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 curate data on court cases, judges' prior rulings, water pollution and child mortality over a period of nearly forty years. Leveraging random judge assignment in the courts of India, we estimate the effect of pro-environmental orders on district-level measures of surface water toxicity. We observe that 'green' orders from the judiciary are preceded by decreases in maximum values of observed surface water toxicity levels. This suggests that the appointment of these judges could potentially expedite environmental improvements, even before the formal decision is made. These lower pollution levels do not however, translate into reductions in neonatal and infant mortality over the subsequent months. Moreover, we find that several years after the orders' decision date, both pollution and mortality increase relative to the pre-decision levels. These findings suggest that even though court orders can lower environmental toxicity in the short-run, they do not drive long-term substantive enhancements in water quality or health outcomes.

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1 Introduction

Polluted water kills more than 1 million people a year, mostly 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 over 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). Studies of policies that have cleaned ambient water have confirmed that such policies lead to a decline in child mortality and the reduced spread of infectious diseases (J. Zhang and Xu 2016; Alsan and C. Goldin 2019; Do, Joshi, and Stolper 2018; Ashraf et al. 2021; Galiani, Gertler, and Schargrodsky 2005; Bhalotra et al. 2021 and many others).

Protecting ambient surface water is a complex task. Since water is a moving resource that has many competing uses during the processes of urbanization and industrialization, traditional definitions of property rights are difficult to apply (Glaeser, Johnson, and Shleifer 2001). The resolution of water-related disputes through litigation can be expensive, unpredictable, ineffective, and unenforceable. In wealthy countries, regulation has emerged as an efficient way of achieving socially desirable outcomes (Shleifer et al. 2012). Regulatory systems now play a critical role in regulating surface water quality across the world, in both rich and poor countries (Getches 2009; Woodhouse and Muller 2017).

In the past three decades however, concerns about the challenges of climate change, the emergence of multilateral environmental agreements, and concerns about the limits of regulation have placed judiciaries at the forefront of environmental policymaking (Percival 2016; Percival 2017; Malleson 2016).[2] In India, for example, public interest litigation at the Supreme Court has enabled

[1]The precise number of deaths due to water pollution varies depending on the definition of access to safe water. The Lancet's 2016 Global Burden of Disease study 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 estimate the number of pollution deaths to be approximately 800,000 per year (WHO and UNICEF 2021.)

[2]Agenda 21, the program of action for sustainable development that emerged from the United Nations Conference

citizens who are affected by environmental toxicity to elevate their concerns and demand greater enforcement of India's regulations (Malleson 2016; 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). Even in the United States, shifting ideologies in legislative and executive branches of government have prompted courts to take a stand on upholding environmental regulations such as the Clean Air and Clean Water Acts (Schmalensee and Stavins 2019, Keiser and Shapiro 2019).

Can judicial policies improve actual surface water quality in high-pollution contexts? While there is some evidence of localized impacts of specific judicial rulings, there is currently no study of the large-scale empirical impact of judicial policies on surface water toxicity over a considerable period of time. In this paper, we examine the impacts of judicial policies on water quality in India, a high-pollution setting where regulation has broadly been viewed to have failed to curtail the growing challenge of water toxicity (Greenstone and Hanna 2014).

Our empirical approach begins with the compilation of a unique database of court orders related to cases on water toxicity from the Indian judiciary. We curate court orders from India's high courts, Supreme Court, and Green Tribunal that have cited India's landmark regulations on water toxicity since 1987.[3] We read each of these, labeling them as a "green order" if they may have a favorable impact on water ambient water quality.

Next, we analyze the causal relationship between green orders and actual environmental and health outcomes. Since orders may be endogenous to outcomes, we use an IV econometric framework in which the textual features of judges assigned to the cases predict the likelihood of a green order. For each judge, we construct a corpus of orders that were written *prior* to the case related to water toxicity. 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 unrelated 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 orders on infant mortality rates at the district level. This approach has already been 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

on Environment and Development in Rio de Janeiro, Brazil emphasized the need to "provide an effective legal and regulatory framework" and explicitly highlighted the role of judiciaries in establishing "administrative procedures for legal redress and remedy of actions affecting environment and development" and providing "access to individuals, groups, and organizations with a recognized legal interest".(Chapter 8, Agenda 21, Nations (1992)).

[3]Our focus is entirely on court *orders*. These are a mix of final and interim verdicts. One order can pertain to several cases and conversely, a single case can be associated with many orders. Given that cases take an average of 8 years to resolve, and all interim orders can have significant implications, these orders and judgments are best considered in our set of judicial policies.

others).

Our results highlight a notable decrease in one indicator of industrial pollution, namely chemical oxygen demand (COD), during the years leading up to a green order. In the year in which a green order is passed, we also observe a reduction in biological oxygen demand (BOD). These effects, however, are confined to the years before and the year of the order. We do not see any persistent impacts in either of these measures of surface water toxicity. On the contrary, we find some evidence of a medium to long-term increase in pollution levels. We also find that green orders are associated with an increase in infant mortality in the second and third years following an increase in the fraction of green orders. We interpret this as suggestive evidence that judicial action can succeed in lowering short-term pollution, but in the long-run, the lack of enforcement, inadequate oversight or the resultant economic slowdown from the departure of key firms may increase vulnerability. These 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 data sources we curated for this project. Section 4 presents empirical models. Section 5 presents the 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). Regulation has been inconsistently effective (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; Ghosh 2019).[4]

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. This act establishes and defines the powers of the Central and State Pollution Control Boards (CPCB and SPCBs), outlines the measures that the Boards must take to prevent and control water pollution, specifies the requirements for testing

[4]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 when it is pertinent to another citizen or the broad interests of society at large Bhuwania 2017.

water at state laboratories, and outlines penalties and punishments for breaking these laws. Though this law excludes certain types of pollution such as groundwater and non-point sources of water pollution such as agricultural runoff and water discharged from municipal sources, it established the basic frameworks of water governance in India.

The Water Act was amended in 1988, to bring it in line with additional legislation that was passed after the Bhopal Gas Disaster, the Environment Act. The amended act gives the central government the power to appoint officers to 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. Over the years, some additional acts have been passed to address water pollution. These include the Water (Prevention and Control of Pollution) Cess Act of 1977, the Municipal Solid Wastes (Management and Handling) Rules Act of 2000 and the Solid Waste Management Rules (SWM), 2016. The Water Act, however, remains at the core of environmental regulation pertinent to water toxicity in India.

2.2 Monitoring and Compliance

The CPCB and SPCBs have a variety of methods to ensure compliance and enforcement of water toxicity. They can issue and revoke consent to operate, require self-monitoring and reporting, conduct sampling, inspect facilities, require corrective action, and prescribe compliance schedules. The principal tool for ensuring compliance, however, 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 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 the heaviest polluters and provide only minimal inspections to the vast majority of firms. However, the regulators 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 (nationwide) 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 (statewide) 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, biomedical waste, and electronic waste in their respective states (World Bank 2013). On the whole, the implementation of the Water Act has been weak and 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; Ghosh 2019).[5] Over the past 30 years, the judiciary issued landmark verdicts on issues of water toxicity. In a time series analysis, 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.

Environmental jurisprudence for water has evolved alongside the regulatory system. In early cases that featured citizen complaints about regulatory failure, they have turned to the constitution to find and derive explicit as well as implicit legal arguments. Three articles in particular stand out: (1) Article 21, which guarantees Indian citizens the fundamental right to life, (2) 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 and (3) Article 51 A(g) which defines one fundamental duty of citizenship to "maintain a hygienic environment".

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 (Ghosh 2019). Though these principles were not articulated in In-

[5] 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 2017). The commitment to environmental jurisprudence intensified after the massive Bhopal gas disaster (C. M. Abraham and S. Abraham 1991; Dias 1994).

dian statutory law, they have become, mutatis mutandis, regarded as an essential part of Indian environmental 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 as has been done in several recent papers that analyze demographic changes in India (Drèze and Murthi 2001; Mohanty et al. 2016; Singh et al. 2017).[6]

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 orders that were passed by the National Green Tribunal of India, the state high courts, and the Supreme Court of India that include a mention of India's most significant water regulations, the Water (Prevention and Control of Pollution) Act of 1974 and/or the Environment Protection Act of 1986. This unique data set consists of 978 observations. 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 year of filing and registration, the date of disposal, transfers between courts, acts involved, case types, and judge, litigants and advocate names.

To determine whether a particular order 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 orders, our coders also identified the precise location of the order, the geographic scope of the order (within the district, across all districts in a state, or across the entire country), the names of the judges who ruled on the order, the basic attributes of the case

[6] 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.

and the month and year of the order. 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. Panel (B) of Figure 1 gives a spatial overview for the location and concentration of these cases.

3.2 Judge Biographies and Case Histories

Our analysis also incorporates the biographical characteristics of judges. Since there is no publicly accessible database of judges for the courts of India, we curate this information from official sources.

Given that we are examining cases that are based on legislation from 1974, we can 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 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. For each of these judges, we are able to extract a complete case history from our judicial database.[7]

3.3 Environmental Data

To measure water quality, we use two sources of data. The first is the water 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 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

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

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 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 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.[8] 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 on BOD and COD, which are quite sensitive to industrial pollution.

We supplement this data on water pollution with additional data on air pollution. This is largely to control for industrial activity. We rely on PM 2.5, which refers to a category of particulate pollutants 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

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

are known to affect human health are not recorded consistently in our study period. We note that while these data are quite detailed, India's data systems for water in the 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 both the pollution data and legal 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).[9] We rely on the pregnancy histories of female respondents aged 15-55 in these surveys to construct estimates of child mortality at the district-year-month level.

We supplement these data with additional data on control variables. This includes data on nighttime light intensity and forest cover (Asher et al. 2021) that are available after 1991, and air pollution that is available after 1998 (Van Donkelaar et al. 2021).

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.[10] 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 6,270 observations that covers 153 districts for the period 1984 to 2020 (Table 2). This includes 516 court orders, with approximately 2 judges per order. The average order 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 the impact on mortality at the district-year-month level has 188,298 observations covering 678 districts over the period 1989 to 2020 and is matched to 772 court orders (Table 2).

[9]We choose these two surveys mainly because they cover large populations, and are conducted approximately 10 years apart, giving us broad temporal as well as geographic coverage. Their methods of defining infant mortality are also similar enough to be reconciled (Joshi, Borkotoky, et al. 2020.

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

4 Empirical Strategy

4.1 Construction of Variables

Green orders: 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.[11] [12] Specifically, we take the median of the scores assigned to an order across the coders who coded the order and define it as a "green order" if the median assigned environmental impact is positive.[13]

We matched all orders in our sample to the districts where the environmental dispute originated and where the eventual court decision applied. 401 of the 978 orders pertained to a specific location.[14] A further 115 in the sample lacked information on the district of origin, but it was clear that the decisions applied to the entire jurisdiction of the court. For these cases, we assumed that on the date of the judgment, the order applied to all the districts in the state. An additional 2 orders 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 an order that has been coded as applicable to a district applies to that specific district.

Figure 2 presents some information on the trends in these orders, as well as the types of orders over time. We note that there has been an increase in the number of orders that cite water pollution regulations throughout the sample period. Almost all orders come from cases that feature the government as the petitioner or the respondent (Figure 2, top panel). The analysis of keywords featured in the order suggests that more than half of all cases are contested on issues related to pollution that is caused by firms (Figure 2, bottom panel). A broad range of issues are considered in these cases. Toxicity and environmental permits are discussed in at least half of all orders. Judges use a mix of arguments drawn from the Indian constitution (Article 21, the Right to Life being particularly important) and arguments drawn from international law (such as the commitment to Sustainable Development and the "polluter pays" principle). The average case in our sample, however, is contested between the firm and the government, with the judge citing Indian as well as

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

[12] We drafted a detailed training manual that 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.

[13] Coders were asked to form an opinion on whether an order 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).

[14] Both coders identified the same location.

international law in their response.

Descriptive statistics of the key variables in our working samples for pollution and mortality are presented in Table 1 and Table 2. Note that in both these samples, the average order has a green score of 0.35 (the range is -2 to 2). 21 percent of the orders are from constitutional cases and 25 percent are appeal cases. More than 80 percent feature the government as the respondent and more than 10% feature the government as the petitioner, suggesting once again that the government is a key actor and there is almost no litigation between private parties in our sample. There are on average 1.7-1.8 judges per order.[15]

Numeric Representations of Judge Writing Styles: Our analysis posits that a judge's decision in an environmental case can be predicted from their writing styles in non-environmental cases heard in the past. To extract judges' writing styles in past orders, 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).[16]

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 orders or judgments the judge presided on as a sole author, excluding the judge's environmental cases (as defined in our sample). For each of these orders, we use the trained D2V model to assign a 25-dimensional vector to the order, which summarizes the order's 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 orders' writing styles. This gives us, for each judge, a 25-dimensional vector that 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 orders related to water pollution, we do not observe individual judges' decisions but only the final, common order. For an order c with bench B in district d and year t, we model an order passed by a judge as follows:

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

[15]In the full sample of 978 orders (not shown here), 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.

[16]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 orders) 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 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.

The variable on the left-hand side, GreenOrder_{cdt}, is defined as described in the above section "Green orders" and captures the median score assigned by the manual coders of how pro-environmental an order c 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 order c. X_c is a vector of case characteristics (such as a dummy variable that takes the value 1 if the case is an appeal from a lower court and 0 otherwise, and a dummy variable that takes the 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 3 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-left panel presents the two-dimensional visualization of the case vectors (colored by the hand-labeled impact score), the top-right panel presents the judge-level embedding (colored by the mean impact score of the cases the judge has adjudicated) and 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. 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 orders. As the graph in the bottom panel illustrates, this variation loosely corresponds to the incidence of keywords 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).[17] These results corroborate our findings and are all presented in the Online Appendix to this paper.

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 court-issued green orders on pollution levels and health outcomes. We first employ a simple OLS framework to examine the impact of a green order (versus a non-green order) 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.

[17]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.

4.2.1 Setup: Simple OLS Estimation

We begin with a simple approach that assumes that green orders 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 orders and outcomes:

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

Here Y_{dt} can be either measures of pollution ($Pollution_{dt}$) or mortality ($Mortality_{dt}$) in district d at time t, $FracGreenOrders_{dt}$ measures the fraction of water pollution orders in district d which are coded as green 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 orders 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.

Green orders are defined at the order level, but these are aggregated at the district-year level. For the set of orders C in district d at time period t, we define the variable $FracGreenOrders_{dt}$ as follows:

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

$\mathbb{1}\{|C_{dt}| > 0\}$ is a dummy variable that takes the value 1 if district d has at least one environmental order in time-period t and 0 otherwise. For the outcome variables, $Pollution_{dt}$ is a measure of pollution in district d at time t. In our basic regressions, it is the maximum value of either BOD or COD in a district-year. We focus on maximum values of pollution per district-year (and not, for instance, at medium values) for two reasons. First, in a district with several rivers and pollution monitors, litigation is likely to occur around the one with the largest polluters and highest pollution levels. Second, water pollution has an exponential risk function for health outcomes. $Mortality_{dt}$ is the percentage of children born in district d in period t who lost their lives within 1 month (or 1 year) of their date of birth. We also examine the incidence of mortality in the first year conditional on one month survival. Although we also display mortality regressions at the district-year level, our main specification for the impact of green order on infant mortality is at the district-year-month level since this provides the closest insights into the event study.

The main challenge in estimating this equation is that green orders 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 factors.

We address the issue of the potential endogeneity of green orders 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 assumption is grounded in the formal rules of the courts as well as new empirical research (Ash et al. 2021).[18] We exploit the random judge assignment process to predict the emergence of green orders based on the past writing styles of judges and observable judge characteristics.

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

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

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

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

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 orders in district d at time t and B_c represents the set of judges on the bench of order c. The last instrument, $JudgePostGrad_{dt}$, measures the share of judges deciding an order in district d in year t with a postgraduate degree. Under the assumption of random judge assignment, and with the appropriate construction of our instrumental variables, β_2 in Equation 4

[18] 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.

can be interpreted as a causal estimate of the impact of green orders 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 order impacting multiple districts at the same time, a method that we refer to as "identical order" clusters (IOC).[19] 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 order. We refer to this as "At least one common order" clusters (COC).

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 the 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.[20]

This framework is not fully suitable for our purpose in this paper. Within our sample of 978 orders, there are only a few judges who appear multiple times in the water case subset. It is important to note that although we possess the complete set of orders for each judge, the majority of these orders are unrelated to water pollution. Furthermore, our sample includes numerous orders where a panel of three judges collaboratively makes decisions, and we solely have access to the final outcome without individual voting records. Despite these limitations, we firmly believe that our modified approach remains well-suited for the specific purpose of examining environmental outcomes, such as the local ambient water quality within a specific geographical area.

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

[20]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.

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 at that time as well as subsequent 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 orders pertain to specific environmental disputes that pertain to local firms and local institutions, orders 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 first examine the first-stage regression at the two levels of aggregation. The top-left panel of Figure 4 presents a binned scatter plot with a linear fit line that is obtained from the leave-one-out cross-validation estimation of Equation 5 on the sample of court orders.[21] Here, we regress a dummy variable that takes the value 1 if an order is pro-green (and 0 otherwise) on the full set of vectors that summarize a judge's writing style and additional control variables. The control variables also include a dummy variable that takes the value 1 if a judge has a post-graduate degree (and 0 otherwise), a dummy variable that takes the value 1 if the case is an appeal case (and 0 otherwise), a dummy variable that takes the value 1 if one of the parties contesting the case is the government (and 0 otherwise), and a dummy variable that takes the value 1 if the case is a constitutional case (and 0 otherwise). We note that in the top-left panel of Figure 4, we see a strong positive relationship between pro-green orders and judges' writing styles, conditional on these control variables. We interpret this as evidence that pro-environmental orders are strongly associated with judges' style of writing.

The top-right panel presents results of a similar regression, with the Y-axis altered to represent

[21] The leave-one-out cross-validation approach excludes the current case from the sample over which the relationship is being estimated. Plots are generated using the *binscatter2* command in STATA 17.

the predicted likelihood of an order being green based on case-level control variables. Here we can see that, consistent with randomization, the prediction of green orders from controls seems uncorrelated with our instrumental variable, which is the prediction based on the judge's writing style. Taken together, the results suggest that the assignment of a judge affects the types of orders that emerge from the court.

The lower panel of Figure 4 presents the results of the same regressions as the top row with the data aggregated at the district-year level, where all district-years in the sample have at least one order. We see that the results are very similar to the order-level ones. These results give us confidence in our econometric strategy, particularly the identifying assumption about judge randomization.

Appendix Figure A1 presents an additional visualization of the random assignment. We overlay three (interrupted) time series for each district in the state of Maharashtra. One time series is the prediction of green orders using all judges in the court who are available to be assigned. This time series is smooth as the composition of judges changes slowly over time. A second time series is the prediction of green orders using the judges assigned to the cases. This (interrupted) time series varies idiosyncratically above and below the first one. The last (interrupted) time series is the fraction of green orders, which moves around in a manner associated with the second time series. The higher variability of the judges who are assigned (over those who could be assigned) is an additional check of our empirical strategy. Similar results for additional states of India are presented in our Online Appendix (Figures OA4 to OA21).

5.2 Impacts on Pollution

To obtain an estimate of the impact of green orders on pollution levels, we estimate Equations 2 (OLS estimation) and 4 (IV). Table 3 presents the results from four different sets of specifications for BOD: omission of the districts and years that have no environmental order 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).

Note that in the buildup to the preferred specification in the full sample (Panel A), there is a negative and statistically significant coefficients in the OLS and IV specifications. Specifically, the point estimate of the IV regression (Table 3, Column 8) is -0.241 and is significantly different from zero at a 1% level. These results are confirmed when using weak instrument robust confidence intervals (Table OA7). The effect size suggests that a district that goes from having no green orders to all green orders (conditional 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.

Estimates of the effective first-stage F-statistic are reported in Table 3 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). We present identification-robust confidence intervals for all our tables in Online Appendix Tables OA7 to OA22.[22]

5.3 Impacts on Additional Pollutants

Table 4 presents the results of our preferred specification for additional water quality outcomes that include COD, TOTCOLI, conductivity, and temperature. COD is widely used as a measure of industrial pollution, but note that it is observed over fewer district-years than BOD or any of the other pollutants. The other three indicators of water quality we consider here 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, and both BOD and COD are far more sensitive to this form of toxicity, we do not expect impacts of judicial verdicts on these measures on TOTCOLI, conductivity or temperature (WHO and UNICEF 2012).

Table 4 presents the estimated impact on these additional water quality outcomes next to our preferred estimates for BOD (from Tables 3), as well as corresponding effective F-statistics from the first-stage regressions. We note that all the obtained coefficients are negative. Only the negative impact of the policy for BOD is significantly different from zero. The negative coefficient from the COD regression is of similar magnitude as the BOD results, while the point estimates for TCOLI, conductivity and temperature are all much smaller. Table 5 presents the results for three-year moving averages of the dependent variables. In this sample, which has additional observations due to interpolation, we now see negative coefficients of similar size for BOD as well as COD that are statistically significant at the 5 and 10 percent level respectively. The effect sizes suggest that for a district that goes from having no green orders to some green orders (conditional on having some

[22]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 orders". 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 inverted 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. These confidence intervals are efficient regardless of the strength of the instruments (Andrews, Stock, and Sun 2019).

water pollution cases) in a three-year period, the maximum observed values of these pollutants decline by 15% and 18% over these years. The estimates related to the other three pollution measures are still much smaller and not significantly different from zero.

