0.48	0.45	0.60	0.62	0.48	0.50
	(0.20)	(0.20)	(0.20)	(0.20)	(0.21)	(0.21)	(0.20)
Age Shares	X						X
Village Infrastructure		X					X
Literacy Rate			X				X
Employment Rate				X			X
Employment Shares					X		X
Healthcare Access						X	X
R^2	0.92	0.90	0.89	0.88	0.88	0.89	0.93
N	638	626	626	626	606	634	604
Clusters	319	313	313	313	303	317	302

Notes: Estimation results for the specification in Equation (2). Sample includes all districts with non-missing data in the collapsed pre- and post-collapse sample (combined sample of census-urban and census-rural areas). We include a series of control variables for which we have observations both before and after 1994. Column 1 controls for population age shares in five-year intervals. Column 2 controls for the share of villages that have roads, have medical facilities, have educational facilities, have communications infrastructure, have electrical power infrastructure, and have access to irrigation. Column 3 controls for the literacy rate. Column 4 controls for the total employment rate. Column 5 controls for employment shares in agriculture, manufacturing, and services. Column 6 controls for the number of doctors, health workers, health centers, and hospitals per 100,000 people. Column 7 combines all the controls from columns 1 to 6. Each regression includes district and zonal council-by-year fixed effects. Observations are population-weighted. We report Conley standard errors that are serially correlated at the district level, and are allowed to be spatially correlated up to 200km.

Table A7.
Results for All-Cause Death Rate Using
BIOCLIM Classifications ($\overline{Y} = 10.2$)

Panel A. High & Medium Suitability Score Terciles				
	(1)	(2)	(3)	(4)
HVS×Livestock×Post-1994			0.70	0.62
			(0.27)	(0.26)
HVS×Post-1994	0.62	0.54	0.13	0.10
	(0.15)	(0.12)	(0.18)	(0.17)
Livestock×Post-1994			-0.05	-0.02
			(0.22)	(0.22)
R^2	0.73	0.74	0.74	0.74
N	2,754	2,754	2,754	2,754
Clusters	153	153	153	153
Panel B. Above Median Suitability Score				
	(1)	(2)	(3)	(4)
HVS×Livestock×Post-1994			0.77	0.75
			(0.27)	(0.29)
HVS×Post-1994	0.62	0.55	0.01	-0.03
	(0.15)	(0.15)	(0.20)	(0.23)
Livestock×Post-1994			0.11	0.10
			(0.17)	(0.18)
R^2	0.73	0.74	0.74	0.74
N	2,754	2,754	2,754	2,754
Clusters	153	153	153	153
Weather Controls		X		X

Notes: Estimation Results for the specification in Equations (2) and (3). The treatment classification uses predicted suitability scores for the diclofenac-affected-vultures from the BIOCLIM habitat suitability model. We either split the suitability score into terciles and define treated districts as the third and second terciles (Panel A), or split districts as above or below the median suitability score, and define treated districts as those above the median (Panel B). Sample includes balanced district data, combining urban and rural areas, from 1988 to 2005. Reported mean of 10.2 deaths per 1,000 people is for the pre-treatment period of 1988 to 1992. Observations are population-weighted. We report Conley standard errors that are serially correlated at the district level, and are allowed to be spatially correlated up to 200km.

both organic and inorganic uses of oxygen. We should expect to see both BOD and COD levels increase with greater availability of carrion in the environment.

Turbidity is a measure of water quality that generally shows improvement in water quality as it goes down. However, in the case of a decline in scavengers, turbidity declines as well. This is because scavengers tend to increase turbidity through the act of tearing carrion flesh. As shown in other aquatic environments, the absence of scavengers reduces turbidity (Santori et al. 2020).

In Table A8, we report results that are consistent with the above predictions, albeit, imprecisely estimated. BOD and COD values increase in the high vulture suitability district after the onset of diclofenac use in livestock. This effect is entirely driven by the census urban districts (columns 2, 3, 5, and 6), similar to how the decline in dissolved oxygen and increase in fecal coliform was as well (see Table 5). Turbidity declines in water bodies monitored in census urban districts (columns 8 and 9), which is consistent with previous findings on declines in scavenger populations.

Table A8.
District Water Quality DD & DDD Estimates

	Biological Oxygen Demand			Chemical Oxygen Demand			Turbidity		
	U&R		U	U&R		U	U&R		U
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
HVS×Urban×Post-1994		1.5			11.4			-6.4	
		(0.7)			(3.1)			(4.9)	
HVS×Post-1994	0.7	0.2	1.8	1.8	-2.2	9.6	-0.6	1.3	-5.5
	(0.4)	(0.4)	(0.7)	(1.7)	(1.8)	(2.8)	(3.5)	(4.2)	(4.6)
Urban×Post-1994		-0.6			-6.9			-0.2	
		(0.5)			(2.5)			(3.4)	
$\overline{Y}_{\leq 1993}$	4.01	4.01	5.03	25.32	25.32	28.61	36.44	36.44	40.30
R^2	0.74	0.74	0.75	0.71	0.71	0.75	0.79	0.79	0.78
N	4,337	4,337	2,062	4,144	4,144	1,967	3,600	3,600	1,671
Clusters	221	221	140	217	217	135	208	208	129

Notes: Estimation results for DD and DDD specifications. Each regression includes district-by-area-by-type fixed effects where area is either urban or rural, and type is the water body type (well, river, or lake). In addition, each regression includes year fixed effects. Sample consists of district-level data for census-urban (U) and census-rural (R) areas, from 1988 to 2004. Observations are population-weighted. We report Conley standard errors that are serially correlated at the district level, and are allowed to be spatially correlated up to 200km.

A.14.1 Additional Analysis for Fecal Coliform

In the main text, we report a large increase in fecal coliform in urban areas that were highly suitable for vultures, following the vulture population collapse—more than doubling the concentration, allowing us to reject an increase below 64%. At first glance, this might appear to be an implausible effect magnitude. Here, we provide a more descriptive analysis to help contextualize this specific result. First, in Figure A10, we plot the distribution of the logged values of fecal coliform in our sample, a comparison of the logged fecal coliform values in India relative to states in the United States in 2004, as well as the year-on-year and post- versus pre-collapse changes.

We proceed to estimate a quantile regression, for the deciles of the logged values of fecal coliform, and examine whether the estimated DD treatment effect meaningfully varies across the distribution. Because the results in the main analysis are noisy, our focus here is more descriptive—do we observe any evidence of a gradient across the distribution? In Figure A11, we observe an effect size close to zero through almost the entire distribution when using the census urban & census rural sample. However, in the census urban sample, we see suggestive evidence for higher increases in logged values of fecal coliform at higher decile values of the distribution. The analysis in Figures A11 along with the summary statistics in Figure A10 provide three important insights that are helpful when interpreting the results in Table 5: (i) fecal coliform levels in India are high, much higher than potential priors based on high-income countries; (ii) there is support in the data for large fluctuations, consistent with magnitudes we report in the DD estimation; and (iii) the reported effect on fecal coliform is predominately driven by census urban areas, and mostly by areas that experience high levels of fecal coliform pollution.

A.15 Evaluating Changes to Healthcare Access

Changes to healthcare access and utilization could also explain changes in mortality. This presents a threat to our identification strategy if healthcare access and utilization changed differentially between the high- and low-suitability districts after 1994. In Table 1, we document that the two groups of districts show no systematic difference in the number of hospitals and healthcare centers, or in the number of doctors and healthcare workers in 1991.

Here we use data from the 2001 and 2011 censuses to test whether those healthcare access metrics changed after 1994 in the high- relative to low-vulture-suitability districts. In Table A9, we report estimates that show no difference between the two groups of districts. This finding holds when we use the same set of districts as in the main analysis, or if we use the full set of districts that appear in the census. This result alleviates concerns that our main finding is capturing changes to the healthcare infrastructure that are somehow correlated with the location and timing of the vulture collapse.

A.16 Evaluating Changes to District Characteristics

We expand on the previous analysis of healthcare access and add several other placebo outcomes that should not be affected by the collapse in vulture populations. For each

Table A9.
Estimation Results for Healthcare Access

	Main Sample		Census Sample	
	Per-Capita Hospitals & Health Centers	Per-Capita Doctors & Health Workers	Per-Capita Hospitals & Health Centers	Per-Capita Doctors & Health Workers
	(1)	(2)	(3)	(4)
Residuals	0.12	1.52	0.14	3.59
	(0.28)	(2.52)	(0.27)	(5.05)
$\overline{Y}$	1.80	17.87	1.78	21.29
R^2	0.769	0.721	0.678	0.584
N	449	449	972	972
Clusters	153	153	324	324

Notes: Estimation results for the specification in Equation (2). The sample uses data from the Indian census on the number of hospitals, health centers, doctors, and health workers in 1991, 2001, and 2011, and converts them to per capita rates. The results in columns 1 and 2 are for the districts that have fully balanced death rate data and are used in the main analysis. The results in columns 3 and 4 are for all the balanced districts in the census data. Each regression includes district and zonal council-by-year fixed effects. Observations are population-weighted. The reported mean for the outcome is the population-weighted mean. We report Conley standard errors that are serially correlated at the district level, and are allowed to be spatially correlated up to 200km.

outcome, we have at least one year of data before, and one year of data after the collapse. We summarize the results in Figure A12, where we do not find that alternative explanations in the form of diverging employment or district infrastructure are consistent with the data. The overall differences are often very small relative to the mean of each outcome, and even when they are precisely estimated they move in the direction that would suggest improving health conditions in the treatment group.

A.17 Sensitivity Analysis Using Jackknifing

Because we use population weights in the analysis, it is possible that one very large district (in terms of population) had an increase in mortality or in reporting of vital statistics that happened around the same time as the vulture die-offs. If such a district exists, then it will receive a high weight in the regression, distorting the actual effect, and leading us to incorrectly interpret a spurious effect as a causal one. In order to rule out that our results are driven by an extreme outlier, we repeat the main estimation leaving one district out of the sample each time. The resulting distribution of coefficients in Figure A13 is narrowly centered around the estimate we recover using the full sample. The results from the jackknife procedure allow us to reject that a single district is driving the estimation.

We also conduct the leave-one-out exercise by excluding one state at a time. This allows us to evaluate whether any potential changes in the reporting of vital statistics might be driving the estimated effect in a manner that is not already captured by the inclusion of state-level trends in Figure A7. We recover a narrow distribution of the coefficients with mostly overlapping 95% confidence intervals.

A.18 Permutation Inference Analysis

As an additional robustness test, we also run a permutation inference analysis. Using permutation inference analysis allows us to rule out that our research design is failing to capture any cross-sectional or temporal features that are responsible for the observed effect.

