Just Water? Environmental Jurisprudence, Water Quality and Infant Mortality in India

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Toxic ambient water can be deadly, particularly in developing countries where pollution levels are high. We explore the impacts of judicial policies on surface water quality in India. We compile court cases, judges' cases histories, river pollution and child mortality at the district level. Leveraging random judge assignment, we estimate the effect of "green" verdicts on district-level pollution in India. We find that rulings precipitated immediate reductions in surface water pollution, particularly in the Ganga River basin. Effects are confined to the year of the ruling and not persistent. We also find limited impacts on neonatal and infant mortality.

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1 Introduction

Polluted water kills more than 1 million people a year, most of them in low- and middle-income countries (Forouzanfar et al. 2016; WHO and UNICEF 2021).[1] Recent estimates suggest that worldwide freshwater extraction has been growing at about 1% per year for decades and more than 80% of wastewater from municipalities and industries has been released back into the environment without prior treatment. Nearly all the rivers in Asia, Africa and Latin America are now significantly polluted (WHO and UNICEF 2021).

Ambient water pollution has an adverse impact on health, particularly in developing countries where ambient water toxicity is high. In China, the deterioration of water quality by a single grade (on a six-grade scale) has been shown to increase the digestive cancer death rate by 9.7% (Ebenstein 2012). In India, surface water toxicity that exceeds the official water quality standards has been shown to raise the risk of neonatal mortality by 10–14 percentage points (Do, Joshi, and Stolper 2018). The heavy use of fertilizers has also contributed to neonatal and infant mortality in agricultural areas (Brainerd and Menon 2014).

Treating ambient water has been known to deliver a broad range of benefits such as a reduction in child mortality and a decline in the prevalence of infectious diseases (J. Zhang and Xu 2016; Alsan and C. Goldin 2019; Do, Joshi, and Stolper 2018; Ashraf, Glaeser, Holland, et al. 2021; Galiani, Gertler, and Schargrodsky 2005; Bhalotra et al. 2021 and many others). Cleaning ambient water, however, requires significant investment, state capacity, and public support (Ashraf, Glaeser, and Ponzetto 2016; Ahuja, Kremer, and Zwane 2010). Executive and legislative branches of government across the world have pursued a variety of approaches towards water governance, most of which have been controversial (Woodhouse and Muller 2017; Van der Meer 2017).

[1] The precise number of deaths due to water pollution varies depending on the definition of access to safe water. The Lancet's Global Burden of Disease study in 2016 considered access to safe water at both the water's source and at the point of use to arrive at their estimate. The World Health Organization, UNICEF and the Joint Monitoring Program consider only access to an improved water source at the point of use and estimates the number of pollution deaths to be approximately 800,000 per year (WHO and UNICEF 2021.)

Long-term planning and investment are particularly difficult in contexts where public trust in government is low or declining and the awareness of the benefits of clean water are not widespread (OECD 2017, Norris 2017). Too often, wastewater makes its way into ambient water despite laws and oversight systems designed to prevent this (Joshi and Shambaugh 2018; Woodhouse and Muller 2017). Even in the United States, where polls place water pollution among the top of citizen concerns, more than half of the rivers and a significant number of drinking water systems violate government standards (Keiser and Shapiro 2019b).

The failures of executive and legislative efforts to safeguard water quality have often prompted judiciaries to respond to citizen concerns (Percival 2016; Percival 2017; Malleson 2016). In the United States, for example, significant shifts in the ideologies of executive and legislative branches have prompted courts to uphold environmental regulation such as the Clean Air and Clean Water Acts (Schmalensee and Stavins 2019, Keiser and Shapiro 2019a). In India, public interest litigation at the Supreme Court has created strong localized impacts (Bhuwania 2017). In China, the establishment of local environmental courts has been shown to enhance environmental investment by firms and improve environmental outcomes in cities (Q. Zhang, Yu, and Kong 2019).

To date, however, there has been no empirical study of the broad effect of judicial policy on environmental outcomes. This paper examines the impacts of judicial policies on water quality in India, a high pollution setting where the executive and legislative branches of government are viewed as ineffective in controlling the level of ambient water pollution and water governance is weak (Greenstone and Hanna 2014). We identify the impacts of judicial rulings on pollution and health outcomes by exploiting the random assignment of cases to judges in Indian courts. This approach has already shown to be useful in the first step of causal inference for a wide range of questions (Chen 2019; Chen, Moskowitz, and Shue 2016; Dobbie, J. Goldin, and Yang 2018; and many others).

Our empirical approach begins with the compilation of a unique database of cases related to water toxicity from the Indian judiciary. We curate cases heard at the high courts, Supreme Court and Green Tribunal of India since 1987. We examine these cases and hand-code them as "green verdict" if the verdict was likely to have a pro-environmental effect. We link the profiles of judges who hear these cases to the database. For each judge we construct a corpus of rulings that were written *prior* to the case related to water toxicity. We then analyze the causal relationship between green verdicts and actual environmental outcomes. Since rulings may be endogenous to outcomes, we use an IV framework, with the textual features of cases to predict the likelihood of a green verdict. Our key identifying assumption is that judges are randomly assigned within the courts of India (Ash et al. 2021). This variation allows us to construct a novel instrument that captures a judge's writing style in cases not related to water toxicity, which is predictive of their decisions in water toxicity cases. Finally, we deploy the same instrumental variables framework to look at the effects of green verdicts on mortality rates at the district-level.

We find that rulings precipitate some reductions in chemical oxygen demand (COD) and biological oxygen demand (BOD), two common measures of industrial pollution in surface water. The impacts are particularly pronounced in the Ganga basin, where previous research has argued that water toxicity levels are among the highest in India (Alley 2002; Brainerd and Menon 2014; Do, Joshi, and Stolper 2018; Dutta, Dubey, and Kumar 2020). One district in the Ganga basin experienced a 43.7% and 24.1% decline in the highest observed annual COD and BOD readings, respectively. These effects, however, are confined to the year of the ruling and do not show persistence. We find no significant effect of green verdicts on additional measures of water pollution.

We also find that the rulings are associated with small but positive impacts on infant mortality at the district-year level. These impacts are pronounced two years after the verdict, and quickly diminish thereafter. We interpret this as suggestive evidence that judicial policies can succeed in lowering short-term pollution, but the resultant economic slowdown may increase economic vulnerability. In the long-run, issues of enforcement and oversight limit the power of the judiciary to bring real improvements in health at the grassroots of society.

The remainder of this paper is organized as follows. Section 2 presents some background information on environmental jurisprudence in India. Section 3 provides an overview of the many sources of data that were curated for this project. Section 4 presents empirical models. Section 5 presents results. We discuss the implications of our results in section 6. The final section concludes.

2 Context

India faces a growing challenge of surface water toxicity, particularly in urban centers (Global Alliance on Health and Pollution 2019; Sharma et al. 2020). Though it has a variety of environmental laws that aim to limit pollution in specific areas such as air, water, waste, soil, noise, and radiation, enforcement has remained weak (World Bank 2013; UNDP 2009). Courts have played an increasingly active role in formulating judicial remedies, particularly after the 1970s when the opportunity for public-interest litigation emerged within the courts of India (Bhuwania 2017; S. Ghosh 2019).[2]

2.1 Water Laws

The most significant piece of legislation pertinent to water in post-colonial India is the Water (Prevention and Control of Pollution) Act of 1974. The Act has 64 sections, which establish and define the powers of the Central and State Pollution Control Boards (CPCB and SPCBs), outline the measures that the Boards must take to prevent and control water pollution, specify the requirements for testing water at state laboratories, and outline penalties and punishments for breaking these laws.

While the act went a long way towards establishing water governance, it had some important limitations. First, it left out some key sources of pollution. Groundwater and non-point sources of water pollution such as agricultural runoff and water discharged from municipal sources were not included. The act also limits the

[2]Public interest litigation in India relaxes the traditional rule of *locus standi* which means that even people who are not directly involved in the case may bring matters of public interest to the attention of the court. Any citizen of India is thus able to file a case that is pertinent to another citizen or the broad interests of society at large Bhuwania 2017.

accountability of the CPCB and SPCBs by limiting the opportunities for citizens or companies to contest their actions in civil courts.[3] As a result, citizen concerns related to water quality did not bring their concerns to the courts in the immediate aftermath of this Act.

The Water Act of 1974 was ultimately subsumed into broader environmental legislation. In the aftermath of the Bhopal Gas Disaster in 1986, the government passed the Environment Act. The act intends to establish a framework for the central government to coordinate with various state authorities.[4] The central government was given the power to appoint officers into key roles at the pollution control boards, impose penalties for non-compliance with the regulations, and close firms. It provides specific details on the handling of offenses by companies, citizens and government agencies.[5]

2.2 Monitoring and Compliance

The Water Act provides the CPCB and SPCBs with a variety of policies to ensure compliance and enforcement of environmental laws. They can issue and revoke consent to operate, require self-monitoring and reporting, conduct sampling, inspect facilities, require corrective action and prescribe compliance schedules. They cannot, however, alter the guidelines or standards specified by the central government.

The principal tool of ensuring compliance with water laws in India is inspection (Duflo et al. 2018). Section 21 of the Water Act empowers SPCB officials to take samples of any sewage or trade effluent and also enter the premises of firms to ensure

[3]The act clearly says that "*No civil court shall have jurisdiction to entertain any suit or proceeding in respect of any matter which an appellate authority constituted under this Act is empowered by or under this Act to determine, and no injunction shall be granted by any court or other authority in respect of any action taken or to be taken in pursuance of any power conferred by or under this Act*." This effectively means that actions taken by those who work for the CPCB and SPCBs cannot be charged with offenses under the Act.

[4]India has a federal system of government with government at two levels: the center and the states. The constitution specifies the division of responsibilities between them.

[5]More recently, additional acts have been passed to address water pollution. These include the Municipal Solid Wastes (Management and Handling) Rules in the year 2000. This, however, was replaced by Solid Waste Management Rules (SWM), 2016.

compliance with orders and directives(Abbot 2009; Epple and Visscher 1984).

In practice, this system does not work as planned. Deficient staffing and budgets have curtailed its effectiveness (World Bank 2013; UNDP 2009). In an experiment, Duflo et al. (2018) doubled the rate of inspection for treatment plants and required that the extra inspections be assigned randomly. The authors demonstrate in a structural model that it is efficient for the regulator to aggressively target discretionary inspections to heaviest polluters and provide only minimal inspections to the vast majority of firms. They do not have adequate information on actual levels of polluting behavior.

Implementation of the Water Act also varies significantly across states World Bank 2013). Standards and guidelines specified in the policy are interpreted in a variety of ways. A recent World Bank report points out that the frequency of on-site visits to verify compliance is determined by the pollution potential (red/orange/green) and size (based on the value of capital investment) of the industry. Although CPCB has set its guidelines regarding the frequency of visits, individual states differ in their implementation of this guidance (World Bank 2013). For example, red category facilities are supposed to be inspected once a month in Gujarat, once per quarter in Orissa, and once every two years in West Bengal although the guidelines set by CPCB is once in three months for large and medium scale industries.

The list of responsibilities for SPCBs has also grown over time. They are routinely charged with carrying out training workshops for firms and given new responsibilities such as issuance of notifications for hazardous waste, bio-medical waste, and electronic waste in their respective states (World Bank 2013). In summary, implementation of the Water Act can be weak or inconsistent.

2.3 The Role of Courts in Environmental Policy

India's judiciary has taken an activist stance towards environmental conservation (Rajamani 2007; Bhuwania 2017; Malleson 2016; S. Ghosh 2019).[6] Over the past

[6]In the aftermath of India's political emergency of 1976, the judiciary took on this challenge through a renewed commitment to protecting citizen's fundamental rights (Dias 1994; Bhuwania

30 years, the judiciary issued landmark verdicts on issues of water toxicity. The first of these, *MC Mehta v. Union of India*, successfully curtailed the levels of pollution in the Ganga river in 1987, and the drop in pollution has been shown to have lowered child mortality downstream (Do, Joshi, and Stolper 2018). Other well-known cases at the Supreme Court include *Vellore Citizens Welfare Forum v. Union of India*, *Subhash Kumar v. State of Bihar & Ors.* and *Samit Mehta v. Union of India & Ors*. More recently, with the establishment of the Green Tribunal in 2011, numerous cases related to water pollution have emerged from the judiciary.

Faced with environmental laws that were deficient in their coverage, compliance mechanisms and liability provisions, the courts had to improvise. Early landmark cases show that the courts had to refer to the constitution to find and derive explicit as well as implicit legal arguments. One frequently cited source is Article 21 of the Constitution, which guarantees Indian citizens the fundamental right to life.[7] Articles 47 and 48 A, which fall under the non-binding "Directive Principles of State Policy", require the government to improve public health and protect and improve the environment. Finally, Article 51 A(g) defines one fundamental duty of citizenship to "maintain a hygienic environment".

These constitutional provisions, interpreted broadly, provide Indian courts with considerable scope to design environmental jurisprudence. Over time, this legal framework has also absorbed additional legal principles drawn from international and foreign legal systems. Terms like "sustainable development", the "polluter pays" principle, and the "public trust" doctrine have entered Indian environmental and legal discourse over the past three decades (S. Ghosh 2019). Though these principles were not articulated in Indian statutory law, they have become, mutatis mutandis, regarded as an essential part of Indian environmental law.

2017). The commitment to environmental jurisprudence intensified after the massive Bhopal gas disaster (C. M. Abraham and S. Abraham 1991; Dias 1994).

[7]This act states that "No person shall be deprived of his life or personal liberty except according to procedures established by law".

3 Data

Estimating the impact of environmental litigation on environmental as well as human capital outcomes requires data with comprehensive information on all three sets of variables. We compile a unique database of all cases that pertain to water pollution that have been heard in the higher judiciary of India for the past 30 years and combine this with data on both water pollution measurements from river monitoring stations and infant mortality from population surveys. We aggregate and then link these data together at the district-year level.[8]

The different components of the working sample we construct for our analysis are summarized below. Greater details on the processes of data compilation are provided in the online appendix.