In summary, we see strong negative and significant impacts of the judicial verdicts on BOD as well as COD. The estimates for the other water quality measures (TOTCOLI, conductivity and temperature) are smaller and not significantly different from zero. These findings align with our descriptive analysis (Fig 2), indicating that green orders hold significant relevance for firms, potentially exerting influencing them to either adopt pollution-mitigation strategies or else relocate from the areas of jurisdiction of these orders.

We perform a series of robustness checks for these results. Appendix Table A1 presents estimates 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).[23] Our measure of forest cover, also calculated from satellite data, is intended to be a proxy of the broad 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 here, COD is seen as having a negative and statistically significant impact despite the inclusion of these controls for socio-economic activity.

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 (Tables OA1, OA2, and OA3 respectively). Note that the results are very similar to what we have reported here. We also present the results of specifications that use the mean values of the dependent variables as well as the minimum values (Tables OA4 and OA5). Here, we do not observe any statistically significant impact of green orders on any of the outcomes. That we observe impacts of the green orders on maximum observed values at the yearly level, but not in the means or minimum values, is consistent with concerns over water quality being triggered by irregularities in recorded pollution in most settings, and the maximum values being the appropriate measure for this study.

[23] 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.

5.4 Dynamic Impacts on Pollution

Next, we estimate Equation 4 with dynamic effects: we consider effects between three years in advance of the order and five years after. To do so, we run independent regressions of Equation 4 with each time all explanatory variables (and instruments) shifted (from t-3 up to t+5). We conduct the event study analysis using two sets of dates: Publication dates (Panel A) and filing dates (Panel B). The publication date is the most important from the standpoint of our analysis – it is the official date for the court order to go into effect. But the date on which a case is filed can also be significant. The average case duration is 8 years in the Indian court system. Between the filing date and the publication date of the order, stakeholders may anticipate the final ruling prior and/or alter their behavior due to the public or media scrutiny that often accompanies the filing of judicial cases.

We present the coefficients and confidence intervals for three leads and five lags for the maximum observed values of two pollutants – BOD and COD – in Figure 5.[24] Panels (A) and (B) present the regression results for filing dates and publication dates, respectively.

We make four observations from this graph. First, note that in the event study plots that use filing dates (Figure 5, Panel A), we do not see significant impacts prior to the filing date of a case. This corroborates our identification strategy, which exploits random variation in the judges assigned to the case. We should not see any effects of a judge assigned to the case prior to that case being filed.

Second, in the event study plots using the publication dates (Figure 5, Panel B), note that we see some significant effects immediately after the date of publication (Lag 0). This is the same result that we reported earlier - the maximum observed values of BOD in a year drop in the immediate aftermath of a pro-green court order, but there is no statistically significant effect on the corresponding values for COD.

Third, we see significant negative effects in the lags of Panel A and leads of Panel B, highlighting that effects can occur already during the litigation process and before the final order.

Finally, note that in the years after the green order (Lags 1 and beyond), we see no statistically significant impact for either BOD or COD. This suggests that green orders are associated with immediate declines in pollution, but we see no long-term impacts in our sample. If anything, pollution levels *increase* in the long run (Lag 5 in Figure 5, Panel B).

Figure 6 presents similar results for the sample for which both BOD and COD are defined, i.e., the common support for these variables. Note that in the analysis for filing dates on this restricted sample (Figure 6, Panel A), we see a drop in the max observed values of BOD and COD in the

[24]The same estimates but with confidence intervals robust to weak instruments are presented in Online Appendix Figure OA1.

aftermath of the ruling, and we also see that the coefficients for the maximum observed observations of the pollutant remain negative and statistically significant for three years after the filing. We see no such effects for the decision dates (Figure 6, Panel B). There is a reduction in pollution prior to the ruling, but a steady rise in the maximum observed values of pollutants in the aftermath of the green orders. In year 5 the coefficients even become positive and statistically significant. The results are very similar when we use the common support for all indicators (Figure 6, Panel C and D).

In summary, these results suggest that the maximum observed values of pollutants show a decline in the immediate aftermath of filing dates and prior to decision dates, and some pollutants appear to show a decline in the publication year. In the years following the publication, pollution levels revert to initial levels. Finally, five years after publication, maximum pollution levels even increased significantly. We interpret this as evidence that court activity and rulings can affect water toxicity in the short run, but long-term compliance may be a challenge.

5.5 Impacts on Mortality

To estimate the impact of green rulings on mortality, we follow the same approach as we used for pollution. We emphasize however, that this analysis will be conducted at the district-year-month level (and not the district-year level). We consider three measures of mortality as dependent variables in our estimation of Equation 4 (IV): 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 the fraction of green orders on mortality outcomes in a district-year-month.

Here too we focus on the immediate contemporaneous effect, i.e. mortality impacts in the immediate aftermath of the court ruling, as well as the dynamic effects. Given that child health will take time to be impacted by the changes in pollution or human behavior that accompany the court decision, the lagged effects are particularly important.[25]

Results of the estimation of Equation 4 for the three dependent variables, in a sample with (and without) controlling for air pollution, are presented in Table 6. The first three columns present the results of estimations that do not include a district-level control variable for air pollution, as measured by PM2.5 levels. Columns 3–6 present the results of estimations including air pollution

[25]In "ideal" data, we would have specific dates and location codes for children's births and match them to the dates of the order, 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 microanalysis would be quite unreliable.

as a control variable. The IV regression is implemented using the same set of methods as the earlier results pertinent to pollution (Table 3). i.e., the full set of 26 instruments is used in the first stage, and the effective first stage F-statistic is presented.

For now, we note that in the first three columns of Table 6, all the coefficients take both positive and negative values, but the coefficients are close to zero and not statistically significant. This suggests that the orders were overall associated with almost no impacts on child mortality. In columns (4)-(6), we estimate these effects while controlling for air pollution on a smaller sample. Here we find no statistically significant impact of green orders on the likelihood of death in the first year or first month of life. We do, however, find a small positive impact of green orders on the likelihood of death in the first year that is conditional on survival in the first month (0.00873). The estimate suggests that an increase from 0% to 100% for the fraction of green orders results in a 0.8 percentage points increase in conditional infant mortality. This represents a modest impact considering that mortality levels in India were falling over this period and were well below 10% for all three measures of mortality (Table 2).

What do these results imply for the impact of courts on mortality levels in specific locations in India? Our results should be interpreted cautiously in answering this question. Our sample of districts with green orders, as illustrated in Figure 1, is relatively small. Previous time series analysis conducted by Do, Joshi, and Stolper (2018) identified localized downstream effects along a single river. Given the substantial ecological, demographic, and institutional diversity across India, combined with the infrequency of mortality in recent years, detecting robust effects may pose challenges. Future research may indeed find robust localized effects of green orders in some locations and not others and this may be driven by a variety of factors that are outside the scope of this study.

We test the robustness of the results in several ways. First, given that the measure of air pollution is not available in all the district-year-months of our baseline specification, we verify in Appendix Table A2 whether the positive significant effect is driven by the different samples because we are controlling for PM2.5. We observe that the estimates from the reduced sample but without PM2.5 in columns (4) - (6) are almost identical to the estimates when controlling for PM2.5 in columns (7) to (9).

Second, we estimate the regression at the district-year level. This allows us to include in addition to air pollution also the maximum reported intensity of night lights and the maximum reported level of forest cover as proxies for socio-economic activity. Appendix Table A3 presents results for these estimates, columns (1) - (3) for the baseline regression, columns (4) - (6) including PM2.5 as a control variable and columns (7) - (9) including also night lights and forest cover as district-level controls. The results are similar across all specifications, small and statistically insignificant.

Third, Online Appendix Table OA6 presents the same regression results as Table 6 but uses the 25-dimensional vectors from the LSA algorithm (rather than from the D2V algorithm) as instruments. Estimates are similar to the D2V estimates from Table 6 although the coefficient in column (6) is not significantly different from zero.

Lastly, Online Appendix Tables OA10, OA15, OA14, and OA22 present the same regression estimates with identification-robust confidence intervals.

Overall, these results suggest that there is either no, or else a very modest positive impact of pro-environmental judicial verdicts on some measures of mortality in the immediate aftermath of decisions. While our approach cannot provide insights into the mechanisms for this, it is plausible that economic mechanisms are at play. For example, the closure or reduced economic activity of firms may have increased economic vulnerability in the local population and raised the barriers to accessing health care.

5.6 Dynamic Impacts on Mortality

Figure 7 presents the dynamic effects of green orders on mortality. Panels A-C present each of the coefficients of interest - *Died<1Y*, *Died<1M* and *Died<1Y |1M* respectively for the leads and lags at the monthly level. To be consistent with the yearly pollution estimates, we present estimates for three years before, and five years after the publication dates of orders. We focus our analysis solely on the publication date of the order - we cannot construct any estimates of mortality vis-à-vis the filing dates because we lack data on the cases' filing month. Panels A-C of Figure 7 present each of the coefficients of interest - *Died<1Y*, *Died<1M* and *Died<1Y |1M* respectively for the leads and lags at the monthly level.

We note considerable clustering of the coefficients around the horizontal 0 line, especially in the period before the decision. For the years after the decision, many estimates are close to zero, however, we can distinguish some slightly positive estimates, especially in years 2 and 3 after the decision. Again, this is consistent with the findings we presented earlier.

Panel D of Figure 7 presents a smoothed version of these estimates. It presents the monthly estimates aggregated at the yearly level for the regression that includes control variables for air pollution. Panel E of Figure 7 presents estimates from the district-year-level regressions. Here too, we note no noteworthy statistically significant impacts of green rulings on mortality up to the decision date. However, we observe a significant increase in all three measures of infant mortality in the second and third years after the decision. These results together with the results presented earlier suggest that even though courts can have some influence in lowering surface water toxicity, presumably by forcing firms to adopt pollution-mitigation strategies, shutdown their operations, or else relocate elsewhere, in the long run these strategies may increase vulnerability in the local population and actually have adverse effects on early childhood mortality.

5.7 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) as well as district and year fixed effects. Implicit in this assumption is that these variables fully explain the emergence of green orders in polluted locations. The next step of our analysis is to examine whether these green orders 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 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 orders on judge characteristics in a geographically neighboring district and then examine whether these green orders in neighboring districts affect pollution in the districts in our sample.[26] IV estimations are once again performed with the full set of 26 instruments. We present tables with normal standard errors while the tables with AR confidence intervals can be found in the Online Appendix.

Results are presented in Table 7. Note that we observe a negative and statistically significant effect of fraction of green orders in neighboring districts on COD (Column 1). For all other measures of water quality, we observe negative or very small positive coefficients, but which are not significantly different from zero (Columns 2–5). We examine the robustness of this result to the exclusion of districts that have major cities. As seen in Appendix Table A4, the result remains robust in this sample.

Table 8 expands the methodology we described for neighboring districts to the analysis of the entire state. We observe negative coefficients for COD, BOD, conductivity, and temperature and a positive coefficient for TOTCOLI, but none of the coefficients is significantly different from zero.[27]

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

[26]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 orders in neighboring districts (excluding orders in the district itself) and divide that number by the total number of water pollution orders in all neighboring districts.

[27]In Table 8 we note a significant negative impact on BOD, but the weak instrument robust confidence interval in Table OA12 includes zero.

observed values of BOD and 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.

6 Discussion

Our estimates of the impact of green orders on water pollution levels are the first documented empirical evidence of the judiciary's success in India's water quality regulation 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.

It is worth emphasizing that the impacts we report here pale in comparison to some other events that have reduced water toxicity. Consider, for example, 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).[28] 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 during these lockdowns and are thus not widely viewed as a solution to water toxicity.

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 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 order in our sample is directed towards firms, and a green ruling thus imposes restrictions on these polluting firms. A typical order may impose restrictions on economic activity for such firms. This may induce a loss of income and employment in a community, which can undermine the long-term popularity of the 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

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

technologies that have been widely adopted to treat effluent from toxic industries, intended to address citizen concerns (Woodhouse and Muller 2017). For example, green rulings in industrial clusters with a variety of horizontally linked small firms have often required the clusters to build Common Effluent Treatment Plants (CETPs).[29] Previous research has found these to be expensive and quite 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 (Joshi and Shambaugh 2018). The lack of long-term planning for funding the maintenance and operations of these large and expensive technologies has resulted in a "boom-bust cycle" featuring an initial period of decline in water toxicity followed by a convergence to the pre-construction average and then even an increase beyond that level. The "boom-bust cycle" has been demonstrated in some detail for India's first CETP which 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 two years before water toxicity levels reached the pre-verdict stage and a similar pattern is seen for all CETPs that were constructed in India between 1986 and 2004 for which data is available (Joshi and Shambaugh 2018). In the years that followed, public-private partnerships, featuring governments, multilateral organizations, and private companies, have built these technologies all over India but their effectiveness in curbing long-term pollution remains unclear (Shambaugh and Joshi 2021).

Finally, the failure of the judiciary to have a 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 (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 its 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 term, they 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 however, needed to elucidate the key mechanisms that link judicial verdicts to these outcomes at the local level throughout India.

[29]For our current study, we examine the placement of 52 CETPs (out of a total of 88) that were built in India between 1986 and 2004 in the districts in our sample that have data on both court orders and surface water toxicity. We find that most of these were placed in districts with green orders in the preceding 5 years. These results are available upon request.

7 Conclusion

This paper provides an empirical study of the broad impact of judicial orders 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 orders 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 infant mortality as key outcomes.

Our results suggest that an increase in the fraction of pro-environmental orders is precipitated by reductions in chemical oxygen demand (COD) and biological oxygen demand (BOD), two common measures of industrial pollution in surface water. However, posterior to the decision date, pollution levels revert to initial levels and are even increasing in the longer run.

We find that the reduction in river pollution prior to the decision dates does not lead to a decrease in infant mortality. Moreover, our results show a modest but discernible *increase* in infant mortality two to three years after the order, 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 an order may actually increase economic vulnerability. In the long term, 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) Water Pollution Orders per District

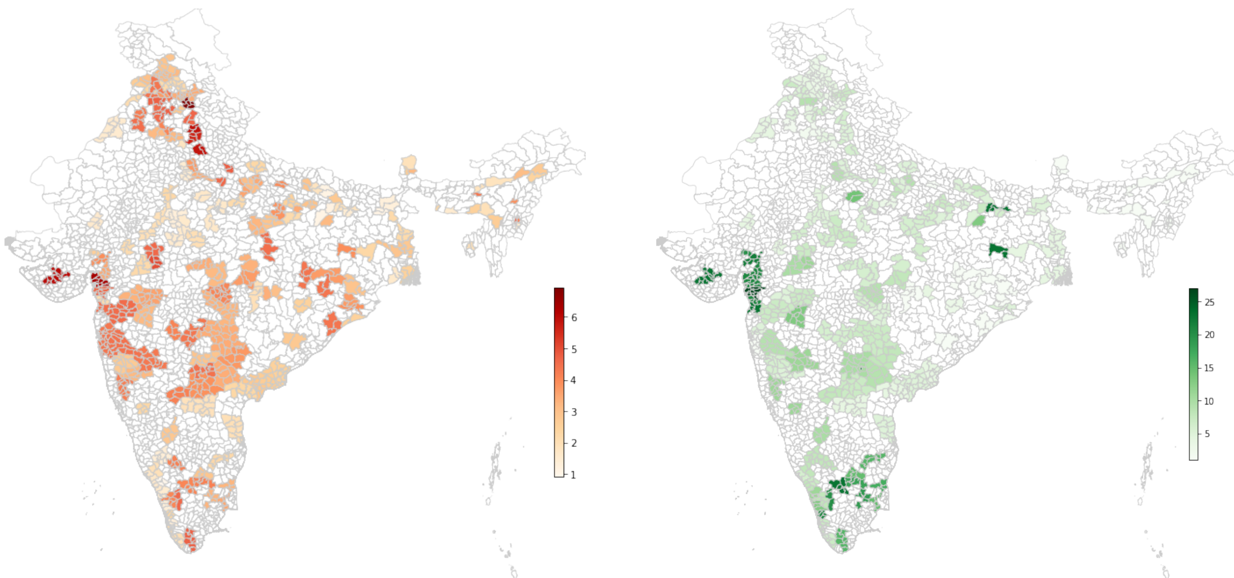


Figure 1: Spatial distribution BOD and Judicial Orders

Note: 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 orders in the Indian Supreme Court, Green Tribunal and High Courts related to water pollution per district between 1982 - 2020.

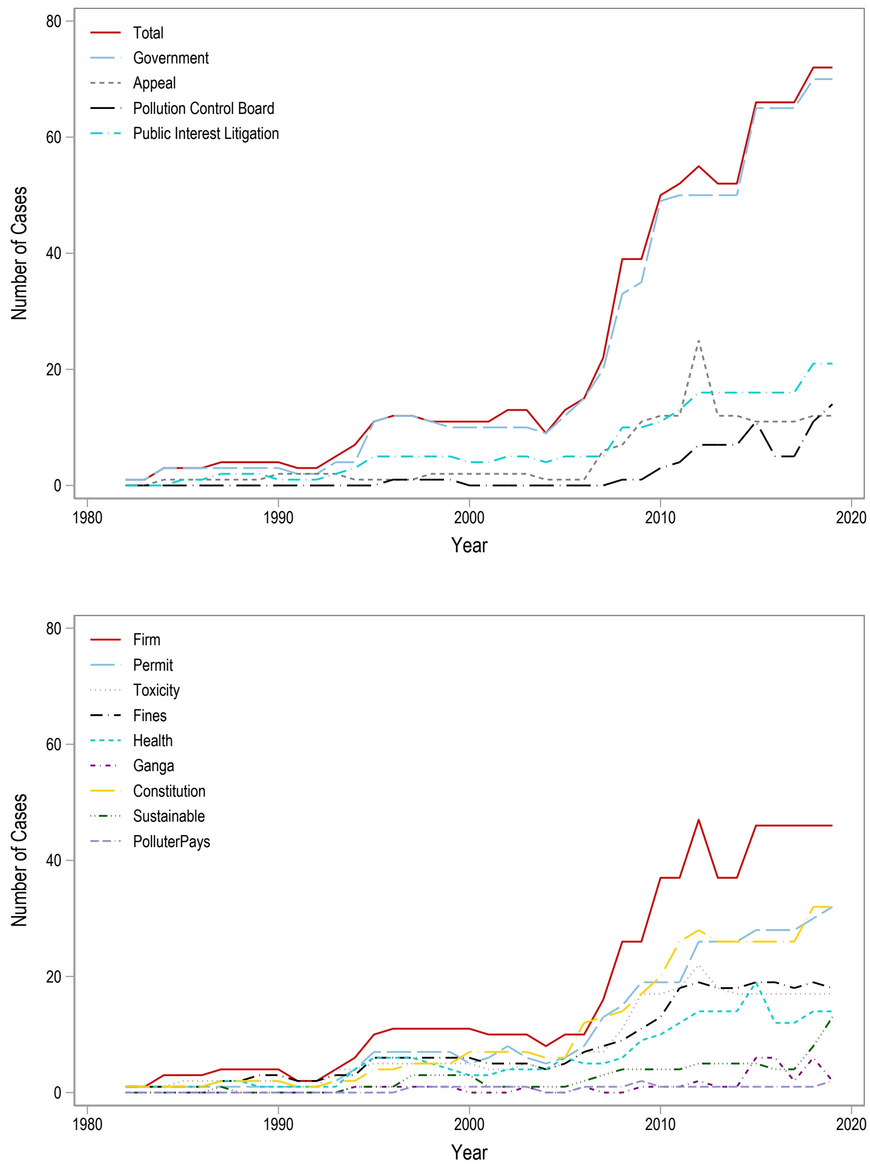


Figure 2: Varieties of Orders

Note: The graph is based on the full sample of 978 court orders that cite the Water (Prevention and Control of Pollution) Act of 1974. All variables are yearly counts of orders with a specific characteristics. In the top panel, "Total" depicts the number of orders per year. "Government" displays the number of orders with the government as either petitioner or respondent. "Appeal" counts the number of orders from appeal cases. "Pollution Control Board" is the number of orders mentioning the Central or State Pollution Control Boards. "Public Interest Litigation" counts the number of orders from public interest litigation cases. In the bottom panel, "Firm" counts the number of cases with a firm as either petitioner or respondent. The other eight variables are based on keyword searches in the full text of orders.