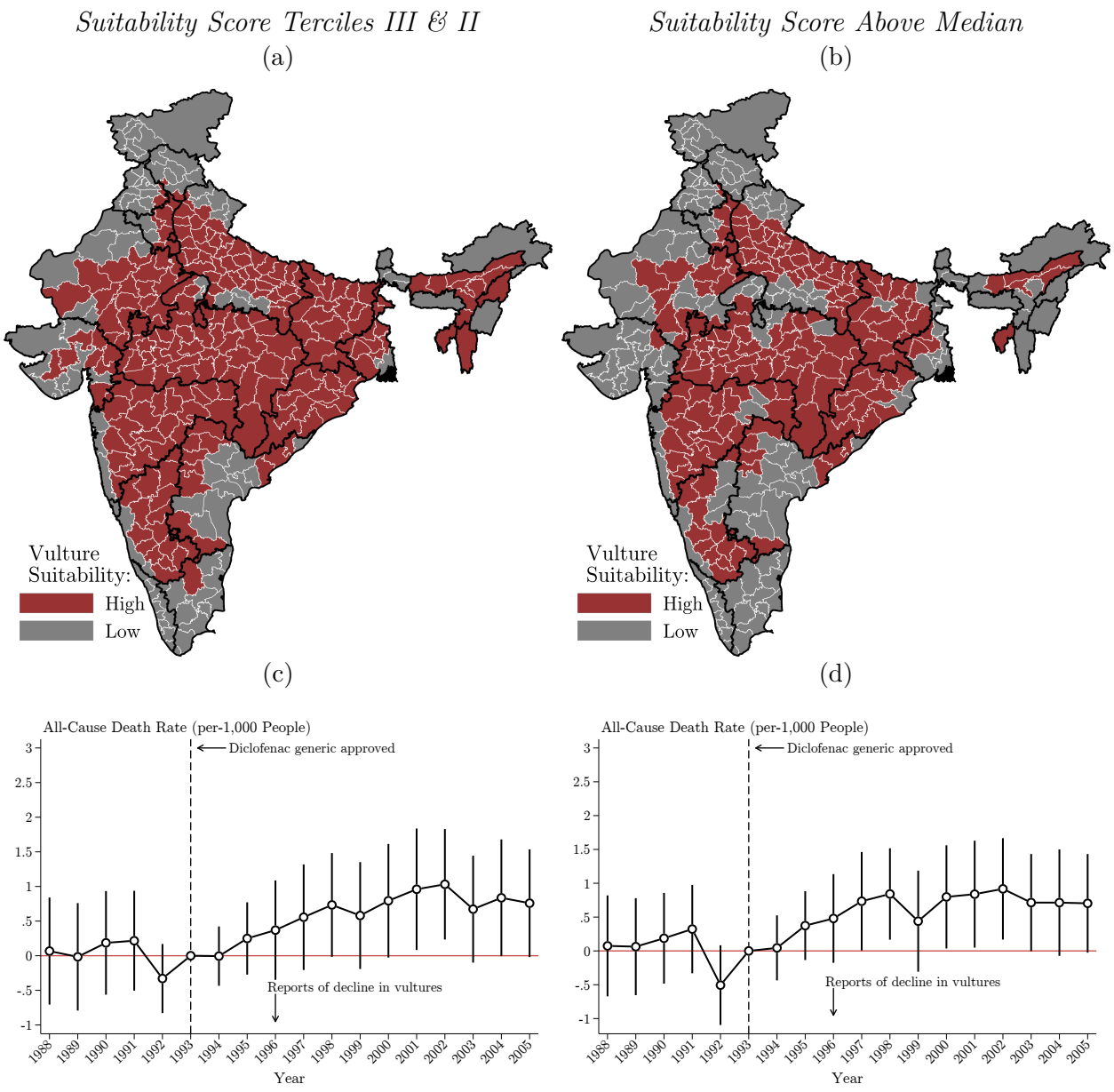
We randomly re-assign the treatment across the districts and re-estimate the effect using the specification in Equation (2), repeating the process 1,000 times. We either fully randomize the treatment dummy across districts and years (full), maintain the same temporal structure but randomly assign districts as either treated after 1994 or not (block), or randomly assign the years that are flagged as treated within the districts that are truly part of the treatment group (within). We plot the permutation distributions in Figure A15, where each one of the distributions is centered around zero. More importantly, the estimated effect from the non-permutation sample is in the far right tail of each distribution, resulting in an exact p-value well below 1%.

A.19 Robustness to Excluding Coastal Districts

Treatment districts using the habitat classification are mostly in the interior of the country. We might be concerned that including coastal districts might bias our results if death rates were differentially evolving after 1994. To check this, we classify each district using a coastal

dummy variable. We summarise the population-weighted mean all-cause death rates for the low-suitability districts separately for coastal and interior districts. Then, we re-estimate the event-study specification by excluding those districts from the sample. We report our results in Figure A16 using versions of Figure 3C and Figure 4 from the main text. We find that qualitative patterns remain unchanged. It even appears that death rates in the coastal districts were slightly increasing over time, which attenuated our estimates in Figure 4, as seen in the variation of that analysis, which excludes coastal districts.

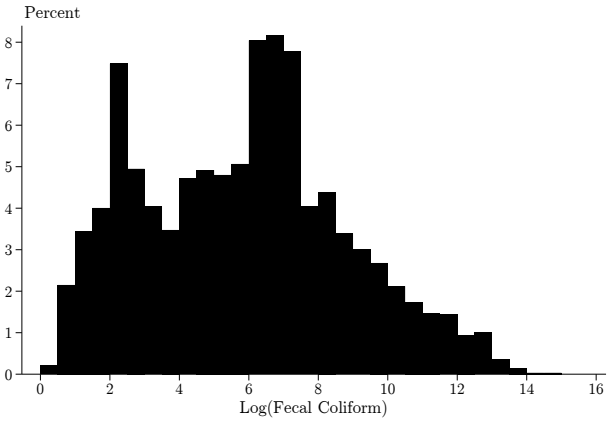
Figure A9: Classifying Treated Districts Using the BIOCLIM Habitat Suitability Model



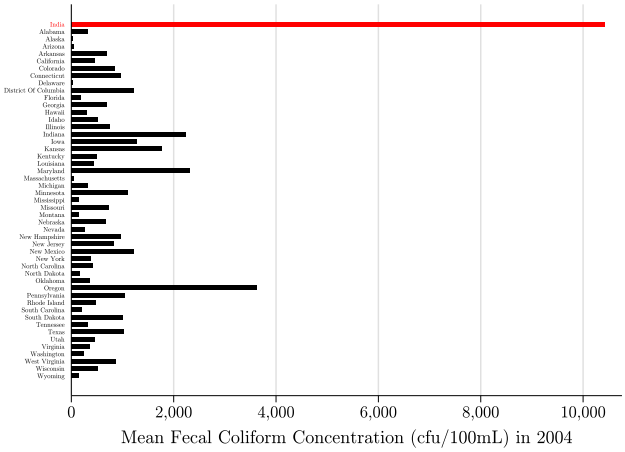
Notes: The treatment classification uses predicted suitability scores for the diclofenac-affected vultures from the BIOCLIM habitat suitability model. We either split the suitability score into terciles and define treated districts as the third and second terciles (a and c), or split districts as above or below the median suitability score, and define treated districts as those above the median (b and d).

Figure A10: Summary Statistics Regarding Fecal Coliform Pollution in India

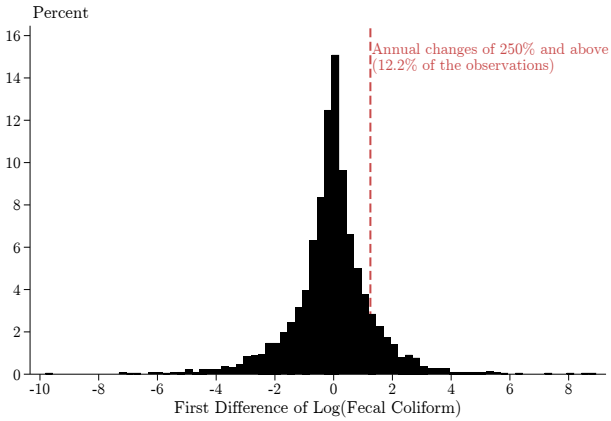
(a) Distribution of Log(Fecal Coli.)



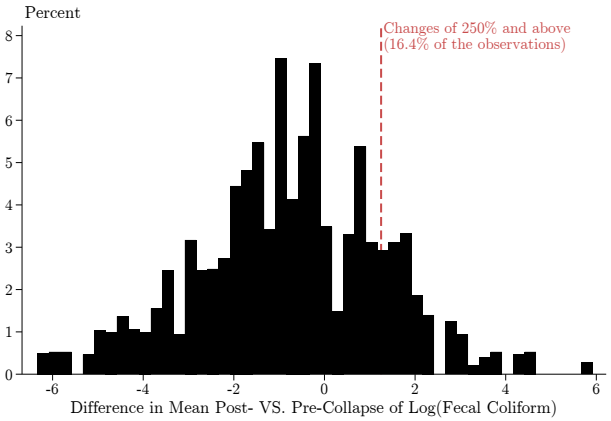
(b) 2004 Comparison India VS. Unite States



(c) Year-On-Year Changes



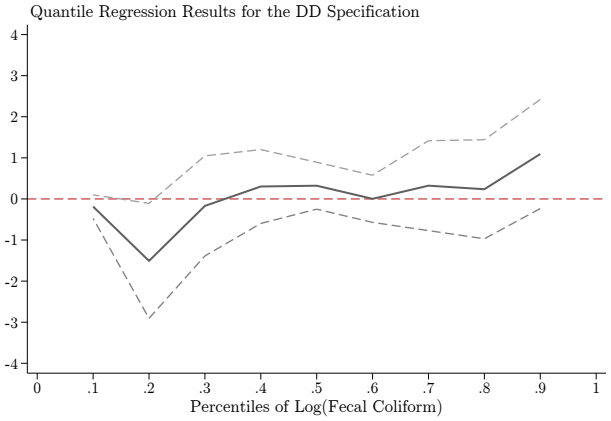
(d) Changes Post- VS. Pre-Collapse



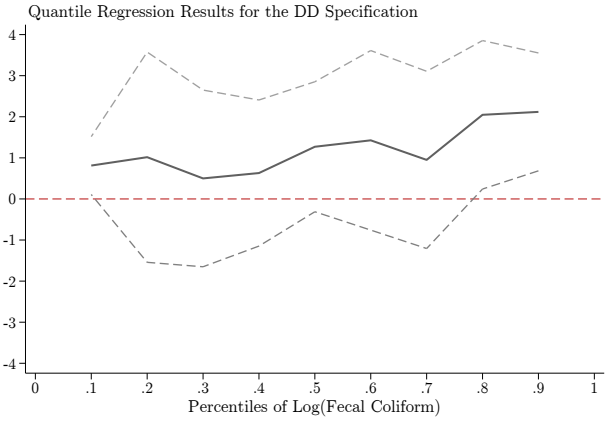
Notes: Summary statistics on fecal coliform data in the sample (panels a, c, and d), as well as a comparison of mean fecal coliform concentration between India and the United States in 2004 (the last year of our water quality data).

Figure A11: Quantile Regression Results for Log(Fecal Coli.)

