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

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# Online Appendix

# 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 roads 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.

## A.2 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 is an abrupt shift in the reporting regime in 1988 where the vital statistics start reporting vital event counts instead of rates. We prefer to use data reported under the same regime, as this allows to fully control the conversion to rates. Second, the number districts that are fully balanced from 1988 to 2005 are 156, 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 A2). Specifically, we do not observe a differential time trend in the years leading 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.3 Accounting for State-Level Temporal Trends

To account for potential differential trends in reporting of vital statistics data that systematically change by state, we repeat the estimation in Equation (1) and include either 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 A3 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 are 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.

## A.4 Examining Heterogeneity Between Urban & Rural District Areas

In Table A1, we explore the degree to which death rates respond differently to the collapse in vulture populations in either urban or rural areas. Because urban areas have larger populations, are denser, and 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 urban areas. When we use the district-level data reported by urban or rural area, we find a higher average treatment effect in urban relative to rural areas, but the effects are not statistically different from each other.

## A.5 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 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 the flat plains of the midwest in the United States.

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 scores.

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 A4, and the average treatment effects in Table A2. Across the two alternative treatment classification schemes, we recover similar magnitudes for the change in 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.6 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 6), 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 both organic and inorganic uses of oxygen. We should expect to see both BOD and COD levels increase with a 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 A3, 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 urban district (columns 2, 3, 5, and 6), similar to how the decline in dissolved oxygen and increase in fecal coliforms was as well (see Table 6). Turbidity declines in water bodies monitored in urban districts (columns 8 and 9), which is consistent with previous findings on declines in scavenger populations.

## A.7 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 census to test whether those healthcare access metrics changed after 1994 in the high- relative to low-vulture-suitability districts. In Table A4, 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.8 Evaluating Changes to District Characteristics

We expand on the previous analysis on healthcare access and add several other placebo outcomes that should not be affected by the collapse in vulture populations. For each outcome, we have at least one year of data before, and one year of data after the collapse. We summarize the results in

Figure A5, 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.9 Sensitivity Analysis Using Jackknifing

In our analysis, 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 A6 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 A3. We recover a narrow distribution of the coefficients with mostly overlapping 95% confidence intervals.