3.1 Legal cases

There is no publicly available database of environmental litigation in India that is suitable for statistical analysis. To address this gap, we extracted all judgments passed by the National Green Tribunal of India, the state High Courts, and the Supreme Court of India that include a mention of the Water (Prevention and Control of Pollution) Act of 1974, Air (Prevention and Control of Pollution) Act of 1981, and the Environment Protection Act of 1986. This unique data set consists of approximately 4,000 observations (978 observations for the Water Act and 3,021 for the Air Act). We focus here on the water cases only. By scraping publicly available websites, we were able to obtain texts of judgments as well as meta information on all pending and disposed cases, such as the dates of filing, registration and disposals, transfers between courts, judge, litigants and advocate names, acts involved and case types.

[8]Analysis of demographic data in India is increasingly being conducted at the district level (Drèze and Murthi 2001; Government of India, 2017; Mohanty et al. 2016; Singh et al. 2017; Spears, A. Ghosh, and Cumming 2013). Since the average Indian district contains a population of about 2-3 million people, and many critical decisions about policy are made at this level, district-level aggregates are meaningful and show considerable variation across the country (Government of India, 2017).

To determine whether a particular judgment is likely to have a positive impact on the environment, we rely on manual reading, interpretation and categorization by a team of law students. In addition to the environmental impact of cases, our coders also identified the precise location of the ruling, the geographic scope of the ruling (within the district, across all districts in a state or across the entire country), the names of the judges who ruled on the case, the basic attributes of the case and the month and year of the ruling. Details of the specific variables we employ in our analysis are presented in the next section. Summary statistics of the 516 cases that were successfully matched to the pollution data and the 777 cases that were successfully matched to the mortality data are presented in Table 1.

In our review of the cases, we noted that they touch on a variety of themes. Most of them deal with pollution and environmental contamination, but judges deliberate on these issues in a variety of ways. In a very simple analysis of the incidence of keywords, we found the word "Pollution" in all the cases. India's "Constitution" is referenced in nearly half of these.[9] A third of the cases appear to be filed as Public Interest Litigation (PIL). The words "Public Interest" and "Public Trust" are cited 289 and 44 times respectively. Some terms from international law are also cited. "Polluter Pays" and "Sustainable Development" are cited 115 and 75 times respectively.

3.2 Judge Biographies and Case Histories

Our analysis also incorporates the biographical characteristics of judges. There is no publicly accessible database of judges for the courts of India. We have thus sourced and combined the lists of judges who have served at the High Courts and Supreme Court of India since the date of the establishment of the courts.

Given that we are examining cases that are based on legislation from 1974, we are able to focus our attention on the post-1974 period. We draw these data from two sources: (a) the Judges Handbooks that have been released by the Supreme Court

[9]Among these 477 references, Articles 21, 47, 48 and 51 are cited 145, 11, 60 and 44 times respectively. The "Right to Life" is specifically mentioned 84 times. Other sections of the constitution are also routinely mentioned.

of India in 2014 and 2018; (b) the websites of the various High Courts that list the names, biographies and career trajectories of the judges who have ever served at these courts.

Summary statistics of the sample of judges who matched with the environmental cases are presented in Table 1. Note that 97 percent of the judges are male, and we observe about 1.87 environmental cases per judge. For each of these judges, we are able to extract a complete case history from our judicial database.[10]

3.3 Environmental Data

To measure water quality, we use two sources of data. The first is the river pollution data that were compiled from the annual reports of India's CPCB. These data were originally curated and digitized by Greenstone and Hanna (2014) and then further refined by Do, Joshi, and Stolper (2018). For this analysis, we further extended the dataset's time-coverage to the year 2019, the last year available from the CPCB. The dataset now includes 2,865 monitors over the time period 1986–2019. Our second source of data on water pollution is India's Water Resources Information System (WRIS). This is a repository of national water resources data that receives input from many central and state agencies and provides a "Single Window" source of updated data on water resources and related themes. The data covers 153 districts from 1984 to 2020.

The two sources of water data differ in the number of observations, districts covered and the specific locations within districts. They also differ in the types of pollution indicators that are reported. To address these issues, we combine both types of data and then aggregate the combined sample at the district-level. Since the CPCB does not report mean values of pollution after 2014, we rely on the maximum observed values in any given district and month for the entire period. Given that concerns over water quality can be triggered by irregularities in recorded pollution

[10]To do this, we scraped data from the public website Indian Kanoon. This yielded 7.2 million text cases in total. We were able to successfully identify judge names for 2.6 million of these cases. We then use fuzzy string matching to match the judges from the judge bios dataset to these cases. We have on an average 202 cases per judge (from these 2.6 million cases).

in most settings, we believe the maximum values are appropriate for study in our research design. Details of this process are described in the online appendix.

Our main indicators of river quality are biological-oxygen-demand (BOD) and chemical-oxygen-demand (COD). These are common indicators of industrial water pollution (Brown and Caldwell 2001). BOD captures the amount of dissolved oxygen needed by water-borne, aerobic organisms to break down organic material present at a certain temperature (usually 20 degrees Celsius) and over a specific time period (usually five days). COD captures the amount of oxygen that can be consumed by reactions in a measured solution. The units for both measures of pollution are milligrams of oxygen consumed per liter (mg/l). We consider the logarithm of the maximum observed value per district-year of these two pollutants as primary pollutants of interest.

We also consider a few other indicators of water quality: total coliforms (TOTCOLI), conductivity and temperature. TOTCOLI is an oft-used measure of domestic (as opposed to industrial) pollution, which was a major focus of water policy in India. It is measured as the "most probable number" of coliform organisms per 100 milliliters of water (MPN/100 ml, reported in thousands). Conductivity is a measure of the ability of water to pass an electrical current. Dissolved salts can increase salinity and conductivity while inorganic chemicals (such as oil) reduce conductivity. According to the US Environmental Protection Agency, conductivity is only useful as a general measure of water quality. Each water body tends to have a relatively constant range of conductivity that, once established, can be used as a baseline for comparison with regular conductivity measurements. Significant changes in conductivity could then be an indicator that a discharge or some other source of pollution has entered the aquatic resource.[11] Our last measure of water quality, temperature, can be a measure of water pollution (though it can increase conductivity) in situations where industrial discharge is consistently at a higher (or lower) temperature than ambient water. We rely on TOTCOLI, conductivity and temperature largely as falsification checks. We expect to find smaller impacts of pro-environmental cases on these measures of pollution than BOD and COD, which

[11] https://www.epa.gov/national-aquatic-resource-surveys/indicators-conductivity accessed October 10, 2022

are quite sensitive to industrial pollution.

We supplement this data on water pollution with additional data on air pollution. This is largely for the purpose of controlling for industrial activity. We rely on the measure PM 2.5, which refers to a category of particulate pollutant in the air that is 2.5 microns or less in size.

This list of pollution measures is admittedly limited to basic indicators. Other pollutants that are known to affect human health are not recorded consistently in our time period. We note that while these data are quite detailed, India's data systems for water in the time period being considered here are limited in their coverage, robustness, and efficiency (Government of India 2018). Detailed data on a wide range of pollutants, particularly the presence of toxic heavy metals, is unavailable for the past 30 years.

3.4 Mortality

To construct district-level estimates of child mortality in India, we draw on two national population-based household surveys that have been used to measure national and sub-national health outcomes in India that are representative at the district level and cover the time-period of the pollution data and legal case-data. These are the second round of the District Level Household Survey (DLHS-2: 2002-04) and the fourth round of the National Family Health Survey (NFHS-4: 2015-16). The DLHS-2 has been previously used to analyze the impacts of pollution on mortality (Do, Joshi, and Stolper 2018). The NFHS-4, conducted 13 years after the DLHS-2, is also representative at the district level and has been used to examine demographic trends (Joshi, Borkotoky, et al. 2020).

We supplement these data with additional data on control variables. This includes data on nighttime light intensity and forest cover (Asher et al. 2021). These series are only available after 1991.

Summary statistics for key variables in each dataset are presented in Table 1. Combining data on pollution, court cases and judge case histories at the district-year level results in the loss of some observations from each data source.[12] Our working sample for examining pollution outcomes—the area of common support for court cases, judge histories and any pollution measurement—consists of a sample of 8,856 observations that covers 153 districts for the time period 1984 to 2020 (Table 1). This includes 516 court cases, with approximately 2 judges per case. The average case in this common support showed a slight bias towards having a positive environmental impact, as evaluated by our coding team (Table 1). Similarly, our working sample for examining mortality, court cases and judge case histories at the district-year level produces a sample of 24,169 observations that covers 678 districts for the time period 1974 to 2020 and is matched to 777 court cases (Table 2).

4 Empirical Strategy

4.1 Construction of Variables

Green Verdicts: To determine whether a particular judgment is likely to have a positive impact on the environment, we rely on manual reading, interpretation and categorization by a team of law students.[13][14] Specifically, we take the median of the scores assigned to a case across the coders who coded the case and define it as "green verdict" if the median assigned environmental impact is positive.[15]

Descriptive statistics in Table 1 and Table 2 suggest that the average case in our sample has a green score of 0.25 (the range is -2 to 2). 21 percent of cases are

[12] See Online Appendix section A for details on the aggregation process.

[13] These students, located in India, were trained by a lawyer with expertise of Indian law to read the judgments and label them based on their likely impact on the environment.

[14] We drafted a detailed training manual which provides information on how to use the portal, how to read and extract information from the judgment and FAQs. To ensure consistency in how cases were read and evaluated, we created a case coding portal using oTree, which is an open-source framework for interactive tasks and games. To avoid errors and double-check the labels assigned by students, each judgment was assigned to at least two students for labeling independently. Discrepancies in labeling will be reconciled by assigning the judgment to a third student.

[15] Coders were asked to form an opinion on whether a case was likely to have "a positive effect on the environment" on a scale of -2 to 2 (-2: strongly anti-environment; -1: mildly anti-environment; 0: no impact on the environment; 1: mild positive effect on the environment and 2: strong positive effect on the environment).

constitutional cases and 26 percent are appeals. 82 percent feature the government as the respondent and only 21 percent feature the government as the petitioner. There are on average 2 judges per case.[16]

We matched all cases in our sample to the districts where the environmental dispute originated and where the eventual court decision applied. 401 of the 978 cases clearly pertained to a specific location.[17] A further 115 in the sample lacked information on the district of origin but it was clear that the decisions were applicable to the entire jurisdiction of the court. For these cases, we assumed that on the date of the judgment, the verdict applied to all the districts in the state. An additional 2 cases in our sample were pertinent to the entire country. Here we again assumed that on the date of the judgment, the verdict applied to the entire country. This approach assumes that a ruling that has been coded as applicable to district d applies to that specific district.

Numeric Representations of Judge Writing Styles: For our analysis, we exploit the fact that judges' writing styles in non-environmental cases are predictive of their decisions in environmental cases. To extract judges' writing styles, we train the "doc2vec" algorithm (D2V) on the full corpus of all 7,235,533 judgments we have in our data (Le and Mikolov 2014).[18]

Then, for each judge who ruled on environmental cases in our sample, we compile the corpus of their single-authored, non-environmental case histories, i.e. the set of all rulings or judgments the judge presided on as a sole author, excluding the judge's environmental cases. For each of these cases we use the trained D2V model to assign a 25-dimensional vector to the case, which summarizes the case's

[16]Of the 978 cases, 12 cases do not have the names of the judges who heard the case, 489 cases were heard by a single judge, 431 have two judges and 37 have three.

[17]Both coders identified the same location.

[18]D2V is a package that provides an efficient framework for text analysis and natural language processing (NLP). The algorithm takes a corpus of texts (here, judge rulings) as an input, applies a neural network algorithm that analyzes the co-occurrence of specific words in relation to other words, and creates a 25-dimensional vector representation of the entire body of text. Stop words such as "is", "are", "the", "and", "we", "our", "ours", "ourselves", "you", "your", "yours," etc. are removed from the list of tokens. It is assumed that the closer tokens are to each other, the greater is their semantic relationship. The 25 dimensions produced with D2V are ultimately a numeric representation of the semantic meaning of each token within a wider body of language.

writing style. These vectors can be interpreted as numeric representations of the semantic structure of a body of text. Finally, for each of these judges, we take the average of the vectors over all their non-environmental cases' writing styles. This gives us, for each judge, a 25-dimensional vector which captures the judges' writing style excluding their environmental cases. We are able to successfully implement this approach for 302 judges in our pollution sample and 398 judges in the mortality sample.

A complicating factor in our analysis is the issue of co-authorship of judgments. In many of our cases related to water pollution, we do not observe individual judges' decisions but only the final, common decision. For a case c with bench B in district d and year t, we model the case outcome as:

$$Green_{cdt} = \tilde{\alpha}_1 \overline{D2V}_{1B_c} + \tilde{\alpha}_2 \overline{D2V}_{2B_c} + ... + \tilde{\alpha}_{25} \overline{D2V}_{25B} + \tilde{\gamma} X_c + \tilde{\xi}_d + \tilde{\delta}_t + \tilde{u}_{cdt}. \quad (1)$$

The variable on the left-hand side, $Green_{cdt}$, is defined as described in the above section "Green Verdicts" and captures the median score assigned by the manual coders of how pro-environmental a case is. $\overline{D2V}_{1B}$ is the mean of the first dimension of the D2V representation of writing styles of all judges sitting on the bench of case c. X_c is a vector of case characteristics (such as a dummy variable that takes value 1 if the case is an appeal from a lower court and 0 otherwise, and a dummy variable that takes value 1 if the government appears as a petitioner or a respondent and 0 otherwise), and $\tilde{\xi}_d$ and $\tilde{\delta}_t$ represent district and year fixed effects.