(a) census urban & census rural Areas

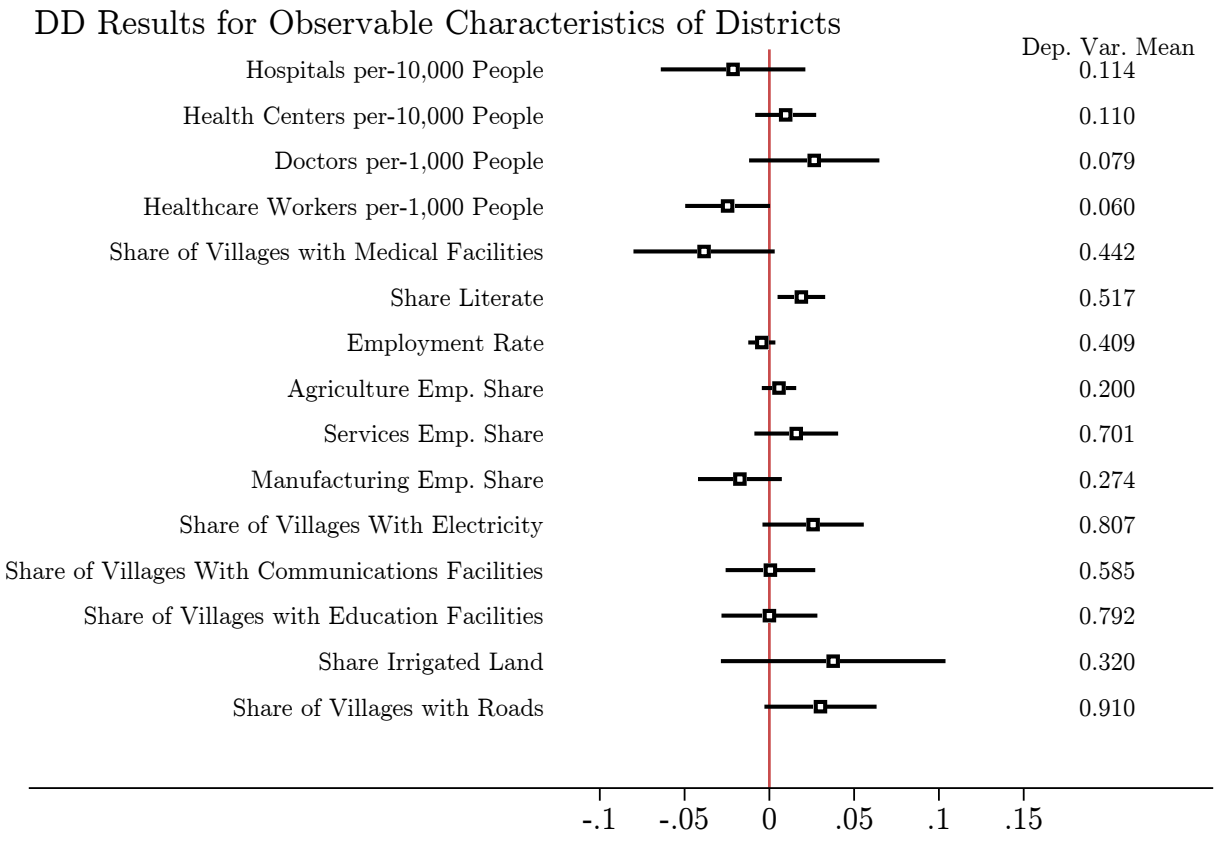


(b) census urban Areas Only



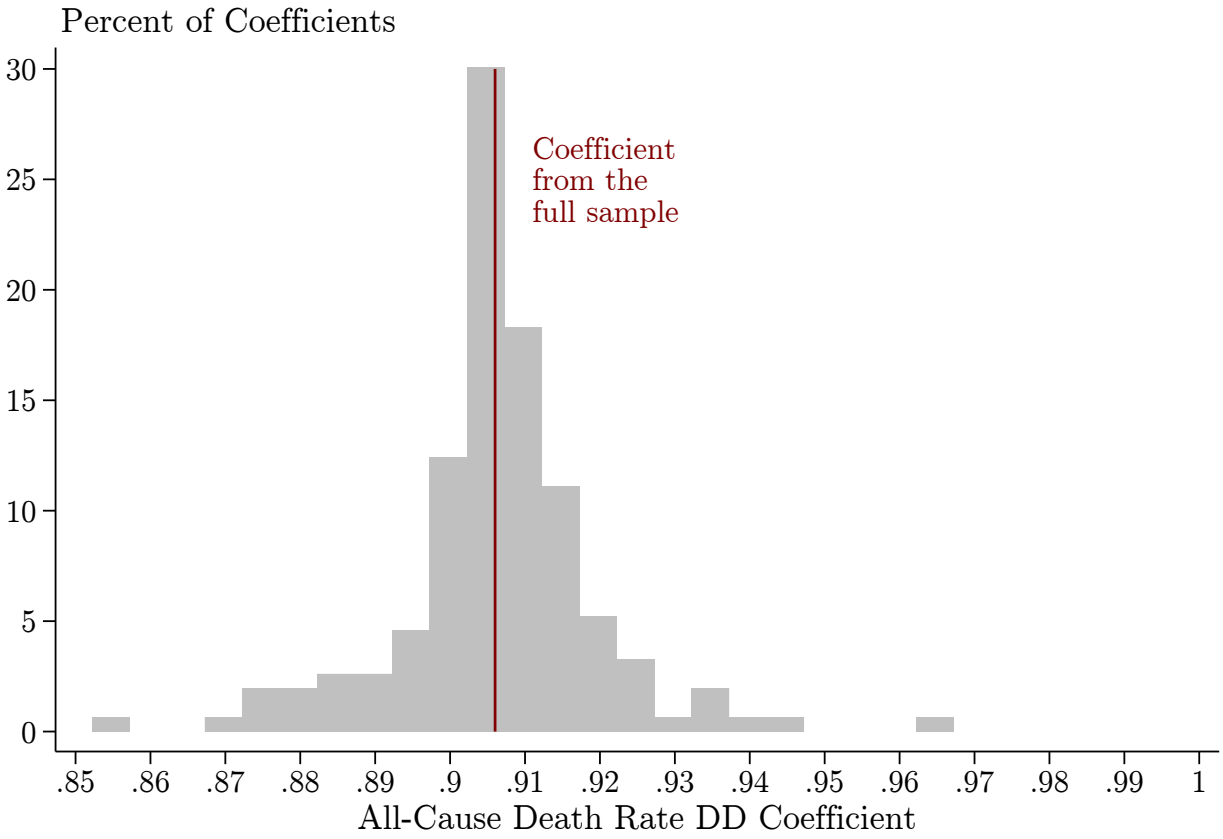
Notes: Quantile regressions, estimated at decile values of the logged fecal coliform distribution. 95% CIs are calculated using robust standard errors.

Figure A12: Summary of Placebo Results



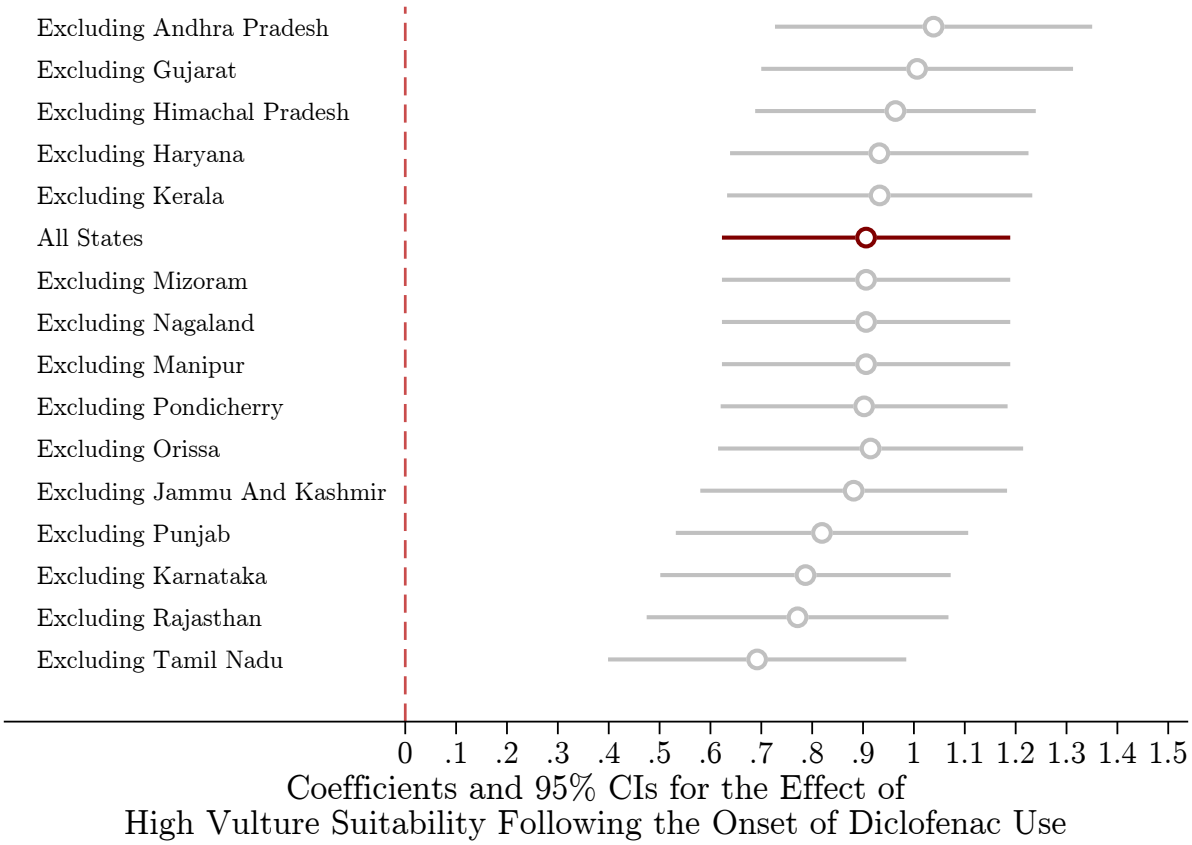
Notes: Estimation results for the specification in Equation (2). Each regression includes district and zonal council-by-year fixed effects. The sample includes all the districts in the balanced sample reported in the main analysis. Observations are population-weighted. We report 95% CIs that are calculated using Conley standard errors, which are serially correlated at the district level, and are allowed to be spatially correlated up to 200km.

Figure A13: Distribution of Leave-One-District Out DD Estimation Results



Notes: The distribution of coefficients from repeating the estimation in Equation (2) when leaving one district out each time. The vertical line shows the coefficient from the full balanced sample.

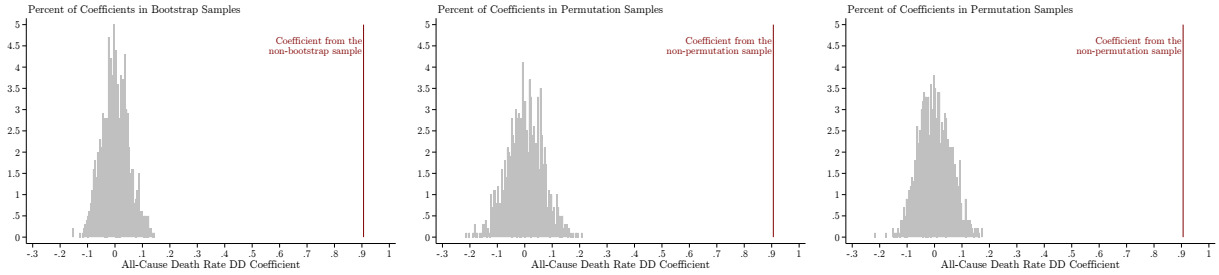
Figure A14: Distribution of Leave-One-State Out DD Estimation Results



Notes: The distribution of coefficients and 95% CIs from repeating the estimation in Equation (2) when leaving one state out each time. The maroon line shows the coefficient and 95% CI from the full balanced sample.

Figure A15: Permutation Inference DD Estimation Results

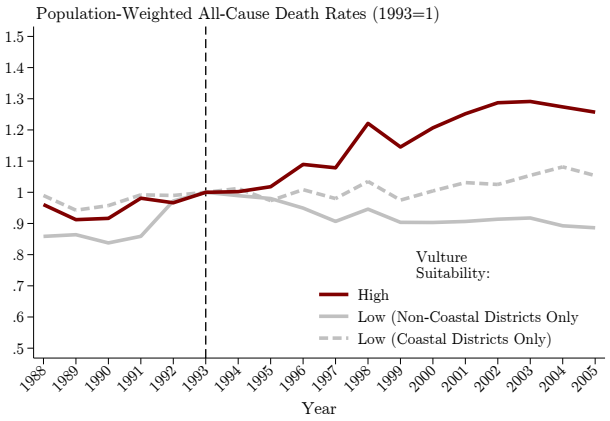
(a) Full (b) Block (c) Within



Notes: Distribution of coefficients from permutation samples where the treatment is randomly assigned. The vertical line shows the estimated coefficient from the non-permutation sample.

Figure A16: Robustness to Excluding Coastal Districts

(a) Highlighting Coastal Districts



(b) Excluding Coastal Districts

Notes: Variations on Figure 3C and Figure 4 from the main text. In Panel (a), we plot the mean all-cause death rate for three groups: (i) non-coastal treatment districts, (ii) non-coastal control districts, and (iii) coastal districts. In Panel (b), we exclude coastal districts from the sample and repeat the main DD event-study estimation.

B Diclofenac Use Onset

In her book chapter discussing the decline of vultures in India, Subramanian (2015) writes that "Diclofenac had been restricted as the intellectual property of pharmaceutical titan Novartis, but when the patent expired around 1990, India's generic drug industry, coupled with a thriving black market, flooded the country with cheap highly potent diclofenac." (p. 178). To better establish the timeline of when diclofenac use became prevalent in the livestock sector in India, we looked for evidence on the exact timing of the expiration of the patent. In Figure B1, we include three annotated extracts from Federal Drug Administration (FDA) records and documentation. Combined, these show that there was a change in 1993 pertaining to the patent Novartis had regarding diclofenac, and that the code associated with that change is associated with approval for a generic version of the drug.

Recall surveys were conducted by Cuthbert et al. (2014) in 2004 with 29 veterinary clinics in India. Among the questions asked, veterinary professionals were asked about when they began offering certain non-steroidal, anti-inflammatory drugs to livestock farmers. The summary of the responses reported a median onset year for diclofenac of 1994.

