Environmental Litigation as Scrutiny: A Four Decade Analysis of Justice, Firms, and Pollution in India

Sandeep Bhupatiraju, Daniel L. Chen, Shareen Joshi, Peter Neis, and Shashank Singh*

October 24, 2024

This study investigates the impact of judicial enforcement on environmental outcomes in India, using a unique dataset spanning four decades that includes court cases, pollution data, corporate finances, and infant mortality rates. Leveraging the quasi-random assignment of cases to judges and their writing styles, we find evidence consistent with litigation as scrutiny. Findings show that environmental litigation leads to temporary reductions in pollution and affects firm performance during legal proceedings. However, pollution levels rebound post-litigation, with no significant effect at anytime on infant mortality. This highlights the limited efficacy of judicial environmental interventions in highly polluted contexts like India.

JEL Codes: Q53, Q56, C36, K32, K40

Keywords: environmental justice, development, pollution, infant mortality.

---

*Bhupatiraju: World Bank, 1818 H Street Washington, DC 20433 (e-mail: sbhupatiraju@worldbank.org); Chen: Toulouse School of Economics, Université Toulouse Capitole, Toulouse, France (e-mail: daniel.chen@iast.fr); Joshi: Walsh School of Foreign Service, Georgetown University, 3700 O Street, Washington DC, 20057 (e-mail: shareen.joshi@georgetown.edu); Neis: Université Clermont Auvergne, CNRS, IRD, CERDI, F-63000, Clermont-Ferrand, France (e-mail: peter.neis@uca.fr); Singh: The University of Chicago Booth School of Business (e-mail: shashank.singh@chicagobooth.edu). We are grateful to Lechuan Qiu, Ritesh Das, Samik Maini, Viknesh Nagarathinam, Shevani Tiwari, Shilpa Rao, Sunny Anand, Kasturi Kadalam, Praharsha Enagandula, Akhilesh Rajagopalan, Connor Brennan, Aanika Veedon and an outstanding team of law students from National University of Juridical Sciences in India for valuable research assistance in coding cases. We are also grateful to Samuel Asher, Patrick Behrer, Jonathan Colmer, Vincenzo Di Maro, Quy Toan Do, Jishnu Das, Shibani Ghosh, Jessica Goldberg, Paul Novosad, Vikram Raghavan, Vasujith Ram, Manaswini Rao, Vijayendra Rao, Martin Ravallion, Nicholas Robinson, Daniel Rogger, Sheetal Sekhri, Mrinal Satish, Nayantara Vohra and Andrew Zeitlin for very helpful advice, critical insights and very stimulating discussions. We are also grateful to the World Bank Research Support Budget and Georgetown University's Laudato Si grant opportunity for financial support. Daniel L. Chen acknowledges IAST funding from the French National Research Agency (ANR) under the Investments for the Future (Investissements d'Avenir) program, grant ANR-17-EUR-0010. Peter Neis gratefully acknowledges the support received from the *Agence Nationale de la Recherche* of the French government through the program "*Investissements d'avenir*" (ANR-10-LABX-14-01). This research received financial support from the research foundation TSE-Partnership and ANITI funding. The findings, interpretations, and conclusions expressed in this work do not necessarily reflect the views of the World Bank, its Board of Executive Directors, or the governments they represent.

1 Introduction

In the face of escalating global environmental challenges, judiciaries are playing a pivotal role in the pursuit of environmental justice.[1] Since the year 2000, there has been explosive growth in the number of environmental courts as well as the case-loads within them.[2] Judges in these courts have often taken a proactive and activist stance towards environmental protection. In the United States, for example, courts have repeatedly upheld environmental regulations such as the Clean Air and Water Acts even when the policy debates related to environmental regulation have become increasingly partisan, polarized and gridlocked (Schmalensee and Stavins 2019; Keiser and Shapiro 2019).

This paper offers insights into the ramifications of judicial policies on water quality and human capital in India, a region grappling with some of the highest pollution levels in the world (Greenstone, Hasenkopf, and Lee 2022). Existing research has shown limited success in executive and legislative efforts to combat environmental toxicity (Greenstone and Hanna 2014; Duflo et al. 2018; World Bank 2013). Judges have frequently taken a proactive stance on environmental protection, often prioritizing the interests of aggrieved citizens over private and state interests. This raises a significant puzzle: Can judicial decisions truly make a difference in countries with weak institutions, such as India? Echoing the theories of Acemoglu, Johnson, and Robinson (2005) and Rodrik, Subramanian, and Trebbi (2004), this question motivates our exploration of the broader and long-term consequences of a comprehensive set of judicial policies.

In this study, we rigorously examine three interrelated issues. First, we investigate the effect of pro-environmental judicial rulings on river toxicity levels, both before and after these decisions. Our analysis seeks to understand the magnitude and direction of these impacts. Second, we explore whether the observed changes in river toxicity can be attributed to corporate adaptations in response to these judicial interventions. Third, we assess the extent and persistence of these effects, particularly in relation to public health and economic outcomes. To this end, we use infant and neonatal mortality rates as proxies to evaluate the potential long-term health implications of reduced river toxicity resulting from pro-environmental legal actions. Our approach integrates legal, environmental, and economic perspectives to provide a comprehensive understanding of the multifaceted impacts of environmental jurisprudence.

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 all court orders from India's high courts, Supreme Court, and Green Tribunal that have cited India's landmark regulations on water

[1] Agenda 21, the program of action for sustainable development that emerged from the United Nations Conference on Environment and Development in Rio de Janeiro, Brazil pledges 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 provide "access to individuals, groups, and organizations with a recognized legal interest" (Chapter 8, Agenda 21, Nations (1992)).

[2] There are currently estimated to be 2,116 environmental courts operating in 67 countries (UNEP 2022; Setzer and Higham 2022)

toxicity since 1987.[3] We read each of these, labeling them as a ”green order” if they may have a favorable impact on ambient water quality, i.e., the judgment is expected to improve the quality of water in lakes, rivers, streams, etc. by reducing pollution, controlling runoff, or implementing other protective measures.

Next, we explore the causal relationship between green orders and tangible outcomes. While we mainly focus on environmental outcomes, we also examine impacts of green orders on infant mortality and firm financial status. Given that orders may be endogenous to these outcomes, we employ an instrumental variable (IV) approach that depends on the judges' random assignment (Ash et al. 2021; Chandra, Kalantry, and Hubbard 2023). We analyze the general writing habits of judges from all cases they have previously heard in their careers to forecast the chance of a green order in our sample of cases. This creates a unique instrument that reflects a judge's writing style unrelated to water toxicity, yet predicts their decisions on such cases. We use this IV framework to analyze the impact of green orders on river toxicity at the district-level, on firm financial outcomes at the firm-level and on district-level infant mortality rates. In addition, we show our results are invariant to recent developments in weak instrument robust estimation strategies (Young 2022; Andrews, Stock, and Sun 2019.)