Figure 2 presents some visualizations of this approach. We rely on a technique called t-distributed Stochastic Neighbor Embedding (t-SNE) to produce two-dimensional representations of the original 25 vectors. The top panel presents the two-dimensional visualization of the case vectors (colored by the hand-labeled impact score), the middle panel presents the judge level embedding (colored by the mean impact score of the cases the judge has adjudicated) and the lowest panel presents the judge embedding along with the vector representation of key phrases which were jointly trained along with the case vectors by D2V. Similar cases in these graphs cluster together. We note that there is considerable variation in the writing style across judges, and also considerable variation across cases. As the graph in the bottom panel illustrates, this variation loosely corresponds to the incidence of key words from Indian environmental jurisprudence.

The D2V algorithm is, of course, not the only tool available for textual analysis. Throughout this research project, we have relied on a second method—Latent Semantic Analysis (LSA)—to check the robustness of our findings (Dumais 2004).[19]

With these key variables constructed, we next move on to a discussion of our identification strategy.

4.2 Identification Strategy

Our main goal is to estimate the impact of green verdicts on pollution levels and health outcomes. We first employ a simple OLS framework to examine the impact of a green verdict (versus a non-green verdict) conditional on the presence of any litigation related to water toxicity in a district of India. To address the issues of endogeneity that emerge in this framework, we will then move to an instrumental variables framework.

4.2.1 Setup: Simple OLS Estimation

We begin with a simple approach that assumes that green verdicts from the courts of India are exogenous and also local in scope and impact. In that scenario we would expect the following regression to identify the relationship between green verdicts and outcomes:

$$Y_{dt} = \beta_1 + \beta_2 FracGreenVerdicts_{dt} + \beta_3 \mathbb{1}\{|C_{dt}| > 0\} + X_{dt}\theta + \epsilon_{dt} \tag{2}$$

Here Y_{dt} can be either measures of pollution ($Pollution_{dt}$) or mortality ($Mortality_{dt}$)

[19]Latent Semantic Analysis assumes that words that are close in meaning will occur in similar pieces of text. A matrix containing word counts per document is constructed from a large piece of text and a mathematical technique called singular value decomposition is deployed to reduce the number of rows of this matrix. Documents are then compared by taking the cosine of the angle between the two vectors formed by any two columns. Values close to 1 represent very similar documents while values close to 0 represent very dissimilar documents.

in district d at time t, $FracGreenVerdicts_{dt}$ measures the fraction of water pollution cases in district d which are coded as green verdict at time t (i.e. the median score assigned in the manual coding process described above is greater than 0), C_{dt} is the number of water pollution cases in district d at time t, and X_{dt} is a vector of district and location-by-time characteristics, which includes year and district fixed effects.[20] The variable $\mathbb{1}\{|C_{dt}| > 0\}$ is a dummy variable that takes the value 1 if the district d has at least one environmental case in time-period t and 0 otherwise. $Pollution_{dt}$ is a measure of pollution in district d at time t. In our basic regressions it is the maximum value of either BOD, COD or TOTCOLI in a district-year.[21] $Mortality_{dt}$ is the percentage of children born in a district d in year t who lost their lives within 1 month and 1 year of their date of birth. We also examine the incidence of mortality in the first year conditional on one month survival.

The main challenge in estimating this equation is that green verdicts from the courts are likely to be endogenous to environmental as well as mortality outcomes: pollution is affected by economic growth, the proliferation of particular types of pollutants in the environment, as well as investments in education, the growth of awareness in a population, the pressures of democratic politics and other fators. We address the issue of the potential endogeneity of green verdicts in an instrumental variables framework.

4.2.2 Instrumental Variables Framework

Our instrumental variables framework starts with the assumption that environmental cases in the courts of India are effectively randomly assigned to judges. This

[20]Green verdicts are defined at the case-level, but these are aggregated at the district-year level. For the set of cases C in district d at time period t, we define the variable $FracGreenVerdicts_{dt}$ as follows:

$$FracGreenVerdicts_{dt} = \begin{cases} \frac{1}{|C_{dt}|} \sum_{c \in C_{dt}} Green_c & if\ |C_{dt}| > 0 \\ 0 & if\ |C_{dt}| = 0. \end{cases} \tag{3}$$

[21]There are two reasons why we focus on the maximum value of pollution per district-year (and not, for instance, at medium values). In a district with several rivers and pollution monitors, litigation is likely to occur around the one with the highest polluters / pollution levels. Also, water pollution has an exponential risk function for health outcomes.

assumption is grounded in the formal rules of the court as well as new empirical research (Ash et al. 2021).[22] We exploit the random judge assignment process to predict the emergence of green verdicts based on the past writing styles of judges and observable judge characteristics.

Our main equation, in static form, is as follows:

$$Y_{dt} = \beta_1 + \beta_2 \widehat{FracGreenVerdicts}_{dt} + \beta_3 \mathbb{1}\{|C_{dt}| > 0\} + \theta X_{dt} + \epsilon_{dt}. \tag{4}$$

Here the variables are defined as in equation 2, but $\widehat{FracGreenVerdicts}_{dt}$ is the predicted value of the fraction of green verdicts in district d at time t. This prediction is derived from the following first stage equation:

$$\begin{gathered} FracGreenVerdicts_{dt} = \hat{\alpha}_1 D2V_{1dt} + ... + \hat{\alpha}_{25} D2V_{25dt} + \hat{\alpha}_{26} JudgePostGrad_{dt} + \\ \hat{\beta}_3 \mathbb{1}\{|\#|Cases_{dt} > 0\} + \hat{\theta} X_{dt} \ + \eta_{dt} \end{gathered} \tag{5}$$

The first 25 instruments based on judges' writing styles, described earlier in this section, are represented as follows:

$$D2V_{1dt} = \frac{1}{|C_{dt}|} \sum_{c \in C_{dt}} \overline{D2V}_{1B_c} = \frac{1}{|C_{dt}|} \sum_{c \in C_{dt}} \frac{1}{|B_c|} \sum_{j \in B_c} D2V_{1j}. \tag{6}$$

Here C_{dt} represents the set of cases in district d at time period t and B_c represents the set of judges on the bench of case c. The last instrument, $JudgePostGrad_{dt}$, measures the share of judges deciding a case in district d in year t with a postgraduate degree. Under the assumption of random judge assignment, and with the appropriate

[22]The rules of case assignment in the judiciary of India are clearly specified in its "roster system": decisions regarding case allocations are made by the chief justice of a court and this allocation must adhere to stringent rules that ensure that judges do not work with parties with whom they have had any familial or social connection. Petitioners and respondents are not allowed to request a specific judge. Unless a case is already at the final argument stage (after completion of evidence, etc.), a change in the roster results in a change in the judge hearing the case, which introduces further variation into case-assignment. In their exploration of the impacts of caste, gender and religion on outcomes, Ash et al. (2021) argue that the case-assignment is basically a "coin flip" in this system.

construction of our instrumental variables, β_2 in equation 4 can be interpreted as a causal estimate of the impact of green verdicts issued in district d at time t on outcomes. The presence of litigation and other control variables, however, do not have a causal interpretation.

Overall, our main instrumental variable specification features a single endogenous regressor with 26 instruments employed in the first stage. We rely on the *ivreg2* and *weakiv* packages in Stata 17 to conduct cluster-robust weak-instruments tests that are suitable for settings with non-homoskedastic errors (Olea and Pflueger 2013; Pflueger and Wang 2015). Standard-errors are clustered to account for the systematic variations that emerge from having a single case impacting multiple districts at the same time, a method that we refer to as "small pond" clustering.[23] For robustness, we also cluster standard errors by defining larger groups that include all district-year pairs that are linked by at least one common case. We refer to this as "large pond" clustering.

We also use the LSA model of text analysis to check the robustness of our findings throughout the paper.

4.2.3 Comparison with Other Approaches to Identification

Several recent papers have exploited the random assignment of judges to study the impact of justice system processes on outcomes (Aizer and Doyle Jr 2015; Arnold, Dobbie, and Yang 2018). Aizer and Doyle Jr (2015) for example, study the impact of juvenile incarceration on future (crime / human capital) outcomes of individuals. Their instrumental variable is a measure of tendency (i.e leniency) of the randomly assigned judge j. To calculate this, the authors calculate for each judge and each individual, the rate at which the judge has incarcerated all other juveniles excluding a particular individual.[24]

[23] All district-year pairs that are affected by the same set of green verdicts are grouped together.

[24] This "leave out mean" is computed via a JIVE, which is helpful in settings where the number of judges goes up if the number of cases increases. In this example, the average judge has 607 juvenile cases and the authors know the outcome (and some characteristics) of each of these cases. That allows them to construct this leave-out instrument.

We are unable to follow this approach for our sample. Our sample of 978 cases contains only a handful of judges who appear multiple times in the sample of water cases. Although we have the universe of cases for each judge, most of the cases are not related to water pollution. Additionally, many cases in our sample have a bench of three judges deciding together and we only observe the final outcome and not each judge's individual vote. Despite this caveat however, we believe that our adaptation of this approach is suitable for the specific purpose of examining environmental outcomes such as local ambient water quality in a specific geographic area.

4.2.4 Dynamic Effects

It is plausible that the potential effect of a judgment occurs over time rather than all at once. To take this into account, we must interpret each judgment as a policy and use (together with the IV approach) a distributed lag model. We thus adapt the approach described above to also estimate a dynamic model with leads and lags for the judicial policies.

To do this we assume that a verdict in district d at time t will impact pollution in that very district in that time period as well as subsequent time-periods. This is justified in light of how India's common law system works. Judges establish common law through written opinions that are binding on future decisions of lower courts in the same jurisdiction. Moreover, given that many of these rulings pertain to specific environmental disputes that pertain to local firms and local institutions, rulings are quite specific and require actions such as the closure of a firm, the installation of special equipment or the imposition of fines to ensure greater compliance with environmental laws.

5 Results

5.1 First Stage

Given that the first-stage regression pertains to cases in the courts, but the overall regression pertains to districts, we take a small detour to understand the first-stage at the case-level. In the top-left panel of Figure 3 we estimate equation 5 using the leave-one-out cross-validation approach to generate a prediction of the likelihood of a green verdict with the set of judge writing characteristics. We see that these judge characteristics are indeed highly predictive for the likelihood of a green verdict.

Separately, in the top-right panel, we also run a regression of the predicted likelihood of a case having a green verdict, taking into account only control variables, using the full set of judge writing characteristics and controls. The control variables at the case level include a dummy variable that takes value 1 if the case is an appeal case (and 0 otherwise), a dummy variable that takes value 1 if one of the parties contesting the case is the government (and 0 otherwise), and a dummy variable that takes value 1 if the case is a constitutional case (and 0 otherwise).

Here we can see that, consistent with randomization, the prediction of green verdicts from controls seems uncorrelated with the prediction from the full set of judge characteristics.

In the lower panel of Figure 3, we aggregate our variables on a district-year level and run the same regressions as in the top row for all district-years which have at least one case. We see that the results are very similar to the case-level ones. This analysis corresponds to our main econometric specification.

5.2 Impacts on Pollution

To obtain an estimate of the impact of green verdicts on pollution levels, we estimate equation 2 (OLS estimation) and 4 (IV). Tables 3 and 4 present the results from three different sets of specifications: omission of the districts and years that have no environmental verdicts at all (columns 1 and 2), inclusion of dummies for those districts and years (columns 3 and 4), inclusion of dummies and fixed effects for districts and years (columns 5 and 6) and the inclusion of dummies, fixed effects and covariates related to the cases (constitutional case, appeal case, and the involvement of the government as a respondent in the case) in the full specification (columns 7 and 8). For each of the dependent variables— log(BOD) and log(COD)—all regressions are performed on the full sample of observations (Panel A), as well as the narrower sample of the Ganga basin (Panel B), where the issue of pollution has been highly salient (Singh, 2006; Do, Joshi, and Stolper 2018).

Estimates of the effective first-stage F-statistic are reported in Tables 3 and 4 for all IV specifications. Given that the model is over-identified, and the data is non-homoskedastic, recent literature recommends reporting the identification-robust Anderson-Rubin (AR) confidence intervals (Young 2022; Andrews, Stock, and Sun 2019).[25] [26] This is efficient regardless of the strength of the instruments (Andrews, Stock, and Sun 2019).

For the dependent variable COD, estimates for all the specifications performed on the full sample (Panel A) in Table 3 are negative. In all these instances however, the AR confidence interval includes 0, suggesting that we cannot rule out a zero effect of the policy.

In the Ganga basin however, we see a stronger effect, particularly in our preferred full specification (Panel B, Table 3, Columns 7 and 8). Here we note that both the OLS and IV estimates for the variable "Fraction of Green Verdicts" are negative and statistically significant. The OLS estimate, -0.431 (Table 3, column 7), lies within a confidence interval $[-0.642, -0.221]$. The IV estimate stands at -0.437 (Table

[25]Given the concerns related to weak instruments in this analysis we refrain from presenting the standard errors and p-values of the coefficients and emphasize that the AR confidence interval provides the most reliable inference about statistical significance (Andrews, Stock, and Sun 2019).

[26]To calculate confidence intervals (CI) robust to weak inference, we apply a two step approach. In our main specification we use 26 variables (25 D2V + one dummy variable that takes value 1 if the judge has a postgraduate degree and 0 otherwise) to instrument for "Fraction of Green Verdicts". We then calculate the effective first-stage F statistic of Olea and Pflueger 2013, reported by STATA's *weakivtest* package and the critical value for a maximum asymptotic bias of 5%. If the effective F-stat is larger than this critical value, we use standard Wald CIs. If it is below the threshold, we use the inversed K test from STATA's *twostepweakiv* package, allowing for inefficient weight matrices in K statistics. For simplicity, we refer to the created CIs as AR Confidence intervals.

3, column 8) and lies in the confidence interval $[-0.577, -0.298]$. The coefficient can be interpreted as the change in the maximum value of a pollutant value in a given year (conditional on a district having any environmental case at all) if the fraction of green verdicts in a district change from 0% to 100%. According to this estimate, a district in the Ganga basin that goes from having no green verdicts to all green verdicts (conditioned on having some water pollution cases) in a given year experiences a 43.7% decline in the highest observed COD value in the district that year.