Figure B1: FDA Documents Regarding Diclofenac & Generic Drug Approval

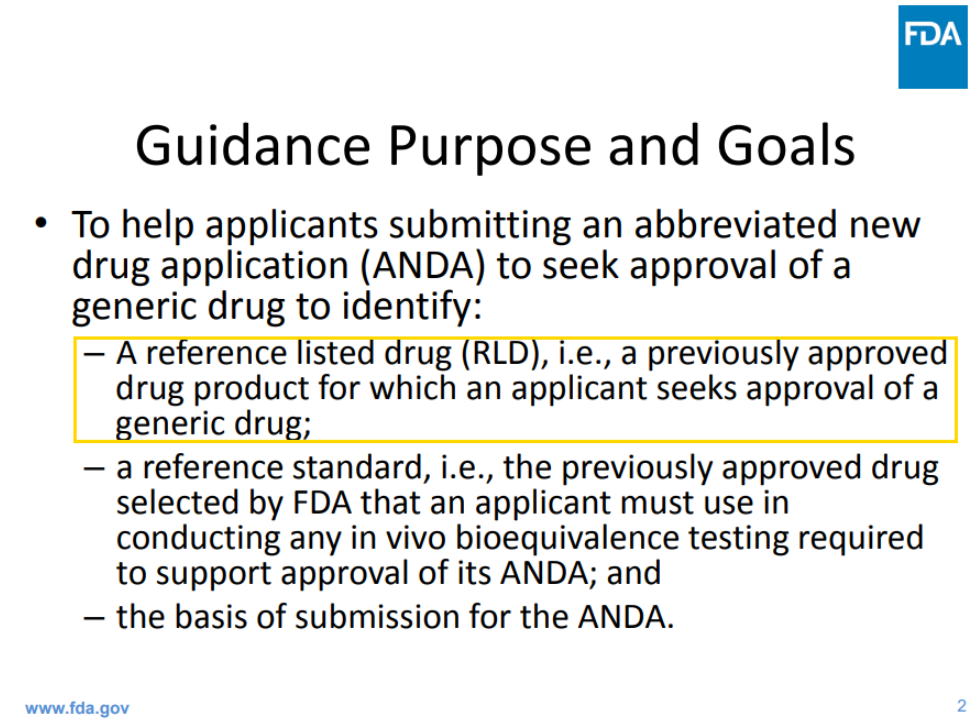
(a) Change to Novartis' Diclofenac Patent in 1993

		DICLOFENAC POTASSIUM						
		CAPSULE;ORAL						
		DICLOFENAC POTASSIUM						
		@ STRIDES PHARMA	25MG		A210078	001	Dec 03, 2019	Jun DISC
		TABLET;ORAL						
		CATAFLAM						
		+ @ NOVARTIS	50MG		N020142	002	Nov 24, 1993	Jan CRLD
		DICLOFENAC POTASSIUM						
	AB	AMICI	50MG		A076561	001	Mar 18, 2004	Oct CAHN
	AB	ANDA REPOSITORY	50MG		A076561	001	Mar 18, 2004	Sep CAHN
>D>	AB	! MYLAN	50MG		A075463	001	Jul 26, 1999	Nov CAHN
>A>	AB	! RK PHARMA	50MG		A075463	001	Jul 26, 1999	Nov CAHN
	AB	RUBICON	50MG		A075229	001	Nov 20, 1998	Aug CAHN

(b) Change Code CRLD

CFTG	Change. A TE Code is added when a first time generic for an innovator is approved.
CMFD	Change. The product is moved from the Discontinued Section due to a change in marketing status.
CMS1	Change. Miscellaneous addition to list.
CMS2	Change. Miscellaneous deletion from list.
CPOT	Change. Potency amount/unit.
CRLD	Change. Reference Listed Drug
CHRS	Change. Reference Standard
CTEC	Change. Therapeutic Equivalence Code
CTNA	Change. Trade Name
DISC	Discontinued. The Rx or OTC listed product is not being marketed and will appear in the discontinued section in the next edition.

(c) Documentation Regarding RLD Changes



Source: Panels (a) and (b) were obtained from "APPROVED DRUG PRODUCTS WITH THERAPEUTIC EQUIVALENCE EVALUATIONS," 40th Edition. This document can be downloaded from: https://www.fda.gov/media/72973/download (Accessed on: 12/15/2020). Panel (c) was obtained from "Draft Guidance for Industry: Referencing Approved Drug Products in ANDA Submissions". This document can be downloaded from: https://www.fda.gov/media/102266/download (Accessed on: 12/15/2020).

C Data

C.1 BirdLife International Species Distribution Maps

We requested access to the geodatabase with all the digitized maps for all bird species maintained by BirdLife International (BLI). Access is provided for non-commercial uses.[34] The data include information about whether the species are extant or extinct, along with discrete categories regarding the likelihood of the two. The data also include information on whether the species is native or not, and whether their presence is yearly, during the breeding season, or other form of seasonality.[35]

We extract the maps for all vulture species in India. We consider the areas where they are labeled as extant, probably extant, possibly extant, and possibly extinct. We include ranges classified as possibly extinct as those still reflect potential presence in the past thirty years. For each district, we calculate the overlap of the habitat area, and repeat this for each species. This provides us with three overlap values for the three diclofenac-affected vulture species. We calculate the mean value of those overlap scores, and use those to assign the suitability category.

The data in the species distribution maps provided by BLI is the most complete source of information regarding the habitat areas of bird species around the world. BLI also assesses the conservation status and extinction risk as part of the Red List, produced by the International Union for Conservation of Nature.[36] BLI uses both published and unpublished sources of information to determine the boundaries of each range. Some unpublished sources of information include specific interviews with local experts, as well as confidential records.[37] The maps are known to err on the side of including areas that might not contain the species (Ramesh et al. 2017). This means that the true distribution of the species is a subset of the area in the distribution map. This could lead us to incorrectly consider districts as treated districts, when in fact they should be classified as control districts, resulting in attenuated estimates.

C.2 Examining the Reporting Accuracy of the CRS Data

One known limitation of CRS data in India is that many vital statistics events go unrecorded, and as a result, the CRS under-reports the true magnitude of mortality. Although there is no alternative to the CRS as far as district-level data is concerned, at the national level a commonly used source of information is the Sample Registration System, which samples less than one percent of the population, but is designed to recover a nationally representative sample (Rao and Gupta 2020).

We obtain the raw SRS records in order to compare the gap in reporting. While we do find that at the national level, the CRS underestimates mortality rates by about a factor of

[34] Application can be filled out at: http://datazone.birdlife.org/species/requestdis

[35] BLI provides a summary of these categories here: http://datazone.birdlife.org/species/spcdistPOS

[36] The Red List is a set of species assessments that classifies species as threatened or non-threatened with respect to extinction risk, across several sub-categories.

[37] Some records are considered confidential as their release might jeopardize the species if they are actively traded in domestic and international wildlife trade markets.

two relative to the SRS, when controlling for state and zonal council-by-year fixed effects, both sources of data allow us to recover similar trends in mortality rates. Specifically, we compare the CRS data to the SRS data in order to evaluate if underreporting of mortality in the CRS data is introducing bias in the trends in addition to underestimating the magnitude. The data in the SRS are reported at the state level. To compare the CRS and SRS, we take a population-weighted mean of the district- or state-level data, respectively, to obtain a national-level estimate for the all-cause death rate. We plot the levels of all-cause death rates, by source of data, by year, in Figure C1.

There is a clear difference in levels (Figure C1, dashed lines) between the all-cause death rate in the CRS relative to the SRS data. The SRS death rate is nearly double the CRS-reported death rate. However, when residualizing the death rates on a set of unit and time fixed effects (Figure C1, reported in the solid lines), the two death rates follow similar trends.[38]

We interpret the agreement between the residualized levels in Figure C1 as evidence that conditional on fixed effects, the CRS data manage to capture similar trends to those in the SRS data. In addition, the results from this comparison also highlight that the correct baseline level that we should use when comparing the relative change in mortality is nearly twice as large, reducing the relative size of the effect when using the CRS mean level by half.

The fixed effect specifications we describe in Section 4 compare changes over time and are robust to several forms of under-reporting. This allows us to recover the level differences in mortality. Interpreting our level estimates *relative* to a baseline level of mortality, using the mean mortality reported in the CRS data is undesirable because it would overestimate the size of relative changes. Consequently, in the interpretation of the analysis, we interpret the magnitude of the coefficients relative to the mean level from the SRS data, which reflects the national-level death rate (see Section C.5 below for details).

C.3 Stable District Boundaries

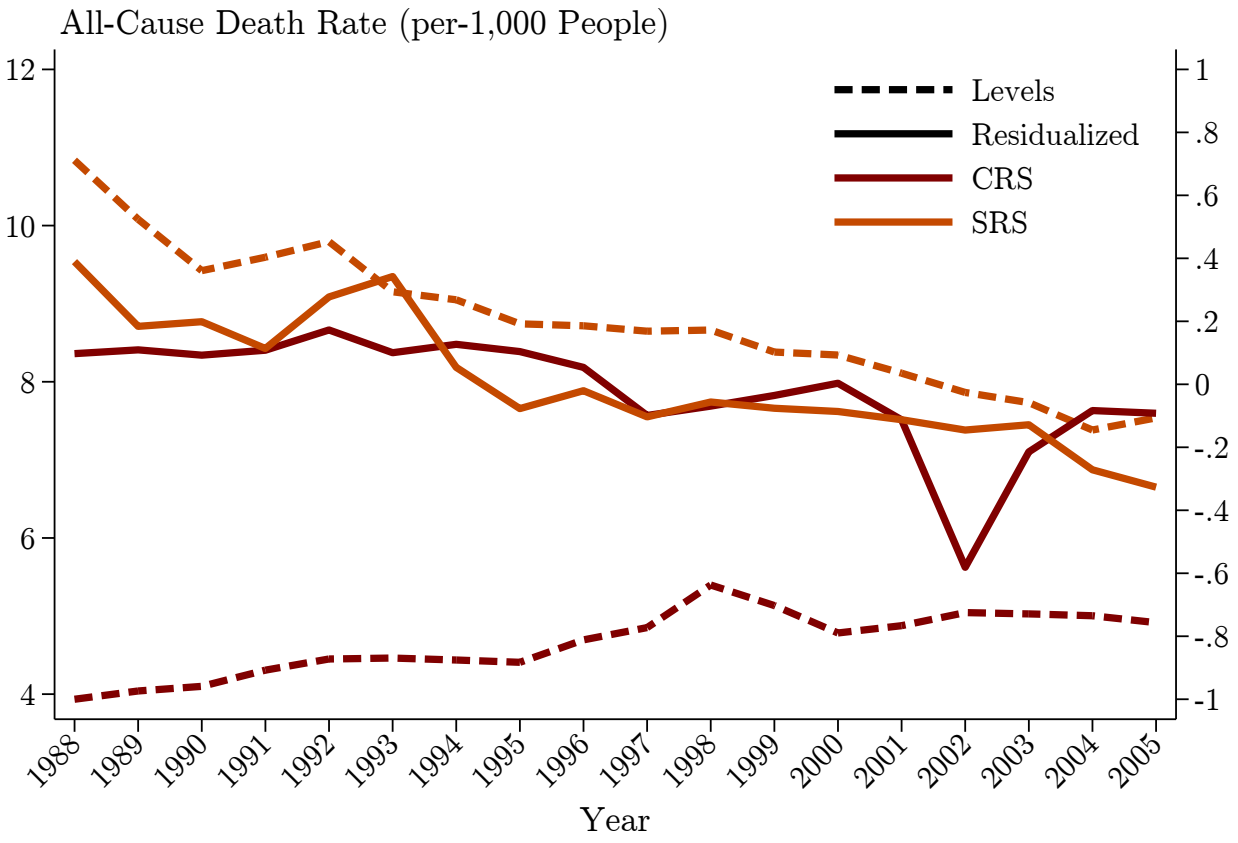
Historically, districts in India underwent considerable changes. Among these changes, some districts were split into new districts, while others had their borders re-drawn. This means that using the administrative definitions of districts, as is, will result in units entering and exiting the sample, and inconsistent geographic ranges over time. To overcome this, we stabilize districts relative to their 1981 borders. In the case that district split, we re-code them as their parent district. In the case where district borders change, we combine different districts as one unit. This builds on previous re-coding work performed in Greenstone and Hanna (2014) and Kumar and Somanathan (2009).

C.4 Changes to CRS Reporting in 1988

The VSI-CRS data experienced a shift in the reporting regime in 1988. From 1981 to 1987, the data are reported as rates, using interpolated population between censuses. From 1988 to 2005, the data are reported as counts. We use population data from the censuses to calculate

[38] Specifically, we include district-by-area or state-by-area, for urban and rural areas, fixed effects, as well as year fixed effects.