We find that an increase in the fraction of green orders leads to a district wide reduction in biological oxygen demand (BOD) in the year of the decisions. Similarly, we observe reductions in both, BOD and chemical oxygen demand (COD) during the judicial process, i.e. post-filing and pre-decision. 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 find a similar pattern for the impact on the financial status of firms. Prior to filing a case and prior to decisions, firms with green orders see a decrease in their income, assets, expenditures and liabilities compared to their counterparts with similar cases that are not beneficial to the environment. After the decision, however, we do not observe any statistically significant difference in firm outcomes between these two types of firms. We even find suggestive evidence for a relative strengthening in the financial health of firms with green orders.

We also find that a higher share of green orders are associated with an increase in infant mortality in the second and third years following the decisions. Taken together, we interpret this as suggestive evidence that judicial action can succeed in lowering short-term pollution, potentially because firms experience the litigation itself as scrutiny. However, 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.

[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.

We assess the robustness of our results in a variety of ways. First, we look at pre-trends as an omnibus test for randomization. We ask whether outcomes are associated with the green orders prior to the case opening. Second, we consider different samples of the data, and we control for other factors that may drive pollution outcomes, such as economic activity and forest cover. Third, we use different measures of writing styles. Fourth, we use identification-robust confidence intervals. Finally, we expand our investigation beyond the districts directly affected by the judicial rulings. This allows us to explore the possibility of spillover effects in adjacent areas, thereby offering a more comprehensive assessment of the impacts of these rulings. All of our auxiliary results point towards there being limited or very modest positive impacts of pro-environmental judicial orders on pollution and mortality, prior to and in the immediate vicinity of decisions, but observe negligible or even adverse effects on long-term environmental and health outcomes, indicating a complex interplay between judicial interventions, environmental policies, and actual health and economic outcomes.

We contribute to three areas of literature. First, we contribute to the literature on the role of policies in regulating water quality at scale. Many studies have already documented the significant productivity and health benefits of large investments into infrastructure such as sewage systems (Alsan and Goldin 2019), piped water systems (Galiani, Gertler, and Schargrodsky 2005; Ashraf, Glaeser, Holland, et al. 2021), disinfection programs (Bhalotra et al. 2021) and regulatory systems (Zhang and Xu 2016). These policies, however, emanate from the executive and legislative and entail significant investment, state capacity, and public support (Ashraf, Glaeser, and Ponzetto 2016; Ahuja, Kremer, and Zwane 2010). To date, there has been only evidence of localized impacts of judicial policies (Do, Joshi, and Stolper 2018; Zhang, Yu, and Kong 2019). This paper provides the first nationwide analysis of the impacts of judicial policies on surface water toxicity in a high pollution setting like India.

Second, we contribute to the literature at the intersection of law and economics that exploits the random assignment of judges to estimate the impact of judicial verdicts on outcomes. Our work represents a notable shift in the approach that typically uses the ”judge leniency” design to serve as an instrumental variable, where judge leniency is calculated from the decisions on other cases by the same judge. Due to the infrequency of environmental case assignments to judges, we use a method derived from natural language processing (NLP) to assess judges’ overall writing trends across all types of cases to predict the likelihood of green orders. This gives us an innovative instrument - a judge’s writing style, which, although not directly related to water toxicity, can foretell their decisions in these cases. We then apply the same IV framework to scrutinize the impact of green orders on socio-economic outcomes.

Finally, our study contributes to a deeper understanding of the role of courts in sustainable economic development. Numerous studies have established a correlation between the importance of courts and legal systems in supporting policies aimed at improving the performance of markets (Djankov et al. 2003; Visaria 2009; Papaioannou and Karatza 2018; Chemin 2020; Rao 2021). We expand our focus to the complex realm of water, a natural resource that challenges conventional property rights definitions (Glaeser, Johnson, and Shleifer 2001). In the past, adjudicating water-related disputes has historically been challenging for courts due to a lack of scientific data, limited technical expertise among judges, and the risks of powerful interests subverting the process of justice (Behrer et al. 2021; Shleifer et al. 2012). Our paper illustrates that recent innovations within the judiciary – in this instance, public interest litigation and the creation of separate environmental courts – are a promising direction for courts to expand their influence in environmental management in developing countries.

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 main data sources on judicial orders and pollution outcomes. Section 4 presents the main empirical strategy. Section 5 presents the results on environmental outcomes. Section 6 presents the analysis on firm financial outcomes. Section 7 presents the analysis on the impact of judicial orders on neo-natal and infant mortality. The final section concludes.

2 Institutional Context

India's judiciary has taken an activist stance towards environmental conservation for the past four decades (Rajamani 2007; Bhuwania 2017; Malleson 2016; Ghosh 2019).[4].[5].

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 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

[4]This is part of a broader global trend that is largely driven by the growing levels of citizen concerns over issues of environmental conservation and the weaknesses of executive and legislative frameworks for environmental governance (Percival 2016, Percival 2017, Woodhouse and Muller 2017

[5]The rise of judicial activism can be traced to specific events in recent history: the political emergency of 1976 and the devastating Bhopal Gas disaster of 1984 forced the judiciary to strengthen its response to citizen grievances and protect fundamental rights. Below we review key pieces of water legislation, the challenges of execution and the evolution of the jurisprudence that was used by activist judges since the 1980s Ghosh 2019

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) of 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 has not worked 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 Courts and Judges

Environmental litigation in India encompasses a diverse range of forms. The Central Pollution Control Boards (CPCBs) and State Pollution Control Boards (SPCBs) hold the legal authority to initiate cases against companies at high courts when they fail to comply with environmental regulations. Private citizens also have the right to file grievances against polluters at high courts. Additionally, citizens can institute legal actions against government bodies for not fulfilling non-discretionary duties. Furthermore, they can file complaints seeking court injunctions to prevent potential pollution situations, such as opposing the construction of a new factory that may cause environmental harm.

Environmental cases have almost always been technically complex and controversial (Mehta 1999, Krishnaswamy and Swaminathan 2019, CUTS 2020). In 2010, the National Green Tribunal (NGT) of India was established to provide specialized support for environmental cases (Gill 2016; Ghosh 2019; Malleson 2016). The NGT holds jurisdiction to review government decisions concerning projects that impact the environment, including environmental clearances and the granting of consent or licenses to operate industries. It is authorized to hear individual cases involving actual or potential harm resulting from violations of environmental laws. The NGT is empowered to provide relief and compensation to pollution victims and order the restoration of environments damaged by pollution. While the tribunal has garnered significant international and national recognition, and is often cited as a model for developing nations, rigorous assessments of its effectiveness are yet to be conducted (Gill 2016).