We see similar results for BOD (Table 4). We note that in the buildup to the preferred specification in the full sample (Panel A), we see negative coefficients in the OLS and IV specifications, and these fall into confidence intervals that exclude a zero-effect. Specifically, the point estimate of the IV regression (Table 4, Column 8) is -0.241 and this falls into the confidence interval $[-0.494; -0.0702]$. This suggests that a district in the Ganga basin that goes from having no green verdicts to all green verdicts (conditioned on having some water pollution cases) in a given year experiences a 24.1% decline in the highest observed BOD value in the district that year and the confidence interval for this rules out a zero-effect. Unlike the case of the COD regressions, we observe weaker effects for BOD in the Ganga basin.

5.3 Impacts on Additional Pollutants

Table 5 presents the results of our preferred specification for additional water quality outcomes that include the logarithm of TOCOLI, conductivity and temperature. These three indicators of water quality are sensitive to natural ecological drivers of water quality and are not widely used as measures of industrial pollution (WHO and UNICEF 2012). Given that most of our environmental litigation pertains to industrial activity, we do not expect impacts of judicial verdicts on these measures.

The estimates from our preferred specification (in Tables 3 and 4) are also included here, along with the corresponding F-statistics and AR confidence intervals from the first-stage regressions. We note that all the obtained coefficients are negative. The AR confidence interval, robust to weak instruments concerns (Andrews, Stock, and Sun 2019), suggests that the negative impact of the policy is only observed for BOD and COD. We cannot rule out the zero-effect of the policy for TOTCOLI, water conductivity and temperature.

Similar results are obtained for the Ganga basin (Panel B, 5). We see a strong negative impact of green verdicts mainly on COD and temperature. The AR confidence interval includes 0 for BOD and conductivity and is undefined for TOTCOLI.

A word is in order about why we may observe some impact of the judicial policies on maximum observed values of water temperature. While some variations in water temperature can be induced by climatic variation and seasonality, industries may also discharge effluent that is at a higher (or lower) temperature than natural water, creating thermal pollution (WHO, 2012). Even small temperature differences between discharged water and natural ambient water can trigger changes in natural ecologies. Thermal pollution can exacerbate the problems of water toxicity by incubating bacteria and other contaminants that undermine the quality of surface water (WHO and UNICEF 2012).

In summary, we see strong negative impacts of the judicial verdicts on COD and temperature levels in the full sample as well as the Ganga basin. We see similar results for BOD, though the results are weaker in the Ganga basin for this pollutant. We do not see significant impacts of judicial verdicts on TOTCOLI or water conductivity in our sample, though this must be interpreted cautiously in light of the AR confidence interval.

We perform a series of robustness checks for these results. Appendix Table A1 presents additional robustness checks of these results with additional control variables for nighttime lights and forest cover (Asher et al. 2021). We regard the measure of nighttime lights, calculated from weather satellite recordings, as a proxy for local economic activity in settings where disaggregated data is unavailable from any official sources (Bruederle and Hodler 2018).[27] Our measure of forest cover, also calculated from satellite data, is intended to be a proxy of the broad

[27]Bruederle and Hodler (2018) examine the correlation of nighttime lights with measures of household wealth, education and health from DHS surveys in cluster locations as well as grid cells that are approximately 50 × 50 km and find a positive correlation.

strain on environmental resources: population growth, urban development, the spread of agriculture and industrialization all result in the loss of forest cover while environmental policies improve it (Crespo Cuaresma et al. 2017).

Since these are only available after 1991, our estimation must be performed on a smaller sample. We nevertheless continue to see negative coefficients and for COD, the AR confidence interval continues to exclude 0, suggesting that the results remain robust even in this smaller sample. Appendix Table A2 presents the results for the three year moving averages of the dependent variables, and again the key results appear to be robust, with the negative coefficient for BOD now appearing negative and statistically significant.

In the online appendix to this paper, we also present a set of results of estimations with the LSA model as well as estimations with both the D2V and LSA models together. We also check the robustness of these results to using mean levels of pollution and minimum levels of pollution for the whole sample as well as the Ganga basin. We do not discuss these in detail. We simply note that the results are very similar to what we have reported here.

5.4 Dynamic Impacts

Next we estimate the equation (4) with dynamic effects: we consider effects three years in advance of the ruling, and five years after. The coefficients for these three leads and five lags are presented for three pollutants—BOD, COD and TOT-COLI—in Figure 4.

We note that in the immediate aftermath of the filing date, the coefficients are negative and statistically significant at the 1% level for both BOD and COD. We believe this is largely driven by the curbing of pollutant behavior during the time that the case is being deliberated at the courts. The filing of an environmental case against a polluter generates considerable publicity in India (Baxi 1985; Sathe 2002). The courts are highly salient in the state-society interface (Kapur, Mehta, and Vaishnav 2018). Most cases are resolved within about 3 years. Indeed, the average tenure of a judge at a court in our sample is also about 3 years. We can expect a firm that is subject to an environmental case to be scrutinized by pollution inspectors, particularly if it is a large polluter to begin with (Duflo et al. 2018). As discussed earlier, the Water Act is largely enforced through the CPCB and SPCBs that lack the capacity to ensure compliance with environmental laws or court mandates.

We also note that the three pollutants decline in the immediate aftermath of the verdict, though this is short-lived and pollution levels rise thereafter. Our measure of organic pollution—TOTCOLI—rises most significantly, suggesting that the ruling may ultimately drive firms to alternate technologies that produce organic rather than chemical effluent.

The overall result of the eventual rise in toxicity in the years after the ruling is consistent with many past analyses of court-led environmental activism in India. They have short-term impact, but for long-run enforcement of policies, they rely on the executive and legislature, neither of which is equipped to confront environmental toxicity. As a result, the period of adherence that follows strong verdicts is often not sustained (S. Ghosh 2019). Water clean-up projects that are designed in the aftermath of such rulings for example, are often built in the format of public–private partnerships and the scale of the projects becomes unsustainable almost immediately after the project is constructed (Shambaugh and Joshi 2021; Joshi and Shambaugh 2018). Many water clean-up projects along the Ganga River became rent-seeking opportunities almost immediately after they were created, leading to persistent pollution despite considerable judicial activism to protect the river (Alley 2002).

5.5 Impacts on Mortality

Table 6 estimates the second-stage impacts of green verdicts on mortality. We consider three measures of mortality as dependent variables in our estimation of equation (4): death in the first year of life (column 1), death in the first month of life (column 2), and death in the first year conditional on surviving the first month (column 3). These are abbreviated in the tables as *Died<1Y*, *Died<1M* and *Died<1Y |1M* respectively. The coefficient of interest to us is β_2 in equation (4), which measures the impact of predicted green verdicts on mortality outcomes in a district-year.

We estimate the equation on three important samples. The first two samples are the post-1989 period for the full sample of all districts in India and all the districts of the Ganga basin respectively. Note that 1989 marks the implementation of the first official ruling related to water toxicity in India, in the aftermath of public interest litigation (Sathe 2002; Rajamani 2007; Do, Joshi, and Stolper 2018; Joshi and Shambaugh 2018; S. Ghosh 2019). By examining the post-1989 period, we also ensure that both demographic surveys cover an equal number of years for which retrospective information on births and deaths are calculated in our mortality sample. Our third sample is the post-1997 period. 1997 marks the first year for which we have detailed data on control variables for the districts of India: nightlights, forest cover and air pollution.

Results of the estimation of equation (4) for the three dependent variables, in all three samples, are presented in Table 6. Panel (A) of this table presents results of estimations with no district-level variables. Panel (B) presents results of estimations with the full set of covariates. The IV regression is implemented using exactly the same set of methods as the earlier results pertinent to pollution (3 and 4). I.e., the full set of 26 instruments are used in the first stage, and the effective F-statistic as well as the AR confidence intervals are presented to address concerns related to weak instruments. One difference between the previous estimation and the current estimation, however, is that the key endogenous variable, *Fraction of Green Verdicts*, is here lagged by two years (instead of the year immediately following the ruling). This is because mortality is a censored variable. Given that health impacts of pollution can occur *in utero*, we believe that the full effect of the ruling can only be observed two years later.[28]

Note that in Panel (A) of Table 6, we note that the coefficients for *Died<1Y* and *Died<1Y |1M* are positive and significant in the full sample. The AR confidence interval excludes 0 in both these regressions, suggesting that the rulings were overall

[28]In "ideal" data, we would have specific dates and location codes for children's births and match them to the dates of the ruling, thus calculating the correct levels of exposure to the new policy regime. Given that we are relying on demographic surveys that ask women to recall their birth history as late as 14 years after giving birth, however, such a micro-analysis would be quite unreliable.

associated with a small increase in child mortality. The magnitude of the effect is small but in both these cases the AR confidence interval excludes 0. The estimate suggests that if the fraction of green verdicts goes from 0 to 100%, mortality would increase by between 0.05% to 1.4%. This admittedly wide confidence interval represents a modest impact considering that mortality levels in India were falling over this time period and well below 10% for all three measures of mortality (Table 2).

Estimates in the Ganga Basin are higher for the post-1989 period (Columns 4–6, Table 6), but smaller for the post-1997 period (Columns 7–9, Table 6). In the Ganga basin, for the post-1997 period, the AR confidence interval includes 0 for all three estimates of mortality suggesting that there may be no statistically significant effect of green verdicts on mortality.

Panel (B) of Table 6 presents the results of estimations for the full sample as well as the Ganga Basin with reported levels of air pollution as an additional district-level control variable. Our rationale for including air-pollution as a control is simply to better control for the level of industrial activity at the district level. The AR confidence interval includes 0 for two of the three estimates of mortality in the full sample. For infant mortality that is conditional on surviving the first month of life (*Died<1Y |1M*), we again observe a positive and significant coefficient in the full sample (Panel B, column 3, Table 6). The estimate suggests that an increase from 0% to 100% for the fraction of green verdicts results in a 0.2% to 0.7% increase in mortality.

Overall, these results suggest that there is a very modest positive impact of judicial verdicts on some measures of mortality in the same district as the ruling in the full sample that covers 1989–2020. This may be driven by an economic mechanism. For example, the closure or reduced economic activity of firms may have increased economic vulnerability in the local population and raised the barriers for accessing health care. We emphasize however, that the results diminish in later time periods. This too can be explained by economic factors such as increased access to piped water, improved health systems and greater awareness. The effect, however, remains robust to the addition of control variables that capture some forms of economic activity. Additional research is needed to explain these effects.

We also emphasize that these results must be interpreted cautiously. As seen in Figure 1, our sample of districts with green verdicts is small. In previous work, Do, Joshi, and Stolper (2018) found localized effects along a single river. The considerable ecological, demographic and institutional diversity of India together with the rarity of mortality in recent years may make it difficult to find strong effects. Examining localized effects of green verdicts in this sample is an important next step for our research.

We test the robustness of the results in several ways. First, we include additional control variables: i.e., the maximum reported intensity of night lights, the maximum reported level of forest cover, and the maximum level of air-pollution (particulate matter) in a year. Appendix Table A3 confirms that even in this reduced sample, the key results for mortality remain robust. Second, given that our control variables may be biased by including or excluding locations that are non-random from the standpoint of industrial activity, we also examine the robustness of the result in the sample for this variable is defined, and we continue to see that our key result remains robust—mortality conditional on surviving the first month of life continues to take a positive coefficient though it is small in magnitudes and other measures of mortality do not take values that are statistically significant (Appendix Table A4).

5.6 Impacts beyond the Targeted Districts

Our empirical strategy hinges on the assumption that judges are randomly assigned once we condition on case characteristics and judge characteristics (which include histories of their previous judgments) and also district and year-month fixed effects. Implicit in this assumption is that these variables fully explain the emergence of green verdicts in polluted locations. The next step of our analysis is to examine whether these green verdicts also affect pollution levels in *surrounding* or *neighboring* locations. The primary mechanism for this would be a deterrent effect—given the salience of judicial activity in India, owners of a polluting firm may be motivated to reduce their own pollution (or adopt pollution-mitigation technologies) to reduce the likelihood of an inspection, public scrutiny or attention to their behavior (Duflo et al. 2018). A similar argument can be made for all the districts in a state where firms are monitored by a single SPCB.

To explore this, we modify our IV framework to first regress green verdicts on judge characteristics in a geographically neighboring district and then examine whether these green verdicts in neighboring districts affect pollution in the districts in our sample.[29] IV estimations are once again performed with the full set of 25 instruments. Again, we present the AR confidence intervals.

Results are presented in Table 7. Note that we observe a negative and statistically significant effect of neighboring district green verdicts on COD (Column 1). For all other measures of water quality, we observe negative coefficients, but the AR confidence interval includes 0 (Columns 2–5). Table 8 expands the methodology we described for neighboring districts to the analysis of the entire state. Here the AR confidence interval is no longer defined for COD (Column 1), and as seen in the case of Table 7, we see negative coefficients for all other measures of water quality, but the AR confidence interval here too includes 0 (Columns 2–5). We examine the robustness of this result to the inclusion of controls and the exclusion of districts that have major cities. As seen in Appendix Table A5, the result remains robust in this sample.

One interpretation of these results is that judicial cases may deter polluting firms in neighboring districts and perhaps districts in other parts of the state. This results in a decline in the maximum observed values of COD in a given year in these areas. This effect, however, is not present for other measures of water quality that are less responsive to industrial pollution.

[29]We use geospatial maps with district boundaries to construct lists of neighboring districts for each district in our sample. For each district, we count the number of green verdicts in neighboring districts (excluding cases in the district itself) and divide that number by the total number of river pollution cases in all neighboring districts.

6 Discussion

Our estimates of the impact of green verdicts on water pollution levels are the first documented empirical evidence of the judiciary's success in India's regulation of water quality over the past three decades. Our key result is that judicial verdicts appear to reduce some measures of surface water pollution but these effects are small, short-lived and insufficient to improve infant mortality.