Figure C1: Comparing All-Cause Death Rates in CRS & SRS Data



Notes: Data from the CRS and SRS databases on all-cause death rates. District and state-level data are aggregated to the national level using population weights. Death rates are residualized (solid lines) on region (district or state), as well as zonal council-by-year fixed effects.

population growth rates, and use an exponential growth function to interpolate population during intercensal years. We then calculate all-cause death rates using the interpolated population data. In our main results, we use the data from 1988 to 2005 as the earlier data were calculated differently and are perhaps less comparable. In the Online Appendix, we provide the results for the full 1981 to 2005 period.

C.5 Representative National All-Cause Death Rates

As discussed above and in the main text, the CRS data allows us to recover the *differences* within districts over time even if the *levels* are under-reported. To correctly interpret the changes in mortality, we use the SRS sample to recover nationally representative means. We use a report that provides these values, annually, for the entire country, as well as the census urban and census rural areas. In Figure C2, we re-produce the key table in the report which summarizes those values. We use the values from 1988 to 1992 and calculate mean all-cause death rates of 10.2, 11, and 7.2, for all, census rural, and census urban samples, respectively.

Figure C2: Nationally Representative SRS Values

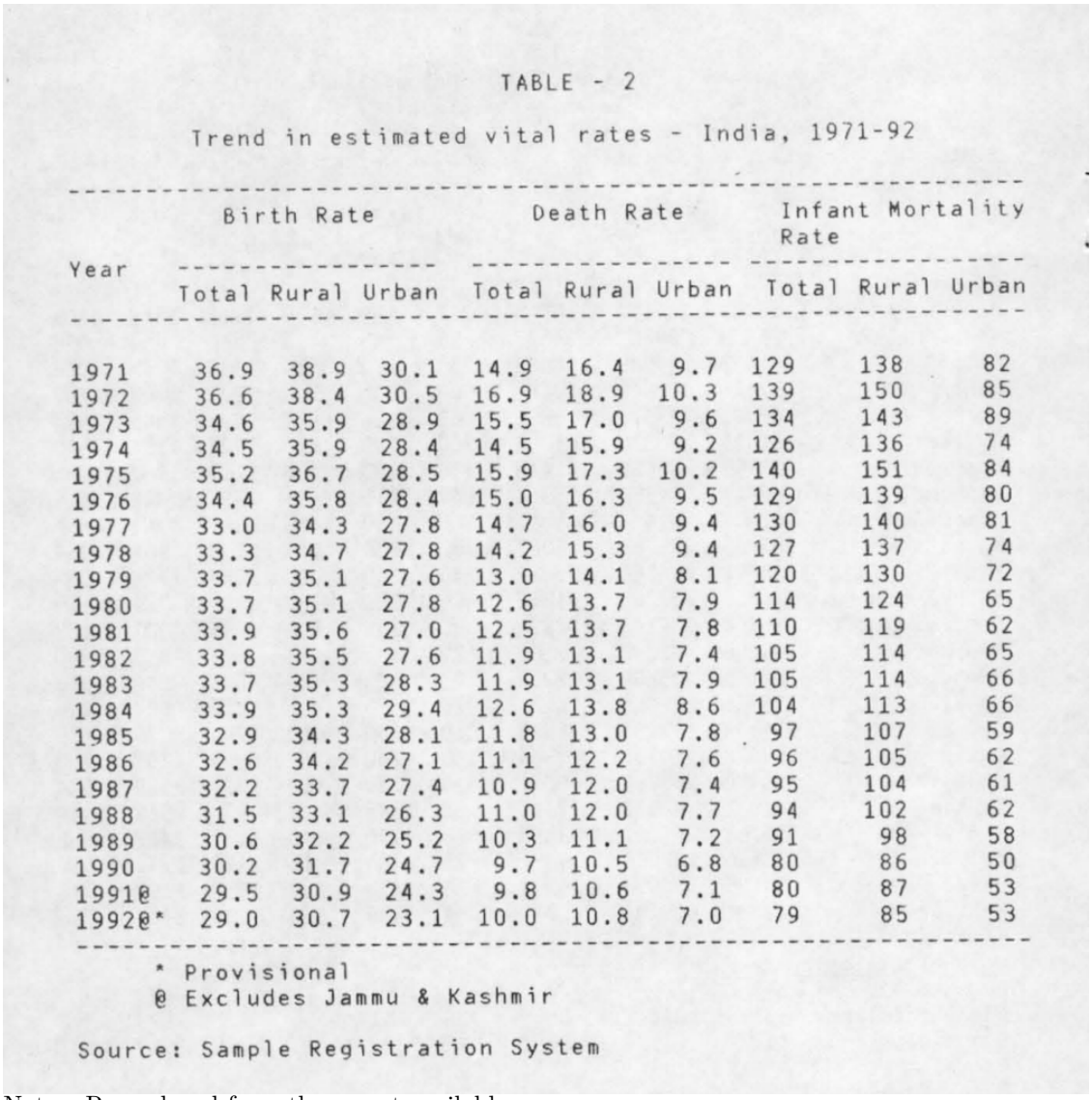


TABLE - 2

Trend in estimated vital rates - India, 1971-92

Year	Birth Rate			Death Rate			Infant Mortality Rate		
	Total	Rural	Urban	Total	Rural	Urban	Total	Rural	Urban
1971	36.9	38.9	30.1	14.9	16.4	9.7	129	138	82
1972	36.6	38.4	30.5	16.9	18.9	10.3	139	150	85
1973	34.6	35.9	28.9	15.5	17.0	9.6	134	143	89
1974	34.5	35.9	28.4	14.5	15.9	9.2	126	136	74
1975	35.2	36.7	28.5	15.9	17.3	10.2	140	151	84
1976	34.4	35.8	28.4	15.0	16.3	9.5	129	139	80
1977	33.0	34.3	27.8	14.7	16.0	9.4	130	140	81
1978	33.3	34.7	27.8	14.2	15.3	9.4	127	137	74
1979	33.7	35.1	27.6	13.0	14.1	8.1	120	130	72
1980	33.7	35.1	27.8	12.6	13.7	7.9	114	124	65
1981	33.9	35.6	27.0	12.5	13.7	7.8	110	119	62
1982	33.8	35.5	27.6	11.9	13.1	7.4	105	114	65
1983	33.7	35.3	28.3	11.9	13.1	7.9	105	114	66
1984	33.9	35.3	29.4	12.6	13.8	8.6	104	113	66
1985	32.9	34.3	28.1	11.8	13.0	7.8	97	107	59
1986	32.6	34.2	27.1	11.1	12.2	7.6	96	105	62
1987	32.2	33.7	27.4	10.9	12.0	7.4	95	104	61
1988	31.5	33.1	26.3	11.0	12.0	7.7	94	102	62
1989	30.6	32.2	25.2	10.3	11.1	7.2	91	98	58
1990	30.2	31.7	24.7	9.7	10.5	6.8	80	86	50
1991@	29.5	30.9	24.3	9.8	10.6	7.1	80	87	53
1992@*	29.0	30.7	23.1	10.0	10.8	7.0	79	85	53

* Provisional
@ Excludes Jammu & Kashmir

Source: Sample Registration System

Notes: Reproduced from the report available on:
https://unstats.un.org/unsd/demographic/meetings/wshops/1993_China_CRVS/docs/1993_Doc.26_India.pdf
(Accessed August 22, 2023).

D Additional Details on the Empirical Setting

D.1 Additional Details on the Role of Vultures as Keystone Species

The ecological and epidemiological dynamics of scavengers, pathogens, and infectious diseases help explain the causal link between diminishing vulture populations and human health. While some animal species will feed on carrion if available, for vultures, it is the only source of food. As a result, vultures have evolved as very efficient scavengers. Vultures have an extremely acidic stomach, that ranges from just above zero to two pH.[39] In comparison, an average human has a pH level of two in their stomach, making it ten to a hundred times less acidic than that of a vulture. This is one of the key adaptations that allows vultures to safely consume carrion, and also results in most bacteria not surviving their digestive system (D. L. Ogada et al. 2012; Roggenbuck et al. 2014).

Vultures are extremely effective at reducing a carcass to its bones, and can consume the carrion of an entire cow within forty minutes (D. L. Ogada et al. 2012). Other scavenging species are not good substitutes from a sanitation point of view because they leave the flesh behind. Recent experimental evidence confirms that non-vulture species are not able to compensate and functionally replace vultures in terms of scavenging efficiency (Hill et al. 2018). For this reason, the historic presence of large and stable vulture populations simultaneously reduced pathogen and bacteria concentrations in the environment, as well as crowded out other mammalian scavengers such as dogs and rats that transmit various diseases including rabies (Moleón et al. 2014). In the absence of vultures, the composition of species that feed on carcasses changes towards dogs and rats.[40]

The removal of carrion from the environment by vultures becomes more important in low to middle-income countries where these birds have effectively substituted for expensive infrastructure to safely dispose of animal carcasses. The limited availability of infrastructure such as animal incinerators has led to so-called "animal landfills" on the outskirts of population centers across India. Anecdotal accounts describe how with vultures no longer available, the rotting meat and its scent build up, attracting feral dogs (Subramanian 2011). Attacks by dogs are common, and they mostly represent an immediate deadly threat to small children. However, with India being a global epicenter for rabies, any animal bite can result in death (Braczkowski et al. 2018). The combination of dogs and rats serving as vectors of infectious diseases and being far less efficient scavengers than vultures, make carcass dumps a breeding ground for disease (D. L. Ogada et al. 2012).

Livestock agriculture also becomes a source of water pollution when farmers need to dispose of dead animals (Engel et al. 2004; Kwon et al. 2017). A 2016 Supreme Court ruling in the state of Uttarkhand recognized that animal carcass dumping in water bodies is an ongoing problem, even in water bodies that are considered sacred: "It is tragic that the Ganga, which has since time immemorial, purified the people is being polluted by man in numerous ways, by dumping of garbage, throwing carcass of dead animals and discharge of

[39] Acidity is measured on a logarithmic scale. Water has a pH of seven, and lower values are considered more acidic. Acids that are dangerous to come in direct contact with have pH values of four and below.

[40] As Dr. Asad Rahmani, Director of the Bombay Natural History Society, put it: "Now there are dogs. They eat anything, live or dead. There are dogs on the ground but the skies are empty" (Subramanian 2011).

effluents" (Sharma and Singh 2016).

The presence of animal landfills near and in census urban centers has been documented extensively in academic writing and news articles. Senacha et al. (2008) study the concentration of diclofenac residue across different animal dumping sites, and classify many of the sites as residing in urban areas. In their review of the historic importance of vultures in India, Van Dooren (2010) writes that in "urban and semi-urban environments, they found abundant food in carcass dumps, as well as in tanneries, slaughter yards, garbage dumps, and bone mills." They further emphasize that "especially in urban environments, vultures have provided an incredibly valuable service to humans." Singh et al. (2013) begin their paper on the challenges that India is facing with veterinary urban hygiene by writing that: "India is confronted with many hygiene problems in urban areas that are related to animal populations." They continue to describe how dead animals in urban areas are "left to rot in the open" and that "diseases in urban parts of the country have shown a rapid growth, due to the co-habitation of their hosts in areas around animal populations where proper sanitation is not maintained."

Journalists writing on the collapse of vulture populations have also noted the urban landscape as the nexus of vultures and dead animals. McGrath (2007) writes that "In urban areas, haulers take dead animals to official dumps." Sanjayan (2013) writes that "Huge dumps have sprouted near urban centers where thousands of dead cows, along with the occasional horse or camel, are brought to rot." Pati (2016) writes about the civic authorities attempting "to stop the present unscientific disposal of animal carcasses near urban areas."

Finally, the interaction of widespread dairy cultivation with cultural practices regarding dead animals has resulted in a historically large reliance on scavengers in India. Restricting the amount of carrion and the time it remains in open fields is of specific importance in India because of prevailing social norms regarding the handling of meat. Hindus will not consume cows whereas Muslims will not consume animals not killed according to *halal*.

We summarize the interactions between vultures, mammalian scavengers, environmental quality, and public health in Figure 1. Within the ecosystem interaction group of vultures, mammalian scavengers (dogs and rats), and livestock carrion, the former two are competing for the food source (dead animals). Greater availability of dead carrion supports larger populations of both scavenger types, efficient (vultures), and inefficient (dogs and rats). Because both types compete for the same food source, each type indirectly limits the population growth of the other type. Following the decline in vulture populations, which we describe in detail in the next section, environmental quality declines due to the increase in the inefficient scavengers, which lead to more carrion rotting in the open, and the rise in vectors of infectious diseases. Combined, the decline in vultures leads to worse public health outcomes.