The Indian justice system stands out for the remarkable opportunities it provides to citizens for expressing environmental grievances (Percival 2017). Judges have played a pivotal role in creating such avenues. This is most notably exemplified by the efforts of two Supreme Court judges, Bhagwati and Iyer, who introduced modifications to court procedures in the early 1980s, leading to the establishment of ”Public Interest Litigation” (PIL) in India. PIL empowers citizens and non-governmental organizations to approach the courts on behalf of others, enabling them to voice concerns about environmental degradation and advocate for environmental safeguards on behalf of vulnerable communities unable to express their grievances. Since its inception, PIL has served as a platform for some of the most significant environmental cases contested at the Supreme Court of India, with demonstrated localized impacts on pollution and demographic outcomes along India's rivers (Do, Joshi, and Stolper 2018, Shambaugh and Joshi 2021, Joshi and Shambaugh 2018).

Environmental jurisprudence in India reflects these trends of judicial activism and strong citizen engagement (Baxi 1985; Abraham 1999; Ghosh 2019). Citizen grievances featuring claims about the violations of fundamental rights are quite common in the courts of India[6] Judges have

[6]India is now one of the 100+ countries whose constitution includes provisions for environmental protection (Setzer and Higham 2022. Moreover, several constitutional articles deal with environmental protection. Article 21 guarantees Indian citizens the fundamental right to life. It states that ”No person shall be deprived of his life or personal liberty except according to procedures established by law”. Articles 47 and 48A fall under the non-binding ”Directive Principles of State Policy” and require the government to improve public health and protect and improve the

frequently placed considerable emphasis on public rather than private interests than many other countries (Percival 2017; Scanlan 2017). They have drawn arguments from a diverse set of sources that include ancient Indian traditions as well as Western legal codes. Environmental rulings in India frequently feature arguments draw on concepts of *dharma* and quotes from sacred Hindu texts (Mehta 1999). They also cite concepts like ”sustainable development,” the ”polluter pays” principle, and the ”public trust” doctrine (Ghosh 2019). Although none of these principles were not explicitly articulated in Indian statutory law, they have been emerged as integral components of Indian environmental law, with necessary adjustments and adaptations to suit the Indian context (Abraham 1999). This complex writing style of judges is noteworthy in its own right, and has inspired some of the quantitative methods we use in this paper.

In summary, the Indian judiciary has shown a proactive and assertive approach towards addressing environmental issues. Judges have played a significant role in shaping the arc of this process, creating new interpretations of constitutional provisions, establishing new platforms for implementation of existing laws and expanding the body of jurisprudential thought in this area.

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).[7]

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

environment. Article 51 A(g) defines one of the fundamental duties of citizenship to ”maintain a hygienic environment” also directly mentions the environment. Only Article 21 and Article 47 were present at the time of the first constitution of India that was passed in 1950. The remaining articles were added via constitutional amendments in 1974.

[7] 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.

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. With 978 environmental cases treated as distinct policies or treatments over several decades, the dataset is notably robust. This is especially significant compared to typical differences-in-differences studies in the US, which often utilize far fewer policies across the 50 states.

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 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.[8]

[8] 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).

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. This is a repository of national water resources data that receives input from many central and state agencies and provides a "Single Window" source of updated data on water resources and related themes. The data covers 153 districts from 1984 to 2020.

The two sources of water data differ in the number of observations, districts covered, and the specific locations within districts. They also differ in the types of pollution indicators that are reported. To address these issues, we combine both types of data and then aggregate the combined sample at the district level. Since the CPCB does not report mean values of pollution after 2014, we rely on the maximum observed values in any given district and month for the entire period. Given that concerns over water quality can be triggered by irregularities in recorded pollution 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, conductivity, and temperature. The total coliform metric 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.[9] Our last measure of water quality,

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

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.

This list of pollution measures is admittedly limited to basic indicators. Other pollutants that are known to affect human health are not recorded consistently in our 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.

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. We also collect data on air pollution, that is available after 1998 (Van Donkelaar et al. 2021), 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.

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).

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

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

[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

coders who coded the order and define it as a "green order" if the median assigned environmental impact is positive. 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). The median value of these opinions was assigned to the order.

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.[13] 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 international law in their response.

Descriptive statistics of the key variables in our working sample for pollution 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.[14]

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

independently. Discrepancies in labeling will be reconciled by assigning the judgment to a third student.

[13] Both coders identified the same location.

[14] 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.

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).[15]

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.

Though these 25 dimensional vectors have no intuitive interpretation, similar techniques have been used to quantify the differences between Republican and Democrat judges in the United States (Lu and Chen 2024). In a nutshell, this research suggests that the political and ideological stances of judges are reflected in their writing style. In this context, the analysis of past cases allows us to predict the pro-greeness of environmental orders.

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:

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

The variable on the left-hand side, $\mathrm{GreenOrder}_{cdt}$, 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 two-dimensional representations of orders and judges based on the original 25 dimensional vectors generated by D2V used in the study. These visualizations are generated through

[15] 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 t-distributed Stochastic Neighbor Embedding (t-SNE) technique. t-SNE is a machine learning algorithm designed for visualizing high-dimensional data by projecting it onto a lower-dimensional space, emphasizing the preservation of local structure so that similar data points cluster together in the resulting representation.

The left panel of the figure presents a visualization of the original 25-dimensional vectors that represent the writing style of our sample of environmental cases. Each point corresponds to one order of an environmental case, and the colors represent the hand-labeled impact score assigned to each order. Note that the clustering of cases with similar writing styles also results in the grouping of cases with similar impact scores, showing the effectiveness of D2V in understanding the nuances of legal text and distinguishing pro-environmental writing styles.

The right panel displays judge-level embeddings. A judge-level embedding is an aggregation of the judges' single author writings across all cases not including the environmental cases. Each point represents a two-dimensional visualization of the 25-dimensional writing style for judges with at least one environmental case, and the colors represent the mean impact score over all environmental cases that the judge has adjudicated. Note that the clustering of judges with similar writing styles also clusters together judges whose environmental cases have similar impact scores.

Altogether, these diagrams substantiate the reasoning behind our first-stage regression analysis. The coalescence of groupings derived from writing styles and impact scores across both cases and judges, along with the widespread distribution of distinct writing styles among judges, underscore a significant intellectual variety in Indian environmental law. Moreover, they hint at the notion of 'activist' judges, those who don't just make judgments that favor the environment but also articulate the rationale for these verdicts in their written works.

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).[16] 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

[16]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.

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.