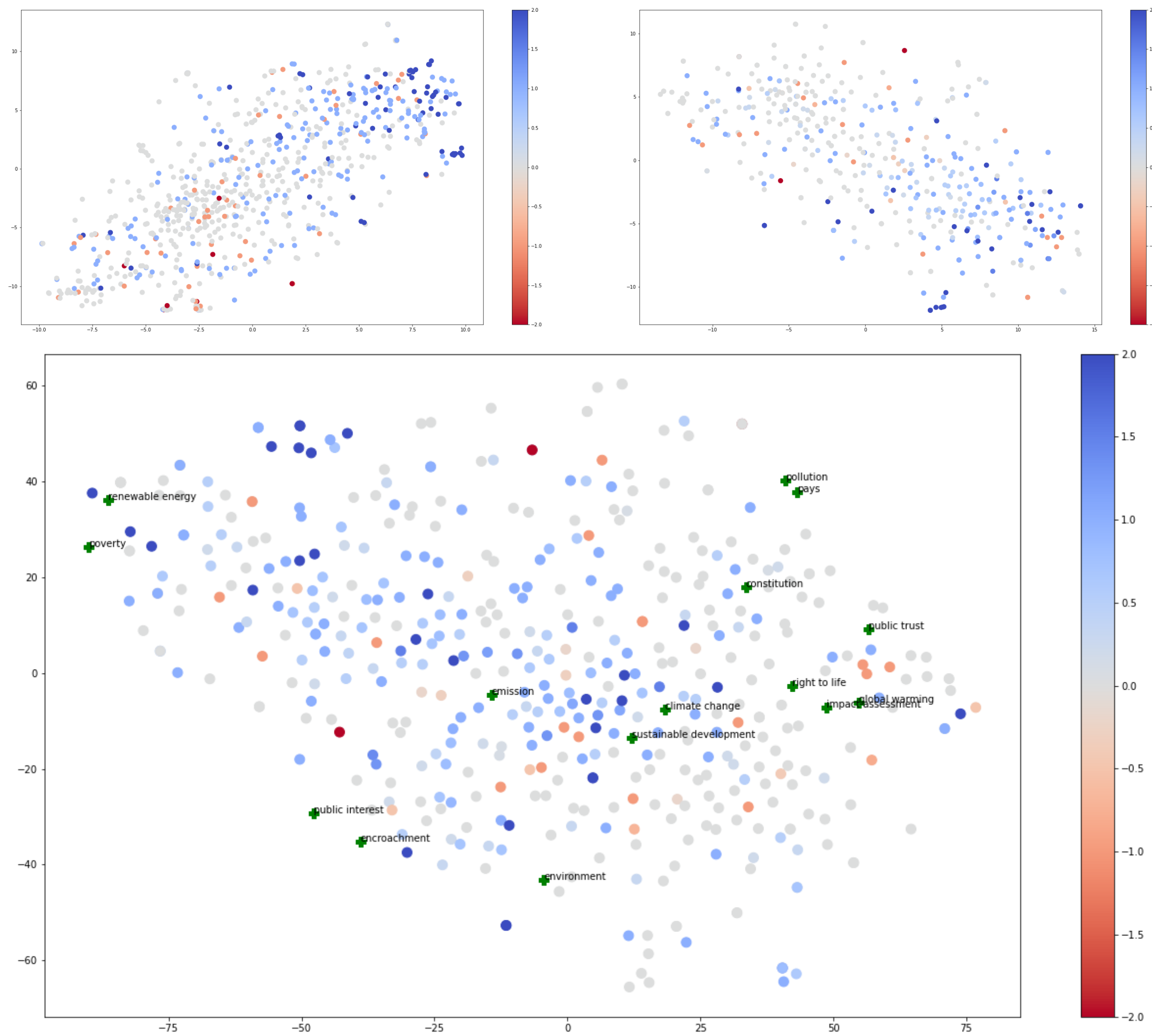
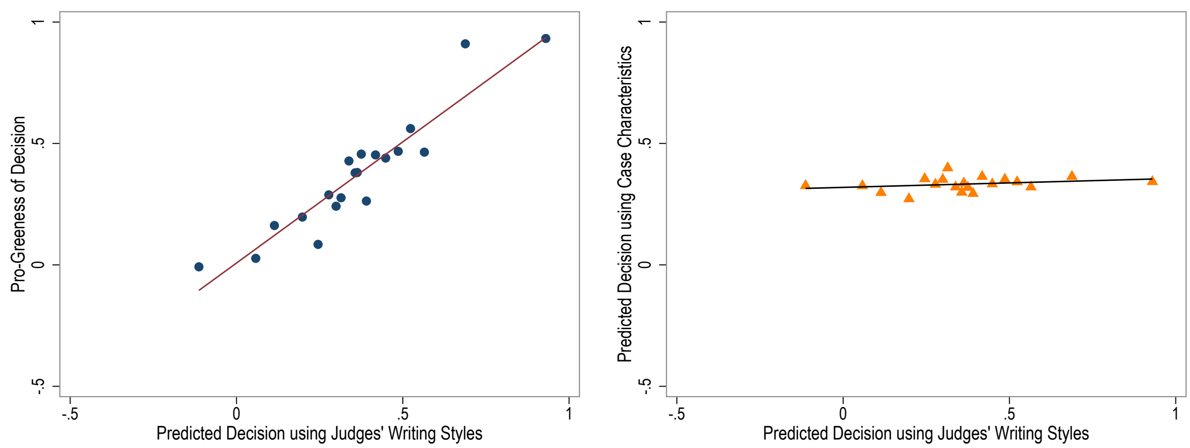


Figure 3: Visual Illustration of Judges' writing Styles

Note: Each order in our corpus is represented as a 25 dimensional vector using D2V. The top-left panel presents the two dimensional visualization of the order vectors (colored by the hand-labeled impact score). The top-right panel presents the judge level embedding (colored by the mean impact score of the orders 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 order vectors by D2V.

A. Order-Level



B. District-Year-Level: With Orders

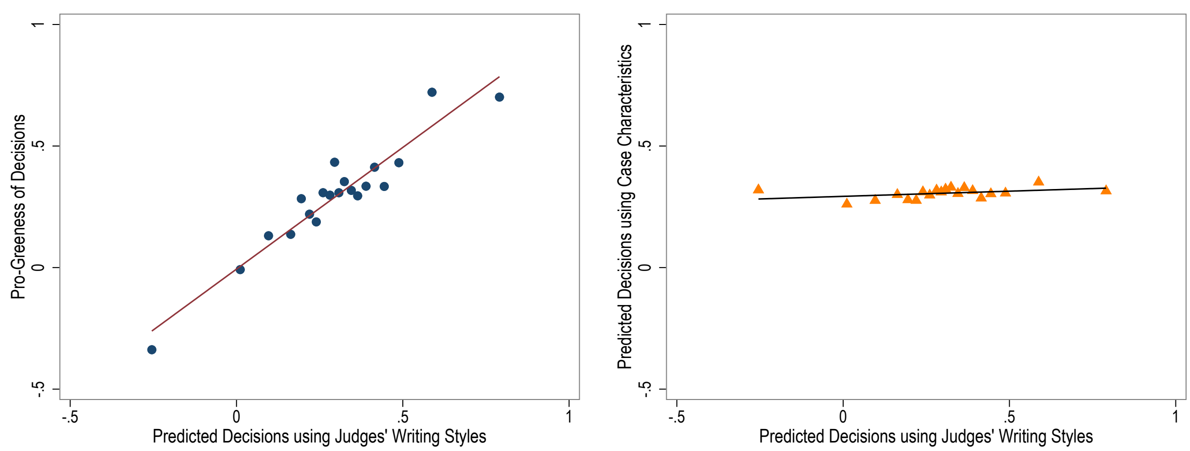


Figure 4: Graphical First Stage

Note: Panel (a) is on an order-level and Panel (B) on a district-year level including only district-years with at least one order; (ii) Graphs on the left are binscatters of the orders' (residualized) median pro-greeness on the (residualized) pro-greeness predicted by judge characteristics; (iii) Graphs on the right are binscatters of the (residualized) pro-greeness predicted by order characteristics on the (residualized) pro-greeness predicted by judge characteristics; (iv) Judge characteristics include the 25 measures of judges' writing styles; (v) Order characteristics include a dummy variable that takes value 1 if the order is related to 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).

A. Pollution: Filing Year

B. Pollution: Decision Year

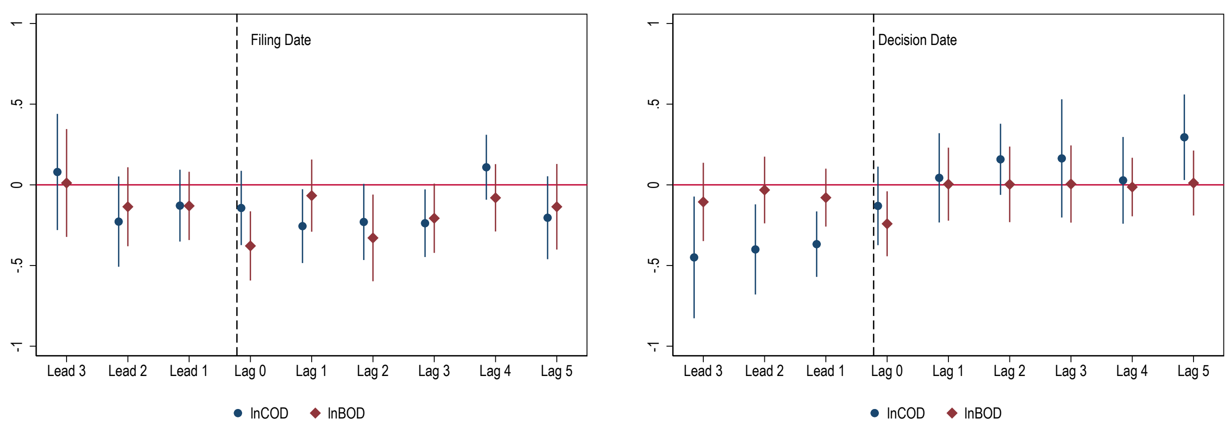


Figure 5: Dynamic Impacts of Green Orders on Pollution

Note: Every estimate is an independent regression. Outcomes are pollution measures per district in year t, regressed on Fraction of green orders, a dummy equal to one if the number of orders is greater than 0, district and year fixed effects and several aggregated order characteristics. Filing year regressions (panel A) define the order as being issued in the year that the case was first filed, while the decision year regressions (panel B) define the order based on the actual decision year. The explanatory variables are shifted from $t-3$ up to $t+5$. The variable $FracGreenOrders$ 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 "identical order cluster" (IOC) level. Confidence intervals are at the 95%-level.

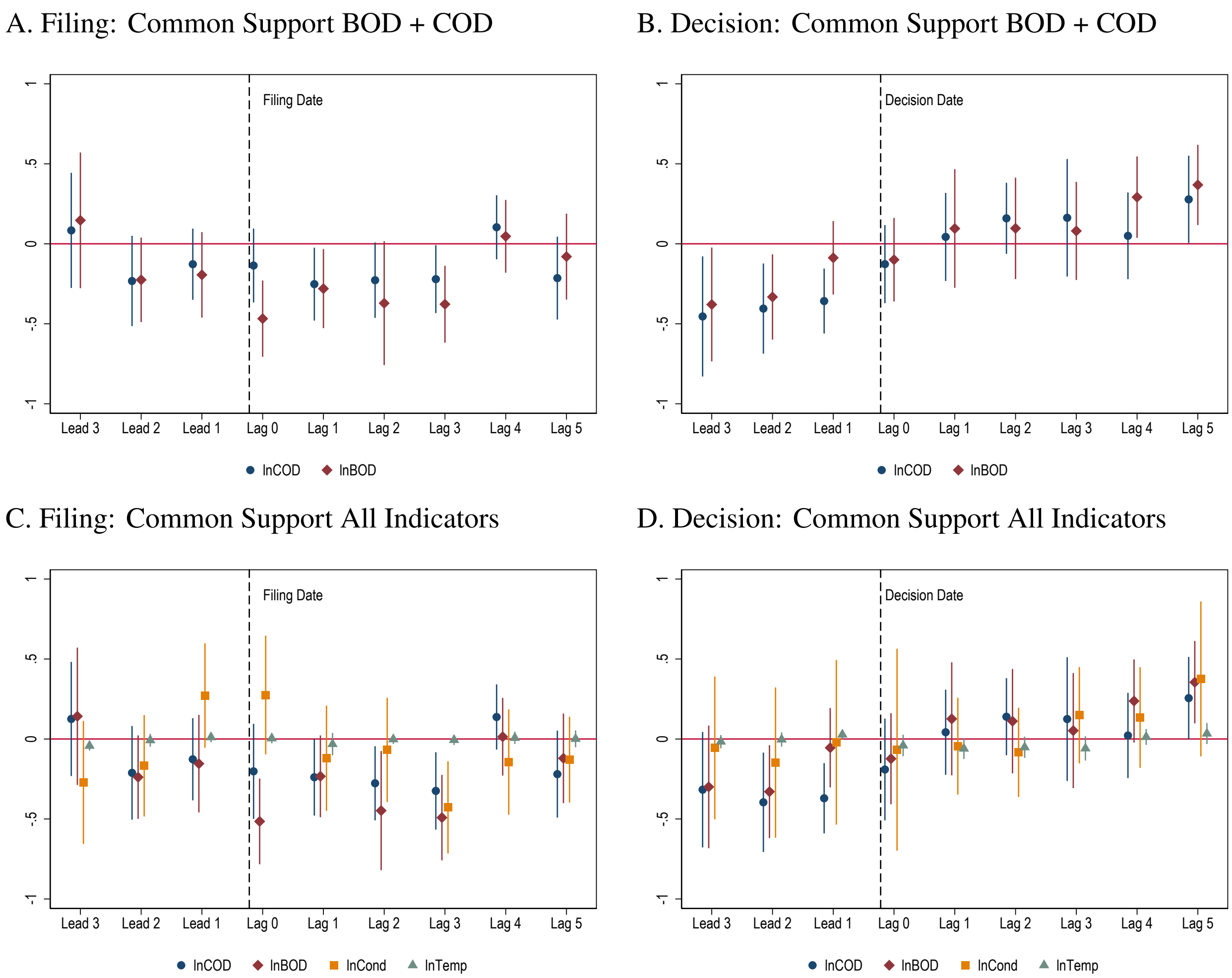


Figure 6: Dynamic Impacts of Green Orders on Pollution with Common Support

Note: All notes from Figure 5 apply. Additionally, panels A and B are based on the common support of the samples of the BOD and COD regressions. Panels C and D are based on the common support of the samples of the BOD, COD, Conductivity, and Temperature regressions.

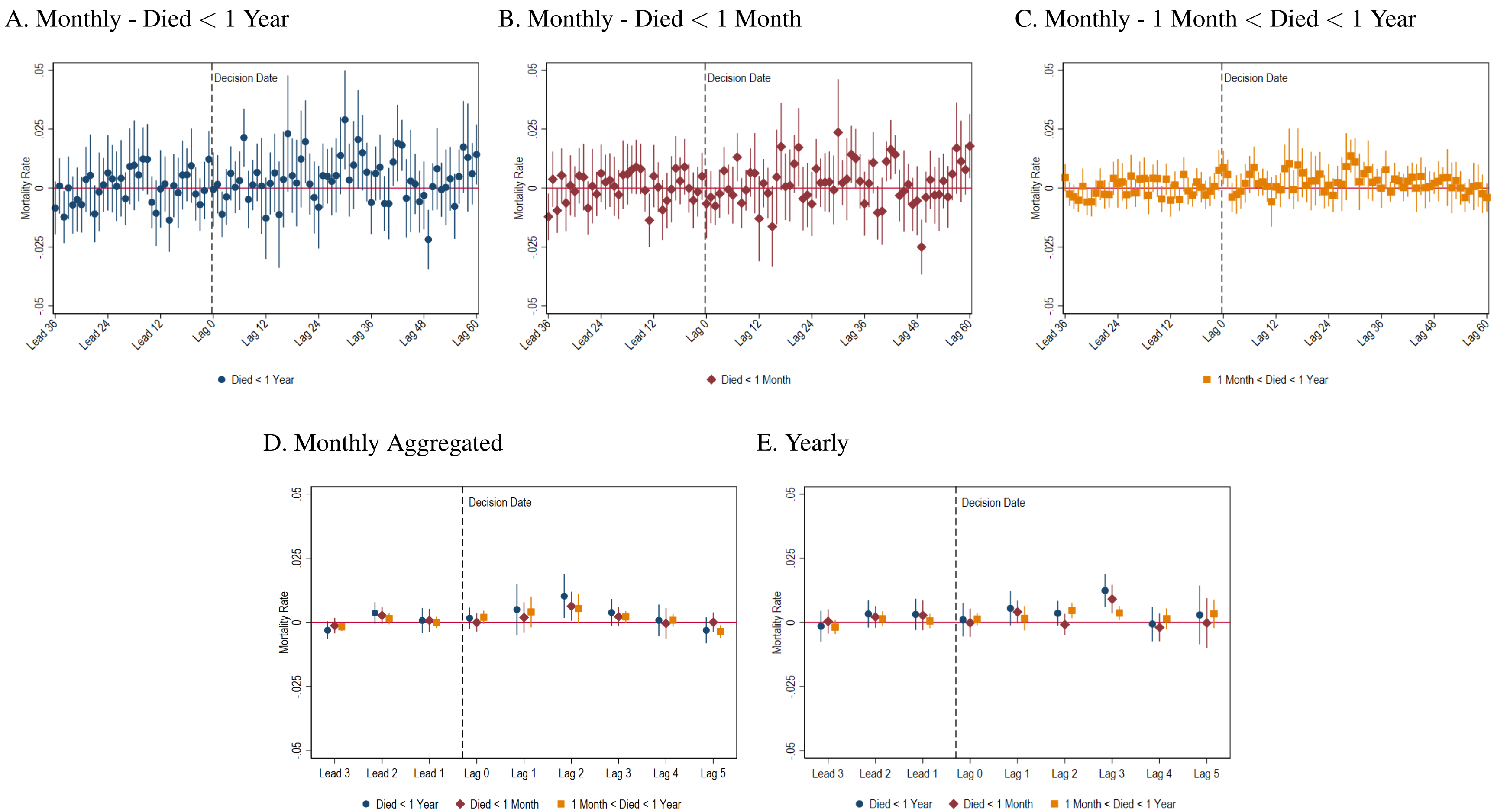


Figure 7: Dynamic Impacts of Green Orders on Infant Mortality (With Air Pollution Control)

Note: Every estimate is an independent regression of mortality shares on Fraction of green orders, a dummy equal to one if the number of orders is greater than 0, district, year and (for Panels A, B, and C) month fixed effects and several aggregated case characteristics. The outcome variables of Panels A, B, and C are, respectively, the share of infants in a district, year and month that died during their first year of life, that died during their first month of life, and that died during their first year of life conditionally on having survived the first month. The explanatory variables are shifted from $t-36$ up to $t+60$ where $t=0$ is the year and month of the orders. The variable $FracGreenOrders$ is instrumented for by a 25 dimensional vector summarizing judges writing styles and the fraction of judges with a postgraduate degree. Panel D presents the same monthly estimates as Panels A, B, and C but aggregated at the yearly level. Panel E display yearly regressions, with the explanatory variables shifted from $t-3$ up to $t+5$ where $t=0$ is the year of the orders. Standard errors are clustered on the "identical order cluster" (IOC) level. Confidence intervals are at the 95%-level.