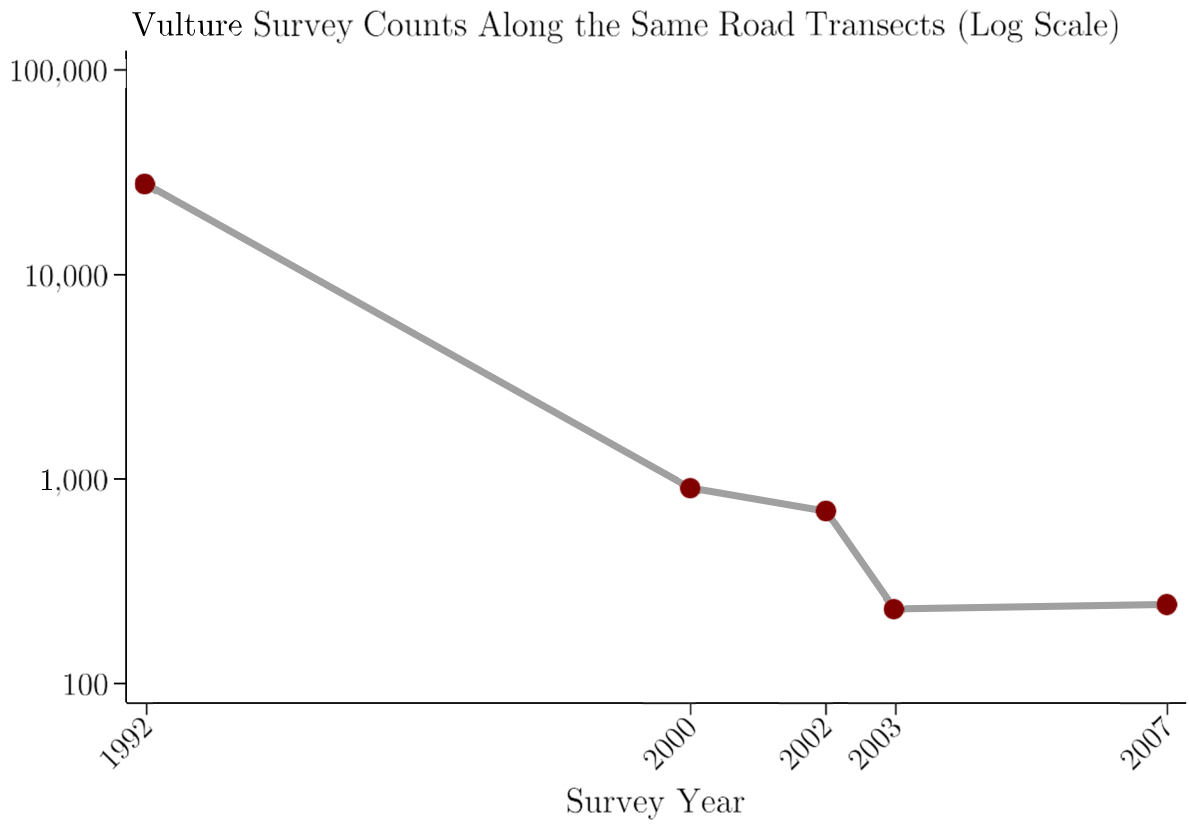
## A.10 Permutation Inference Analysis

As an additional robustness test we also run a permutation inference analysis. Using permutation inference analysis allows us to evaluate whether we are underestimating the standard errors of the coefficients by clustering at district level (e.g. due to spatial clustering of the standard errors), as well as ruling 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 ran-

domly 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 A8, where each one of the distributions is centered around zero. More importantly, the estimated effect from the non-permutation sample is in far right tail of each distribution, resulting in an exact p-value well below 1%.

Figure A1: Vulture Counts From Repeated Surveys Along Road Transects



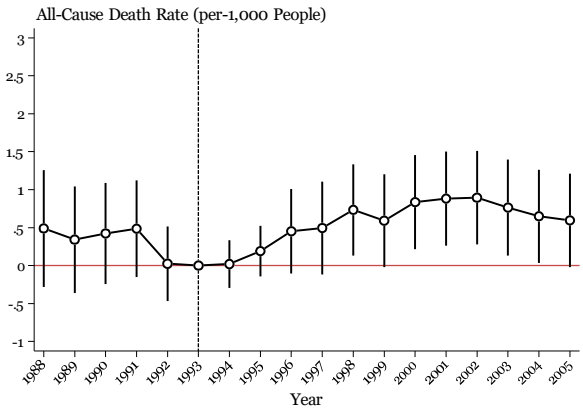

Notes: Each dot is the sum of surveyed vultures, in log scale, along the same 70 road transects for the three diclofenac-affected-species. Data are reproduced from Prakash et al. (2007).

Figure A2: All-Cause Death Rates DD Estimation Results With Earlier Years

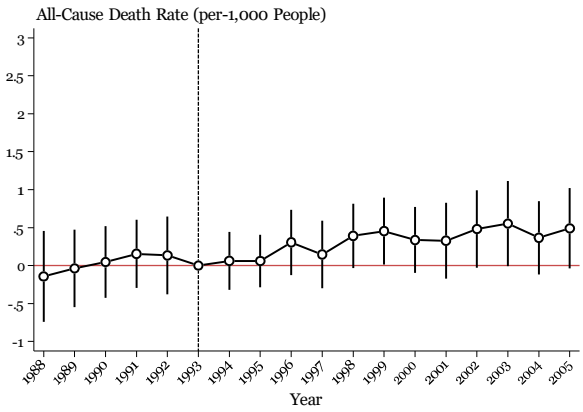

Notes: Estimation results from Equation (1). Comparing the third and second terciles to the first tercile of vulture habitat overlap. Expanding the sample to 1981, while still using a balanced sample, lowers the number of districts 156 to 104. The regression includes district and zonal council-by-year fixed effects. Observations are population-weighted. Standard errors are clustered at the district level.