Here it is worth emphasizing that the impacts we report here pale in comparison to the recent stringent Indian Covid-19 lockdown (March 2020-June 2020). A recent study has found a reduction in irrigation and power demands, increased water storage, increased flow and a significant improvement in the concentrations of pollutants such as dissolved oxygen, BOD and nitrates (Dutta, Dubey, and Kumar 2020).[30] The comparison of judicial verdicts with the lockdown, however, is problematic considering that economic activity nearly came to a halt in India and across many other parts of the world.

The impact of judicial policies reported here does, however, compare favorably with those taken by the executive and the legislative branches of government, as reported in other studies, for the same time period and even the same data as we have considered here (Greenstone and Hanna 2014). As was noted in the introduction and section on Context (section 2 of this paper), there is a long record of governance failures by the executive and legislative branches of government. That we find *any* effect of judicial policies is important and noteworthy. The salience of the judiciary in Indian life, the high levels of trust for this institution and the coverage of judicial decisions by the media likely contribute to at least short-term compliance with judicial policies (Baxi 1985; Bhuwania 2017; Kapur, Mehta, and Vaishnav 2018).

That being said, a question that emerges from our findings is why judicial verdicts have only a short-term impact on pollution. Here we note that a typical ruling in our sample imposes restrictions on polluters. This may induce a loss of income and employment in a community, which can undermine the long-term popularity of the

[30] Dutta, Dubey, and Kumar (2020) even found that the river became fit for drinking for the first time in years.

policy among critical stakeholders (Alley 2002; Stiglitz, Sen, and Fitoussi 2010).

The lack of effectiveness of judicial policies may also be driven by the limitations of the technologies that have been widely adopted to treat effluent from toxic industries intended to address citizen concerns (Woodhouse and Muller 2017). Besides polluters behaving differently, firms or local governments may respond to judicial policy with attempts to clean up the environment through technology. However, technologies such as Common Effluent Treatment Plants (CETPs) for example, are expensive and cumbersome to build even as they have been widely promoted by institutions such as the World Bank as a convenient end-of-pipe solution to the problem of industrial pollution. Public-private partnerships, featuring governments, multilateral organizations and private companies, have built these technologies in India (Shambaugh and Joshi 2021). The lack of long-term planning for funding the maintenance and operations of these large and expensive technologies, however, lead to their long-term ineffectiveness (Joshi and Shambaugh 2018). The "boom-bust cycle" that is inherent in such projects can be seen at the level of India's first CETP that was built in the city of Kanpur to mitigate water toxicity from the tannery industry in the aftermath of a powerful judicial verdict: this project was effective for about 2 years before water toxicity levels reached the pre-verdict stage and a similar pattern is seen for all 88 CETPs that were constructed in India between 1986 and 2004 (Joshi and Shambaugh 2018).

Finally, the failure of the judiciary to have long-term impact may also be driven by the overall complexity of environmental governance in India. As noted earlier, there is a large corpus of laws on the books, but the enforcement systems are complex, and no single entity is ultimately responsible for protecting water resources (S. Ghosh 2019). Unlike air quality, which is more observable and traceable to a source, water toxicity can be invisible to the naked eye and transported undetected in flowing waterways to locations far away from the original source (Greenstone and Hanna 2014; Do, Joshi, and Stolper 2018).

In a nutshell, our results suggest that even though judiciaries can lower pollution in the short-run, it cannot bring about sustainable long-term improvements in toxicity and health outcomes. That may require the participation and commitment of all three branches of government as well as citizens. Further research is needed to elucidate the mechanisms.

7 Conclusion

This paper provides an empirical study of the broad impact of judicial rulings on environmental outcomes in India, a developing country with some of the highest levels of water toxicity in the world. Our analysis is based on a novel dataset that combines legal, environmental and demographic variables at the level of districts. Our empirical model seeks to identify the causal relationship between a green verdict and actual environmental outcomes. Since rulings may be endogenous to outcomes, we use an IV framework, with the textual features of the judges who preside over these cases to predict the likelihood of a green verdict. In the second stage of analysis we consider both pollution and mortality as key outcomes.

Our results suggest that the rulings precipitated some reductions in chemical oxygen demand (COD) and biological oxygen demand (BOD), two common measures of industrial pollution in surface water. The impacts are particularly pronounced in the Ganga basin, where pollution and industrial activity have been particularly salient. The rulings also led to modest but discernible increases in infant mortality two years after the ruling, though this dissipated shortly after. We interpret this as suggestive evidence that judicial policies can succeed in lowering short-term pollution, but this is insufficient to improve health outcomes. On the contrary, the economic slowdown that occurs in the aftermath of a ruling may actually increase economic vulnerability. In the long-run the many issues of enforcement and oversight limit the power of the judiciary to bring real improvements in health at the grassroots of society.

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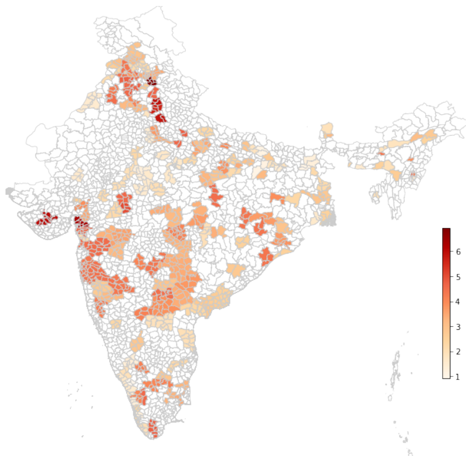
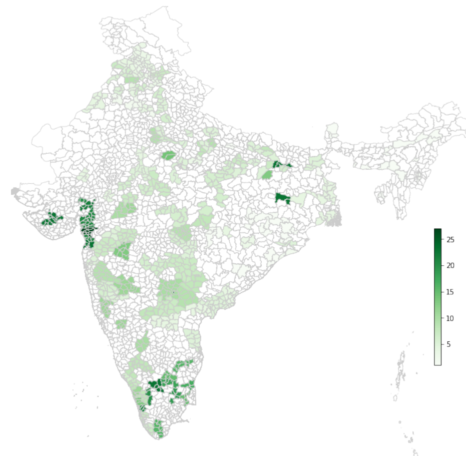
Figures and Tables

(A) Max of log(BOD mg/l) per District



(B) River Pollution Cases per District



(C) Overlap between Cases and Pollution

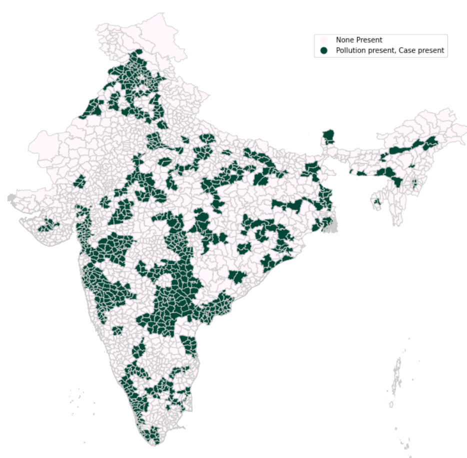


Figure 1: Coverage of Pollution Data, River Pollution Cases and their Overlap in Indian Districts

Notes: Panel A displays the coverage and spatial distribution of the maximum log-value of BOD measured in any river and any year per district. Panel B displays the number of cases in the Indian Supreme Court, Green Tribunal and High Courts related to river pollution per district between 1982 - 2020. Panel C displays the geographic overlap on a district level in which river pollution cases are observed and river pollution data is available.

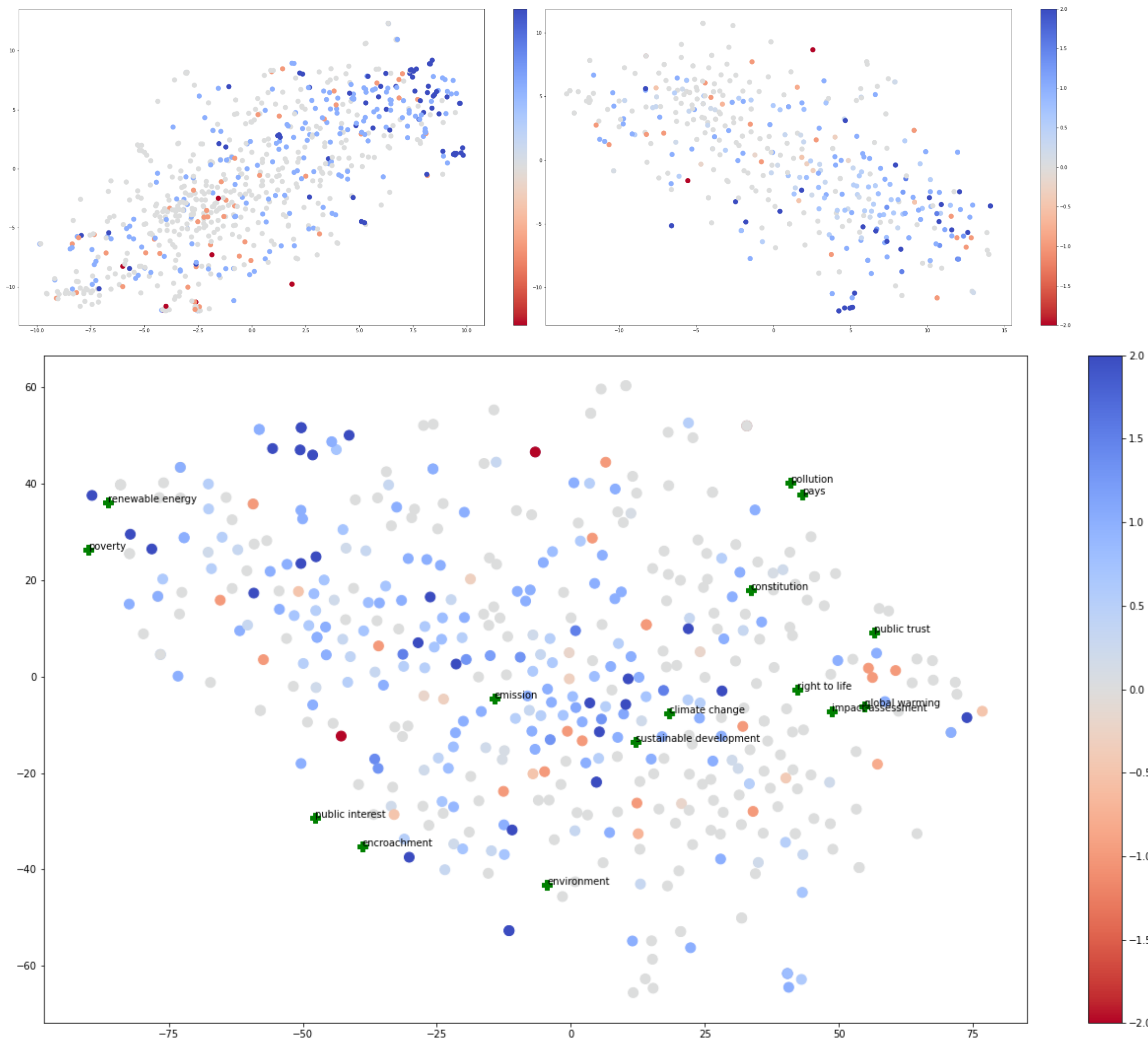


Figure 2: Visual Illustration of Judges' writing Styles

Notes: Each case in our corpus is represented as a 25 dimensional vector using D2V. The top-left panel presents the two dimensional visualization of the case vectors (colored by the hand-labelled impact score). The top-right panel presents the judge level embedding (colored by the mean impact score of the cases the judge has adjudicated). The bottom panel presents the judge embedding along with the vector representation of key phrases which were jointly trained along with the case vectors by D2V.

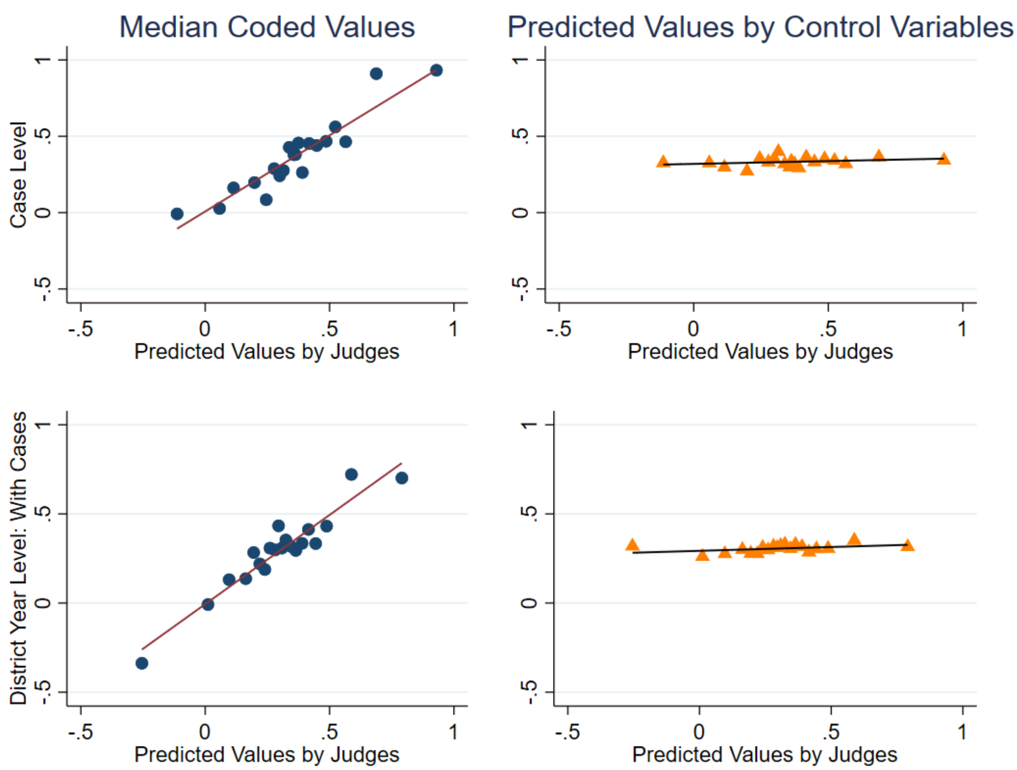
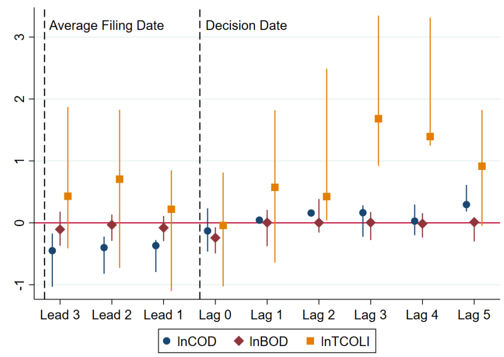


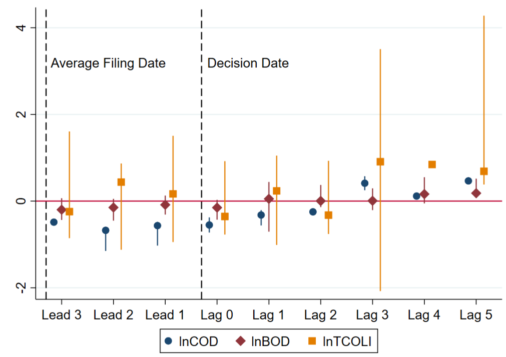
Figure 3: Graphical First Stage

Notes: (i) The top row is on a case-level and the lower row on a district-year level including only district-years with at least one year; (ii) Graphs on the left are binscatters of (residualized) median codings of cases on the (residualized) predicted codings by judge characteristics; (iii) Graphs on the right are binscatters of the predicted (residualized) median case codings by case characteristics on predicted (residualized) median case codings by judge characteristics; (iv) Judge characteristics (in the left panel) include the 25 measures of judge writing style; (v) Case characteristics (in the right panel) include a dummy variable that takes value 1 if the case is an appeal case (and 0 otherwise), a dummy variable that takes value 1 of one of the parties contesting the case is the government (and 0 otherwise), and a dummy variable that takes value 1 if the case is a constitutional case (and 0 otherwise).