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	772	0.25	0.43	0.0	1.0
Constitutional	772	0.23	0.42	0.0	1.0
Government is Respondent	772	0.86	0.35	0.0	1.0
Government is Petitioner	772	0.12	0.32	0.0	1.0
Number of Judges	772	1.75	0.76	0.0	3.0
Environmental Impact (Median Coding)	772	0.35	0.71	-2.0	2.0
Average PM2.5 (μg/m3)	662	50.38	32.93	8.6	228.7
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	6,270	0.16	0.37	0.0	1.0
Number of Green Orders	6,270	0.24	0.75	0.0	13.0
Fraction of Green Orders	6,270	0.04	0.18	0.0	1.0
Average Number of Judges / Case	6,270	0.29	0.72	0.0	3.0
Share of Appeal Cases	6,270	0.03	0.16	0.0	1.0
Share of Constitutional Cases	6,270	0.05	0.22	0.0	1.0
Share of Cases w/ Government as Petitioner	6,270	0.02	0.12	0.0	1.0
Share of Cases w/ Government as Respondent	6,270	0.14	0.34	0.0	1.0
Max BOD (mg/l)	5,650	12.53	33.86	0.0	1,025.0
Max COD (mg/l)	3,053	55.65	80.25	1.1	1,750.0
Max Total Coliform (mpn/100 ml)/10^6	5,057	15.09	514.20	0.0	23,000.0
Max Temperature (°C)	5,614	29.69	6.29	0.0	269.0
Max Conductivity (µmhos/cm)/10^3	5,476	1.94	7.33	0.0	81.8
log Max BOD (mg/l)	5,649	1.66	1.14	-1.6	6.9
log Max COD (mg/l)	3,053	3.49	1.02	0.1	7.5
log Max Total Coliform (mpn/100 ml)	5,057	8.47	3.03	0.7	23.9
log Max Temperature (°C)	5,541	3.39	0.16	2.2	5.6
log Max Conductivity (µmhos/cm)	5,475	5.99	1.64	-1.3	11.3
log Max BOD (mg/l) (MA)	6,254	1.67	1.14	-1.6	6.9
log Max COD (mg/l) (MA)	5,742	3.41	0.97	0.1	7.5
log Max Total Coliform (mpn/100 ml) (MA)	5,888	8.52	3.03	0.7	23.9
log Max Temperature (°C) (MA)	6,185	3.38	0.21	0.3	5.6
log Max Conductivity (µmhos/cm) (MA)	6,237	6.02	1.62	-1.3	11.3
District-Month Level Data - Mortality Sample					
Case Present	188,298	0.01	0.10	0.0	1.0
Fraction of Green Orders	188,298	0.01	0.07	0.0	1.0
Average Number of Judges / Case	188,298	0.02	0.19	0.0	3.0
Share of Appeal Cases	188,298	0.00	0.05	0.0	1.0
Share of Constitutional Cases	188,298	0.00	0.05	0.0	1.0
Share of Cases w/ Government as Petitioner	188,298	0.00	0.03	0.0	1.0
Share of Cases w/ Government as Respondent	188,298	0.01	0.09	0.0	1.0
Infants dying aged <1 Year (%)	188,298	0.05	0.10	0.0	1.0
Infants dying aged <1 Month (%)	188,298	0.04	0.08	0.0	1.0
Infants dying, conditional on surviving first month (%)	188,183	0.02	0.06	0.0	1.0

Table 3: Comparison of Yearly log(BOD) Specifications

	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 Orders	0.177	0.209	0.177	0.209	-0.183***	-0.270**	-0.162**	-0.241**
	(0.127)	(0.175)	(0.127)	(0.175)	(0.0709)	(0.106)	(0.0706)	(0.103)
Dummy for Presence of an Order			0.202***	0.194**	0.0814*	0.107*	0.0366	0.0619
			(0.0710)	(0.0763)	(0.0473)	(0.0556)	(0.113)	(0.118)
District-years with no orders	Dropped	Dropped	Dummied	Dummied	Dummied	Dummied	Dummied	Dummied
Year and District FEs					Yes	Yes	Yes	Yes
Covariates							Yes	Yes
Clustering	IOC	IOC	IOC	IOC	IOC	IOC	IOC	IOC
Eff. First Stage F		6.567		10.24		.		8.856
N	859	859	5649	5649	5649	5649	5649	5649

Note: (i) Orders are defined as green orders 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 orders is equal to 0 if there a no environmental orders in a district-year; (iii) Robust standard errors are constructed using "identical order clusters (IOC)" of district years, pooling together in one cluster all district-years with exactly the same set of water pollution orders; (iv) Included covariates are the district-year means of order characteristics such as whether the government is a respondent and if it is an appeal and or a constitutional case; (v) Fraction of green orders 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.

Table 4: Contemporaneous Impacts on Water Pollution (Yearly)

	(1)	(2)	(3)	(4)	(5)
	ln(COD)	ln(BOD)	ln(TCOLI)	ln(Conductivity)	ln(Temperature)
Fraction of Green Orders	-0.130	-0.241**	-0.0421	-0.0694	-0.0209
	(0.124)	(0.103)	(0.520)	(0.144)	(0.0247)
Dummy for Presence of an Order	0.241*	0.0619	0.159	-0.0711	0.0000132
	(0.131)	(0.118)	(0.494)	(0.143)	(0.0377)
District-years with no orders	Dummied	Dummied	Dummied	Dummied	Dummied
Year and District FEs	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes
Clustering	IOC	IOC	IOC	IOC	IOC
Eff First Stage F	7.816	8.856	9.015	7.895	8.401
N	3053	5649	5057	5475	5541

Note: All notes from Table 3 apply.

Table 5: Impacts on Water Pollution (3 year moving averages)

	(1) ln(COD)	(2) ln(BOD)	(3) ln(TCOLI)	(4) ln(Conductivity)	(5) ln(Temperature)
Fraction of Green Orders	-0.158*	-0.183**	-0.0511	0.0406	-0.0333
	(0.0827)	(0.0919)	(0.475)	(0.129)	(0.0239)
Dummy for Presence of an Order	0.168**	0.0667	0.290	-0.0446	0.00317
	(0.0727)	(0.104)	(0.459)	(0.118)	(0.0368)
District-years with no orders	Dummied	Dummied	Dummied	Dummied	Dummied
Year and District FEs	Yes	Yes	Yes	Yes	Yes
Case Controls	Yes	Yes	Yes	Yes	Yes
District Controls	-	-	-	-	-
Clustering	IOC	IOC	IOC	IOC	IOC
Eff First Stage F	7.331	7.910	8.189	7.908	7.897
N	5742	6254	5888	6237	6185

Note: All notes from Table 3 apply; Dependent and independent variables are 3-year moving averages.

Table 6: Contemporaneous Impacts on Infant Mortality (Monthly)

	Baseline Regressions			With Air Pollution Controls		
	(1) Died<1Y	(2) Died<1M	(3) Died<1Y |1M	(4) Died<1Y	(5) Died<1M	(6) Died<1Y |1M
Fraction of Green Orders	0.00198	-0.000875	0.00504	-0.000556	-0.00663	0.00873**
	(0.00619)	(0.00633)	(0.00350)	(0.00800)	(0.00751)	(0.00363)
Order Dummy	-0.0112*	-0.00827	-0.00338	-0.00613	-0.00387	-0.00217
	(0.00590)	(0.00522)	(0.00251)	(0.00776)	(0.00763)	(0.00239)
District-year-months with no orders	Dummied	Dummied	Dummied	Dummied	Dummied	Dummied
Month, Year and District FEs	Yes	Yes	Yes	Yes	Yes	Yes
Case Controls	Yes	Yes	Yes	Yes	Yes	Yes
District Controls	-	-	-	PM2.5	PM2.5	PM2.5
Clustering	IOC	IOC	IOC	IOC	IOC	IOC
Eff First Stage F	6.17	6.17	6.15	5.86	5.86	5.84
N	188,298	188,298	188,183	101,096	101,096	101,029

Note: 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.

Table 7: Neighboring Districts

	(1) ln(COD)	(2) ln(BOD)	(3) ln(TCOLI)	(4) ln(Conductivity)	(5) ln(Temperature)
Neighboring Fraction of Green Orders	-0.242*	-0.0911	-0.131	-0.0808	0.00163
	(0.129)	(0.0865)	(0.428)	(0.112)	(0.0194)
Order Dummy	0.224**	0.0240	0.190	-0.124	-0.0316
	(0.110)	(0.0990)	(0.384)	(0.127)	(0.0200)
District-years with no orders	Dummied	Dummied	Dummied	Dummied	Dummied
Year and District FEs	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes
Clustering	IOC	IOC	IOC	IOC	IOC
Eff First Stage F	11.80	14.09	13.38	13.67	14.09
N	3053	5649	5057	5475	5541

Note: 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 orders in neighboring districts (excluding orders in the district itself) and divide that number by the total number of water pollution orders 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 Orders per State	-0.168	-0.226**	0.113	-0.0441	-0.00502
	(0.119)	(0.113)	(0.514)	(0.125)	(0.0213)
Order in State	0.0173	0.0630	0.0164	-0.0358	0.00205
	(0.0584)	(0.0478)	(0.184)	(0.0482)	(0.00886)
Order in District	0.171**	0.0723	0.238	0.0449	-0.000642
	(0.0793)	(0.0585)	(0.245)	(0.0763)	(0.0154)
District-years with no orders	Dummied	Dummied	Dummied	Dummied	Dummied
Year and District FEs	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes
Clustering	IOC	IOC	IOC	IOC	IOC
Eff First Stage F	21.81	14.15	14.93	13.80	13.86
N	3049	5619	5055	5446	5510

Note: All notes of Tables 3 and 7 apply.

A Appendix

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 Orders	-0.535**	-0.240	-0.171	-0.250	-0.0495*
	(0.228)	(0.165)	(0.325)	(0.170)	(0.0292)
Dummy for Presence of an Order	0.159	0.0933	-0.346	-0.0998	0.0230
	(0.126)	(0.232)	(0.267)	(0.123)	(0.0812)
District-years with no orders	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	IOC	IOC	IOC	IOC	IOC
Eff First Stage F	1.361	4.404	3.988	4.553	4.351
N	961	2126	1852	2266	2073

Note: (i) Orders 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 orders is equal to 0 if there a no orders in a district-year; (iii) Robust standard errors are constructed using "identical order clusters (IOC)" of district years, pooling together in one cluster all district-years with exactly the same set of water pollution orders; (iv) District controls, from SHRUGG, include nighttime lights and forest cover; (v) Fraction of green orders 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.

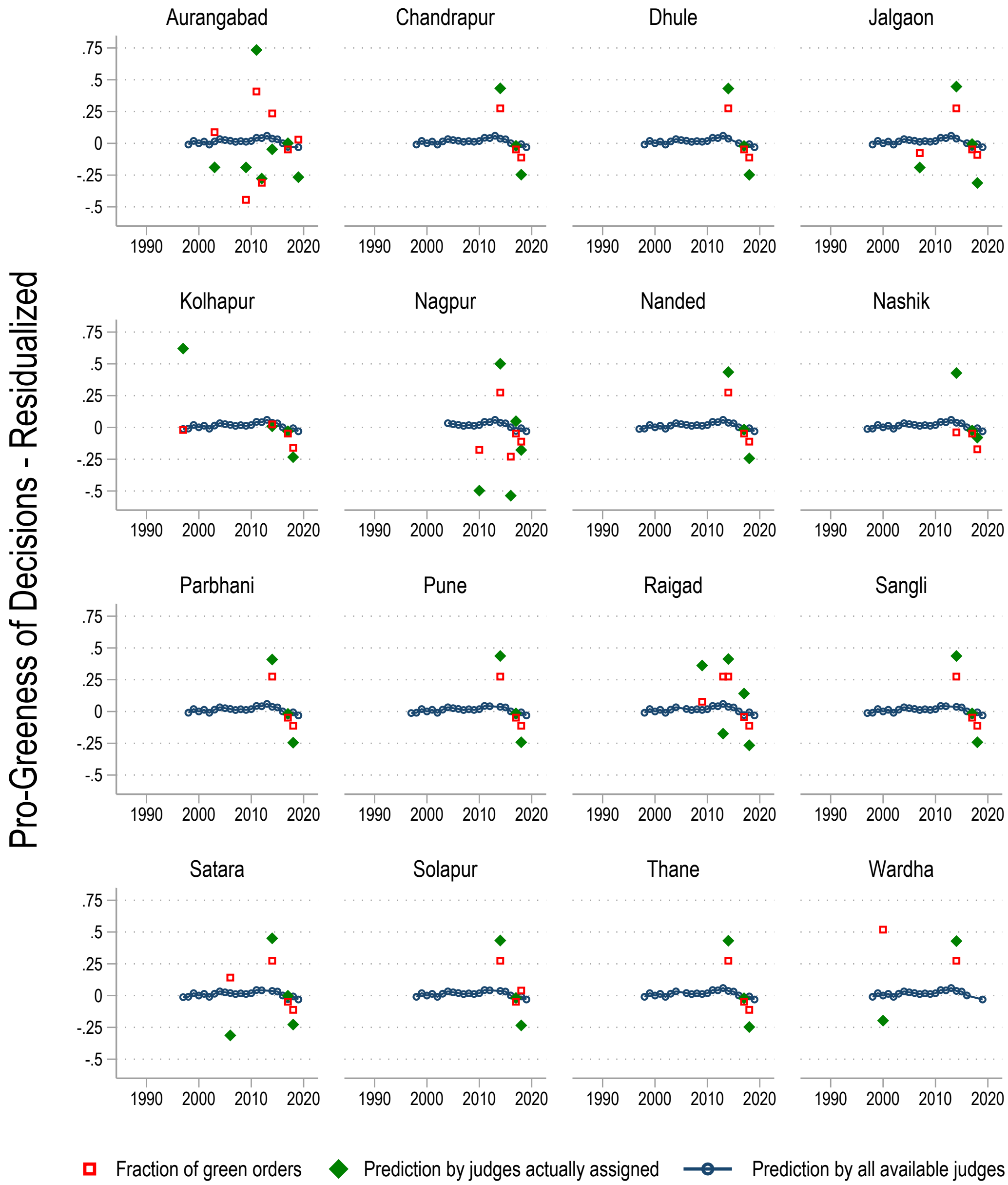


Figure A1: Random Variation in Judge assignment under Bombay HC

Note: (i) The outcome variable is the (residualized) fraction of pro-green orders per district-year. It is residualized by a Case Dummy, the share of orders with government as respondent, the share of appeal cases, share of constitutional cases, and district and year dummies. (ii) Green diamonds depict the (residualized) real coded fraction of green orders in our sample for district-years with at least one order. (iii) Red squares depict the predicted (residualized) fraction of green orders using as instruments the average of the 25 D2Vs and of the postgraduate dummy variable over the bench of judges that heard an order in the district-year. (iv) Blue circles depict the predicted (residualized) fraction of green orders using as instruments the average of the 25 D2Vs and of the postgraduate dummy for *all* judges serving in the year at the HC, i.e. not just judges who heard an order.

Table A2: Impact on Mortality - Sample Selection with Air Pollution Control

	Full Sample			Only if PM2.5 Available			Including PM2.5		
	(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 Orders	0.00198	-0.000875	0.00504	-0.000563	-0.00661	0.00870**	-0.000556	-0.00663	0.00873**
	(0.00619)	(0.00633)	(0.00350)	(0.00800)	(0.00751)	(0.00364)	(0.00800)	(0.00751)	(0.00363)
Order Dummy	-0.0112*	-0.00827	-0.00338	-0.00611	-0.00390	-0.00212	-0.00613	-0.00387	-0.00217
	(0.00590)	(0.00522)	(0.00251)	(0.00776)	(0.00762)	(0.00239)	(0.00776)	(0.00763)	(0.00239)
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	-	-	-	-	-	-	PM2.5	PM2.5	PM2.5
Clustering	IOC	IOC	IOC	IOC	IOC	IOC	IOC	IOC	IOC
Eff First Stage F	6.173	6.173	6.154	5.862	5.862	5.837	5.862	5.862	5.837
N	188298	188298	188183	101096	101096	101029	101096	101096	101029

Note: Notes from Table A1 apply; Regressions are run on three separate samples - the full sample, the sample for which air pollution data is available (without including it as a control) and the results with PM2.5 included as a control variable.

Table A3: Yearly Mortality Regressions

	Baseline Regressions			With Air Pollution Controls			With Air Pollution + Shrug Controls		
	(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 Orders	0.000607	-0.000351	0.00103	0.00106	-0.000127	0.00128	-0.00107	-0.00139	0.000313
	(0.00307)	(0.00266)	(0.00123)	(0.00334)	(0.00281)	(0.00121)	(0.00386)	(0.00296)	(0.00160)
Order Dummy	0.00461*	0.00321	0.00148	0.00490*	0.00334	0.00165	0.00458	0.00390	0.000708
	(0.00279)	(0.00253)	(0.00118)	(0.00290)	(0.00259)	(0.00116)	(0.00310)	(0.00269)	(0.00132)
District-years with no orders	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	-	-	-	PM2.5	PM2.5	PM2.5	PM2.5 + Shrug	PM2.5 + Shrug	PM2.5 + Shrug
Clustering	IOC	IOC	IOC	IOC	IOC	IOC	IOC	IOC	IOC
Eff First Stage F	7.360	7.360	7.360	7.373	7.373	7.373	6.788	6.788	6.788
N	8482	8482	8482	8482	8482	8482	6776	6776	6776

Note: Notes from Table A1 apply. Additionally, (ii) The time-period of the mortality sample spans 1989-2017 (columns 1 to 6) and 1997-2017 (columns 7-9).

Table A4: Neighboring Districts w/o Cities

	(1) ln(COD)	(2) ln(BOD)	(3) ln(TCOLI)	(4) ln(Conductivity)	(5) ln(Temperature)
Neighboring Fraction of Green Orders	-0.273**	-0.0155	-0.120	-0.0683	-0.0159
	(0.124)	(0.0991)	(0.409)	(0.0955)	(0.0205)
Order Dummy	0.227*	0.00257	0.0457	-0.192	-0.0291
	(0.118)	(0.105)	(0.421)	(0.132)	(0.0215)
District-years with no orders	Dummied	Dummied	Dummied	Dummied	Dummied
Year and District FEs	Yes	Yes	Yes	Yes	Yes
Case Controls	Yes	Yes	Yes	Yes	Yes
District Controls	-	-	-	-	-
Clustering	IOC	IOC	IOC	IOC	IOC
Eff First Stage F	10.15	11.54	11.17	12.00	11.45
N	2908	5383	4810	5219	5282

Note: All notes from Table 7 apply. Additionally, the analysis excludes all districts with a city. This implies dropping the districts Ahmedabad, Howrah, Hooghly, Kolkata, Nadia, NCT of Delhi, Raigad, South 24 Parganas, Thane. Other districts with a city but not present in our data are Chennai, Chengalpattu, Kancheepuram, Mumbai, North 24 Parganas, Palghar, Tiruvallur.

Online Appendix

Additional Tables

Table OA1: Pollution Regressions LSA

	(1) ln(COD)	(2) ln(BOD)	(3) ln(TCOLI)	(4) ln(Conductivity)	(5) ln(Temperature)
Fraction of Green Orders	-0.0777	-0.225*	0.275	-0.0545	-0.0161
	(0.130)	(0.116)	(0.557)	(0.177)	(0.0256)
Dummy for Presence of an Order	0.219	0.0567	0.0593	-0.0750	-0.00153
	(0.133)	(0.112)	(0.486)	(0.141)	(0.0357)
District-years with no orders	Dummied	Dummied	Dummied	Dummied	Dummied
Year and District FEs	Yes	Yes	Yes	Yes	Yes
Case Controls	Yes	Yes	Yes	Yes	Yes
District Controls	-	-	-	-	-
Clustering	IOC	IOC	IOC	IOC	IOC
Eff First Stage F	11.21	4.912	4.659	4.351	4.791
N	3053	5649	5057	5475	5541

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

Table OA2: Pollution Regressions D2V + LSA

	(1) ln(COD)	(2) ln(BOD)	(3) ln(TCOLI)	(4) ln(Conductivity)	(5) ln(Temperature)
Fraction of Green Orders	-0.136	-0.182**	-0.0761	-0.125	-0.0238
	(0.120)	(0.0899)	(0.488)	(0.135)	(0.0222)
Dummy for Presence of an Order	0.243*	0.0432	0.169	-0.0564	0.000932
	(0.132)	(0.114)	(0.489)	(0.141)	(0.0369)
District-years with no orders	Dummied	Dummied	Dummied	Dummied	Dummied
Year and District FEs	Yes	Yes	Yes	Yes	Yes
Case Controls	Yes	Yes	Yes	Yes	Yes
District Controls	-	-	-	-	-
Clustering	IOC	IOC	IOC	IOC	IOC
Eff First Stage F	9.113	7.367	7.559	6.588	7.108
N	3053	5649	5057	5475	5541

Note: All notes of Table 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 Orders	0.166	-0.157	0.690	-0.0415	-0.0268
	(0.433)	(0.186)	(0.815)	(0.230)	(0.0448)
Dummy for Presence of an Order	0.115	0.0353	-0.0704	-0.0784	0.00186
	(0.193)	(0.123)	(0.561)	(0.160)	(0.0443)
District-years with no orders	Dummied	Dummied	Dummied	Dummied	Dummied
Year and District FEs	Yes	Yes	Yes	Yes	Yes
Case Controls	Yes	Yes	Yes	Yes	Yes
District Controls	-	-	-	-	-
Clustering	IOC	IOC	IOC	IOC	IOC
Eff First Stage F	5.228	9.867	13.55	10.51	9.687
N	3053	5649	5057	5475	5541

Note: All notes of Table 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: Pollution Regressions, 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 Orders	-0.141	-0.0424	0.354	0.00738	-0.0152
	(0.0871)	(0.0961)	(0.532)	(0.144)	(0.0263)
Dummy for Presence of an Order	0.268^{***}	0.0872	-0.0721	-0.0565	-0.0147
	(0.103)	(0.126)	(0.541)	(0.142)	(0.0336)
District-years with no orders	Dummied	Dummied	Dummied	Dummied	Dummied
Year and District FEs	Yes	Yes	Yes	Yes	Yes
Case Controls	Yes	Yes	Yes	Yes	Yes
District Controls	-	-	-	-	-
Clustering	IOC	IOC	IOC	IOC	IOC
Eff First Stage F	7.816	8.400	7.734	7.122	7.767
N	3053	4670	4111	4509	4593

Note: All notes of Table 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: Pollution Regressions, 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 Orders	-0.0509	0.0732	0.440	0.0517	0.00504
	(0.179)	(0.134)	(0.304)	(0.129)	(0.0418)
Dummy for Presence of an Order	0.0941	-0.139	0.0344	0.0256	-0.0396
	(0.197)	(0.161)	(0.350)	(0.105)	(0.0417)
District-years with no orders	Dummied	Dummied	Dummied	Dummied	Dummied
Year and District FEs	Yes	Yes	Yes	Yes	Yes
Case Controls	Yes	Yes	Yes	Yes	Yes
District Controls	-	-	-	-	-
Clustering	IOC	IOC	IOC	IOC	IOC
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 3 apply. For the dependent variables however, we rely on minimum values (as opposed to max values in the remainder of the paper).