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; Chandra, Kalantry, and Hubbard 2023).[17] 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

[17] 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. In the recent book of Chandra, Kalantry, and Hubbard 2023, the authors find that the Supreme Court randomly assigns cases to small benches.

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).[18] 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.[19]

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.

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

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

[19] 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.

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.[20] 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 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

[20] 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.

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 Table A1 presents an additional balance check. We regress the pro-greeness of orders predicted by our 26 instruments on past pollution levels. Columns (1) to (3) are at the order level, columns (4) to (6) aggregated at the district-year level. We observe that overall, past pollution levels are uncorrelated with the predicted pro-greeness of the orders.

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.[21]

In Appendix Table A5 we study the heterogeneity of the impact of pro-environmental orders on river pollution across different involved actors and case types. In columns (1) to (3) we display the impact depending on the government being involved as the petitioner, the respondent, or any of the two, respectively. For both BOD (panel A) and COD (panel B), we observe no significant effect of cases with the government as petitioner, but highly significant effects when the government is involved as respondent. In column (5) we look only at the subset of orders pertaining to constitutional cases and find that these orders have a significant impact on river pollution, while the orders on constitutional cases do not show any significant effect. Finally, from columns (6) and (7), we find that the effects on BOD seem to be driven by non-appeal cases.

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 TOTCOLI, conductivity and temperature are all much smaller. Appendix Table A3 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

[21] 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).

(conditional on having some 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 A6 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).[22] 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.

5.4 Dynamic Impacts on Pollution

Next, we estimate Equation 4 with dynamic effects: we consider effects between fours 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-4 up to t+5). We conduct the event study analysis using two sets of dates: Publication dates and filing dates. The publication

[22]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.

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.

In our main specification we run three sets of independent regressions. First, for what we call ”pre-filing” regressions, we attribute cases to their assigned districts 1 to 4 years prior to the filing year. Similarly, for the ”during litigation” regressions, we assign cases to all years in between their filing and decision dates, and for the ”post-decision” regression we assign them to years 1 to 5 post the decision year.

Figure 5 displays the estimation results for the maximum observed values of two pollutants – BOD and COD. For both COD and BOD we observe no effect for the pre-filing regressions. 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. During the litigation, this is, after the filing and prior to the decision date, we observe a decrease in both pollutants. After the decision, we observe an increase in COD and a positive but statistically significant effect on BOD.

For additional details, we present coefficients and confidence intervals for individual leads and lags regressions in Appendix Figure A2.[23] 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 (Appendix Figure A2, Panel A), we do not see significant impacts prior to the filing date of a case. Second, 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. Third, in the event study plots using the publication dates (Appendix Figure A2, 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. 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 Appendix Figure A2, Panel B).

Appendix Figure A3 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 (Appendix Figure A3, Panel A), we see a drop in the max observed values of

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

BOD and COD in the 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 (Appendix Figure A3, 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 (Appendix Figure A3, 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 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.[24] 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 5. 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 A7, the result remains

[24] 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.

robust in this sample.

Table 6 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.[25]

One interpretation of these results is that judicial cases may deter polluting firms in neighboring districts and perhaps districts in other parts of the state. This results in a decline in the maximum observed values of 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.

A question that emerges from our findings is why judicial verdicts have only a short-term impact on pollution. There are three, non mutually exclusive explanations. First, India is marked by an overly complex environmental governance. 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).

Second, the failure of the judiciary to have a long-term impact can stem from the limitations of the technologies that have been widely adopted to treat effluent from toxic industries, intended to address citizen concerns (Woodhouse and Muller 2017). 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).[26] 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

[25]In Table 6 we note a significant negative impact on BOD, but the weak instrument robust confidence interval in Table OA12 includes zero.

[26]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.

over India, but their effectiveness in curbing long-term pollution remains unclear (Shambaugh and Joshi 2021).

Finally, 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). In the following section, we expand our analysis to the impact on firms.

6 Impact on Firm Performance

Thus far, we have demonstrated that pro-environmental rulings are preceded by a decline in pollution levels. Next, we explore if the reduction in pollution levels is accompanied by changes in the financial status of firms. We postulate that such changes would be indicative of a possible deliberate response from polluting firms to lower their pollution levels.

6.1 Prowess data description

We draw upon data sourced from the Prowess database, which compiles financial information for approximately 54,000 listed private and public companies in India. This database encompasses nearly all companies listed on the National Stock Exchange and Bombay Stock Exchange[27]. These firms collectively contribute to over 70% of the country's industrial output and account for 75% of corporate taxes collected by the Indian government. Widely utilized in academic analyses (Goldberg et al. 2010), the Prowess database is compiled from audited annual reports, information submitted to the Ministry of Corporate Affairs, company filings with stock exchanges, and securities prices from the main stock markets for publicly traded corporations.

We established links between firms identified in environmental orders and the Prowess database. Among the 969 orders in our dataset, 361 orders mention at least one firm, resulting in a total of 438 firm mentions across all orders. Out of these mentions, 369 firms are unique. Employing a fuzzy name matching algorithm, we merged these firms with the broader universe of firms in the Prowess data. Notably, 100 of the 369 unique firms in the judicial orders are covered by Prowess. 87 firms (21 mentioned in green orders, 66 in non-green orders) possess information on all variables of interest, including financial data and judges' information. Out of these, we have balance sheet data for 48 firms within 10 years of filing dates (t-4 to t+5) and for 67 firms within 10 years of decision dates. The summary statistics for these 48 and 67 firms are available in Panel A and B of Table 7.

[27]These registered companies adhere to the disclosure requirements of the 1956 Companies Act. Initially, inclusion in the database was contingent upon meeting specific criteria, such as a minimum turnover of 2.5 crore rupees or the availability of annual reports for at least two years before the date of updating.

6.2 IV specification and results

To estimate the impact of pro-environmental orders on firm performances, we employ a modified version of Equation 4. Specifically, we assess the influence of a pro-environmental order on firm i's financial performance in fiscal year y:

$$Y_{iy} = \beta_1 + \beta_2 \widehat{GreenOrder}_i + \gamma_i + \delta_y + \theta X_i + \epsilon_{iy}.$$

Here, Y_{iy} represents a financial indicator (income, assets, expenses, or liabilities) of firm i in fiscal year y. The variable $\widehat{GreenOrder}$ is a dummy variable set to one if the judicial order associated with the firm is coded as pro-environmental. The terms γ_i and δ_y denote firm and fiscal year fixed effects, respectively. X_i encompasses characteristics of firm i's environmental case, specifically three dummy variables set to one if the order is related to an appeal case, the order is related to a constitutional case, and the government is a respondent in the case.