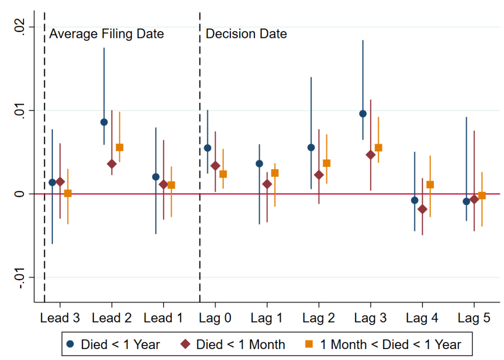
Panel A. Pollution: All India



Panel B. Pollution: Ganga Basin



Panel C. Mortality: All India



Panel D. Mortality: Ganga Basin

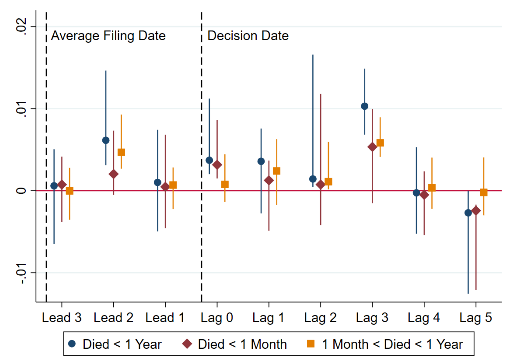


Figure 4: Impact of Green Verdicts on Pollution and Mortality: Individual Lags and Leads Regressions

Notes: Outcomes are either pollution measures (Panel A and B) or infant mortality (Panel C and D) per district in year t, regressed on Fraction of Green Verdicts, a dummy equal to one if the number of cases is greater than 0, district and year fixed effects and several aggregated case characteristics. The explanatory variables are shifted from t-3 up to t+4. Fraction of Green Verdict is instrumented for by a 25 dimensional vector summarizing judges writing styles and the fraction of Judges with a postgraduate degree in the district-year. Standard errors are clustered on the "small pond" level and confidence intervals are robust to weak inference.

Table 1: Summary Statistics for each source of data

Pollution (Monitor-Year)	N	Mean	SD	Min	Max
Max BOD (mg/l)	23413	9.57	38.32	0.0	1,820.0
Max COD (mg/l)	6089	39.95	63.12	0.1	1,750.0
Max Total Coliform (mpn/100 ml)/10^6	19628	6.92	322.18	0.0	23,000.0
Max Temperature (°C)	24622	28.52	5.69	0.0	84.0
Max Conductivity (µmhos/cm)/10^3	22843	2.28	9.44	0.0	513.0
Case Level Data - Pollution Merge					
Appeal	516	0.25	0.44	0.0	1.0
Constitutional	516	0.21	0.40	0.0	1.0
Government is Respondent	516	0.82	0.38	0.0	1.0
Government is Petitioner	516	0.14	0.34	0.0	1.0
Number of Judges	516	1.68	0.76	0.0	3.0
Environmental Impact (Median Coding)	516	0.34	0.72	-2.0	2.0
Average Forest Cover in Location (%)	303	11.85	8.86	2.6	42.4
Average Nightlights in Location (%)	186	10.85	11.03	0.9	62.6
Case Level Data - Mortality Merge					
Appeal	777	0.25	0.43	0.0	1.0
Constitutional	777	0.22	0.42	0.0	1.0
Government is Respondent	777	0.86	0.35	0.0	1.0
Government is Petitioner	777	0.11	0.32	0.0	1.0
Number of Judges	777	1.75	0.76	0.0	3.0
Environmental Impact (Median Coding)	777	0.35	0.70	-2.0	2.0
Average Forest Cover in Location (%)	577	10.29	8.20	0.3	49.8
Average Nightlights in Location (%)	342	15.65	15.44	0.2	62.6
Judge Level Data - Pollution Merge					
Male	302	0.97	0.16	0.0	1.0
Graduate Level Education	302	0.39	0.49	0.0	1.0
Post-Graduate Level Education	302	0.13	0.34	0.0	1.0
Judge Level Data - Mortality Merge					
Male	398	0.96	0.20	0.0	1.0
Graduate Level Education	398	0.38	0.49	0.0	1.0
Post-Graduate Level Education	398	0.12	0.33	0.0	1.0

Table 2: Summary Statistics of the two working samples

District-Year Level Data - Pollution Sample	N	Mean	SD	Min	Max
Case Present	6270	0.16	0.37	0.0	1.0
Number of Green Verdicts	6270	0.24	0.75	0.0	13.0
Fraction of Green Verdicts	6270	0.04	0.18	0.0	1.0
Average Number of Judges / Case	6270	0.29	0.72	0.0	3.0
Share of Appeal Cases	6270	0.03	0.16	0.0	1.0
Share of Constitutional Cases	6270	0.05	0.22	0.0	1.0
Share of Cases w/ Government as Petitioner	6270	0.02	0.12	0.0	1.0
Share of Cases w/ Government as Respondent	6270	0.14	0.34	0.0	1.0
Max BOD (mg/l)	5650	12.53	33.86	0.0	1,025.0
Max COD (mg/l)	3053	55.65	80.25	1.1	1,750.0
Max Total Coliform (mpn/100 ml)/10^6	5057	15.09	514.20	0.0	23,000.0
Max Temperature (°C)	5614	29.69	6.29	0.0	269.0
Max Conductivity (µmhos/cm)/10^3	5476	1.94	7.33	0.0	81.8
log Max BOD (mg/l)	5649	1.66	1.14	-1.6	6.9
log Max COD (mg/l)	3053	3.49	1.02	0.1	7.5
log Max Total Coliform (mpn/100 ml)	5057	8.47	3.03	0.7	23.9
log Max Temperature (°C)	5541	3.39	0.16	2.2	5.6
log Max Conductivity (µmhos/cm)	5475	5.99	1.64	-1.3	11.3
log Max BOD (mg/l) (MA)	6254	1.67	1.14	-1.6	6.9
log Max COD (mg/l) (MA)	5742	3.41	0.97	0.1	7.5
log Max Total Coliform (mpn/100 ml) (MA)	5888	8.52	3.03	0.7	23.9
log Max Temperature (°C) (MA)	6185	3.38	0.21	0.3	5.6
log Max Conductivity (µmhos/cm) (MA)	6237	6.02	1.62	-1.3	11.3
District-Year Level Data - Mortality Sample					
Case Present	15982	0.10	0.30	0.0	1.0
Fraction of Green Verdicts	15982	0.04	0.18	0.0	1.0
Average Number of Judges / Case	15982	0.17	0.58	0.0	3.0
Share of Appeal Cases	15982	0.02	0.14	0.0	1.0
Share of Constitutional Cases	15982	0.02	0.14	0.0	1.0
Share of Cases w/ Government as Petitioner	15982	0.01	0.10	0.0	1.0
Share of Cases w/ Government as Respondent	15982	0.08	0.27	0.0	1.0
Infants dying aged < 1 Year (%)	15982	0.05	0.04	0.0	0.4
Infants dying aged < 1 Month (%)	15982	0.04	0.03	0.0	0.3
Infants dying, conditional on surviving first month (%)	15982	0.02	0.02	0.0	0.3

Table 3: Comparison of Yearly log(COD) specifications

Panel A: All India

	Log of Yearly Maximum COD per District (mg/l)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Fraction of Green Verdicts	-0.00200	-0.0801	-0.00200	-0.0801	-0.170	-0.124	-0.177	-0.130
	[-0.317; 0.313]	[-0.585; 0.107]	[-0.314; 0.310]	[-0.558; 0.0863]	[-0.409; 0.0685]	[-0.301; 0.0523]	[-0.389; 0.0341]	[-0.465; 0.235]
Dummy for Presence of a Case			0.272	0.306	0.0990	0.0783	0.261	0.241
District-years with no cases	Dropped	Dropped	Dummied	Dummied	Dummied	Dummied	Dummied	Dummied
Year and District FEs					Yes	Yes	Yes	Yes
Covariates							Yes	Yes
Clustering	District	District	District	District	District	District	District	District
Eff. First Stage F		4.917		8.346		.		7.816
N	212	212	3053	3053	3053	3053	3053	3053

Panel B: Ganga Basin

	Log of Yearly Maximum COD per District (mg/l)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Fraction of Green Verdicts	-0.135	-0.115	-0.135	-0.115	-0.383	-0.397	-0.431	-0.437
	[-0.410; 0.141]	[-0.194; 0.0709]	[-0.405; 0.136]	[-0.168; -0.0625]	[-0.673; -0.0920]	[-0.539; -0.256]	[-0.642; -0.221]	[-0.577; -0.298]
Dummy for Presence of a Case			0.187	0.177	0.157	0.165	0.465	0.467
District-years with no cases	Dropped	Dropped	Dummied	Dummied	Dummied	Dummied	Dummied	Dummied
Year and District FEs					Yes	Yes	Yes	Yes
Covariates							Yes	Yes
Clustering	District	District	District	District	District	District	District	District
Eff. First Stage F		25.03		53.51		47.38		44.82
N	107	107	1378	1378	1378	1378	1378	1378

Notes: (i) Cases are defined as having a green verdict if the median reader classified them as either having a "mild positive impact" or a "strong positive impact" (see text for more details); (ii) Fraction of Green Verdicts is equal to 0 if there a no environmental cases in a district-year; (iii) Robust standard errors are constructed using clusters among "small ponds" of district years, pooling together in one cluster all district-years with exactly the same set of river pollution cases; (iv) Included covariates are the district-year means of case characteristics such as whether the government is a respondent and if it is an appeal and or a constitutional case; (v) Fraction of green verdicts is instrumented for by the district-year means of 25 textual features representing the writing style of judges and the district-year share of judges with a post-graduate degree. (vi) For IV regressions, confidence intervals are robust to weak instruments.

Table 4: Comparison of Yearly log(BOD) specifications

Panel A: All India

	Log of Yearly Maximum BOD per District (mg/l)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Fraction of Green Verdicts	0.177	0.209	0.177	0.209	-0.183	-0.270	-0.162	-0.241
	[-0.0725; 0.426]	[-0.245; 0.584]	[-0.0720; 0.425]	[-0.238; 0.577]	[-0.322; -0.0439]	[-0.437; -0.102]	[-0.300; -0.0232]	[-0.494; -0.0702]
Dummy for Presence of a Case			0.202	0.194	0.0814	0.107	0.0366	0.0619
District-years with no cases	Dropped	Dropped	Dummied	Dummied	Dummied	Dummied	Dummied	Dummied
Year and District FEs					Yes	Yes	Yes	Yes
Covariates							Yes	Yes
Clustering	District	District	District	District	District	District	District	District
Eff. First Stage F		6.655		10.24		.		8.856
N	859	859	5649	5649	5649	5649	5649	5649

Panel B: Ganga Basin

	Log of Yearly Maximum BOD per District (mg/l)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Fraction of Green Verdicts	-0.0156	0.0951	-0.0156	0.0951	-0.238	-0.198	-0.194	-0.150
	[-0.388; 0.357]	[.; .]	[-0.386; 0.355]	[.; .]	[-0.430; -0.0455]	[-0.350; 0.129]	[-0.389; 0.000329]	[-0.474; 0.109]
Dummy for Presence of a Case			0.257	0.230	0.101	0.0878	-0.0379	-0.0516
District-years with no cases	Dropped	Dropped	Dummied	Dummied	Dummied	Dummied	Dummied	Dummied
Year and District FEs					Yes	Yes	Yes	Yes
Covariates							Yes	Yes
Clustering	District	District	District	District	District	District	District	District
Eff. First Stage F		6.353		9.862		7.228		6.759
N	407	407	2563	2563	2563	2563	2563	2563

Notes: All notes from Table 3 apply.