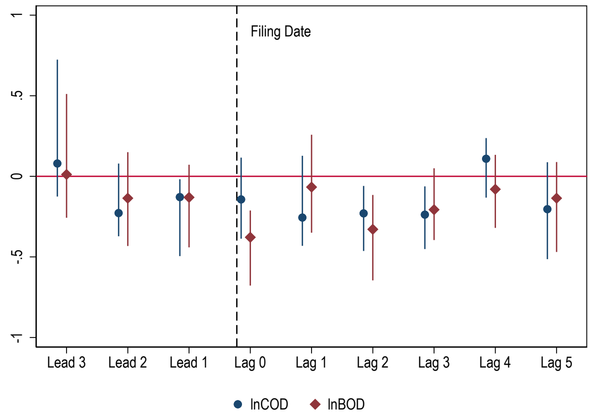
Table OA6: Monthly Mortality Regressions : LSA Instruments

	Baseline Regressions			With Air Pollution Controls		
	(1) Died<1Y	(2) Died<1M	(3) Died<1Y |1M	(4) Died<1Y	(5) Died<1M	(6) Died<1Y |1M
Fraction of Green Orders	0.000268	-0.000737	0.00258	-0.000612	-0.00446	0.00598
	(0.00609)	(0.00590)	(0.00332)	(0.00814)	(0.00662)	(0.00410)
Order Dummy	-0.0108*	-0.00831	-0.00275	-0.00612	-0.00393	-0.00210
	(0.00583)	(0.00516)	(0.00238)	(0.00776)	(0.00765)	(0.00239)
District-years with no orders	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	-	-	-	PM2.5	PM2.5	PM2.5
Clustering	IOC	IOC	IOC	IOC	IOC	IOC
Eff First Stage F	5.074	5.074	5.064	4.197	4.197	4.183
N	188298	188298	188183	101096	101096	101029

All notes of Table 3 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; Analysis is done on a district-year-month level and fixed effects change accordingly to District Year and Month.

Figures with Weak Instrument Robust Confidence Intervals

A. Pollution: Filing Year



B. Pollution: Decision Year

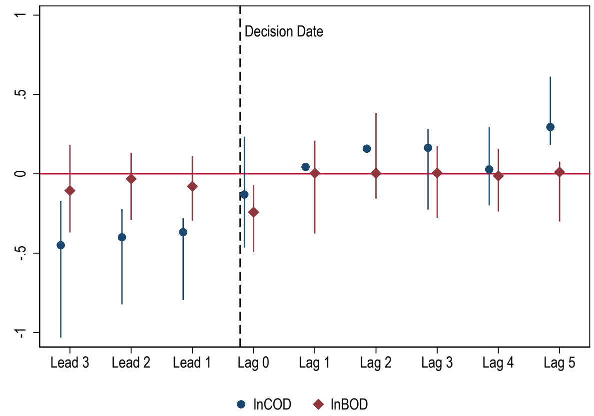
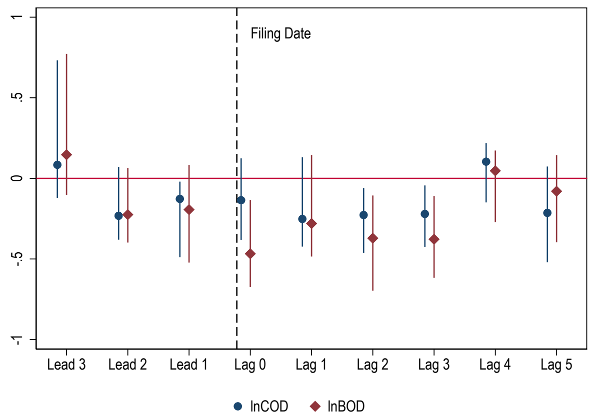


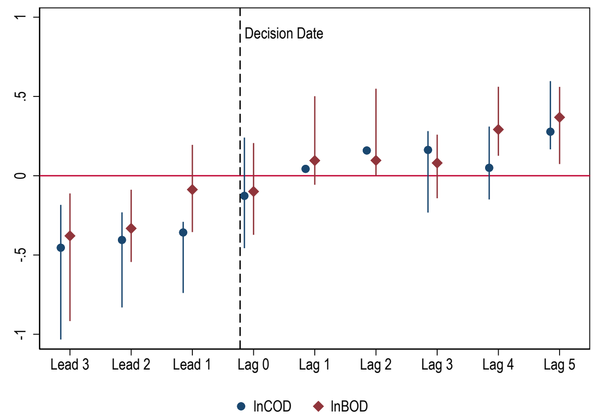
Figure OA1: Dynamic Impacts of Green Orders on Pollution

Note: All notes from Figure 5 apply. Additionally, confidence intervals are robust to weak inference.

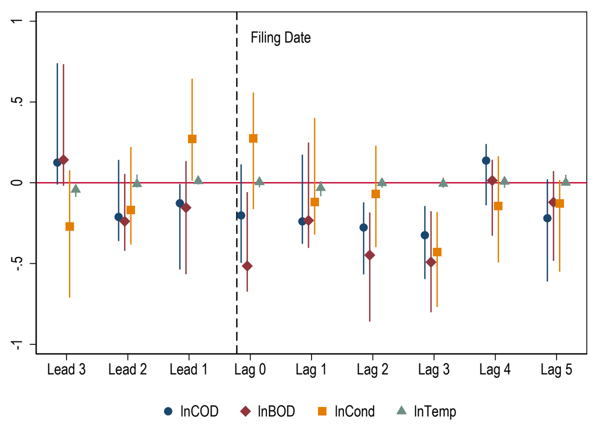
A. Filing: Common Support BOD + COD



B. Decision: Common Support BOD + COD



C. Filing: Common Support All Indicators



D. Decision: Common Support All Indicators

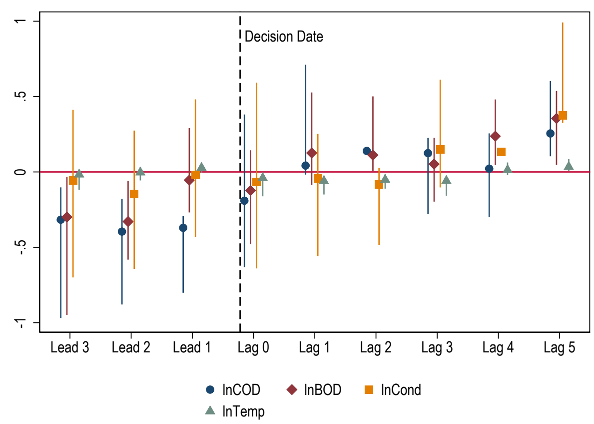


Figure OA2: Dynamic Impacts of Green Orders on Pollution with Common Support

Note: All notes from Figure 6 apply. Additionally, confidence intervals are robust to weak inference.

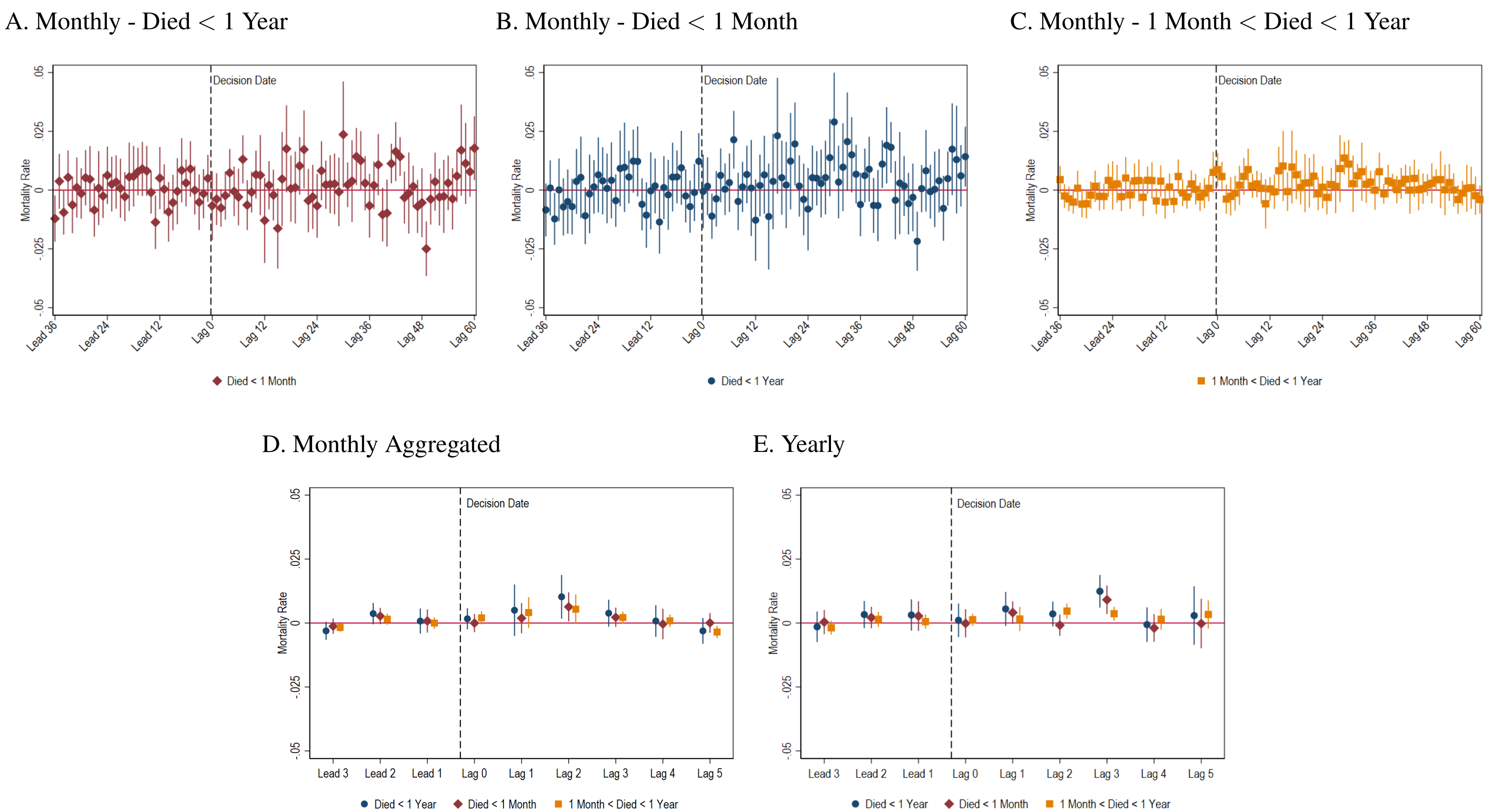


Figure OA3: Dynamic Impacts of Green Orders on Infant Mortality (With Air Pollution Control)

Note: All notes from Figure 7 apply. Additionally, confidence intervals are robust to weak inference.

Tables with Weak Instrument Robust Confidence Intervals

Table OA7: Comparison of Yearly log(BOD) specifications

	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 Orders	0.177	0.209	0.177	0.209	-0.183	-0.270	-0.162	-0.241
	[-0.0719; 0.425]	[-0.234; 0.580]	[-0.0714; 0.425]	[-0.228; 0.574]	[-0.322; -0.0438]	[-0.437; -0.102]	[-0.300; -0.0231]	[-0.494; -0.0701]
Dummy for Presence of an Order			0.202	0.194	0.0814	0.107	0.0366	0.0619
District-years with no orders	Dropped	Dropped	Dummied	Dummied	Dummied	Dummied	Dummied	Dummied
Year and District FEs					Yes	Yes	Yes	Yes
Covariates							Yes	Yes
Clustering	IOC	IOC	IOC	IOC	IOC	IOC	IOC	IOC
Eff. First Stage F		6.567		10.24		.		8.856
N	859	859	5649	5649	5649	5649	5649	5649

Note: (i) Orders 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 orders is equal to 0 if there a no environmental order in a district-year; (iii) Robust standard errors are constructed using "identical order clsuters (IOC)" of district years, pooling together in one cluster all district-years with exactly the same set of water pollution orders; (iv) Included covariates are the district-year means of order characteristics such as whether the government is a respondent and if it is an appeal and or a constitutional case; (v) Fraction of green orders 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 OA8: Contemporaneous Impacts on Water Pollution (Yearly)

	(1)	(2)	(3)	(4)	(5)
	ln(COD)	ln(BOD)	ln(TCOLI)	ln(Conductivity)	ln(Temperature)
Fraction of Green Orders	-0.130	-0.241	-0.0421	-0.0694	-0.0209
	[-0.465; 0.235]	[-0.494; -0.0701]	[-1.028; 0.814]	[-0.255; 0.291]	[-0.0964; 0.0207]
Dummy for Presence of an Order	0.241	0.0619	0.159	-0.0711	0.0000132
District-years with no orders	Dummied	Dummied	Dummied	Dummied	Dummied
Year and District FEs	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes
Clustering	IOC	IOC	IOC	IOC	IOC
Eff First Stage F	7.816	8.856	9.015	7.895	8.401
N	3053	5649	5057	5475	5541

Note: All notes from Table OA7 apply.

Table OA9: Impacts on Water Pollution (3 year moving averages)

	(1) ln(COD)	(2) ln(BOD)	(3) ln(TCOLI)	(4) ln(Conductivity)	(5) ln(Temperature)
Fraction of Green Orders	-0.158	-0.183	-0.0511	0.0406	-0.0333
	[-0.268; 0.0404]	[-0.450; -0.00469]	[-0.940; 0.632]	[-0.0876; 0.370]	[-0.101; 0.0142]
Dummy for Presence of an Order	0.168	0.0667	0.290	-0.0446	0.00317
District-years with no orders	Dummied	Dummied	Dummied	Dummied	Dummied
Year and District FEs	Yes	Yes	Yes	Yes	Yes
Case Controls	Yes	Yes	Yes	Yes	Yes
District Controls	-	-	-	-	-
Clustering	IOC	IOC	IOC	IOC	IOC
Eff First Stage F	7.331	7.910	8.189	7.908	7.897
N	5742	6254	5888	6237	6185

Note: All notes from Table OA7 apply. Dependent and independent variables are 3-year moving averages.

Table OA10: Contemporaneous Impacts on Infant Mortality (Monthly)

	Baseline Regressions			With Air Pollution Controls		
	(1) Died<1Y	(2) Died<1M	(3) Died<1Y |1M	(4) Died<1Y	(5) Died<1M	(6) Died<1Y |1M
Fraction of Green Orders	0.00198	-0.000875	0.00504	-0.000556	-0.00663	0.00873
	[.; .]	[-0.0135; 0.00857]	[0.00269; 0.0161]	[-0.0119; 0.0118]	[.; .]	[0.00782; 0.0193]
Order Dummy	-0.0112	-0.00827	-0.00338	-0.00613	-0.00387	-0.00217
District-year-months with no orders	Dummied	Dummied	Dummied	Dummied	Dummied	Dummied
Month, Year and District FEs	Yes	Yes	Yes	Yes	Yes	Yes
Case Controls	Yes	Yes	Yes	Yes	Yes	Yes
District Controls	-	-	-	PM2.5	PM2.5	PM2.5
Clustering	IOC	IOC	IOC	IOC	IOC	IOC
Eff First Stage F	6.17	6.17	6.15	5.86	5.86	5.84
N	188,298	188,298	188,183	101,096	101,096	101,029

Note: All notes from Table 6 apply. Additionally, confidence intervals are robust to weak instruments.

Table OA11: Neighboring Districts

	(1) ln(COD)	(2) ln(BOD)	(3) ln(TCOLI)	(4) ln(Conductivity)	(5) ln(Temperature)
Neighboring Fraction of Green Orders	-0.242	-0.0911	-0.131	-0.0808	0.00163
	[-0.509; -0.0551]	[-0.299; 0.0592]	[-0.673; 0.945]	[-0.312; 0.119]	[-0.0330; 0.0506]
Order Dummy	0.224	0.0240	0.190	-0.124	-0.0316
District-years with no orders	Dummied	Dummied	Dummied	Dummied	Dummied
Year and District FEs	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes
Clustering	IOC	IOC	IOC	IOC	IOC
Eff First Stage F	11.80	14.09	13.38	13.67	14.09
N	3053	5649	5057	5475	5541

Note: All notes of Table OA7 apply. Additional notes: (i) Neighboring districts are identified using geospatial maps with district boundaries; for each district, we count the number of green orders in neighboring districts (excluding orders in the district itself) and divide that number by the total number of water pollution orders in all neighboring districts.

Table OA12: Impact on the State Level

	(1) ln(COD)	(2) ln(BOD)	(3) ln(TCOLI)	(4) ln(Conductivity)	(5) ln(Temperature)
Fraction of Green Orders per State	-0.168	-0.226	0.113	-0.0441	-0.00502
	[-0.270; 0.00709]	[-0.417; 0.0165]	[-0.759; 0.985]	[-0.237; 0.197]	[-0.0585; 0.0282]
Order in State	0.0173	0.0630	0.0164	-0.0358	0.00205
Order in District	0.171	0.0723	0.238	0.0449	-0.000642
District-years with no orders	Dummied	Dummied	Dummied	Dummied	Dummied
Year and District FEs	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes
Clustering	IOC	IOC	IOC	IOC	IOC
Eff First Stage F	21.81	14.15	14.93	13.80	13.86
N	3049	5619	5055	5446	5510

Note: All notes of Tables OA7 and OA11 apply.

Table OA13: Pollution Regressions with District-Level Controls

	(1) ln(COD)	(2) ln(BOD)	(3) ln(TCOLI)	(4) ln(Conductivity)	(5) ln(Temperature)
Fraction of Green Orders	-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 an Order	0.159	0.0933	-0.346	-0.0998	0.0230
District-years with no orders	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	IOC	IOC	IOC	IOC	IOC
Eff First Stage F	1.361	4.404	3.988	4.553	4.351
N	961	2126	1852	2266	2073

Note: (i) Orders 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 orders is equal to 0 if there a no orders in a district-year; (iii) Robust standard errors are constructed using "identical order clusters (IOC)" of district years, pooling together in one cluster all district-years with exactly the same set of water pollution orders; (iv) District controls, from SHRUGG, include nighttime lights and forest cover; (v) Fraction of green orders 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 OA14: Yearly Mortality Regressions

	Baseline Regressions			With Air Pollution Controls			With Air Pollution + Shrug Controls		
	(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 Orders	0.000607	-0.000351	0.00103	0.00106	-0.000127	0.00128	-0.00107	-0.00139	0.000313
	[-0.00571; 0.00534]	[-0.00644; 0.00277]	[-0.000828; 0.00458]	[-0.00615; 0.00588]	[-0.00668; 0.00287]	[-0.000216; 0.00513]	[-0.00749; 0.00604]	[-0.00665; 0.00304]	[-0.00170; 0.00641]
Order Dummy	0.00461	0.00321	0.00148	0.00490	0.00334	0.00165	0.00458	0.00390	0.000708
District-years with no orders	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	-	-	-	PM2.5	PM2.5	PM2.5	PM2.5 + Shrug	PM2.5 + Shrug	PM2.5 + Shrug
Clustering	IOC	IOC	IOC	IOC	IOC	IOC	IOC	IOC	IOC
Eff First Stage F	7.360	7.360	7.360	7.373	7.373	7.373	6.788	6.788	6.788
N	8482	8482	8482	8482	8482	8482	6776	6776	6776

Note: Notes from Table OA13 apply.

Table OA15: Effects of Sample Selection when adding Air Pollution Control

	Full Sample			Only if PM2.5 Available			Including PM2.5		
	(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 Orders	0.00198	-0.000875	0.00504	-0.000563	-0.00661	0.00870	-0.000556	-0.00663	0.00873
	[.; .]	[-0.0135; 0.00857]	[0.00269; 0.0161]	[-0.0121; 0.0118]	[.; .]	[0.00788; 0.0192]	[-0.0119; 0.0118]	[.; .]	[0.00782; 0.0193]
Order Dummy	-0.0112	-0.00827	-0.00338	-0.00611	-0.00390	-0.00212	-0.00613	-0.00387	-0.00217
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	-	-	-	-	-	-	PM2.5	PM2.5	PM2.5
Clustering	IOC	IOC	IOC	IOC	IOC	IOC	IOC	IOC	IOC
Eff First Stage F	6.173	6.173	6.154	5.862	5.862	5.837	5.862	5.862	5.837
N	188298	188298	188183	101096	101096	101029	101096	101096	101029

Note: Notes from Table OA13 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 OA16: Neighboring Districts w/o Cities

	(1) ln(COD)	(2) ln(BOD)	(3) ln(TCOLI)	(4) ln(Conductivity)	(5) ln(Temperature)
Neighboring Fraction of Green Orders	-0.273	-0.0155	-0.120	-0.0683	-0.0159
	[-0.488; -0.109]	[-0.207; 0.141]	[-0.642; 0.736]	[-0.268; 0.0879]	[-0.0335; 0.0196]
Order Dummy	0.227	0.00257	0.0457	-0.192	-0.0291
District-years with no orders	Dummied	Dummied	Dummied	Dummied	Dummied
Year and District FEs	Yes	Yes	Yes	Yes	Yes
Case Controls	Yes	Yes	Yes	Yes	Yes
District Controls	-	-	-	-	-
Clustering	IOC	IOC	IOC	IOC	IOC
Eff First Stage F	10.15	11.54	11.17	12.00	11.45
N	2908	5383	4810	5219	5282

Note: All notes from Table OA11 apply.