Note that, focusing on firms with a merged order related to river pollution, we omit $\mathbb{1}\{|C_{dt}| > 0\}$ in this regression.

As before, we apply an instrumental variable approach to address potential endogeneity of the green orders. Similar to previous regressions, we utilize as exogenous instruments a 25-dimensional vector capturing the average writing style of the judges on the order and a dummy variable set to one if the average judge on the order holds a post-graduate degree.

Figure 6 illustrates the results of this regression. Panel A presents the results in a similar manner as the pollution results above. We observe no pre-trends prior to the filing dates and no effect on firms during the litigation process. However, there are positive, but not statistically significant effects for all four firm outcomes post-decision.

Panels B and C highlight a nuance of the above results. Panel B portrays estimates around the filing date, and Panel C depicts estimates around the decision date. The left part of each panel showcases results for the subsample 1 to 4 years prior to the filing (or decision) of the environmental case. The right part displays regression results for the subsample 1 to 5 years after the filing (decision).

From Panel B, we observe no significant pre-trends before the filing date. Post filing, however, there is a noteworthy reduction in income and expenses for firms with green cases compared to firms with non-green cases. Around the decision date, in Panel C, we note a significant decrease in assets, expenses, and liabilities before the decision. However, post decision, this effect dissipates: there is no significant impact of pro-green cases on firm financial indicators, and, if anything, there is suggestive evidence for an increase in assets and liabilities following the order.

These findings are consistent with our prior findings regarding river pollutants. Throughout the legal proceedings, districts with a greater proportion of (ultimately) favorable environmental orders experience a reduction in pollutants, and firms anticipating a green order show a reduction of income, assets and other financial indicators. However, post-decision, both pollutant levels and these financial indicators revert, sometimes even surpassing the levels observed in districts and firms that lack such orders. This reaffirms our interpretation that entities, including firms, perceive litigation as scrutiny and proactively respond early in the process. Once more, it underscores the potentially limited long-term impact of the judicial system.

7 Infant Mortality

In the preceding sections, we established a correlation between pro-environmental rulings and a decline in river pollution. Additionally, we observed that firms receiving a green order ultimately experience a decrease in income, assets, expenses, and liabilities from the case filing to the decision date, with both effects diminishing post-decision. The final step of our analysis is to explore the potential impact of these rulings on public health. Specifically, we examine whether the reductions in water toxicity is substantial and enduring enough to mitigate infant mortality.

7.1 Data

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).[28] 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.

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 8).

7.2 Contemporaneous Impacts on Mortality

To estimate the impact of green rulings on mortality, we follow the same approach as we used for pollution. We estimate equation 4, with the following three modifications. First, we emphasize,

[28] 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.

however, that this analysis will be conducted at the district-year-month level.[29]. Second, additional to the year and district fixed effects in the baseline model, we also include a month of the year fixed effect. Third, we consider three measures of mortality as dependent variables: 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.[30]

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 9. 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 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 9, 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 8).

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

[29]As noted in previous work (Do, Joshi, and Stolper 2018), the risk of risk of death in the initial year of a child's life is not uniform. Recent estimates from the United Nations Inter-agency Group for Child Mortality Estimation (UNICME) indicate that for every 1000 live births, 18 deaths occur within the first month of birth, and 11 deaths occurring between the second and twelfth month after birth (Sharrow et al. 2022).

[30]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.

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 A8 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 A9 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 9 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 9 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.

In summary, the findings indicate either no impact or a very modest positive influence of pro-environmental judicial verdicts on certain mortality measures immediately following decisions. Although our approach doesn't offer insights into the underlying mechanisms, it's plausible that economic factors play a role. For instance, the closure or reduced activity of firms might have heightened economic vulnerability in the local population, thereby increasing barriers to accessing healthcare. We believe these are important areas for future research.

7.3 Dynamic Impacts on Mortality

Figure 7 presents dynamic effects of green orders on mortality. On the left, labeled "Pre-Filing", the estimates include up to fours years prior to the filing year. In the center ("During Litigation") the estimates are based on the years in between filing and decision years. The estimates on the right ("Post-decision") are based on the years 1 to 5 post decision. We observe no pre-trends prior to the filing of a case. In the years during the litigation, we observe a positive but not significantly different from zero effect on the three measures of infant mortality. Finally, in the years post decision, the estimated effect or pro-green orders are positive but not statistically significant.

One explanation why we find reductions in pollutants and in firm outcomes, but not in infant mortality prior to the decision, can be that the reduction in pollutants is simply not large enough to bring about significant improvements in the health environment. In their study on the impact of one supreme court ruling (*M.C. Mehta vs. Union of India*) on river pollution and infant mortality, Do, Joshi, and Stolper (2018) find that extreme pollution levels (BOD > 3) decreased by 0.607, the infant mortality rate decreased by 0.005 p.p., and the neonatal mortality rate decreased by 0.024 p.p. following the judgment. Our measured effects on industrial pollution are between 24% and 39% of their effect size, and we do not see any statistically significant drop in mortality associated with this decline. So, although the two effects are of a similar relative size compared with Do, Joshi, and Stolper (2018)'s findings, our findings might be too small in absolute terms to detect significant effects on mortality.

Appendix Figure A4 presents more details on these effects. 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 monthly mortality vis-à-vis the filing dates because we lack data on the cases' filing month. Panels A-C of Appendix Figure A4 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 Appendix Figure A4 presents a smoothed version of these estimates. Here, monthly estimates are aggregated at the yearly level for the regression that includes control variables for air pollution. Panel E of Appendix Figure A4 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 imply that courts can have some influence in lowering surface water toxicity, presumably by forcing firms to adopt pollution-mitigation strategies, shut down their operations, or else relocate elsewhere. However, firms revert to polluting surface water once the attention from litigation has waned, and in the long run these strategies may increase vulnerability in the local population and actually have adverse effects on early childhood mortality.

8 Conclusion

This paper provides an empirical analysis of the impact of judicial orders on environmental outcomes in India, a country grappling with some of the highest levels of water toxicity globally. Utilizing a novel dataset that integrates legal, environmental, and demographic variables at the district level, our study aims to identify the causal relationship between pro-environmental judicial verdicts and actual environmental, health, and economic outcomes. To address endogeneity, we employ an instrumental variable framework, using textual features of judges' past cases to predict the likelihood of green verdicts.

Our findings indicate that an increase in the proportion of pro-environmental judicial orders leads to reductions in chemical oxygen demand (COD) and biological oxygen demand (BOD), which are key indicators of industrial pollution in surface water. However, these improvements are short-lived, as pollution levels tend to revert to their initial states and even increase in the longer term after the decision date.