D.2 Additional Details on the Decline of Vultures in India

Vultures were once a ubiquitous sight across India with a population that may have exceeded 50 million birds. Today, the three species that made up the bulk of the population are considered critically endangered after declining by more than 95%.[41] Their collapse is

[41] The three common names (and scientific names) of the three affected vulture species are: slender-billed (*Gyps tenuerostris*), white-backed (*Gyps bengalensis*), and long-billed (*Gyps indicus*). There is one ad-

attributed to the chemical residue of the painkiller diclofenac in livestock animals, administered by farmers to treat fevers and inflammations. A vulture that feeds on a carcass with diclofenac residue can develop kidney failure within weeks and die.[42] In Figure 2, we plot the classification of districts according to their baseline habitat suitability for the affected vultures (we explain this classification in detail in Section 4.1).

Diclofenac is an old drug, first introduced in 1973 by Ciba-Geigy (now Novartis). It has since become the most widely used non-steroidal anti-inflammatory drug in the world and is prescribed as a painkiller for many conditions (Altman et al. 2015). However, its use as a veterinary drug to treat injuries, inflammations, and fevers in wounded or sick animals was a much more recent development (Cuthbert et al. 2014; Subramanian 2015). This became possible only when low-cost generic versions of the drug were developed around the time of expiry of the original patent.

Anecdotal accounts place the timing of the patent expiration in the early 1990s (Subramanian 2015). Sales data that we purchased from the company IQVIA shows a dramatic growth in the entry of Indian drug manufacturers around this time (see Figure 3a). In order to more precisely determine the onset of diclofenac use, we draw on additional sources of data. We start with formal records regarding the patent and its expiration. The patent originally belonged to the pharmaceutical company Novartis. Using documents from the Federal Drug Administration regarding drug patents, we are able to trace the first approval for a generic version granted to Novartis in 1993. See the Appendix for additional details. This is consistent with a survey of veterinary clinics conducted by Cuthbert et al. (2014) which indicates the first veterinary formulations in India became available in 1994. With these sources of information, we classify 1994 as the first year in which diclofenac was widely used to treat livestock, and assign this as the year of treatment onset.

Reports of vulture declines rapidly followed the veterinary use of diclofenac. Field observations in 1996 found only half of the 353 nesting vulture pairs recorded in 1984 in Keoladeo National Park outside Delhi. Surveys conducted in 1996 reported dead vultures around the nests, in bushes, and hanging from the trees. By 1999, there was not a single living vulture pair documented at the site (Subramanian 2011). After Dr. Vibhu Prakash, at the time a PI in the Bombay Natural History Society, communicated his findings to colleagues, they reported similar patterns they thought were simply idiosyncratic to their study sites. Population declines were so rapid that in 2000, all three species were classified as critically endangered.

At first, several conjectures were made regarding the potential cause. These included the emergence of a new wildlife disease or the effect of pesticide accumulation, as well as deliberate poisoning by Western countries (Subramanian 2015). It took about a decade to establish the root cause when Oaks et al. (2004) used both autopsy data, and experimental exposure of vultures to diclofenac, to show that even trace amounts of diclofenac in the carcasses that vultures feed on result in lethal kidney failure. As a result, the Indian government banned the veterinary use of diclofenac in 2006 (Vibhu Prakash et al. 2012; D. L.

ditional member of the gyps genus, Himalayan Griffon (*Gyps himalayensis*). However, as their name suggests, they are mostly found in the Himalayas, where they do not depend on livestock carcasses that have diclofenac residue that caused the collapse in the other species.

[42] We use the term kidney failure for clarity. The more medically correct terms are renal failure and visceral gout.

Ogada et al. 2012). However, surveys conducted up to 2018 document rampant illicit use of diclofenac in livestock including through the diversion of human doses (Galligan et al. 2020).

Thus despite the 2006 ban, vulture populations remain a miniscule fraction of what they once were. Recovery is difficult because vultures have a low fecundity. A female vulture will lay at most a single egg each year. Vultures take five years until they reach sexual maturity. Assuming they find a mating pair, construct a nest for six weeks, lay a single egg, and successfully feed and ensure the survival of the offspring for four months, a new vulture gets on the path toward reproducing in about five years (D. L. Ogada et al. 2012).

In the absence of vultures, livestock farmers, and municipalities can utilize either labor-intensive or capital-intensive substitutions. Farmers can exercise deep burial but given the number of livestock animals, this adds high labor costs. Since these costs are private while the costs of disposing of animals in carcass dumps or water are socialized, it is not surprising that deep burial remains uncommon. Livestock carrion can be disposed of using specially designed incinerators, yet they are expensive to buy and operate and require a reliable mechanism for making sure that farmers transport dead animals to them. According to a 2020 report by India's Central Pollution Control Board, India has yet to adopt livestock incinerators as a substitution for vultures: "Very few cities have carcass utilization plants and incinerators. One such carcass utilization plant is installed in Delhi and incinerator is under installation in Chandigarh" (Central Pollution Control Board 2020).

D.3 Tabulation of mortality effects of other WASH interventions

We tabulate the mortality effects of other water and sanitation interventions from the literature to aid benchmarking of the effect of losing an ecosystem service providing the safe and quick disposal of meat from livestock carcasses.

Table D1: Tabulation of mortality effects of other water, sanitation, and air-pollution interventions reported in the literature.

Reference	Country	Year	Intervention	Outcome	Effect Size (Reductions)
Geruso & Spears, 2018	India	1992-2006	10% Reduction in Open Defecation	Infant Mortality	8%
Bhalotra et al. , 2021	Mexico	1991-95	Municipal water chlorination	Under 5 Mortality (Diarrhoea)	45%-67% (diarrhoea) $\sim$ 9.4-13.4% (all-cause)
Watson, 2005	USA (Native-American Reservations)	1968-1998	10% increase in homes receiving sanitation improvements	Infant Mortality	2.5%
Cutler and Miller, 2005	USA	1900-1940	Urban clean-water infrastructure (filtration)	Total & Infant Mortality	16% (TMR), 43% (IMR)
Marcella and Goldin, 2019	USA	1880-1920	Urban sewerage and safe-water treatments	Child & Infant Mortality	33.6% (U5MR), 48% (IMR)
Galiani et al 2005	Argentina	1995-1999	Privatization of municipal water companies	Child Mortality	8%
Tanaka, 2015	China	1998-2000	Air Pollution Regulations	Infant Mortality	20%
Ebenstein et. al. 2017	China	2004-2012	Lifetime free coal-based home heating	Life Expectancy,All-Cause Mortality	-20% to -26% (all-cause), -1.2 years (life expectancy)

References

Alan Bester, C, Timothy G Conley, Christian B Hansen, and Timothy J Vogelsang. 2016. "Fixed-b Asymptotics for Spatially Dependent Robust Nonparametric Covariance Matrix Estimators." *Econometric Theory* 32 (1): 154–186.

Alsan, Marcella. 2015. "The Effect of the TseTse Fly on African Development." *The American Economic Review* 105 (1): 382–410.

Altman, Roy, Bill Bosch, Kay Brune, Paola Patrignani, and Clarence Young. 2015. "Advances in NSAID Development: Evolution of Diclofenac Products Using Pharmaceutical Technology." *Drugs* 75 (8): 859. ISSN: 11791950. https://doi.org/10.1007/S40265-015-0392-Z. /pmc/articles/PMC4445819/%20/pmc/articles/PMC4445819/?report=abstract%20https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4445819/.

Arrow, Kenneth J, and Anthony C Fisher. 1974. "Environmental Preservation, Uncertainty, and Irreversibility." *Quarterly Journal of Economics* 88 (2): 312–319.

Barrios, Thomas, Rebecca Diamond, Guido W Imbens, and Michal Kolesár. 2012. "Clustering, Spatial Correlations, and Randomization Inference." *Journal of the American Statistical Association* 107 (498): 578–591.

Bhalotra, Sonia R, Alberto Diaz-Cayeros, Grant Miller, Alfonso Miranda, and Atheendar S Venkataramani. 2021. "Urban Water Disinfection and Mortality Decline in Lower-Income Countries." *American Economic Journal: Economic Policy* 13 (4): 490–520.

Bock, Carl E. 1984. "Geographical correlates of abundance vs. Rarity in some north American winter landbirds." *The Auk* 101 (2): 266–273.

Booth, Trevor H, Henry A Nix, John R Busby, and Michael E F Hutchinson. 2014. "BIOCLIM: the first species distribution modelling package, its early applications and relevance to most current MaxEnt studies." Edited by Janet Franklin. *Diversity & distributions* 20 (1): 1–9.

Borregaard, Michael Krabbe, and Carsten Rahbek. 2010. "Causality of the relationship between geographic distribution and species abundance." *The Quarterly Review of Biology* 85 (1): 3–25.

Braczkowski, Alexander R, Christopher J O'Bryan, Martin J Stringer, James E M Watson, Hugh P Possingham, and Hawthorne L Beyer. 2018. "Leopards provide public health benefits in Mumbai, India." *Frontiers in Ecology and the Environment* 16 (3): 176–182.

Brock, William A, and Anastasios Xepapadeas. 2003. "Valuing Biodiversity from an Economic Perspective: A Unified Economic, Ecological, and Genetic Approach." *The American Economic Review* 93 (5): 1597–1614.

Brown, James H. 1984. "On the Relationship between Abundance and Distribution of Species." *The American Naturalist* 124 (2): 255–279.

Brown, James H, and Brian A Maurer. 1987. "Evolution of Species Assemblages: Effects of Energetic Constraints and Species Dynamics on the Diversification of the North American Avifauna." *The American Naturalist* 130 (1): 1–17.

Brundage, Adrienne. 2021. "Carrion Ecology." In *Wildlife Biodiversity Conservation: Multidisciplinary and Forensic Approaches,* edited by Susan C Underkoffler and Hayley R Adams, 193–210. Cham: Springer International Publishing.

Burgess, Robin, Olivier Deschenes, Dave Donaldson, and Michael Greenstone. 2017. "Weather, Climate Change and Death in India." *Working Paper.*

Burke, Marshall, and Kyle Emerick. 2016. "Adaptation to Climate Change: Evidence from US Agriculture." *American Economic Journal: Economic Policy* 8 (3): 106–140.

Cardinale, Bradley J, J Emmett Duffy, Andrew Gonzalez, David U Hooper, Charles Perrings, Patrick Venail, Anita Narwani, et al. 2012. "Biodiversity loss and its impact on humanity." *Nature* 486 (7401): 59–67.

Carleton, Tamma, Amir Jina, Michael Delgado, Michael Greenstone, Trevor Houser, Solomon Hsiang, Andrew Hultgren, et al. 2022. "Valuing the Global Mortality Consequences of Climate Change Accounting for Adaptation Costs and Benefits." *The Quarterly Journal of Economics,* ISSN: 0033-5533. https://doi.org/10.1093/QJE/QJAC020. https://academic.oup.com/qje/advance-article/doi/10.1093/qje/qjac020/6571943.

Carleton, Tamma A, Amir Jina, Michael T Delgado, Michael Greenstone, Trevor Houser, Solomon M Hsiang, Andrew Hultgren, et al. 2022. "Valuing the Global Mortality Consequences of Climate Change Accounting for Adaptation Costs and Benefits." *The Quarterly Journal of Economics* 137 (4): 2037–2105.

Carmona, Carlos P, Riin Tamme, Meelis Pärtel, Francesco de Bello, Sébastien Brosse, Pol Capdevila, Roy González-M, et al. 2021. "Erosion of global functional diversity across the tree of life." *Science Advances* 7 (13).

Carson, Richard T. 2012. "Contingent Valuation: A Practical Alternative when Prices Aren't Available." *The Journal of Economic Perspectives* 26 (4): 27–42.

Ceballos, Gerardo, Paul R Ehrlich, Anthony D Barnosky, Andrés Garcı a, Robert M Pringle, and Todd M Palmer. 2015. "Accelerated modern human–induced species losses: Entering the sixth mass extinction." *Science Advances* 1 (5): 1–5.