Table OA17: Yearly Pollution Regressions LSA

	(1) ln(COD)	(2) ln(BOD)	(3) ln(TCOLI)	(4) ln(Conductivity)	(5) ln(Temperature)
Fraction of Green Orders	-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 an Order	0.219	0.0567	0.0593	-0.0750	-0.00153
District-years with no orders	Dummied	Dummied	Dummied	Dummied	Dummied
Year and District FEs	Yes	Yes	Yes	Yes	Yes
Case Controls	Yes	Yes	Yes	Yes	Yes
District Controls	-	-	-	-	-
Clustering	IOC	IOC	IOC	IOC	IOC
Eff First Stage F	11.21	4.912	4.659	4.351	4.791
N	3053	5649	5057	5475	5541

Note: All notes of Table OA7 apply. Instruments are constructed using the LSA method (as opposed to the D2V method used in the rest of the paper).

Table OA18: Yearly Pollution Regressions D2V + LSA

	(1) ln(COD)	(2) ln(BOD)	(3) ln(TCOLI)	(4) ln(Conductivity)	(5) ln(Temperature)
Fraction of Green Orders	-0.136	-0.182	-0.0761	-0.125	-0.0238
	[-0.245; 0.224]	[-0.260; 0.0669]	[-1.257; 1.092]	[-0.276; 0.195]	[-0.100; -0.00732]
Dummy for Presence of an Order	0.243	0.0432	0.169	-0.0564	0.000932
District-years with no orders	Dummied	Dummied	Dummied	Dummied	Dummied
Year and District FEs	Yes	Yes	Yes	Yes	Yes
Case Controls	Yes	Yes	Yes	Yes	Yes
District Controls	-	-	-	-	-
Clustering	IOC	IOC	IOC	IOC	IOC
Eff First Stage F	9.113	7.367	7.559	6.588	7.108
N	3053	5649	5057	5475	5541

Note: All notes of Table OA7 apply. Instruments are constructed using both the LSA method and the D2V method used in the rest of the paper.

Table OA19: Yearly Pollution Regressions D2V + LSA + Lasso

	(1) ln(COD)	(2) ln(BOD)	(3) ln(TCOLI)	(4) ln(Conductivity)	(5) ln(Temperature)
Fraction of Green Orders	0.166	-0.157	0.690	-0.0415	-0.0268
	[.; .]	[-0.562; 0.345]	[.; .]	[-0.557; 0.430]	[-0.126; 0.0640]
Dummy for Presence of an Order	0.115	0.0353	-0.0704	-0.0784	0.00186
District-years with no orders	Dummied	Dummied	Dummied	Dummied	Dummied
Year and District FEs	Yes	Yes	Yes	Yes	Yes
Case Controls	Yes	Yes	Yes	Yes	Yes
District Controls	-	-	-	-	-
Clustering	IOC	IOC	IOC	IOC	IOC
Eff First Stage F	5.228	9.867	13.55	10.51	9.687
N	3053	5649	5057	5475	5541

Note: All notes of Table OA7 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 OA20: 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 Orders	-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 an Order	0.268	0.0872	-0.0721	-0.0565	-0.0147
District-years with no orders	Dummied	Dummied	Dummied	Dummied	Dummied
Year and District FEs	Yes	Yes	Yes	Yes	Yes
Case Controls	Yes	Yes	Yes	Yes	Yes
District Controls	-	-	-	-	-
Clustering	IOC	IOC	IOC	IOC	IOC
Eff First Stage F	7.816	8.400	7.734	7.122	7.767
N	3053	4670	4111	4509	4593

Note: All notes of Table OA7 apply. For the dependent variables however, we rely on mean values (as opposed to max values in the remainder of the paper).

Table OA21: 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 Orders	-0.0509	0.0732	0.440	0.0517	0.00504
	[-0.176; 0.552]	[.; .]	[0.127; 1.214]	[-0.150; 0.315]	[-0.0488; 0.112]
Dummy for Presence of an Order	0.0941	-0.139	0.0344	0.0256	-0.0396
District-years with no orders	Dummied	Dummied	Dummied	Dummied	Dummied
Year and District FEs	Yes	Yes	Yes	Yes	Yes
Case Controls	Yes	Yes	Yes	Yes	Yes
District Controls	-	-	-	-	-
Clustering	IOC	IOC	IOC	IOC	IOC
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 OA7 apply. For the dependent variables however, we rely on minimum values (as opposed to max values in the remainder of the paper).

Table OA22: Monthly Mortality Regressions : LSA Instruments

	Baseline Regressions			With Air Pollution Controls		
	(1)	(2)	(3)	(4)	(5)	(6)
	Died$<$1Y	Died$<$1M	Died$<$1Y |1M	Died$<$1Y	Died$<$1M	Died$<$1Y |1M
Fraction of Green Orders	0.000268	-0.000737	0.00258	-0.000612	-0.00446	0.00598
	[-0.0224; 0.0166]	[-0.0228; 0.00808]	[-0.00405; 0.00704]	[.; .]	[.; .]	[.; .]
Order Dummy	-0.0108	-0.00831	-0.00275	-0.00612	-0.00393	-0.00210
District-years with no orders	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	-	-	-	PM2.5	PM2.5	PM2.5
Clustering	IOC	IOC	IOC	IOC	IOC	IOC
Eff First Stage F	5.074	5.074	5.064	4.197	4.197	4.183
N	188298	188298	188183	101096	101096	101029

All notes of Table OA7 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; Analysis is done on a district-year-month level and fixed effects change accordingly to District Year and Month.

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 OA23 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 3).

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 OA23: First Stage Regressions

Panel A: Judge Level	Median Coded Environmental Impact			
	(1)	(2)	(3)	(4)
JudgePostGrad	0.0842	0.262^{*}	0.187^{**}	0.175^{**}
	(0.111)	(0.143)	(0.0873)	(0.0890)
Other Instruments	25 D2V vectors			
Assigned districts	One	All	All	All
District + year FEs	-	-	Yes	Yes
Case-level controls	-	-	-	Yes
Eff First Stage F	2.535	4.047	2.595	2.683
N	764	3313	3313	3313

Panel B: Order Level	Median Coded Environmental Impact			
	(1)	(2)	(3)	(4)
JudgePostGrad	0.184^{*}	0.402	0.185^{*}	0.194^{*}
	(0.104)	(0.254)	(0.0969)	(0.0997)
Other Instruments	25 D2V vectors			
Assigned districts	One	All	All	All
District + year FEs	-	-	Yes	Yes
Case-level controls	-	-	-	Yes
Eff First Stage F	1.639	3.709	4.960	5.122
N	518	2795	2795	2795

Panel C: Order Level	Green Order			
	(1)	(2)	(3)	(4)
JudgePostGrad	0.133^{*}	0.285^{**}	0.157^{***}	0.157^{***}
	(0.0716)	(0.132)	(0.0558)	(0.0567)
Other Instruments	25 D2V vectors			
Assigned districts	One	All	All	All
District + year FEs	-	-	Yes	Yes
Case-level controls	-	-	-	Yes
Eff First Stage F	1.505	4.575	6.583	5.560
N	518	2795	2795	2795

Panel D: District-Year Merged with BOD	Fraction of Green Orders			
	(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 an Order		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 orders	Dropped	Dummied	Dummied	Dummied
Eff First Stage F	6.567	10.24	8.413	8.856
N	859	5649	5649	5649

Panel E: District-Year-Month Merged with Mortality	Fraction of Green Orders			
	(1)	(2)	(3)	(4)
Majority Judges have a Post Graduate Degree (mean)	0.229^{**}	0.229^{**}	0.229^{**}	0.219^{**}
	(0.113)	(0.112)	(0.111)	(0.111)
Order Dummy		0.181	0.180	0.0152
		(0.124)	(0.123)	(0.141)
Other Instruments	25 D2V vectors			
Assigned districts	All	All	All	All
District + Year + Month FEs	-	-	Yes	Yes
Case-level controls	-	-	-	Yes
District-years with no orders	Dropped	Dummied	Dummied	Dummied
Eff First Stage F	3.491	5.484	5.566	6.243
N	1931	260876	260876	260876

Note: All notes from Table 3 apply.

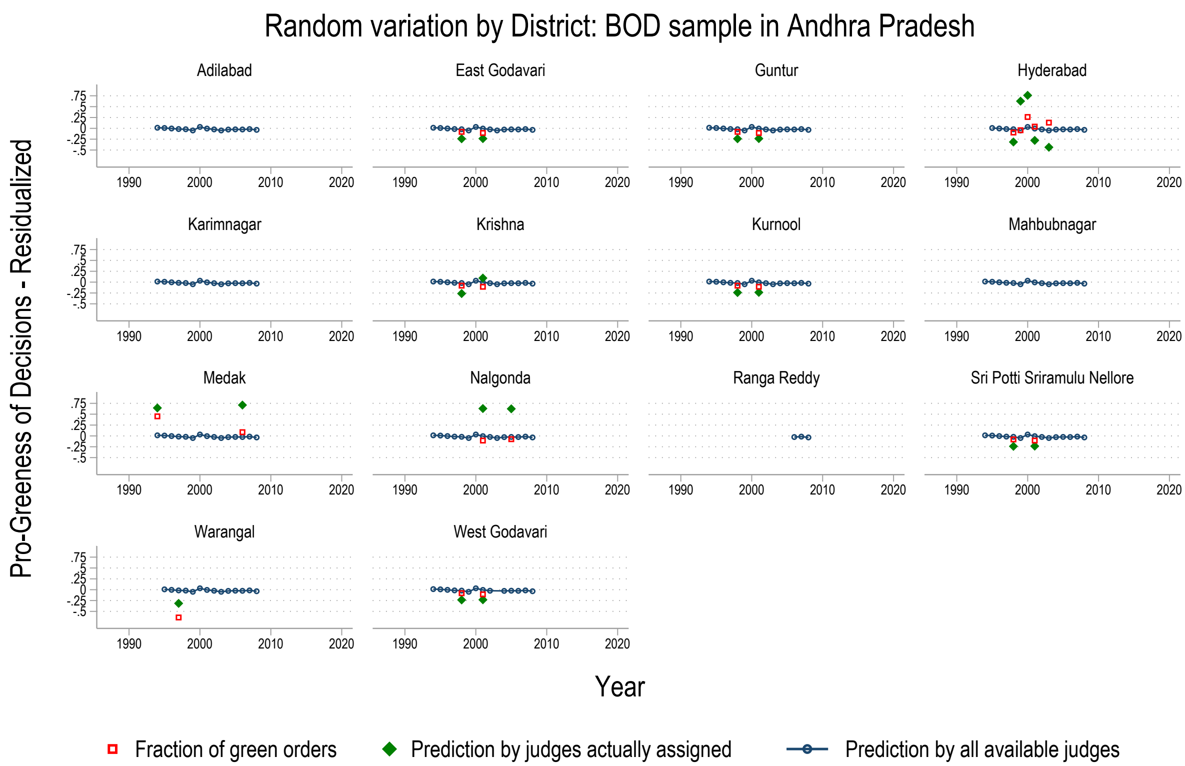


Figure OA4: Random Variation in Judge assignment in Andhra Pradesh

Note: Green diamonds depict the real coded fraction of green cases in our sample for district-years with at least one case. Red squares depict the predicted fraction of green cases using our standard regression using the 26 instruments that include the 25 D2Vs and the average of the postgraduate dummy variable from the judges on the full bench of judges that heard a case with controls for case characteristics (Case Dummy, the share of cases with government as respondent, the share of appeal cases, share of constitutional cases), and district and year dummies. Blue circles represent the same regression as described above but with the 25 D2Vs and the average of the postgraduate dummy for *all* judges serving in the year at the HC, i.e. not just judges who heard a case.

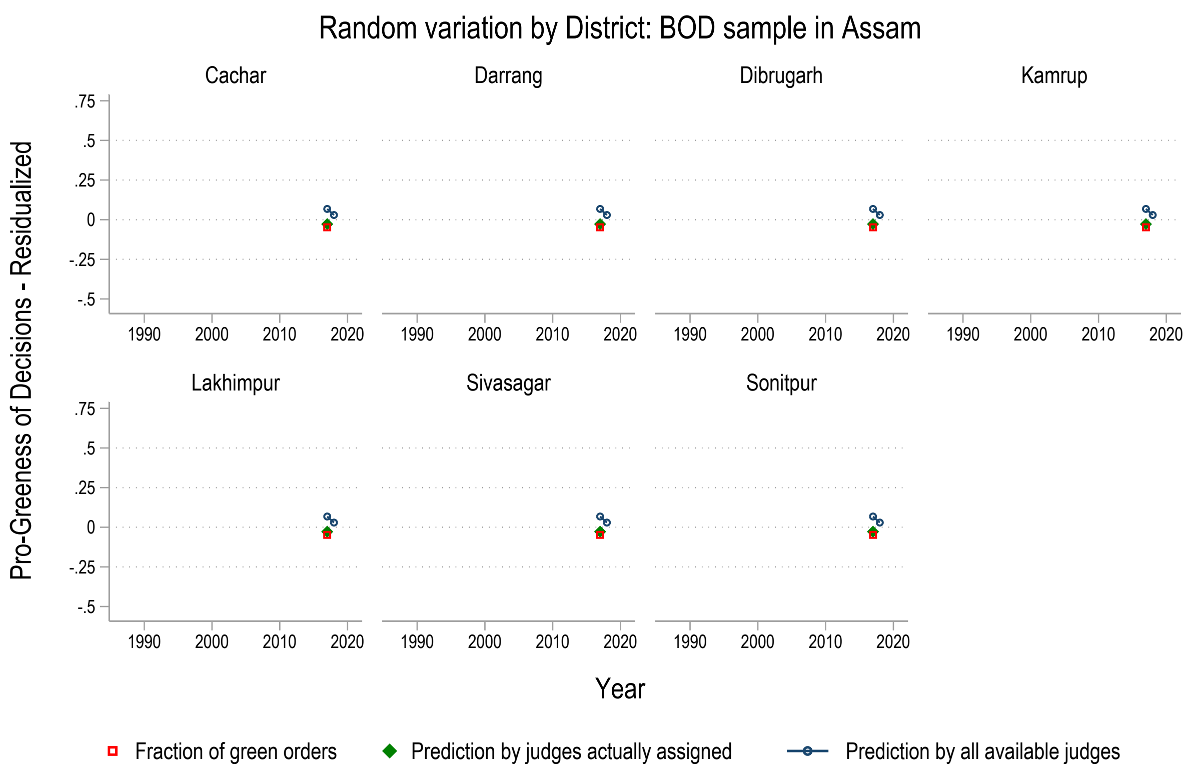


Figure OA5: Random Variation in Judge assignment in Assam

Note: Notes of Figure OA4 apply.

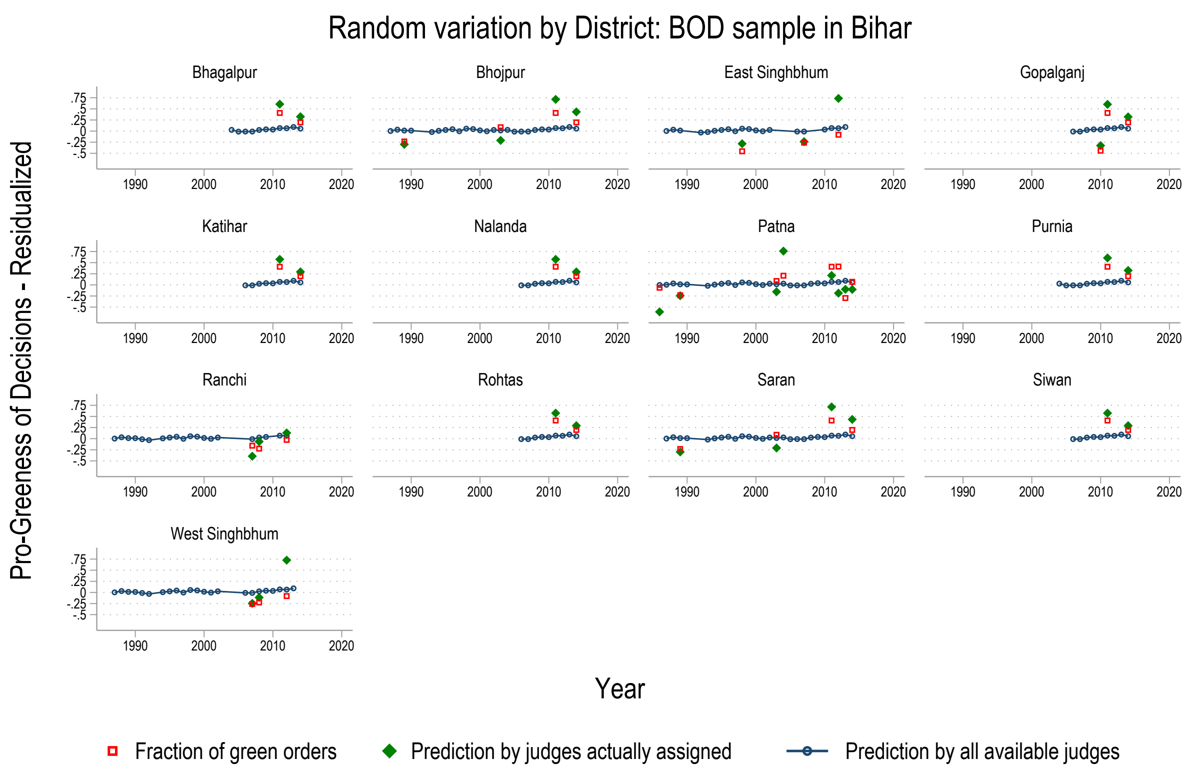


Figure OA6: Random Variation in Judge assignment in Bihar

Note: Notes of Figure OA4 apply.

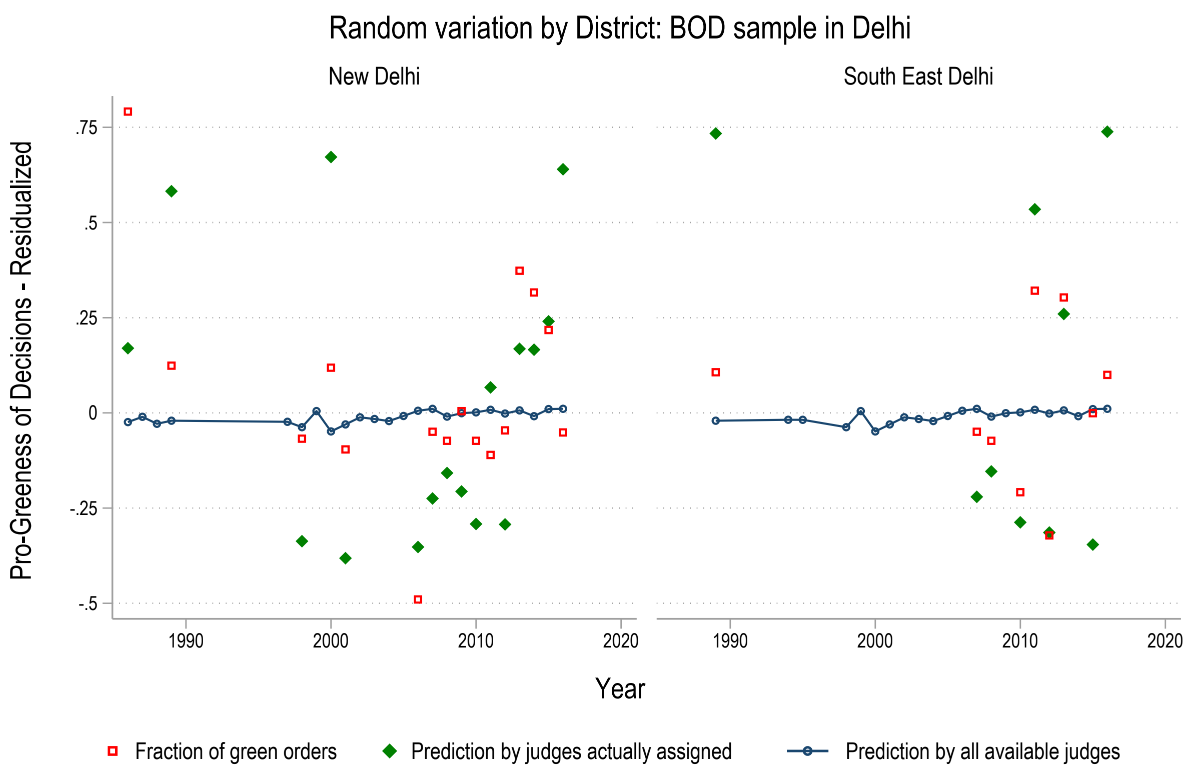


Figure OA7: Random Variation in Judge assignment in Delhi

Note: Notes of Figure OA4 apply.