We observe a similar trend in firm financial outcomes. Specifically, firms mentioned in green orders experience decreases in income, assets, expenditures, and liabilities between the filing date and the decision date compared to firms mentioned in non-green orders. Additionally, we find no evidence that court policy decisions result in decreases in infant mortality prior to the decision. Contrarily, there is a small positive impact of green orders on the likelihood of death between the first month and first year of life.

Our research provides the first empirical evidence of the judiciary's impact on India's water quality regulation over the past three decades. The key takeaway is that while judicial verdicts can temporarily reduce certain measures of surface water pollution, these effects are modest and short-lived, failing to improve infant mortality rates. These findings provide a nuanced perspective on the claim made by India's leading think tank, which attributes the loss of 82,060 jobs and approximately 3.5 billion USD in revenue to five green rulings from the Supreme Court (CUTS 2020).

Compared to the actions of the executive and legislative branches, as reported in other studies using similar data (Greenstone and Hanna 2014), the judicial policies examined in this study show some effectiveness. Despite the long history of governance failures by the executive and legislative branches, the judiciary's influence is notable. The judiciary's significant role in Indian society, high levels of public trust, and extensive media coverage of judicial decisions likely contribute to short-term compliance with judicial policies (Baxi 1985; Bhuwania 2017; Kapur, Mehta, and Vaishnav 2018).

In a nutshell, we find that judicial policies can lower short-term pollution levels, but these measures are insufficient to improve health outcomes. Moreover, the economic slowdown following judicial orders may exacerbate economic vulnerability. In the long term, enforcement and oversight challenges limit the judiciary's ability to effect substantial improvements in health and economic activity at the grassroots level.

References

Abbot, Carolyn (2009). *Enforcing pollution control regulation: strengthening sanctions and improving deterrence*. Bloomsbury Publishing.

Abraham, C Mathew (1999). *Environmental jurisprudence in India*. Vol. 2. Martinus Nijhoff Publishers.

Acemoglu, Daron, Simon Johnson, and James A Robinson (2005). "Institutions as a fundamental cause of long-run growth". In: *Handbook of economic growth* 1, pp. 385–472.

Ahuja, Amrita, Michael Kremer, and Alix Peterson Zwane (2010). "Providing safe water: Evidence from randomized evaluations". In: *Annu. Rev. Resour. Econ.* 2.1, pp. 237–256.

Aizer, Anna and Joseph J Doyle Jr (2015). "Juvenile incarceration, human capital, and future crime: Evidence from randomly assigned judges". In: *The Quarterly Journal of Economics* 130.2, pp. 759–803.

Alley, Kelly D (2002). *On the banks of the Ganga: When wastewater meets a sacred river*. University of Michigan Press.

Alsan, Marcella and Claudia Goldin (2019). "Watersheds in child mortality: The role of effective water and sewerage infrastructure, 1880–1920". In: *Journal of Political Economy* 127.2, pp. 586–638.

Andrews, Isaiah, James H Stock, and Liyang Sun (2019). "Weak instruments in instrumental variables regression: Theory and practice". In: *Annual Review of Economics* 11.1.

Arnold, David, Will Dobbie, and Crystal S Yang (2018). "Racial bias in bail decisions". In: *The Quarterly Journal of Economics* 133.4, pp. 1885–1932.

Ash, Elliott et al. (2021). "Measuring Gender and Religious Bias in the Indian Judiciary". In: *Center for Law & Economics Working Paper Series* 2021.03.

Asher, Sam et al. (2021). "Development Research at High Geographic Resolution: An Analysis of Night Lights, Firms, and Poverty in India using the SHRUG Open Data Platform". World Bank Economic Review.

Ashraf, Nava, Edward L Glaeser, Abraham Holland, et al. (2021). "Water, Health and Wealth: The Impact of Piped Water Outages on Disease Prevalence and Financial Transactions in Zambia". In: *Economica* 88.351, pp. 755–781.

Ashraf, Nava, Edward L Glaeser, and Giacomo AM Ponzetto (2016). "Infrastructure, incentives, and institutions". In: *American Economic Review* 106.5, pp. 77–82.

Baxi, Upendra (1985). "Taking suffering seriously: Social action litigation in the Supreme Court of India". In: *Third World Legal Stud.*, p. 107.

Behrer, A Patrick et al. (2021). "Securing property rights". In: *Journal of Political Economy* 129.4, pp. 1157–1192.

Bhalotra, Sonia R et al. (2021). "Urban Water Disinfection and Mortality Decline in Lower-Income Countries". In: *American Economic Journal: Economic Policy* 13.4, pp. 490–520.

Bhuwania, Anuj (2017). *Courting the people: Public interest litigation in post-emergency India*. Vol. 2. Cambridge University Press.

Bruederle, Anna and Roland Hodler (2018). "Nighttime lights as a proxy for human development at the local level". In: *PloS one* 13.9, e0202231.

Chandra, Aparna, Sital Kalantry, and William HJ Hubbard (2023). *Court on Trial: A Data-Driven Account of the Supreme Court of India*. Penguin Random House India. ISBN: 9780670091584.

Chemin, Matthieu (2020). “Judicial efficiency and firm productivity: Evidence from a world database of judicial reforms”. In: *Review of Economics and Statistics* 102.1, pp. 49–64.

Crespo Cuaresma, Jesus et al. (2017). “Economic development and forest cover: evidence from satellite data”. In: *Scientific reports* 7.1, pp. 1–8.

CUTS (2020). *Economic Impact of Select Decisions of the Supreme Court and National Green Tribunal of India*. URL: https://cuts-ccier.org/pdf/synthesis-report-on-economic-impact-of-select-sc-and-ngt-decisions.pdf.

Djankov, Simeon et al. (2003). “Courts”. In: *The Quarterly Journal of Economics* 118.2, pp. 453–517.

Do, Quy-Toan, Shareen Joshi, and Samuel Stolper (2018). “Can environmental policy reduce infant mortality? Evidence from the Ganga Pollution Cases”. In: *Journal of Development Economics* 133, pp. 306–325.

Drèze, Jean and Mamta Murthi (2001). “Fertility, education, and development: evidence from India”. In: *Population and development Review* 27.1, pp. 33–63.

Duflo, Esther et al. (2018). “The value of regulatory discretion: Estimates from environmental inspections in India”. In: *Econometrica* 86.6, pp. 2123–2160.

Dumais, Susan T. (2004). “Latent semantic analysis”. In: *Annual Review of Information Science and Technology* 38.1, pp. 188–230.

Epple, Dennis and Michael Visscher (1984). “Environmental pollution: Modeling occurrence, detection, and deterrence”. In: *The Journal of Law and Economics* 27.1, pp. 29–60.

Galiani, Sebastian, Paul Gertler, and Ernesto Schargrodsky (2005). “Water for life: The impact of the privatization of water services on child mortality”. In: *Journal of political economy* 113.1, pp. 83–120.