Central Pollution Control Board. 2020. *Guidelines for Carcass Disposal.*

Chandramohan, S., Karikalan Mathesh, John W. Mallord, Vinny Naidoo, K. Mahendran, Manickam Kesavan, Gyanendra K. Gaur, et al. 2022. "Metabolism of aceclofenac to diclofenac in the domestic water buffalo Bubalus bubalis confirms it as a threat to Critically Endangered Gyps vultures in South Asia." *Environmental Toxicology and Pharmacology* 96:103984. ISSN: 1872-7077. https://doi.org/10.1016/J.ETAP.2022.103984. https://pubmed.ncbi.nlm.nih.gov/36182041/.

Chatterjee, Patralekha. 2009. "India's ongoing war against rabies." *Bulletin of the World Health Organization* 87 (12): 890. ISSN: 15640604. https://doi.org/10.2471/BLT.09.021209. /pmc/articles/PMC2789368/%20/pmc/articles/PMC2789368/?report=abstract%20https://www.ncbi.nlm.nih.gov/pmc/articles/PMC2789368/.

Chay, Kenneth Y, and Michael Greenstone. 2003. "The Impact of Air Pollution on Infant Mortality: Evidence from Geographic Variation in Pollution Shocks Induced by a Recession." *Quarterly Journal of Economics* 118 (3): 1121–1167.

Conley, T G. 1999. "GMM estimation with cross sectional dependence." *Journal of econometrics* 92 (1): 1–45.

Corno, L, N Hildebrandt, and A Voena. 2020. "Age of marriage, weather shocks, and the direction of marriage payments." *Econometrica.*

Costanza, Robert, Ralph d'Arge, Jose Paruelo, Stephen Farber, Bruce Hannon, Karin Limburg, Rudolf de Groot, et al. 1997. "The value of the world's ecosystem services and natural capital." *Nature* 387 (6630): 253–260.

Costinot, Arnaud, Dave Donaldson, and Cory Smith. 2016. "Evolving Comparative Advantage and the Impact of Climate Change in Agricultural Markets: Evidence from 1.7 Million Fields around the World." *The Journal of Political Economy* 124 (1): 205–248.

Currie, Janet, Lucas Davis, Michael Greenstone, and Reed Walker. 2015. "Environmental Health Risks and Housing Values: Evidence from 1,600 Toxic Plant Openings and Closings." *American Economic Review* 105 (2): 678–709.

Currie, Janet, and Reed Walker. 2011. "Traffic Congestion and Infant Health: Evidence from E-ZPass." *American Economic Journal. Applied Aconomics* 3 (1): 65–90.

Cuthbert, Richard J, Mark A Taggart, Vibhu Prakash, Soumya S Chakraborty, Parag Deori, Toby Galligan, Mandar Kulkarni, et al. 2014. "Avian scavengers and the threat from veterinary pharmaceuticals." *Philosophical Transactions of the Royal Society of London. Series B, Biological sciences* 369 (1656).

Cutler, David, and Grant Miller. 2005. "The role of public health improvements in health advances: the twentieth-century United States." *Demography* 42 (1): 1–22.

Daily, Gretchen C, Tore Söderqvist, Sara Aniyar, Kenneth Arrow, Partha Dasgupta, Paul R Ehrlich, Carl Folke, et al. 2000. "The Value of Nature and the Nature of Value." *Science* 289 (5478): 395–396.

Dainese, Matteo, Emily A Martin, Marcelo A Aizen, Matthias Albrecht, Ignasi Bartomeus, Riccardo Bommarco, Luisa G Carvalheiro, et al. 2019. "A global synthesis reveals biodiversity-mediated benefits for crop production." *Science advances* 5 (10): eaax0121.

Dell, Melissa, Benjamin F Jones, and Benjamin A Olken. 2014. "What Do We Learn from the Weather? The New Climate-Economy Literature." *Journal of Economic Literature* 52 (3): 740–798.

Deryugina, Tatyana, Garth Heutel, Nolan H Miller, David Molitor, and Julian Reif. 2019. "The Mortality and Medical Costs of Air Pollution: Evidence from Changes in Wind Direction." *American Economic Review* 109 (12): 4178–4219.

Deschênes, Olivier, and Michael Greenstone. 2007. "The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather." *The American Economic Review* 97 (1): 354–385.

Deschênes, Olivier, Michael Greenstone, and Jonathan Guryan. 2009. "Climate Change and Birth Weight." *The American Economic Review: Papers & Proceedings* 99 (2): 211–217.

Dirzo, Rodolfo, Hillary S Young, Mauro Galetti, Gerardo Ceballos, Nick J B Isaac, and Ben Collen. 2014. "Defaunation in the Anthropocene." *Science* 345 (6195): 401–406.

Ebenstein, Avraham. 2012. "The Consequences of Industrialization: Evidence from Water Pollution and Digestive Cancers in China." *The review of Economics and Statistics* 94 (1): 186–201.

Ebenstein, Avraham, Maoyong Fan, Michael Greenstone, Guojun He, and Maigeng Zhou. 2017. "New evidence on the impact of sustained exposure to air pollution on life expectancy from China's Huai River Policy." *Proceedings of the National Academy of Sciences* 114 (39): 10384–10389.

Engel, Bernard A, Kyoung Jae Lim, Jin-Yong Choi, and Larry Theller. 2004. "Evaluating Environmental Impacts." In *Carcass disposal: A comprehensive review.* {National Agricultural Biosecurity Center Consortium USDA APHIS Cooperative Agreement Project}.

Estes, James A, John Terborgh, Justin S Brashares, Mary E Power, Joel Berger, William J Bond, Stephen R Carpenter, et al. 2011. "Trophic downgrading of planet Earth." *Science* 333 (6040): 301–306.

Felius, Marleen. 1995. *Cattle breeds : an encyclopedia.* Doetinchem, Netherlands: Misset.

Ferraro, Paul J, James N Sanchirico, and Martin D Smith. 2019. "Causal inference in coupled human and natural systems." *Proceedings of the National Academy of Sciences of the United States of America* 116 (12): 5311–5318.

Fisher, R A. 1966. *The Design of Experiments.* 8th. 866 Third Avenue, New York, NY 10022: Hafner Publishing Company.

Frank, Eyal. 2024. "The Economic Impacts of Ecosystem Disruptions: Costs From Substituting Biological Pest Control." *Science* 385:eadg0344. https://doi.org/dx.doi.org/10.1126/science.adg0344.

Frank, Eyal G, and Wolfram Schlenker. 2016. "Balancing economic and ecological goals." *Science* 353 (6300): 651–652.

Freckleton, Robert P, David Noble, and Thomas J Webb. 2006. "Distributions of habitat suitability and the abundance-occupancy relationship." *The American Naturalist* 167 (2): 260–275.

Fujiwara, Thomas, Kyle Meng, and Tom Vogl. 2016. "Habit Formation in Voting: Evidence from Rainy Elections." *American Economic Journal. Applied Economics* 8 (4): 160–188.

Galiani, Sebastian, Paul Gertler, and Ernesto Schargrodsky. 2005. "Water for Life: The Impact of the Privatization of Water Services on Child Mortality." *The Journal of Political Economy* 113 (1): 83–120.

Galligan, Toby H, John W Mallord, Vibhu M Prakash, Krishna P Bhusal, A B Sarowar, Fergus M Anthony, Ruchi Dave, et al. 2020. "Trends in the availability of the vulture-toxic drug, diclofenac, and other NSAIDs in South Asia, as revealed by covert pharmacy surveys." *Bird Conservation International,* 1–17.

Geruso, Michael, and Dean Spears. 2018. "Neighborhood Sanitation and Infant Mortality." *American Economic Journal. Applied Economics* 10 (2): 125–162.

Greenstone, Michael, and Rema Hanna. 2014. "Environmental Regulations, Air and Water Pollution, and Infant Mortality in India." *The American Economic Review* 104 (10): 3038–3072.

Hale, Sarah L, and John L Koprowski. 2018. "Ecosystem-level effects of keystone species reintroduction: a literature review." *Restoration Ecology* 26 (3): 439–445.

Hanemann, W Michael. 1994. "Valuing the Environment Through Contingent Valuation." *The Journal of Economic Perspectives* 8 (4): 19–43.

Heal, Geoffrey. 2000. "Valuing Ecosystem Services." *Ecosystems* 3 (1): 24–30.

Hengeveld, Rob, and Jaap Haeck. 1982. "The Distribution of Abundance. I. Measurements." *Journal of Biogeography* 9 (4): 303–316.

Hill, Jacob E, Travis L DeVault, James C Beasley, Olin E Rhodes Jr, and Jerrold L Belant. 2018. "Effects of vulture exclusion on carrion consumption by facultative scavengers." *Ecology and Evolution* 8 (5): 2518–2526.

Hooper, D U, F S Chapin, J J Ewel, A Hector, P Inchausti, S Lavorel, J H Lawton, et al. 2005. "Effects of Biodiversity on Ecosytem Functioning: A Consensus of Current Knowledge." *Ecological Monographs* 75 (1): 3–35.

Hsiang, Solomon, Robert Kopp, Amir Jina, James Rising, Michael Delgado, Shashank Mohan, D J Rasmussen, et al. 2017. "Estimating economic damage from climate change in the United States." *Science* 356 (6345): 1362–1369.

Hsiang, Solomon M. 2010. "Temperatures and cyclones strongly associated with economic production in the Caribbean and Central America." *Proceedings of the National Academy of Sciences of the United States of America* 107 (35): 15367–15372.

Hugo. 2021. *Vultures - small things and big consequences.* https://www.p3mountains.org/post/vultures-small-things-and-big-consequences. Accessed: 2022-3-10.

Ishwar, N.M, S. Das, J. Kumari, V. Prakash, and P.R. Sinha. 2016. *An Economic Assessment of Economic Services Provided by Vultures: A Case Study from the Kanha-Pench Corridor.* The Economics of Ecosystems and Biodiversity India Initiative. GIZ India.

Järvinen, Olli, and Lasse Sammalisto. 1976. "Regional trends in the avifauna of Finnish peatland bogs." *Annales Zoologici Fennici* 13 (1): 31–43.

Jaureguiberry, Pedro, Nicolas Titeux, Martin Wiemers, Diana E Bowler, Luca Coscieme, Abigail S Golden, Carlos A Guerra, et al. 2022. "The direct drivers of recent global anthropogenic biodiversity loss." *Science Advances* 8 (45): eabm9982.

Jones, Benjamin A. 2019. "Tree Shade, Temperature, and Human Health: Evidence from Invasive Species-induced Deforestation." *Ecological Economics* 156:12–23.

Jones, Benjamin A, and Shana M McDermott. 2018. "Health Impacts of Invasive Species Through an Altered Natural Environment: Assessing Air Pollution Sinks as a Causal Pathway." *Environmental & Resource Economics* 71 (1): 22–43.

Keiser, David A, and Joseph S Shapiro. 2019. "Consequences of the Clean Water Act and the Demand for Water Quality." *Quarterly Journal of Economics,* 349–396.

Kremer, Michael, and Charles Morcom. 2000. "Elephants." *American Economic Review* 90 (1): 212–234.

Kumar, Hemanshu, and Rohini Somanathan. 2009. "Mapping Indian Districts across Census Years, 1971-2001 on JSTOR." *Economic and Political Weekly* 44 (41): 69–73. https://www.jstor.org/stable/25663682.

Kumar, Nishant, Aparajita Singh, and Barbara Harriss-White. 2019. "Urban Waste and the Human–Animal Interface in Delhi." *Economic and Political Weekly* 54 (47). Accessed September 16, 2023.

Kuussaari, Mikko, Riccardo Bommarco, Risto K Heikkinen, Aveliina Helm, Jochen Krauss, Regina Lindborg, Erik Ockinger, et al. 2009. "Extinction debt: a challenge for biodiversity conservation." *Trends in ecology & evolution* 24 (10): 564–571.

Kwon, Man Jae, Seong-Taek Yun, Baknoon Ham, Jeong-Ho Lee, Jun-Seop Oh, and Weon-Wha Jheong. 2017. "Impacts of leachates from livestock carcass burial and manure heap sites on groundwater geochemistry and microbial community structure." *PloS one* 12 (8): e0182579.

Lacy, Robert C, and Carl E Bock. 1986. "The Correlation Between Range Size and Local Abundance of Some North American Birds." *Ecology* 67 (1): 258–260.

Liang, Yuanning, Ivan Rudik, Eric Yongchen Zou, Alison Johnston, Amanda D Rodewald, and Catherine L Kling. 2020. "Conservation cobenefits from air pollution regulation: Evidence from birds." *Proceedings of the National Academy of Sciences of the United States of America* 117 (49): 30900–30906.