Table 5: Yearly Pollution Regressions D2V

Panel A: All India	(1) ln(COD)	(2) ln(BOD)	(3) ln(TCOLI)	(4) ln(Conductivity)	(5) ln(Temperature)
Fraction of Green Verdicts	-0.130	-0.241	-0.0421	-0.0694	-0.0209
	[-0.465; 0.235]	[-0.494; -0.0702]	[-1.027; 0.813]	[-0.255; 0.286]	[-0.0964; 0.0207]
Dummy for Presence of a Case	0.241	0.0619	0.159	-0.0711	0.0000132
District-years with no cases	Dummied	Dummied	Dummied	Dummied	Dummied
Year and District FEs	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes
Clustering	Small Pond	Small Pond	Small Pond	Small Pond	Small Pond
Eff First Stage F	7.816	8.856	9.015	7.895	8.401
N	3053	5649	5057	5475	5541

Panel B: Ganga Basin	(1) ln(COD)	(2) ln(BOD)	(3) ln(TCOLI)	(4) ln(Conductivity)	(5) ln(Temperature)
Fraction of Green Verdicts	-0.437	-0.150	-0.310	-0.459	-0.0856
	[-0.577; -0.298]	[-0.474; 0.109]	[.; .]	[-0.614; 0.0137]	[-0.189; -0.0307]
Dummy for Presence of a Case	0.467	-0.0516	0.000286	-0.0482	0.0157
District-years with no cases	Dummied	Dummied	Dummied	Dummied	Dummied
Year and District FEs	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes
Clustering	Small Pond	Small Pond	Small Pond	Small Pond	Small Pond
Eff First Stage F	44.82	6.759	7.420	5.771	6.520
N	1378	2563	2322	2395	2503

Notes: All notes from Table 3 apply.

Table 6: Yearly Mortality Regressions : IV Estimation

Panel A: Mortality Regression

	All India Post 1989			Ganga Basin Post 1989			Ganga Basin Post 1997		
	(1) Died<1Y	(2) Died<1M	(3) Died<1Y |1M	(4) Died<1Y	(5) Died<1M	(6) Died<1Y |1M	(7) Died<1Y	(8) Died<1M	(9) Died<1Y |1M
Fraction of Green Verdicts Lag 2	0.00557	0.00229	0.00368	0.00143	0.000749	0.00110	-0.000104	-0.00103	0.00131
	[0.000581; 0.0140]	[-0.00120; 0.00775]	[0.00121; 0.00715]	[0.000465; 0.0166]	[-0.00419; 0.0118]	[0.000166; 0.00594]	[-0.00423; 0.00708]	[-0.00493; 0.00617]	[-0.000561; 0.00391]
Case Dummy Lag 2	0.000999	0.000552	0.000461	-0.00512	-0.00782	0.00257	-0.0000115	-0.00189	0.00184
District-years with no cases	Dummied	Dummied	Dummied	Dummied	Dummied	Dummied	Dummied	Dummied	Dummied
Year and District FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Case Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District Controls	-	-	-	-	-	-	-	-	-
Clustering	Small Pond	Small Pond	Small Pond	Small Pond	Small Pond	Small Pond	Small Pond	Small Pond	Small Pond
Eff First Stage F	8.722	8.722	8.722	9.548	9.548	9.548	13.98	13.98	13.98
N	14812	14812	14812	7174	7174	7174	5430	5430	5430

Panel B: Mortality Regression with Air Pollution Controls

	All India Post 1997			Ganga Basin Post 1997		
	(1) Died<1Y	(2) Died<1M	(3) Died<1Y |1M	(4) Died<1Y	(5) Died<1M	(6) Died<1Y |1M
Fraction of Green Verdicts Lag 2	0.00219	-0.00181	0.00416	-0.00165	-0.00335	0.00181
	[-0.00393; 0.00634]	[-0.00762; 0.00159]	[0.00169; 0.00692]	[-0.0142; 0.000219]	[-0.0128; 0.0118]	[-0.00247; 0.00382]
Case Dummy Lag 2	0.00488	0.00388	0.00111	0.0122	0.00565	0.00674
District-years with no cases	Dummied	Dummied	Dummied	Dummied	Dummied	Dummied
Year and District FEs	Yes	Yes	Yes	Yes	Yes	Yes
Case Controls	Yes	Yes	Yes	Yes	Yes	Yes
District Controls	Mean PM 2.5	Mean PM 2.5	Mean PM 2.5	Mean PM 2.5	Mean PM 2.5	Mean PM 2.5
Clustering	Small Pond	Small Pond	Small Pond	Small Pond	Small Pond	Small Pond
Eff First Stage F	6.225	6.225	6.225	8.715	8.715	8.715
N	7606	7606	7606	4063	4063	4063

Notes: All notes from Table 3 apply. Additional notes: (i) The dependent variables *Died<1Y*, *Died<1M* and *Died<1Y |1M* refer to death in the first year of life, death in the first month of life, and death in the first year conditional on surviving the first month of life respectively; (ii) The time-period of the mortality sample spans 1989-2017 (columns 1 to 6) and 1997-2017 (columns 7-9).

Table 7: Neighboring Districts

	(1) ln(COD)	(2) ln(BOD)	(3) ln(TCOLI)	(4) ln(Conductivity)	(5) ln(Temperature)
Neighboring Fraction of Green Verdicts	-0.242	-0.0915	-0.132	-0.0809	0.00165
	[-0.509; -0.0551]	[-0.300; 0.0586]	[-0.673; 0.943]	[-0.312; 0.118]	[-0.0330; 0.0506]
Case Dummy	0.224	0.0240	0.190	-0.124	-0.0316
District-years with no cases	Dummied	Dummied	Dummied	Dummied	Dummied
Year and District FEs	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes
Clustering	Small Pond	Small Pond	Small Pond	Small Pond	Small Pond
Eff First Stage F	11.80	14.10	13.39	13.68	14.09
N	3053	5649	5057	5475	5541

Notes: All notes of Table 3 apply. Additional notes: (i) Neighboring districts are identified using geospatial maps with district boundaries; for each district, we count the number of green verdicts in neighboring districts (excluding cases in the district itself) and divide that number by the total number of river pollution cases in all neighboring districts.

Table 8: Impact on the State Level

	(1) ln(COD)	(2) ln(BOD)	(3) ln(TCOLI)	(4) ln(Conductivity)	(5) ln(Temperature)
Fraction of Green Verdicts per State	-0.168	-0.226	0.113	-0.0441	-0.00502
	[-0.270; 0.00709]	[-0.417; 0.0162]	[-0.756; 0.982]	[-0.237; 0.197]	[-0.0585; 0.0282]
Case in State	0.0173	0.0630	0.0164	-0.0358	0.00205
Case in District	0.171	0.0723	0.238	0.0449	-0.000642
District-years with no cases	Dummied	Dummied	Dummied	Dummied	Dummied
Year and District FEs	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes
Clustering	Small Pond	Small Pond	Small Pond	Small Pond	Small Pond
Eff First Stage F	21.81	14.15	14.93	13.80	13.86
N	3049	5619	5055	5446	5510

Notes: All notes of Tables 3 and 7 apply.

A Appendix Tables

Table A1: Pollution Regressions with District-Level Controls

	(1) ln(COD)	(2) ln(BOD)	(3) ln(TCOLI)	(4) ln(Conductivity)	(5) ln(Temperature)
Fraction of Green Verdicts	-0.535	-0.240	-0.171	-0.250	-0.0495
	[-0.844; -0.156]	[-0.542; 0.160]	[-1.130; 0.554]	[-0.574; 0.0194]	[-0.109; 0.0721]
Dummy for Presence of a Case	0.159	0.0933	-0.346	-0.0998	0.0230
District-years with no cases	Dummied	Dummied	Dummied	Dummied	Dummied
Year and District FEs	Yes	Yes	Yes	Yes	Yes
Case Controls	Yes	Yes	Yes	Yes	Yes
District Controls	Shrug	Shrug	Shrug	Shrug	Shrug
Clustering	Small Pond	Small Pond	Small Pond	Small Pond	Small Pond
Eff First Stage F	1.361	4.404	3.988	4.553	4.351
N	961	2126	1852	2266	2073

Notes: (i) Cases are defined as having a green verdict if the median reader classified them as either having a "mild positive impact" or a "strong positive impact" (see text for more details); (ii) Fraction of Green Verdicts is equal to 0 if there a no cases in a district-year; (iii) Robust standard errors are constructed using clusters among "small ponds" of district years, pooling together in one cluster all district-years with exactly the same set of river pollution cases; (iv) District controls, from SHRUGG, include nighttime lights and forest cover; (v) Fraction of Green Verdicts is instrumented for by the district-year means of 25 textual features representing the writing style of judges and the district-year share of judges with a post-graduate degree. (vi) AR confidence intervals are robust to weak instruments.

Table A2: Yearly Pollution Regressions with 3 year Moving Averages

	(1) ln(COD)	(2) ln(BOD)	(3) ln(TCOLI)	(4) ln(Conductivity)	(5) ln(Temperature)
Fraction of Green Verdicts	-0.158	-0.183	-0.0511	0.0406	-0.0333
	[-0.268; 0.0404]	[-0.450; -0.00476]	[-0.939; 0.631]	[-0.0877; 0.370]	[-0.101; 0.0142]
Dummy for Presence of a Case	0.168	0.0667	0.290	-0.0446	0.00317
District-years with no cases	Dummied	Dummied	Dummied	Dummied	Dummied
Year and District FEs	Yes	Yes	Yes	Yes	Yes
Case Controls	Yes	Yes	Yes	Yes	Yes
District Controls	-	-	-	-	-
Clustering	Small Pond	Small Pond	Small Pond	Small Pond	Small Pond
Eff First Stage F	7.331	7.910	8.189	7.908	7.897
N	5742	6254	5888	6237	6185

Notes: Notes from Table A1 apply; Dependent and independent variables are year moving averages.

Table A3: Mortality Regressions with District-Level Controls

	All India Post 1989			Ganga Basin Post 1989			Ganga Basin Post 1997		
	(1) Died<1Y	(2) Died<1M	(3) Died<1Y |1M	(4) Died<1Y	(5) Died<1M	(6) Died<1Y |1M	(7) Died<1Y	(8) Died<1M	(9) Died<1Y |1M
Fraction of Green Verdicts Lag 2	0.00177	-0.00147	0.00335	-0.00456	-0.00581	0.00126	-0.00456	-0.00581	0.00126
	[-0.00263; 0.00816]	[-0.00444; 0.00607]	[0.00104; 0.00586]	[-0.0132; -0.00109]	[-0.0153; -0.00486]	[-0.00251; 0.00290]	[-0.0132; -0.00109]	[-0.0153; -0.00486]	[-0.00251; 0.00290]
Case Dummy Lag 2	0.00444	0.00378	0.000745	0.0184	0.00780	0.0112	0.0184	0.00780	0.0112
District-years with no cases	Dummied	Dummied	Dummied	Dummied	Dummied	Dummied	Dummied	Dummied	Dummied
Year and District FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Case Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District Controls	Shrug	Shrug	Shrug	Shrug	Shrug	Shrug	Shrug	Shrug	Shrug
Clustering	Small Pond	Small Pond	Small Pond	Small Pond	Small Pond	Small Pond	Small Pond	Small Pond	Small Pond
Eff First Stage F	7.551	7.551	7.551	9.005	9.005	9.005	9.005	9.005	9.005
N	7857	7857	7857	3762	3762	3762	3762	3762	3762

Note: Notes from Table A1 apply.

Table A4: Effects of Control Variables and Sample Selection

	Full Sample			Only If Shrug Available			Including Shrug Variables		
	(1) Died<1Y	(2) Died<1M	(3) Died<1Y |1M	(4) Died<1Y	(5) Died<1M	(6) Died<1Y |1M	(7) Died<1Y	(8) Died<1M	(9) Died<1Y |1M
Fraction of Green Verdicts Lag 2	0.00557	0.00229	0.00368	0.00180	-0.00145	0.00336	0.00177	-0.00147	0.00335
	[0.000581; 0.0140]	[-0.00120; 0.00775]	[0.00121; 0.00715]	[-0.00270; 0.00821]	[-0.00449; 0.00610]	[0.00104; 0.00584]	[-0.00263; 0.00816]	[-0.00444; 0.00607]	[0.00104; 0.00586]
Case Dummy Lag 2	0.000999	0.000552	0.000461	0.00434	0.00372	0.000702	0.00444	0.00378	0.000745
District-years with no cases	Dummied	Dummied	Dummied	Dummied	Dummied	Dummied	Dummied	Dummied	Dummied
Year and District FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Case Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District Controls	-	-	-	-	-	-	Shrug	Shrug	Shrug
Clustering	District	District	District	District	District	District	District	District	District
Eff First Stage F	8.722	8.722	8.722	7.495	7.495	7.495	7.551	7.551	7.551
N	14812	14812	14812	7857	7857	7857	7857	7857	7857

Note: Notes from Table A1 apply; Regressions are run on three separate samples – the full sample, the sample for which control variables are available (without the actual controls) and the results with the controls included.

Table A5: Neighboring Districts w/o Cities

	(1) ln(COD)	(2) ln(BOD)	(3) ln(TCOLI)	(4) ln(Conductivity)	(5) ln(Temperature)
Neighboring Fraction of Green Verdicts	-0.273	-0.0159	-0.121	-0.0684	-0.0159
	[-0.488; -0.109]	[-0.208; 0.141]	[-0.642; 0.734]	[-0.265; 0.0879]	[-0.0341; 0.0196]
Case Dummy	0.227	0.00264	0.0459	-0.192	-0.0291
District-years with no cases	Dummied	Dummied	Dummied	Dummied	Dummied
Year and District FEs	Yes	Yes	Yes	Yes	Yes
Case Controls	Yes	Yes	Yes	Yes	Yes
District Controls	-	-	-	-	-
Clustering	Small Pond	Small Pond	Small Pond	Small Pond	Small Pond
Eff First Stage F	10.15	11.55	11.18	12.01	11.45
N	2908	5383	4810	5219	5282

Notes: All notes from Table 7 apply.