Figure A3: All-Cause Death Rates DD Estimation Results With State-Level Trends

(a) State-Linear Time Trends

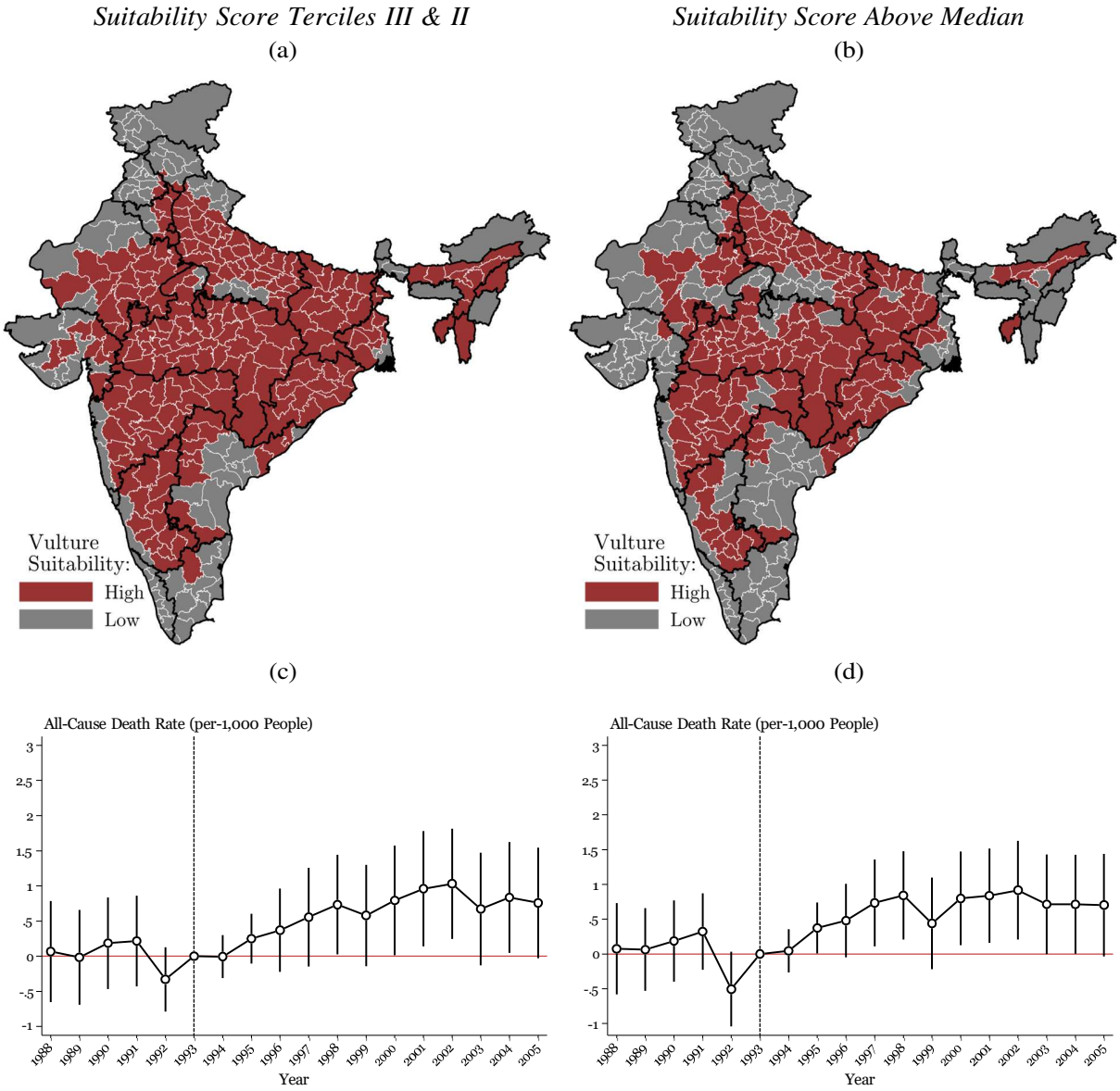



(b) State-by-Year Fixed Effects



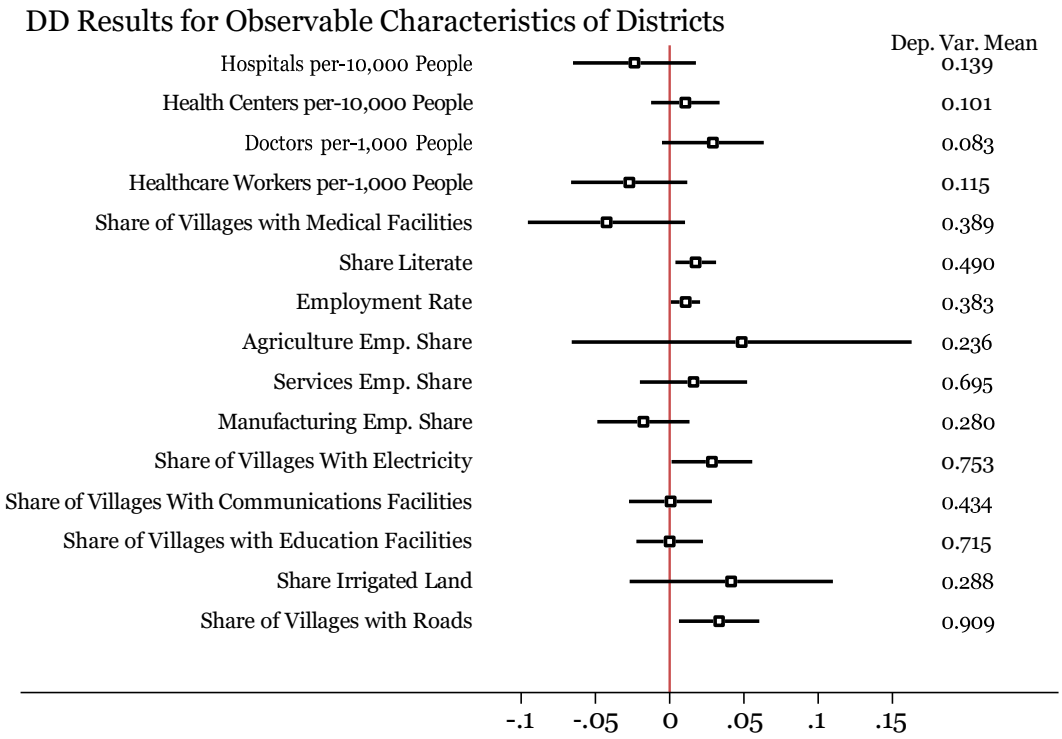

Notes: Estimation results from Equation (1). Comparing the third and second terciles to the first tercile of vulture habitat overlap. All regression include district fixed effects. The regression in (a) includes zonal council-by-year fixed effects and state-level linear time trends, and the regression in (b) includes state-by-year fixed effects. Observations are population-weighted. Standard errors are clustered at the district level.

Figure A4: Classifying Treated Districts Using the BIOCLIM Habitat Suitability Model