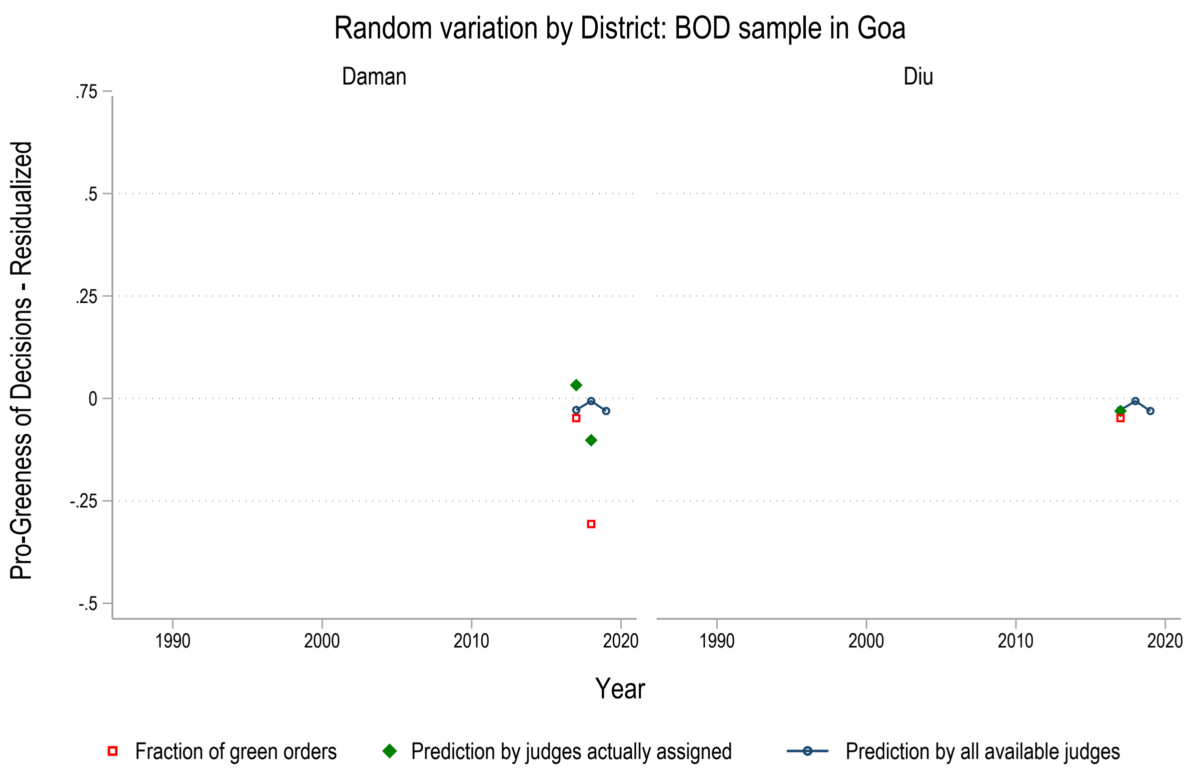


Figure OA8: Random Variation in Judge assignment in Goa

Note: Notes of Figure OA4 apply.

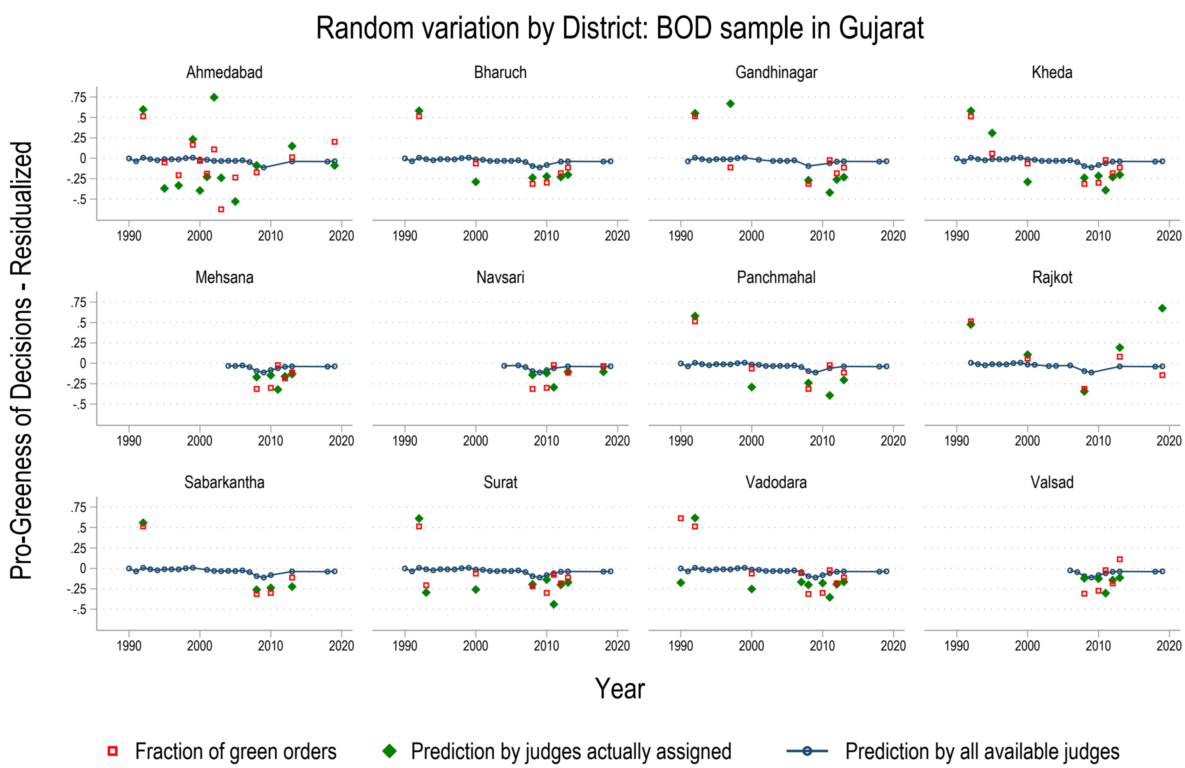


Figure OA9: Random Variation in Judge assignment in Gujarat

Note: Notes of Figure OA4 apply.

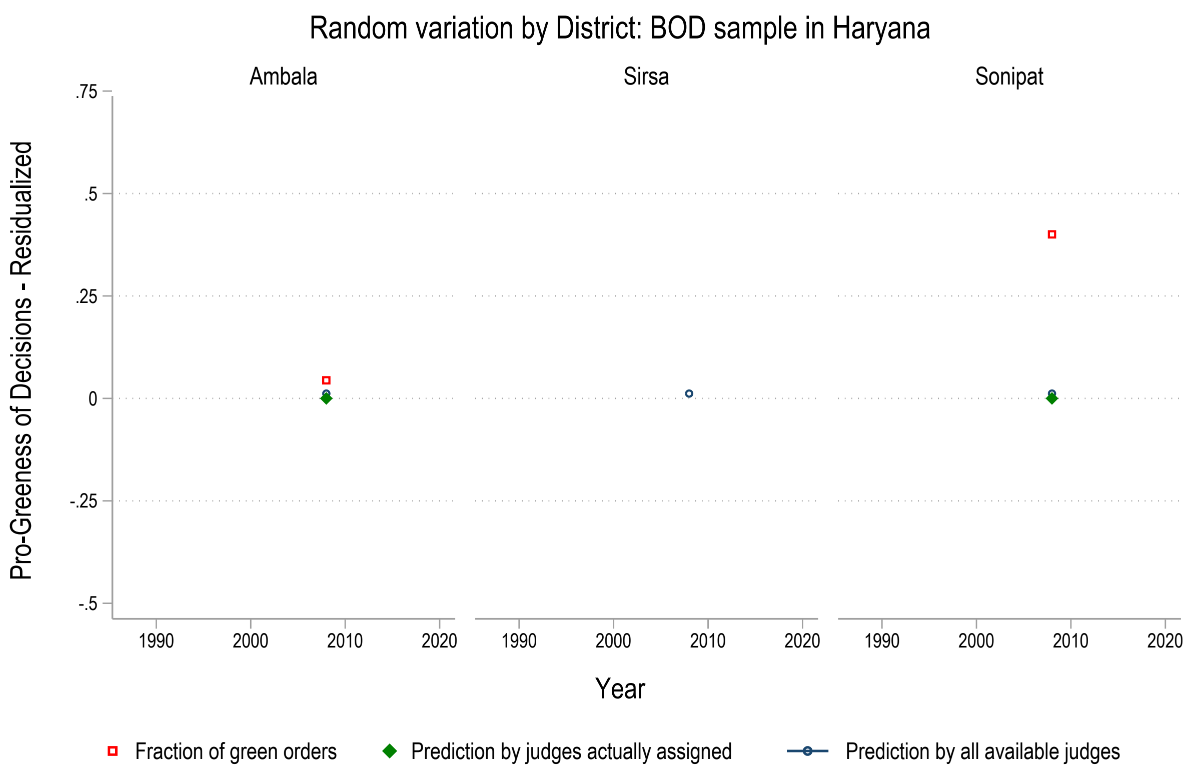


Figure OA10: Random Variation in Judge assignment in Haryana

Note: Notes of Figure OA4 apply.

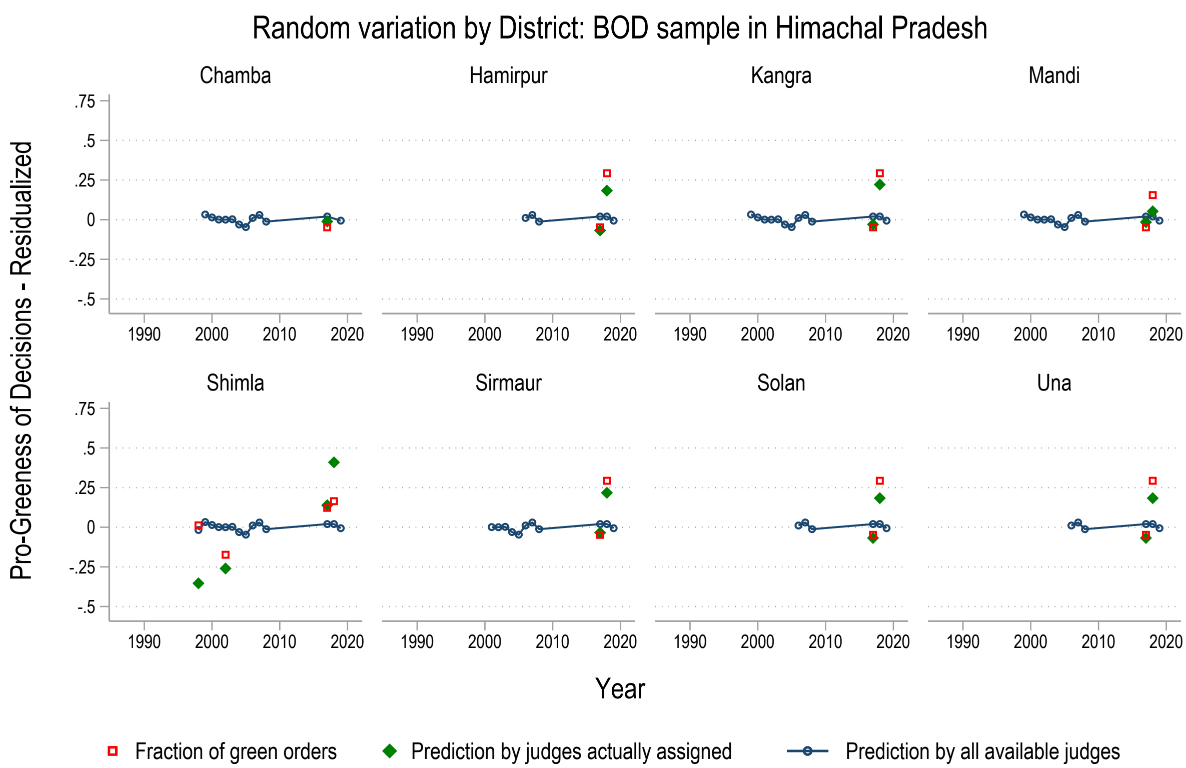


Figure OA11: Random Variation in Judge assignment in Himachal Pradesh

Note: Notes of Figure OA4 apply.

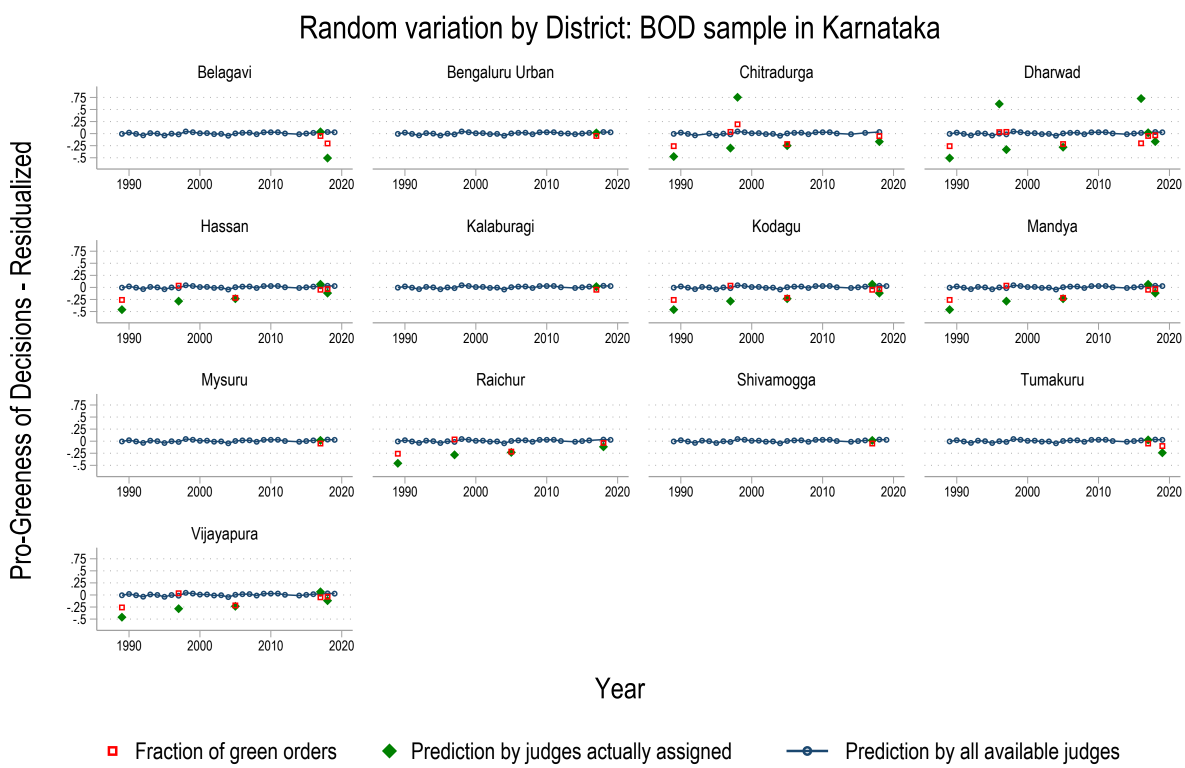


Figure OA12: Random Variation in Judge assignment in Karnataka

Note: Notes of Figure OA4 apply.

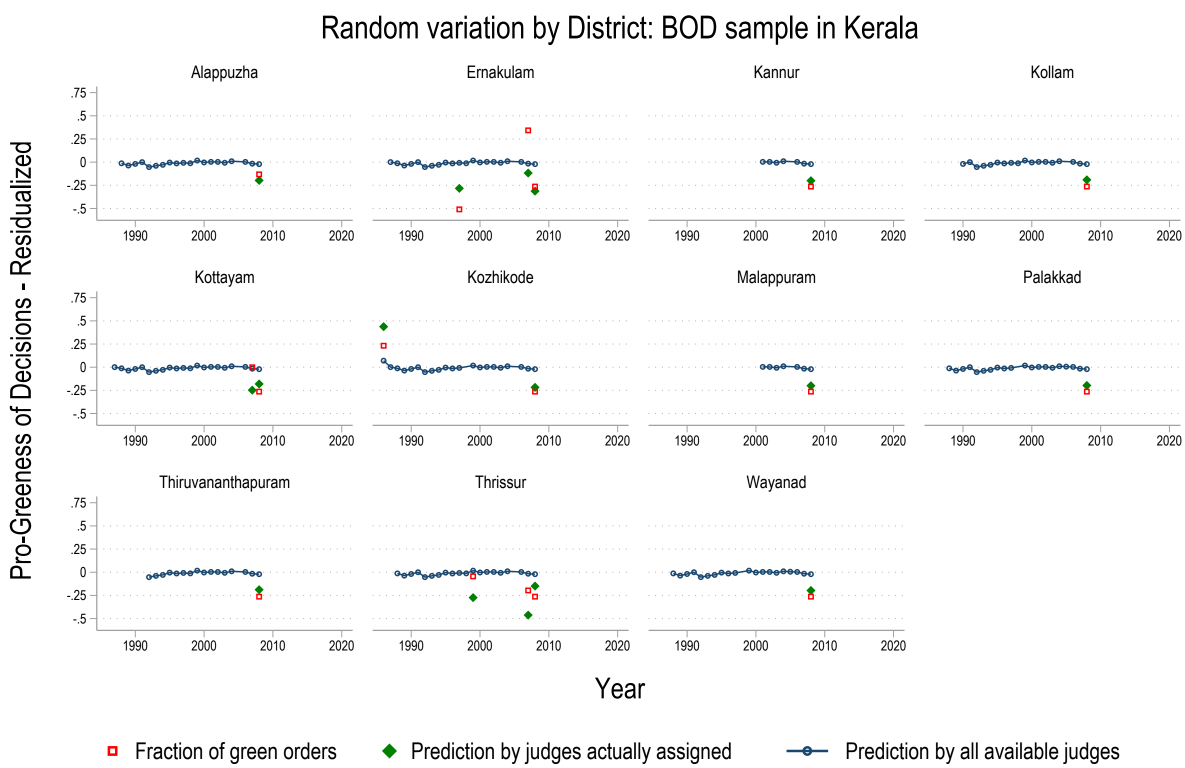


Figure OA13: Random Variation in Judge assignment in Kerala

Note: Notes of Figure OA4 apply.

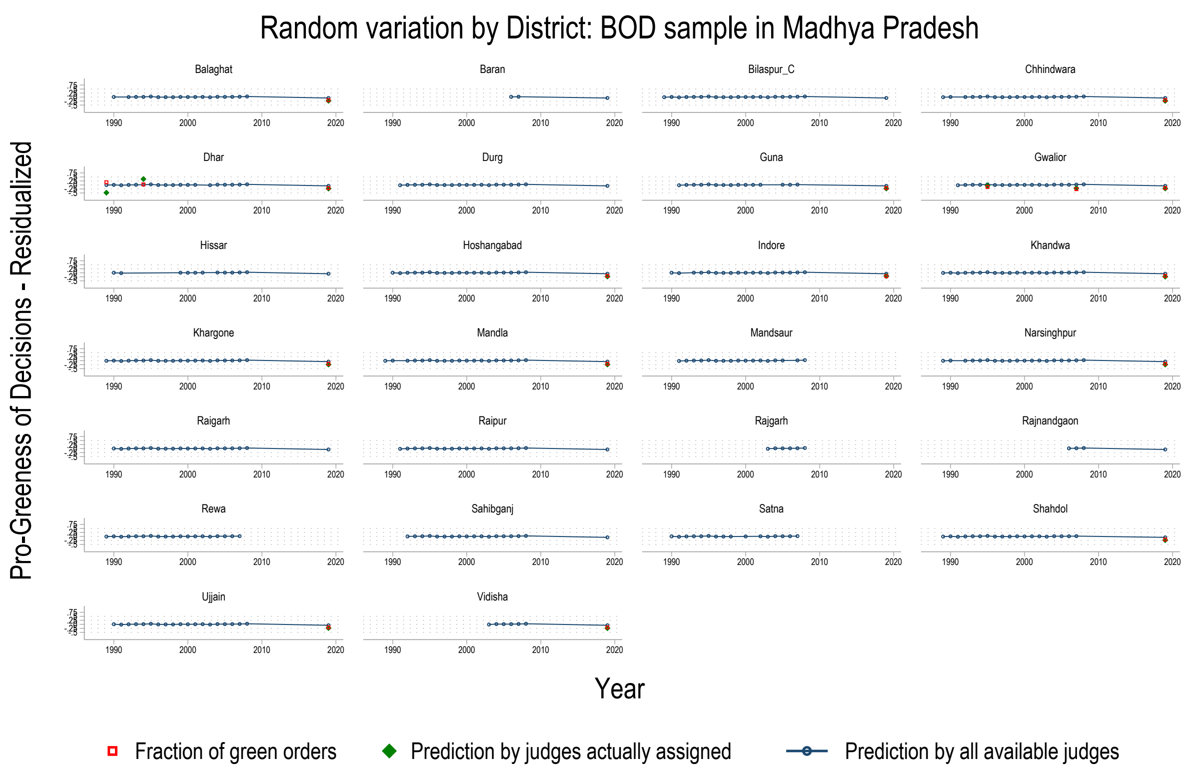


Figure OA14: Random Variation in Judge assignment in Madhya Pradesh

Note: Notes of Figure OA4 apply.