Ghosh, Shibani, ed. (2019). *Indian Environmental Law: Key Concepts and Principles*. Orient BlackSwan.

Gill, Gitanjali N (2016). *Environmental Justice in India: The National Green Tribunal*. Routledge.

Glaeser, Edward, Simon Johnson, and Andrei Shleifer (2001). “Coase versus the Coasians”. In: *The Quarterly Journal of Economics* 116.3, pp. 853–899.

Goldberg, Pinelopi Koujianou et al. (2010). “Imported intermediate inputs and domestic product growth: Evidence from India”. In: *The Quarterly journal of economics* 125.4, pp. 1727–1767.

Government of India (2018). *Composite water management index*. Niti Aayog, National Institution for Transforming India, Government of India.

Greenstone, Michael and Rema Hanna (2014). “Environmental regulations, air and water pollution, and infant mortality in India”. In: *American Economic Review* 104.10, pp. 3038–72.

Greenstone, Michael, Christa Hasenkopf, and Lee (2022). *Air Quality Life Index: Annual Update*.

Joshi, Shareen, Kakoli Borkotoky, et al. (2020). “Poised for a dividend? Changes in the life trajectories of India’s young women over the past two decades”. In: *Plos one* 15.12, e0242876.

Joshi, Shareen and George Shambaugh (2018). “Oversized solutions to big problems: The political economy of partnerships and environmental cleanup in India”. In: *Environmental development* 28, pp. 3–18.

Kapur, Devesh, Pratap Bhanu Mehta, and Milan Vaishnav (2018). *Rethinking public institutions in India*. Oxford University Press.

Keiser, David A and Joseph S Shapiro (2019). “Consequences of the Clean Water Act and the demand for water quality”. In: *The Quarterly Journal of Economics* 134.1, pp. 349–396.

Krishnaswamy, Sudhir and Siddharth Swaminathan (2019). "Public Trust in the Indian Judiciary: The Power to Transform". In: *A Qualified Hope: The Indian Supreme Court and Progressive Social Change*. Ed. by Gerald N. Rosenberg, Sudhir Krishnaswamy, and Shishir (Editors) Bail. Comparative Constitutional Law and Policy. Cambridge University Press, pp. 123–140.

Le, Quoc and Tomas Mikolov (2014). "Distributed representations of sentences and documents". In: *International conference on machine learning*. PMLR, pp. 1188–1196.

Lu, Wei and Daniel L. Chen (Feb. 2024). "Motivated Reasoning in the Field: Polarization of Prose, Precedent, and Policy in U.S. Circuit Courts, 1891-2013". In: *SSRN Electronic Journal*. DOI: 10.2139/SSRN.3205116. URL: https://papers.ssrn.com/abstract=3205116.

Malleson, Kate (2016). *The new judiciary: The effects of expansion and activism*. Routledge.

Mehta, MC (1999). "Growth of environmental jurisprudence in India". In: *Acta Juridica*, p. 71.

Mohanty, Sanjay K et al. (2016). "Distal determinants of fertility decline: Evidence from 640 Indian districts". In: *Demographic Research* 34, pp. 373–406.

Nations, United (1992). *Rio declaration on environment and development*. URL: https://www.un.org/en/conferences/environment/rio1992.

Olea, José Luis Montiel and Carolin E Pflueger (2013). "A robust test for weak instruments". In: *Journal of Business & Economic Statistics* 31.3, pp. 358–369.

Papaioannou, Elias and Stavroula Karatza (2018). "The Greek justice system: collapse and reform". In: *CEPR Discussion Paper No. DP12731*.

Percival, Robert V (2016). "The Greening of the Global Judiciary". In: *Journal of Land Use & Environmental Law* 32, p. 333.

— (2017). "Environmental Laws". In.

Pflueger, Carolin E and Su Wang (2015). "A robust test for weak instruments in Stata". In: *The Stata Journal* 15.1, pp. 216–225.

Rajamani, Lavanya (2007). "Public interest environmental litigation in India: Exploring issues of access, participation, equity, effectiveness and sustainability". In: *Journal of environmental law* 19.3, pp. 293–321.

Rao, Manaswini (2021). *Courts Redux: Micro-evidence from India*. Tech. rep. Working Paper.

Rodrik, Dani, Arvind Subramanian, and Francesco Trebbi (2004). "Institutions rule: the primacy of institutions over geography and integration in economic development". In: *Journal of economic growth* 9, pp. 131–165.

Scanlan, Melissa K (2017). "A comparative analysis of the public trust doctrine for managing water in the United States and India". In: *Routledge Handbook of Water Law and Policy*. Routledge, pp. 23–37.

Schmalensee, Richard and Robert N Stavins (2019). "Policy evolution under the clean air act". In: *Journal of Economic Perspectives* 33.4, pp. 27–50.

Setzer, Joana and Catherine Higham (2022). "Global trends in climate change litigation: 2022 Snapshot". In.

Shambaugh, George and Shareen Joshi (2021). "Bridges over Troubled Waters? The Political Economy of Public-Private Partnerships in the Water Sector". In: *Sustainability* 13.18, p. 10127.

Sharrow, David et al. (2022). "Global, regional, and national trends in under-5 mortality between 1990 and 2019 with scenario-based projections until 2030: a systematic analysis by the UN Inter-agency Group for Child Mortality Estimation". In: *The Lancet Global Health* 10.2, e195–e206.

Shleifer, Andrei et al. (2012). "The failure of judges and the rise of regulators". In: *MIT Press Books* 1.
Singh, Abhishek et al. (2017). "Spatial patterns and determinants of fertility in India". In: *Population* 72.3, pp. 505–526.
Stiglitz, Joseph, Amartya Sen, and Jean-Paul Fitoussi (2010). *Mismeasuring Our Lives: Why GDP Doesn't Add Up.* The New Press.
UNDP (2009). *Analysis of Existing Environmental Instruments in India*. United Nations Development Programme.
UNEP (2022). *Environmental Courts and Tribunals – 2021: A Guide for Policy Makers*. URL: https://wedocs.unep.org/20.500.11822/40309.
Van Donkelaar, Aaron et al. (2021). "Monthly global estimates of fine particulate matter and their uncertainty". In: *Environmental Science & Technology* 55.22, pp. 15287–15300.
Visaria, Sujata (2009). "Legal reform and loan repayment: The microeconomic impact of debt recovery tribunals in India". In: *American Economic Journal: Applied Economics* 1.3, pp. 59–81.
WHO and UNICEF (2012). *Rapid assessment of drinking-water quality: a handbook for implementation*. World Health Organization.
Woodhouse, Phillip and Mike Muller (2017). "Water governance—An historical perspective on current debates". In: *World Development* 92, pp. 225–241.
World Bank (2013). *India : Diagnostic Assessment of Select Environmental Challenges, Volume 2. Economic Growth and Environmental Sustainability, What Are the Tradeoffs?* World Bank.
Young, Alwyn (2022). "Consistency without inference: Instrumental variables in practical application". In: *European Economic Review*, p. 104112.
Zhang, Jing and Lixin Colin Xu (2016). "The long-run effects of treated water on education: The rural drinking water program in China". In: *Journal of Development Economics* 122, pp. 1–15.
Zhang, Qi, Zhi Yu, and Dongmin Kong (2019). "The real effect of legal institutions: Environmental courts and firm environmental protection expenditure". In: *Journal of Environmental Economics and Management* 98, p. 102254.