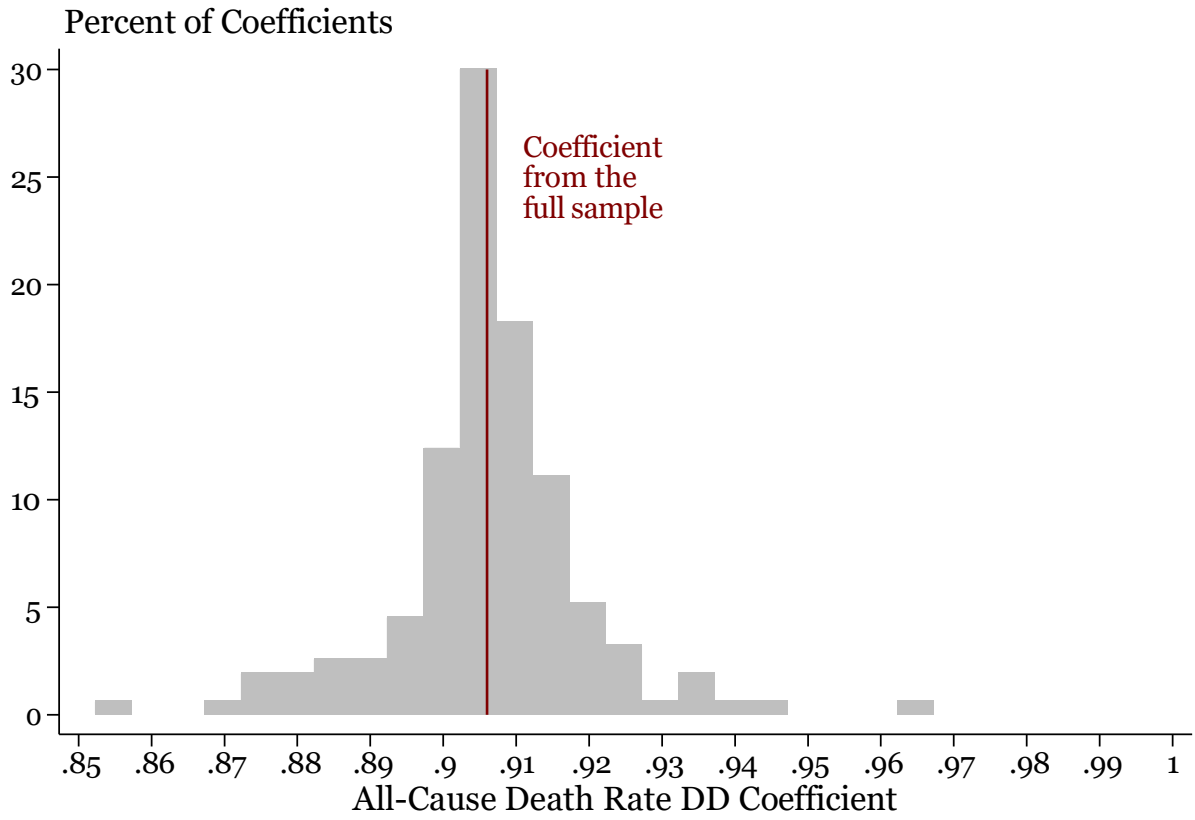

Notes: The treatment classification uses predicted suitability scores for the diclofenac-affected-vultures from the BIOCLIM habitat suitability model. We either split the suitability score into terciles and define treated districts as the third and second terciles (a and c), or split districts as above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

Figure A5: Summary of Placebo Results



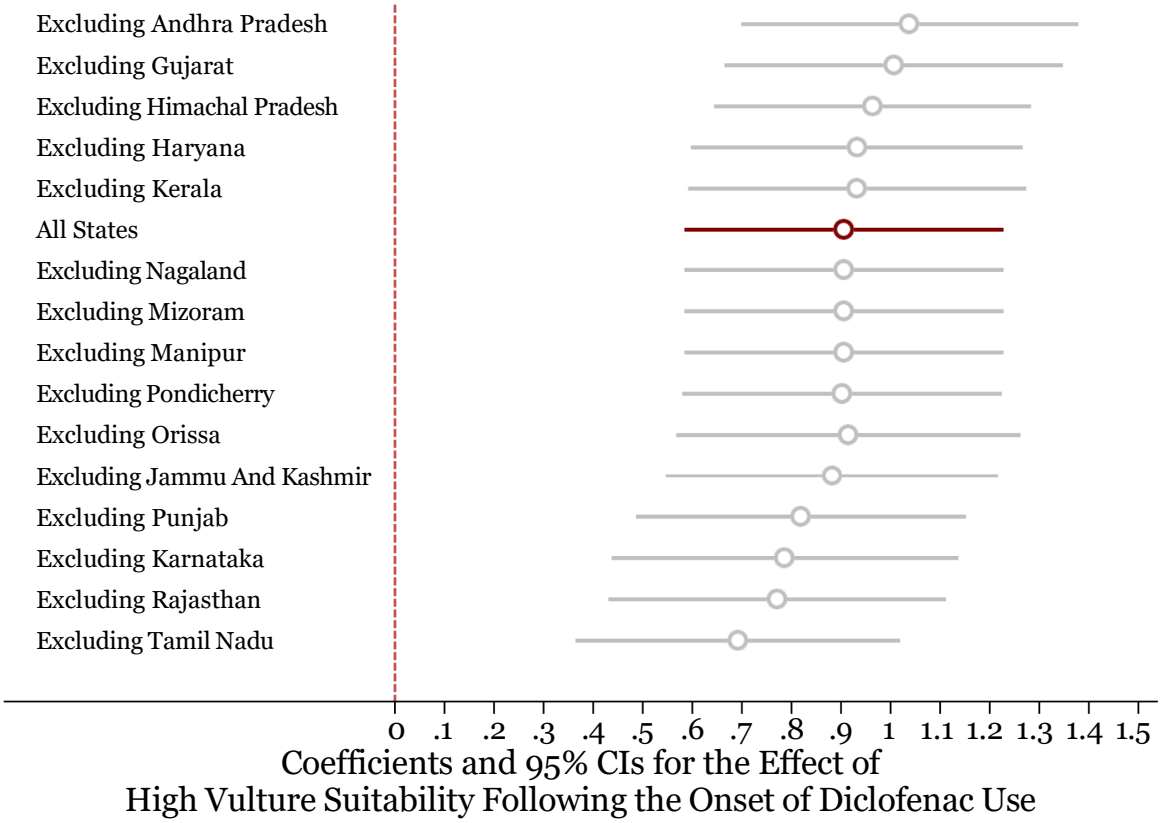

Notes: Estimation results for the specification in Equation (2). Each regression includes district and zonal council-by-year fixed effects. The sample includes all the districts in the balanced sample reported in the main analysis. Observations are population-weighted. Standard errors are clustered at the district level.