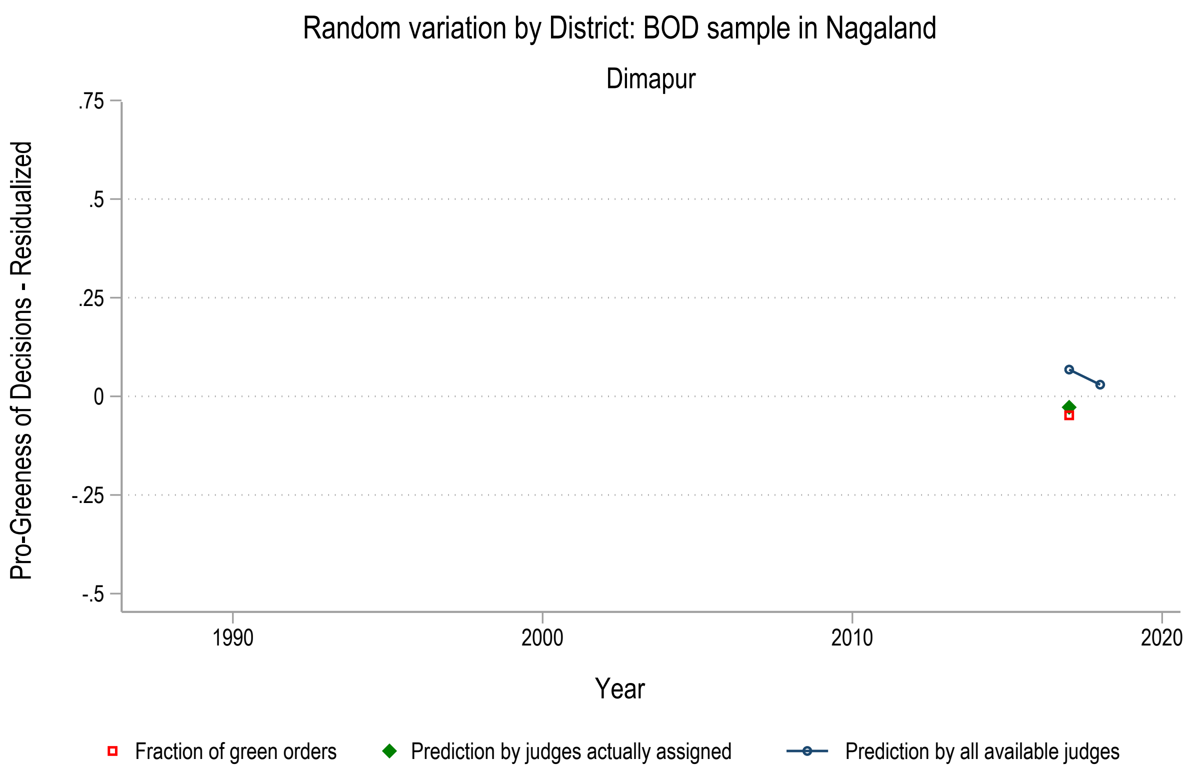


Figure OA15: Random Variation in Judge assignment in Nagaland

Note: Notes of Figure OA4 apply.

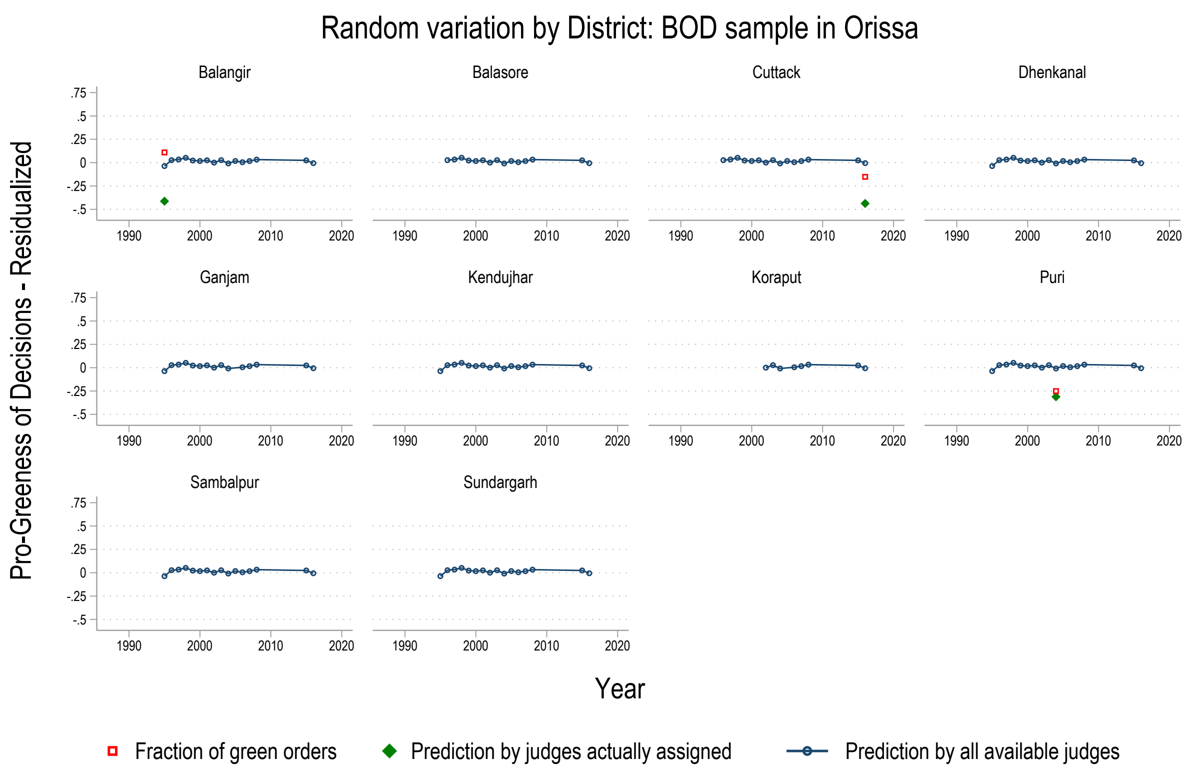


Figure OA16: Random Variation in Judge assignment in Orissa

Note: Notes of Figure OA4 apply.

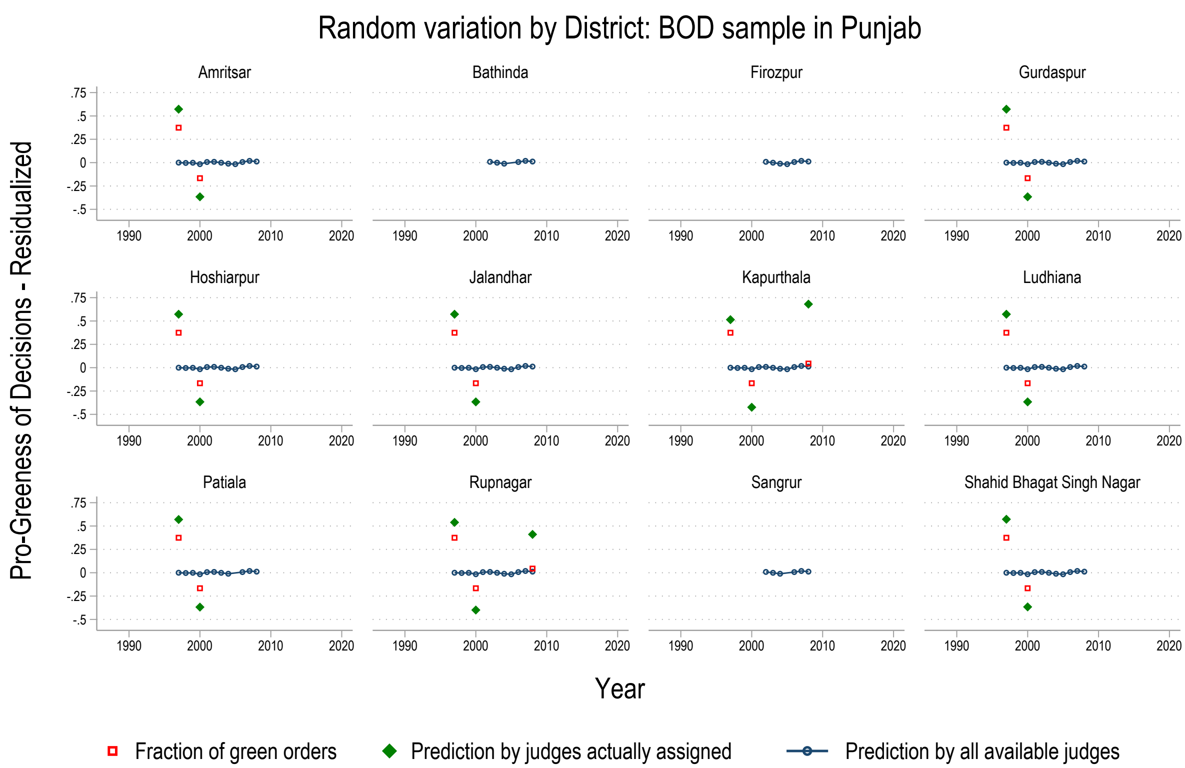


Figure OA17: Random Variation in Judge assignment in Punjab

Note: Notes of Figure OA4 apply.

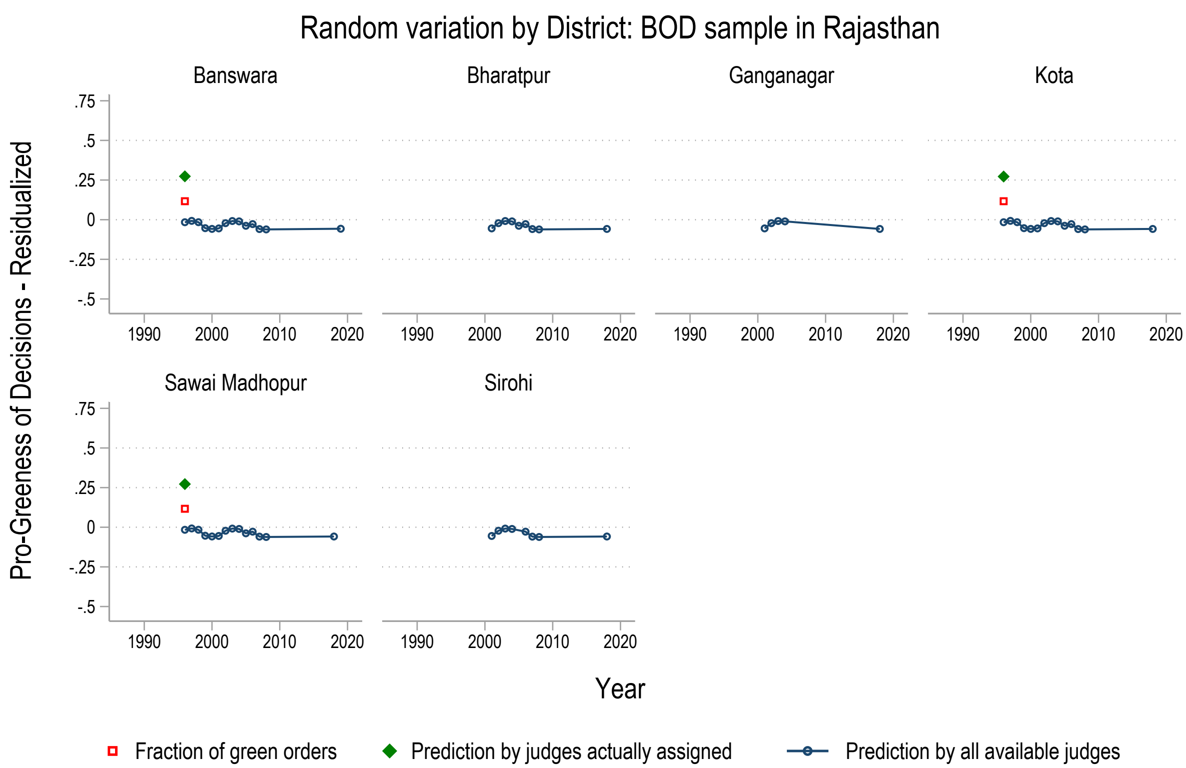


Figure OA18: Random Variation in Judge assignment in Rajasthan

Note: Notes of Figure OA4 apply.

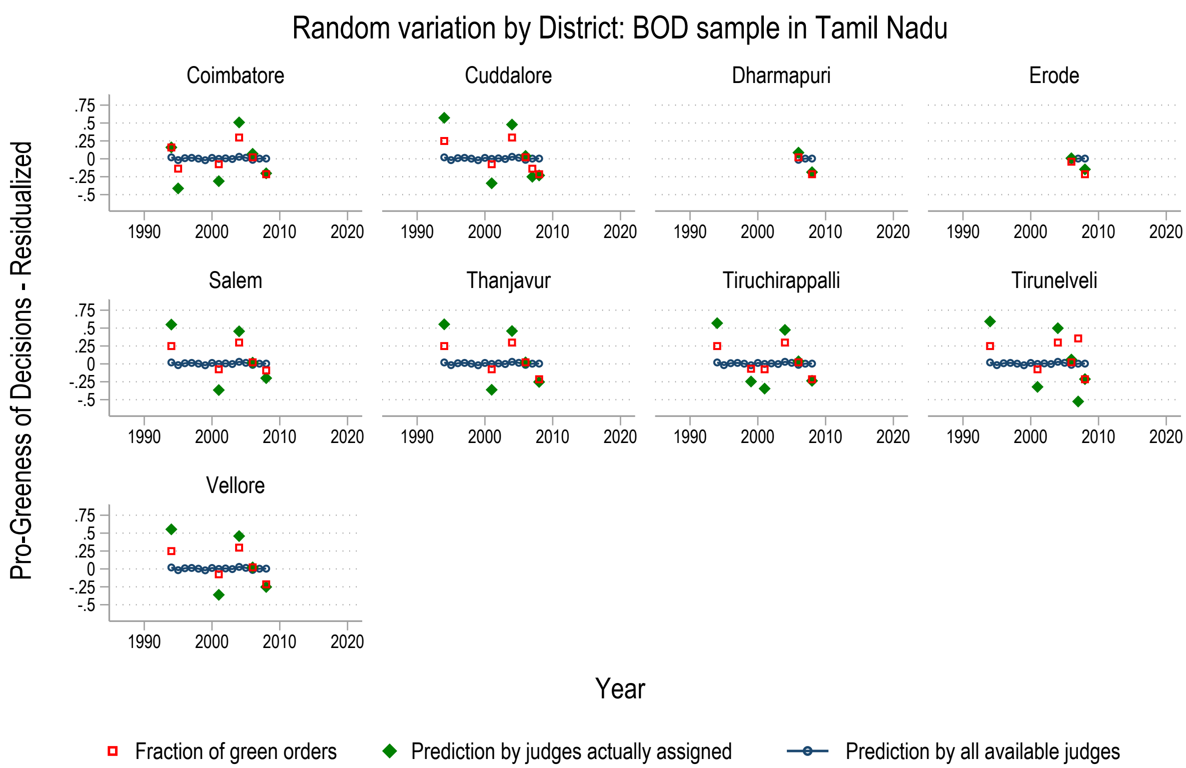


Figure OA19: Random Variation in Judge assignment in Tamil Nadu

Note: Notes of Figure OA4 apply.

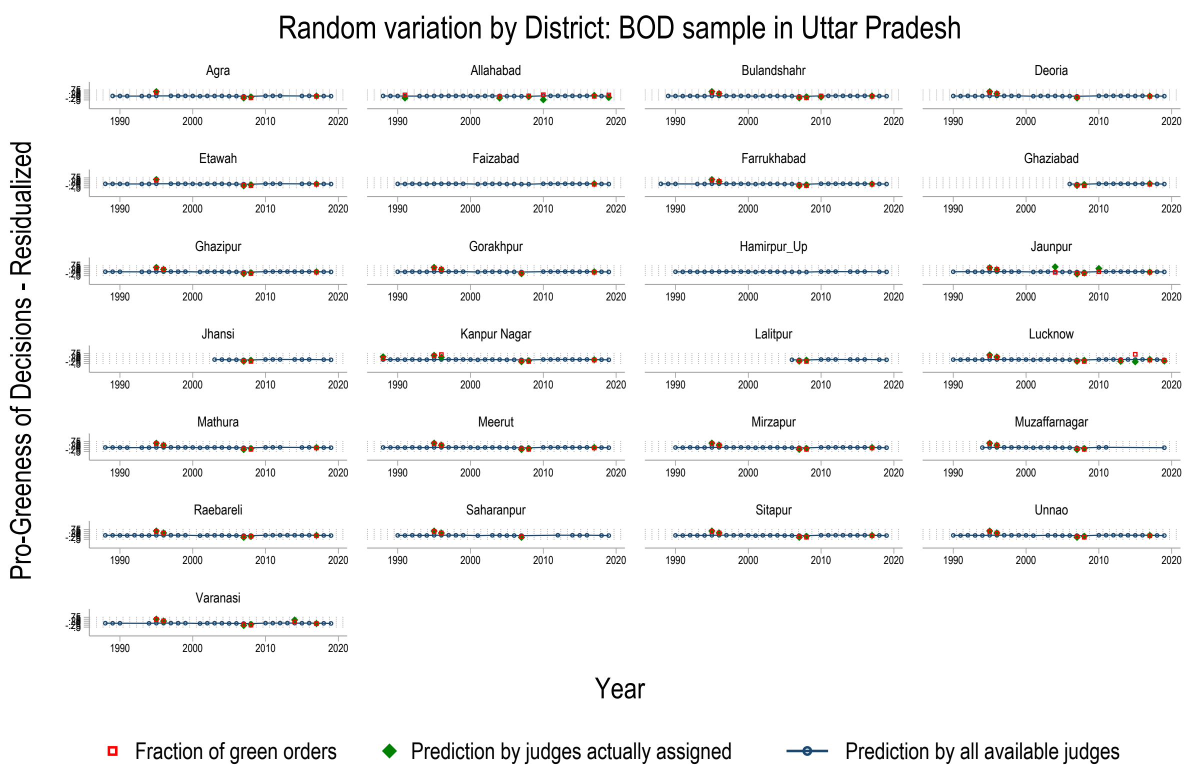


Figure OA20: Random Variation in Judge assignment in Uttar Pradesh

Note: Notes of Figure OA4 apply.

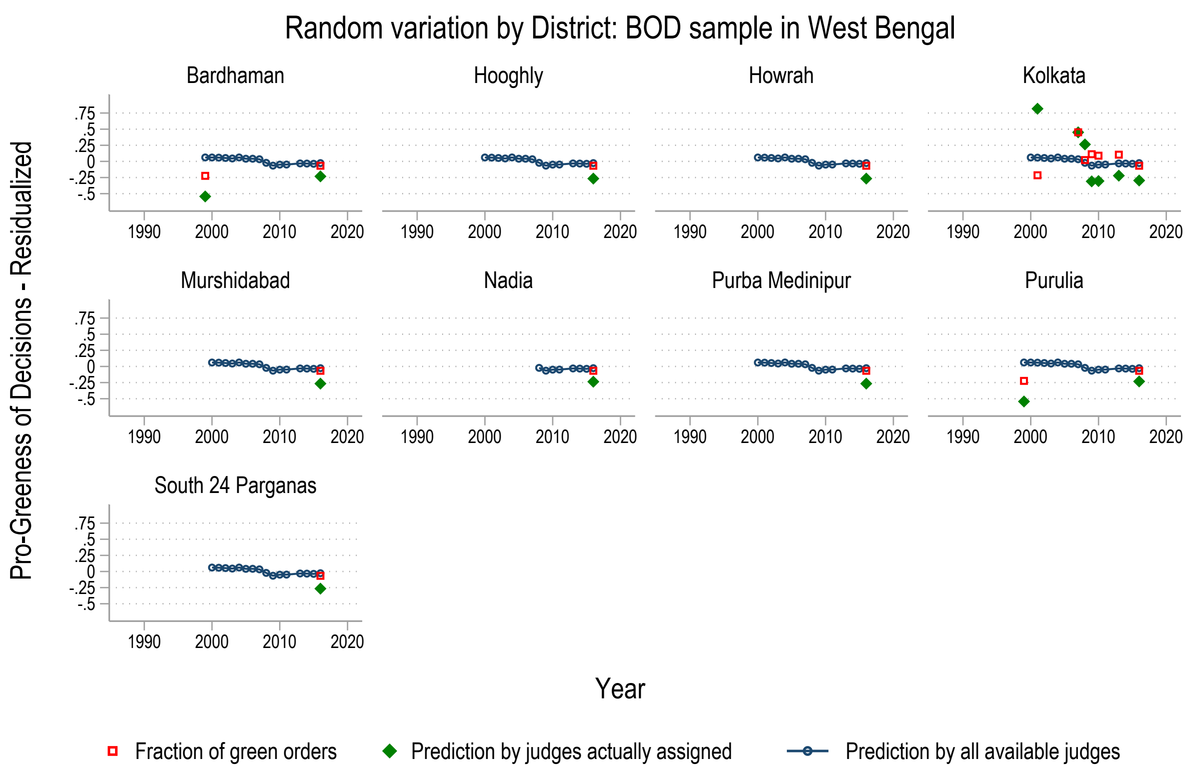


Figure OA21: Random Variation in Judge assignment in West Bengal

Note: Notes of Figure OA4 apply.