Online Appendix

Additional Tables

Table OA1: Yearly Pollution Regressions LSA

	(1) ln(COD)	(2) ln(BOD)	(3) ln(TCOLI)	(4) ln(Conductivity)	(5) ln(Temperature)
Fraction of Green Verdicts	-0.0777	-0.225	0.275	-0.0545	-0.0161
	[-0.236; 0.338]	[-0.558; 0.224]	[.; .]	[-0.274; 0.436]	[-0.0651; 0.0560]
Dummy for Presence of a Case	0.219	0.0567	0.0593	-0.0750	-0.00153
District-years with no cases	Dummied	Dummied	Dummied	Dummied	Dummied
Year and District FEs	Yes	Yes	Yes	Yes	Yes
Case Controls	Yes	Yes	Yes	Yes	Yes
District Controls	-	-	-	-	-
Clustering	Small Pond	Small Pond	Small Pond	Small Pond	Small Pond
Eff First Stage F	11.21	4.912	4.658	4.351	4.791
N	3053	5649	5057	5475	5541

Notes: All notes of Table 4 and 3 apply. Instruments are constructed using the LSA method (as opposed to the D2V method used in the rest of the paper).

Table OA2: Yearly Pollution Regressions D2V + LSA

	(1) ln(COD)	(2) ln(BOD)	(3) ln(TCOLI)	(4) ln(Conductivity)	(5) ln(Temperature)
Fraction of Green Verdicts	-0.136	-0.182	-0.0761	-0.125	-0.0238
	[-0.245; 0.224]	[-0.260; 0.0666]	[-1.267; 1.090]	[-0.276; 0.195]	[-0.100; -0.00732]
Dummy for Presence of a Case	0.243	0.0432	0.169	-0.0564	0.000932
District-years with no cases	Dummied	Dummied	Dummied	Dummied	Dummied
Year and District FEs	Yes	Yes	Yes	Yes	Yes
Case Controls	Yes	Yes	Yes	Yes	Yes
District Controls	-	-	-	-	-
Clustering	Small Pond	Small Pond	Small Pond	Small Pond	Small Pond
Eff First Stage F	9.113	7.367	7.559	6.588	7.108
N	3053	5649	5057	5475	5541

Notes: All notes of Table 4 and 3 apply. Instruments are constructed using both the LSA method and the D2V method used in the rest of the paper.

Table OA3: Yearly Pollution Regressions D2V + LSA + Lasso

	(1) ln(COD)	(2) ln(BOD)	(3) ln(TCOLI)	(4) ln(Conductivity)	(5) ln(Temperature)
Fraction of Green Verdicts	0.166	-0.157	0.690	-0.0415	-0.0268
	[.; .]	[-0.561; 0.345]	[.; .]	[-0.557; 0.430]	[-0.126; 0.0640]
Dummy for Presence of a Case	0.115	0.0353	-0.0704	-0.0784	0.00186
District-years with no cases	Dummied	Dummied	Dummied	Dummied	Dummied
Year and District FEs	Yes	Yes	Yes	Yes	Yes
Case Controls	Yes	Yes	Yes	Yes	Yes
District Controls	-	-	-	-	-
Clustering	Small Pond	Small Pond	Small Pond	Small Pond	Small Pond
Eff First Stage F	5.228	9.867	13.55	10.51	9.687
N	3053	5649	5057	5475	5541

Notes: All notes of Table 4 and 3 apply. Instruments are constructed using both the LSA method and the D2V method used in the rest of the paper. The LASSO algorithm is used for instrument selection.

Table OA4: Yearly Pollution Regressions, D2V, Mean Values

	(1) ln(Mean COD)	(2) ln(Mean BOD)	(3) ln(Mean TCOLI)	(4) ln(Mean Conductivity)	(5) ln(Mean Temperature)
Fraction of Green Verdicts	-0.141	-0.0424	0.354	0.00738	-0.0152
	[-0.257; 0.178]	[-0.0885; 0.233]	[-0.685; 1.351]	[-0.266; 0.231]	[-0.0620; 0.0397]
Dummy for Presence of a Case	0.268	0.0872	-0.0721	-0.0565	-0.0147
District-years with no cases	Dummied	Dummied	Dummied	Dummied	Dummied
Year and District FEs	Yes	Yes	Yes	Yes	Yes
Case Controls	Yes	Yes	Yes	Yes	Yes
District Controls	-	-	-	-	-
Clustering	Small Pond	Small Pond	Small Pond	Small Pond	Small Pond
Eff First Stage F	7.816	8.400	7.734	7.122	7.767
N	3053	4670	4111	4509	4593

Notes: All notes of Table 4 and 3 apply. For the dependent variables however, we rely on mean values (as opposed to max values in the remainder of the paper).

Table OA5: Yearly Pollution Regressions, D2V, Minimum Values

	(1) ln(Min COD)	(2) ln(Min BOD)	(3) ln(Min TCOLI)	(4) ln(Min Conductivity)	(5) ln(Min Temperature)
Fraction of Green Verdicts	-0.0509	0.0732	0.440	0.0517	0.00504
	[-0.176; 0.552]	[.; .]	[0.126; 1.216]	[-0.150; 0.315]	[-0.0488; 0.112]
Dummy for Presence of a Case	0.0941	-0.139	0.0344	0.0256	-0.0396
District-years with no cases	Dummied	Dummied	Dummied	Dummied	Dummied
Year and District FEs	Yes	Yes	Yes	Yes	Yes
Case Controls	Yes	Yes	Yes	Yes	Yes
District Controls	-	-	-	-	-
Clustering	Small Pond	Small Pond	Small Pond	Small Pond	Small Pond
Eff First Stage F	7.816	8.676	8.963	7.895	9.470
N	3053	5609	5013	5471	4868

Note: All notes of Table 4 and 3 apply. For the dependent variables however, we rely on minimum values (as opposed to max values in the remainder of the paper).

Table OA6: Yearly Pollution Regressions, Ganga Bassin, D2V, Mean Values

	(1) ln(Mean COD)	(2) ln(Mean BOD)	(3) ln(Mean TCOLI)	(4) ln(Mean Conductivity)	(5) ln(Mean Temperature)
Fraction of Green Verdicts	-0.353	-0.0265	-0.577	-0.295	-0.0617
	[-0.458; -0.247]	[-0.288; 0.184]	[-2.216; -0.395]	[-0.318; 0.258]	[-0.114; -0.00578]
Dummy for Presence of a Case	0.545	0.107	0.194	-0.234	-0.0325
District-years with no cases	Dummied	Dummied	Dummied	Dummied	Dummied
Year and District FEs	Yes	Yes	Yes	Yes	Yes
Case Controls	Yes	Yes	Yes	Yes	Yes
District Controls	-	-	-	-	-
Clustering	Small Pond	Small Pond	Small Pond	Small Pond	Small Pond
Eff First Stage F	44.82	5.856	6.987	4.919	5.793
N	1378	2108	1887	1952	2079

Note: All notes of Table 4 and 3 apply; Sample is restricted to the Ganga Basin; For the dependent variables however, we rely on mean values (as opposed to max values in the remainder of the paper).

Table OA7: Yearly Pollution Regressions, Ganga Basin, D2V, Minimum Values

	(1) ln(Min COD)	(2) ln(Min BOD)	(3) ln(Min TCOLI)	(4) ln(Min Conductivity)	(5) ln(Min Temperature)
Fraction of Green Verdicts	-0.199	0.320	0.500	0.0983	0.0438
	[-0.333; -0.0649]	[-0.0179; 0.683]	[0.218; 1.267]	[-0.132; 0.470]	[-0.00653; 0.195]
Dummy for Presence of a Case	0.517	0.0510	-0.538	-0.0866	-0.0726
District-years with no cases	Dummied	Dummied	Dummied	Dummied	Dummied
Year and District FEs	Yes	Yes	Yes	Yes	Yes
Case Controls	Yes	Yes	Yes	Yes	Yes
District Controls	-	-	-	-	-
Clustering	Small Pond	Small Pond	Small Pond	Small Pond	Small Pond
Eff First Stage F	44.82	6.840	7.405	5.770	7.653
N	1378	2553	2310	2393	2243

Notes: All notes of Table 4 and 3 apply; Sample is restricted to the Ganga Basin; For the dependent variables however, we rely on minimum values (as opposed to max values in the remainder of the paper).

Table OA8: Yearly Mortality Regressions : LSA Instruments

	All India Post 1989			Ganga Basin Post 1989			Ganga Basin Post 1997		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Died<1Y	Died<1M	Died<1Y |1M	Died<1Y	Died<1M	Died<1Y |1M	Died<1Y	Died<1M	Died<1Y |1M
Fraction of Green Verdicts Lag 2	0.00297	0.0000460	0.00321	-0.000930	-0.00211	0.00153	-0.00208	-0.00324	0.00147
	[-0.00254; 0.00753]	[-0.00468; 0.00300]	[0.00000720; 0.00524]	[-0.00784; 0.00143]	[-0.00773; 0.000343]	[-0.00177; 0.00211]	[-0.00788; -0.000588]	[-0.00837; -0.00200]	[-0.00138; 0.00227]
Case Dummy Lag 2	0.00179	0.00124	0.000605	-0.00473	-0.00735	0.00250	0.000944	-0.000826	0.00176
District-years with no cases	Dummied	Dummied	Dummied	Dummied	Dummied	Dummied	Dummied	Dummied	Dummied
Year and District FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Case Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District Controls	-	-	-	-	-	-	-	-	-
Clustering	Small Pond	Small Pond	Small Pond	Small Pond	Small Pond	Small Pond	Small Pond	Small Pond	Small Pond
Eff First Stage F	7.800	7.800	7.800	15.59	15.59	15.59	21.08	21.08	21.08
N	14812	14812	14812	7174	7174	7174	5430	5430	5430

All notes of Table 4 apply; Additional notes: spans 1989-2017 (columns 1 to 6) and 1997-2017 (columns 7-9); Instruments are constructed using the LSA algorithm rather than the D2V algorithm.

Aggregation at the district-year level

The identification strategy of random judge assignment applies at the level of court-cases. Yet we observe pollution at the level of districts and years. How much does this affect the stability of our estimates? Table OA9 explores the results of the first-stage across a range of specifications on several different samples. Panels (A)–(D) present the first-stage regression coefficients for one of the instrumental variables, a dummy variable that takes value 1 if the judge who heard an environmental case in our sample had a post-graduate degree (and 0 otherwise), in four separate samples: a sample of judges who have ruled on environmental cases, a sample of environmental cases, a sample of cases that is matched with judges, and finally, averages of cases at the district-year level that shares a common support with the pollutant data. In each of these panels, the other 25 instruments and dependent variables are omitted for ease of presentation. The results in each panel build up to the preferred specification that was seen in the pollution regressions discussed earlier (Columns 8 of Tables 3 and 4).

Panel (D) presents the results where all relevant variables are averaged at the district-year level. The instruments are also averages of the attributes of cases at the district-year level. These include the fraction of judges who were assigned environmental cases in a district-year who have a post-graduate degree and a set of 25 textual variables that summarize the corpus of cases in the record of the judges, to create these textual variables we removed all the water pollution cases from the corpus to mitigate concerns of endogeneity.

The results suggest that the coefficient of *JudgePostGrad* is positive and significant in all specifications. Moreover, neither the coefficient nor the effective first-stage F statistic change significantly across all four samples.

Table OA9: First Stage Regressions

Panel A: Judge Level	Median Coded Environmental Impact			
	(1)	(2)	(3)	(4)
JudgePostGrad	0.0842	0.271*	0.240**	0.218**
	(0.113)	(0.143)	(0.0939)	(0.0965)
Other Instruments	25 D2V vectors			
Assigned districts	One	All	All	All
District + year FEs	-	-	Yes	Yes
Case-level controls	-	-	-	Yes
Eff First Stage F	2.474	3.871	4.215	4.173
N	764	4415	4415	4415

Panel B: Case Level	Median Coded Environmental Impact			
	(1)	(2)	(3)	(4)
JudgePostGrad	0.184*	0.433**	0.257**	0.258**
	(0.105)	(0.211)	(0.120)	(0.119)
Other Instruments	25 D2V vectors			
Assigned districts	One	All	All	All
District + year FEs	-	-	Yes	Yes
Case-level controls	-	-	-	Yes
Eff First Stage F	1.630	3.369	3.385	3.887
N	518	3855	3855	3855

Panel C: Case Level	Green Verdict			
	(1)	(2)	(3)	(4)
JudgePostGrad	0.133*	0.315***	0.208***	0.203***
	(0.0704)	(0.121)	(0.0790)	(0.0783)
Other Instruments	25 D2V vectors			
Assigned districts	One	All	All	All
District + year FEs	-	-	Yes	Yes
Case-level controls	-	-	-	Yes
Eff First Stage F	1.476	4.327	5.059	4.652
N	518	3855	3855	3855

Panel D: District-Year Merged with BOD	Fraction of Green Verdicts			
	(1)	(2)	(3)	(4)
Majority Judges have a Post Graduate Degree (mean)	0.276***	0.276***	0.268***	0.284***
	(0.0928)	(0.0915)	(0.0861)	(0.0861)
Dummy for Presence of a Case		0.126**	0.129**	0.0753
		(0.0627)	(0.0600)	(0.0736)
Other Instruments	25 D2V vectors			
Assigned districts	All	All	All	All
District + year FEs	-	-	Yes	Yes
Case-level controls	-	-	-	Yes
District-years with no cases	Dropped	Dummied	Dummied	Dummied
Eff First Stage F	6.655	10.24	8.413	8.856
N	859	5649	5649	5649

Panel E: District-Year Merged with Mortality	Fraction of Green Verdicts			
	(1)	(2)	(3)	(4)
Majority Judges have a Post Graduate Degree (mean)	0.318***	0.318***	0.328***	0.340***
	(0.104)	(0.103)	(0.0933)	(0.0962)
Case Dummy		0.235*	0.206	0.0719
		(0.141)	(0.131)	(0.137)
Other Instruments	25 D2V vectors			
Assigned districts	All	All	All	All
District + year FEs	-	-	Yes	Yes
Case-level controls	-	-	-	Yes
District-years with no cases	Dropped	Dummied	Dummied	Dummied
Eff First Stage F	3.533	6.097	6.953	8.141
N	1577	24306	24306	24306

Notes: All notes from Table 3 apply.