Figure A6: 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.

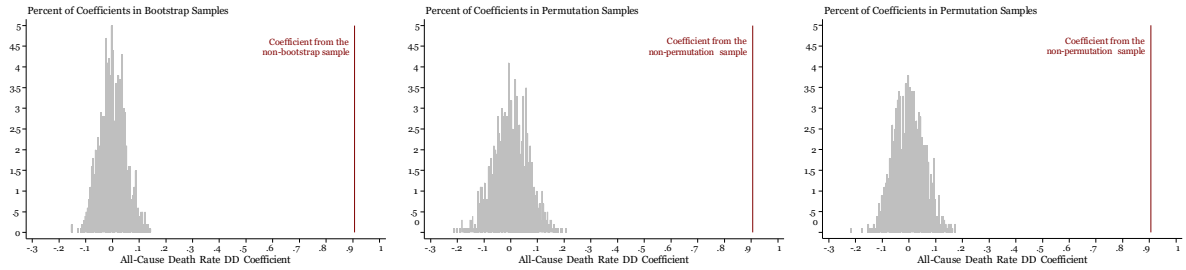
Figure A7: Distribution of Leave-One-State Out DD Estimation Results




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 A8: 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.

Table A1.

All-Cause Death Rate, per-1,000 People ($\bar{Y}$ = 10.7)

Panel A. District Urban Areas

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| HVS×Post-1994 | 0.88 | 0.84 | 0.95 | 0.91 |
| | (0.19) | (0.18) | (0.17) | (0.17) |
| $R^2$ | 0.703 | 0.712 | 0.728 | 0.734 |
| N | 5,562 | 5,562 | 5,562 | 5,562 |
| Clusters | 156 | 156 | 156 | 156 |

Panel B. District Rural Areas

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| HVS×Post-1994 | 0.76 | 0.71 | 0.86 | 0.79 |
| | (0.17) | (0.17) | (0.16) | (0.16) |
| $R^2$ | 0.715 | 0.723 | 0.735 | 0.742 |
| N | 5,670 | 5,670 | 5,670 | 5,670 |
| Clusters | 162 | 162 | 162 | 162 |
| Year FE | X | X | | |
| Zonal Council-by-Year FE | | | X | X |
| Weather Controls | | X | | X |

Notes: Estimation results for the specification in Equation (2). The estimation is comapring high-vulture-suitability (HVS) to low-vulture-suitability, after the onset of diclofenac use (post-1994), relative to years prior to the patent expiration. Reported mean of 10.7 deaths per-1,000 people is for the pre-treatment period of 1988 to 1993, obtained from the UN Population Division Sample includes balanced district level data from 1988 to 2005. All regressions include district fixed effects. Observations are population-weighted. Standard errors are clustered at the district level.

Table A2.
Results for All-Cause Death Rate Using BIOCLIM Classifications ($\bar{Y}$ = 10.7)

Panel A. High & Medium Suitability Score Terciles

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| HVS×Livestock×Post-1994 | | | 0.830 | 0.751 |
| | | | (0.343) | (0.336) |
| HVS×Diclofenac | 0.622 | 0.539 | -0.008 | 0.001 |
| | (0.189) | (0.183) | (0.251) | (0.252) |
| Livestock×Post-1994 | | | -0.208 | -0.173 |
| | | | (0.266) | (0.258) |
| $R^2$ | 0.734 | 0.741 | 0.761 | 0.767 |
| N | 2,754 | 2,754 | 2,466 | 2,466 |
| Clusters | 153 | 153 | 137 | 137 |

Panel B. Above Median Suitability Score

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| HVS×Livestock×Post-1994 | | | 0.908 | 0.885 |
| | | | (0.335) | (0.329) |
| HVS×Diclofenac | 0.622 | 0.553 | -0.129 | -0.143 |
| | (0.184) | (0.178) | (0.258) | (0.260) |
| Livestock×Post-1994 | | | -0.034 | -0.035 |
| | | | (0.220) | (0.214) |
| $R^2$ | 0.733 | 0.741 | 0.761 | 0.768 |
| N | 2,754 | 2,754 | 2,466 | 2,466 |
| Clusters | 153 | 153 | 137 | 137 |
| 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 10.7 deaths per-1,000 people is for the pre-treatment period of 1988 to 1993, obtained from the UN Population Division All regressions include district and zonal council-by-year fixed effects. Observations are population-weighted. Standard errors are clustered at the district level.