Luis, Angela D, Amy J Kuenzi, and James N Mills. 2018. "Species diversity concurrently dilutes and amplifies transmission in a zoonotic host-pathogen system through competing mechanisms." *Proceedings of the National Academy of Sciences of the United States of America.*

Madhok, Raahil, and Sumeet Gulati. 2022. "Ruling the roost: Avian species reclaim urban habitat during India's COVID-19 lockdown." *Biological Conservation* 271:109597.

Marcus, Michelle. 2020. "Testing the Water: Drinking Water Quality, Public Notification, and Child Outcomes." *The Review of Economics and Statistics,* 1–45.

Markandya, Anil, Tim Taylor, Alberto Longo, M N Murty, S Murty, and K Dhavala. 2008. "Counting the cost of vulture decline—An appraisal of the human health and other benefits of vultures in India." *Ecological Economics* 67 (2): 194–204.

Martin, Emily A, Björn Reineking, Bumsuk Seo, and Ingolf Steffan-Dewenter. 2013. "Natural enemy interactions constrain pest control in complex agricultural landscapes." *Proceedings of the National Academy of Sciences of the United States of America* 110 (14): 5534–5539.

Mason, Charles F, Erwin H Bulte, and Richard D Horan. 2012. "Banking on extinction: endangered species and speculation." *Oxford Review of Economic Policy* 28 (1): 180–192.

McGrath, Susan. 2007. *The Vanishing.* https://www.smithsonianmag.com/science-nature/the-vanishing-145631290/. Accessed: 2020-12-13.

Moleón, Marcos, José A Sánchez-Zapata, Antoni Margalida, Martina Carrete, Norman Owen-Smith, and José A Donázar. 2014. "Humans and Scavengers: The Evolution of Interactions and Ecosystem Services." *Bioscience* 64 (5): 394–403.

Nair, Moorthy, Hemant Bherwani, Shahid Mirza, Saima Anjum, and Rakesh Kumar. 2021. "Valuing burden of premature mortality attributable to air pollution in major million-plus non-attainment cities of India." *Scientific Reports* 11 (1): 22771.

"Audacious bid to value the planet whips up a storm." 1998. *Nature* 395 (6701): 430–430.

Nehring, Klaus, and Clemens Puppe. 2002. "A Theory of Diversity." *Econometrica: journal of the Econometric Society* 70 (3): 1155–1198.

Oaks, J Lindsay, Martin Gilbert, Munir Z Virani, Richard T Watson, Carol U Meteyer, Bruce A Rideout, H L Shivaprasad, et al. 2004. "Diclofenac residues as the cause of vulture population decline in Pakistan." *Nature* 427 (6975): 630–633.

Ogada, Darcy, Phil Shaw, Rene L Beyers, Ralph Buij, Campbell Murn, Jean Marc Thiollay, Colin M Beale, et al. 2016. "Another Continental Vulture Crisis: Africa's Vultures Collapsing toward Extinction: African vultures collapsing toward extinction." *Conservation Letters* 9 (2): 89–97.

Ogada, Darcy L, Felicia Keesing, and Munir Z Virani. 2012. "Dropping dead: causes and consequences of vulture population declines worldwide." *Annals of the New York Academy of Sciences* 1249:57–71.

Paine, R T. 1969. "A Note on Trophic Complexity and Community Stability." *The American Naturalist* 103 (929): 91–93.

Pati, Ipsita. 2016. "Do not dump animal carcasses in open, forest dept tells MCG." *Hindustan Times.*

Pimm, S L, C N Jenkins, R Abell, T M Brooks, J L Gittleman, L N Joppa, P H Raven, C M Roberts, and J O Sexton. 2014. "The biodiversity of species and their rates of extinction, distribution, and protection." *Science* 344 (6187): 1246752.

Power, Mary E, David Tilman, James A Estes, Bruce A Menge, William J Bond, L Scott Mills, Gretchen Daily, Juan Carlos Castilla, Jane Lubchenco, and Robert T Paine. 1996. "Challenges in the Quest for Keystones." *Bioscience* 46 (8): 609–620.

Prakash, V, R E Green, D J Pain, S P Ranade, S Saravanan, N Prakash, R Venkitachalam, R Cuthbert, A R Rahmani, and A A Cunningham. 2007. "Recent changes in populations of resident Gyps vultures in India." *Journal of the Bombay Natural History Society* 104 (2): 129–135.

Prakash, Vibhu, Mohan Chandra Bishwakarma, Anand Chaudhary, Richard Cuthbert, Ruchi Dave, Mandar Kulkarni, Sashi Kumar, et al. 2012. "The population decline of Gyps vultures in India and Nepal has slowed since veterinary use of diclofenac was banned." *PloS one* 7 (11): e49118.

Proctor, Jonathan, Solomon Hsiang, Jennifer Burney, Marshall Burke, and Wolfram Schlenker. 2018. "Estimating global agricultural effects of geoengineering using volcanic eruptions." *Nature.*

Radhakrishnan, Sreejith, Abi Tamim Vanak, Pierre Nouvellet, and Christl A Donnelly. 2020. "Rabies as a Public Health Concern in India-A Historical Perspective." *Tropical Medicine and Infectious Disease* 5 (4).

Ramesh, Vijay, Trisha Gopalakrishna, Sahas Barve, and Don J Melnick. 2017. "IUCN greatly underestimates threat levels of endemic birds in the Western Ghats." *Biological conservation* 210:205–221.

Rao, Chalapati, and Mamta Gupta. 2020. "The civil registration system is a potentially viable data source for reliable subnational mortality measurement in India." *BMJ Global Health* 5 (8).

Raynor, Jennifer L, Corbett A Grainger, and Dominic P Parker. 2021. "Wolves make roadways safer, generating large economic returns to predator conservation." *Proceedings of the National Academy of Sciences of the United States of America* 118 (22).

Roggenbuck, Michael, Ida Bærholm Schnell, Nikolaj Blom, Jacob Bælum, Mads Frost Bertelsen, Thomas Sicheritz-Pontén, Søren Johannes Sørensen, M Thomas P Gilbert, Gary R Graves, and Lars H Hansen. 2014. "The microbiome of New World vultures." *Nature Communications* 5:5498.

Sanjayan, M. 2013. *In Indian carcass fields, pollution's impact takes unusual form.* https://www.cbsnews.com/news/in-indian-carcass-fields-pollutions-impact-takes-unusual-form/. Accessed: 2023-8-19.

Santori, Claudia, Ricky-John Spencer, Michael B Thompson, Camilla M Whittington, Thomas H Burd, Samantha B Currie, Timothy J Finter, and James U Van Dyke. 2020. "Scavenging by threatened turtles regulates freshwater ecosystem health during fish kills." *Scientific Reports* 10 (1): 14383.

Schlenker, Wolfram, W Michael Hanemann, and Anthony C Fisher. 2006. "The Impact of Global Warming on U.S. Agriculture: An Econometric Analysis of Optimal Growing Conditions." *The Review of Economics and Statistics* 88 (1): 113–125.

Schlenker, Wolfram, and Michael J Roberts. 2009. "Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change." *Proceedings of the National Academy of Sciences of the United States of America* 106 (37): 15594–15598.

Schlenker, Wolfram, and W Reed Walker. 2015. "Airports, Air Pollution, and Contemporaneous Health." *The Review of Economic Studies.*

Schmeller, Dirk S, Franck Courchamp, and Gerry Killeen. 2020. "Biodiversity loss, emerging pathogens and human health risks." *Biodiversity and conservation.*

Senacha, K R, M A Taggar, A R Rahmani, Y V Jhala, R Cuthber, D J Pain, and R E Green. 2008. "Diclofenac levels in livestock carcasses in India before the 2006 "ban"1." *Journal of the Bombay Natural History Society* 105 (2): 148–161.

Sharma, Rajiv J, and Alok J Singh. 2016. *Writ Petition (PIL) No.140 of 2015.*

Singh, B B, S Ghatak, H S Banga, J P S Gill, and B Singh. 2013. "Veterinary urban hygiene: a challenge for India." *Scientific and Technical Review* 32 (3): 645–656.

Solow, Andrew, Stephen Polasky, and James Broadus. 1993. "On the Measurement of Biological Diversity." *Journal of Environmental Economics and Management* 24 (1): 60–68.

Subramanian, Meera. 2011. "Can the world's fastest growing nation restore its prime scavenger before there are untold human consequences?" *VQR.*

———. 2015. *A River Runs Again: India's Natural World in Crisis, from the Barren Cliffs of Rajasthan to the Farmlands of Karnataka.* Hachette UK.

Swift, Michael John, O W Heal, Jonathan Michael Anderson, and J M Anderson. 1979. *Decomposition in Terrestrial Ecosystems.* University of California Press.

Tanaka, Shinsuke. 2015. "Environmental Regulations on Air Pollution in China and Their Impact on Infant Mortality." *Journal of Health Economics* 42:90–103. ISSN: 0167-6296, accessed September 16, 2023. https://doi.org/10.1016/j.jhealeco.2015.02.004.

Taylor, M Scott. 2011. "Buffalo Hunt: International Trade and the Virtual Extinction of the North American Bison." *The American Rconomic Weview* 101 (7): 3162–3195.

Valiente-Banuet, Alfonso, Marcelo A Aizen, Julio M Alcántara, Juan Arroyo, Andrea Cocucci, Mauro Galetti, Marı a B Garcı a, et al. 2015. "Beyond species loss: the extinction of ecological interactions in a changing world." *Functional ecology* 29 (3): 299–307.

Van Dooren, T. 2010. "Vultures and their people in India: equity and entanglement in a time of extinctions." *Manoa.*

Vijaikumar, M, Devinder M Thappa, and K Karthikeyan. 2002. "Cutaneous anthrax: an endemic outbreak in south India." *Journal of Tropical Pediatrics* 48 (4): 225–226.

Wan, Xinru, Guangshun Jiang, Chuan Yan, Fangliang He, Rongsheng Wen, Jiayin Gu, Xinhai Li, Jianzhang Ma, Nils Chr Stenseth, and Zhibin Zhang. 2019. "Historical records reveal the distinctive associations of human disturbance and extreme climate change with local extinction of mammals." *Proceedings of the National Academy of Sciences of the United States of America* 116 (38): 19001–19008.

Watson, James E M, Danielle F Shanahan, Moreno Di Marco, James Allan, William F Laurance, Eric W Sanderson, Brendan Mackey, and Oscar Venter. 2016. "Catastrophic Declines in Wilderness Areas Undermine Global Environment Targets." *Current Biology* 26 (21): 2929–2934.

Watson, Richard T, Martin Gilbert, J Lindsay Oaks, and Munir Virani. 2004. "The collapse of vulture populations in South Asia." *Biodiversity* 5 (3): 3–7.

Weber, Marcelo M, Richard D Stevens, José Alexandre F Diniz-Filho, and Carlos Eduardo V Grelle. 2017. "Is there a correlation between abundance and environmental suitability derived from ecological niche modelling? A meta-analysis." *Ecography* 40 (7): 817–828.

Weitzman, Martin L. 1992. "On Diversity." *The Quarterly Journal of Economics,* 363–405.

———. 1993. "What to Preserve? An Application of Diversity Theory to Crane Conservation." *The Quarterly Journal of Economics* 108 (1): 157–183.

———. 1998. "The Noah's Ark Problem." *Econometrica,* 1279–1298.

———. 2009. "On Modeling and Interpreting the Economics of Catastrophic Climate Change." *The Review of Economics and Statistics* 91 (1): 1–19.

Young, Alwyn. 2019. "Channeling Fisher: Randomization Tests and the Statistical Insignificance of Seemingly Significant Experimental Results." *The Quarterly Journal of Economics* 134 (2): 557–598.

Ziolkowski, David, Michael Lutmerding, Veronica Aponte, and Marie-Anne R Hudson. 2022. *U.S. Geological Survey North American Breeding Bird Survey Dataset 1966 - 2021.*

Zivin, Joshua Graff, and Matthew Neidell. 2012. "The Impact of Pollution on Worker Productivity." *The American Economic Review* 102 (7): 3652–3673.

Zuckerberg, Benjamin, William F Porter, and Kimberley Corwin. 2009. "The consistency and stability of abundance-occupancy relationships in large-scale population dynamics." *The Journal of Animal Ecology* 78 (1): 172–181.