Table A3.
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×Diclofenac | | 1.5 | | | 11.4 | | | -7.2 | |
| | | (1.1) | | | (7.5) | | | (6.4) | |
| HVS×Diclofenac | 0.7 | 0.2 | 1.8 | 1.8 | -2.2 | 9.6 | -0.7 | 1.4 | -6.0 |
| | (0.5) | (0.5) | (1.1) | (3.1) | (2.1) | (7.3) | (4.0) | (4.4) | (6.3) |
| Urban×Diclofenac | | -0.6 | | | -6.9 | | | -0.2 | |
| | | (0.7) | | | (6.6) | | | (4.3) | |
| $\overline{Y}_{\leq 1993}$ | 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 | 4,339 | 4,339 | 2,062 | 4,146 | 4,146 | 1,967 | 3,600 | 3,600 | 1,671 |
| Clusters | 221 | 221 | 140 | 217 | 217 | 135 | 208 | 208 | 129 |

Notes: Estimation results for the specification in Equation (2). Comapring the third and second tercile of diclofence affected vultures to first tercile, before and after the onset of diclofenac use. 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, etc.). In addition, each regression includes year fixed effects. Sample consists of district-level data for census-urban (U) and rural (R) areas, from 1988 to 2005. Observations are population-weighted. Standard errors are clustered at the district level.

Table A4.
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) |
| HVS×Post-1994 | 0.07 | 1.83 | -0.34 | 2.73 |
| | (0.22) | (2.29) | (0.21) | (2.34) |
| $\overline{Y}$ | 1.79 | 18.03 | 1.80 | 21.37 |
| $R^2$ | 0.772 | 0.728 | 0.702 | 0.589 |
| N | 445 | 445 | 964 | 964 |
| Clusters | 153 | 153 | 337 | 337 |

Notes: Estimation results for the specification in Equation (2). The sample uses data fron 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 popualtion-weighted mean. Standard errors are clustered at the district level.

# 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 survey 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. Summary of the responses reported a median onset year for diclofenac of 1994.

Figure B1: FDA Documents Regarding Diclofenac & Generic Drug Approval

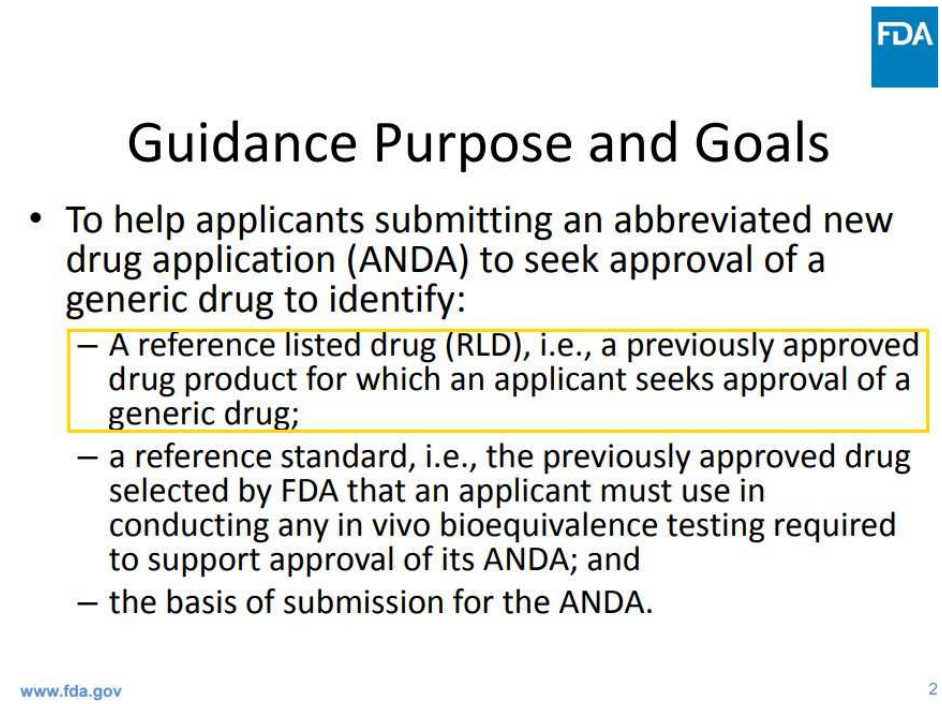
(a) Change to Novartis' Diclofenac Patent in 1993

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | 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.[26] 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.[27]

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 value for the three diclofenac-affected vulture species. We calculate the mean value of those overlap scores, and use those to assign the suitability category.

## 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 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

[26] Application can be filled out at: http://datazone.birdlife.org/species/requestdis
[27] BLI provides a summary of these categories here: http://datazone.birdlife.org/species/spcdistPOS

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.

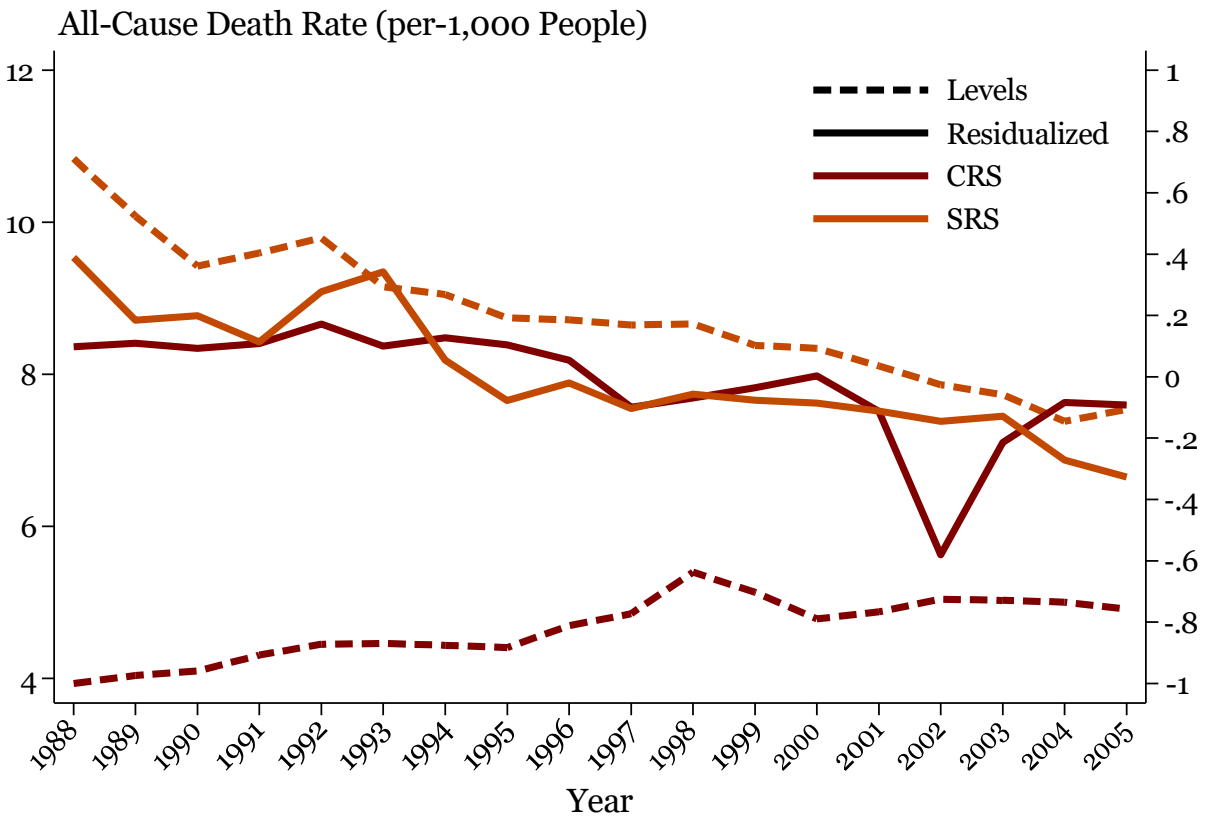
There is a clear difference in levels (Figure C1, dashed lines) between the all-cause death rate in the CRS relative to the SRS data. The SRS death rate is nearly double than the CRS reported death rate. However, when residualizing the death rates on a set of unit and time fixed effects (Figure C1, reported in the solid lines), the two death rates follow similar trends.[28]

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 5 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 over-estimate 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 as reported by the UN Population Division, which reflects the national-level death rate.

[28] 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.