Figures and Tables

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

(B) Water Pollution Orders per District

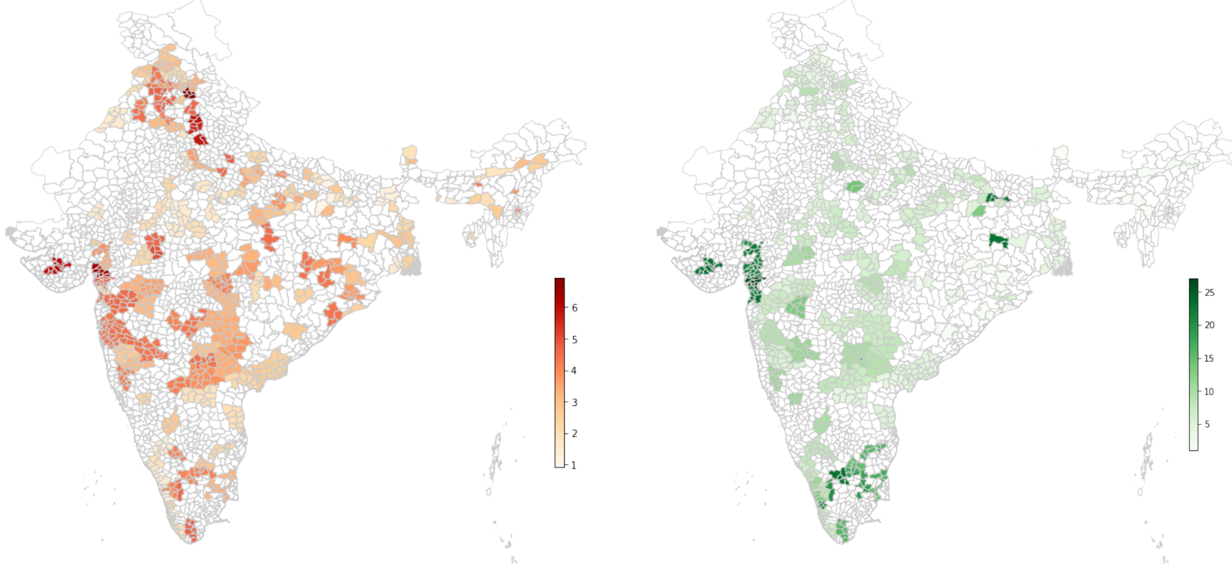


Figure 1: Spatial distribution BOD and Judicial Orders

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.

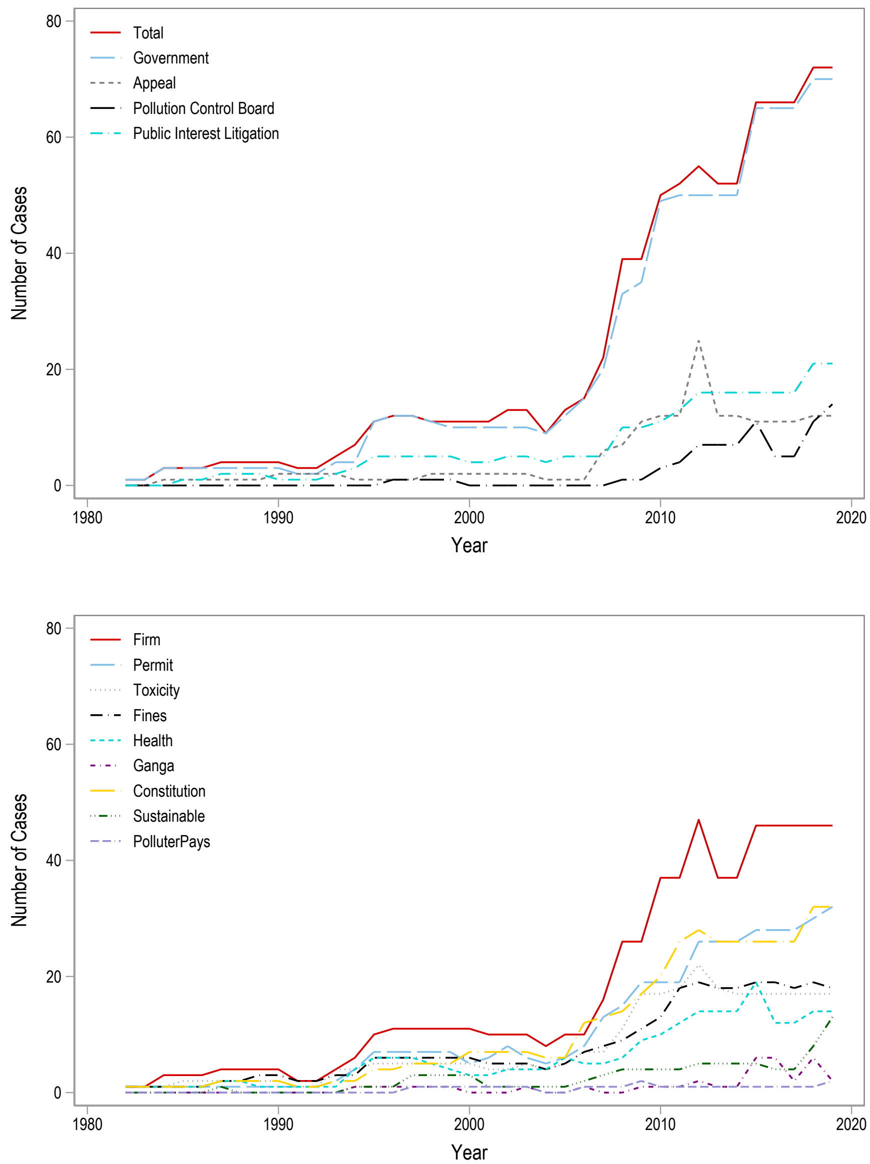


Figure 2: Varieties of Orders

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.

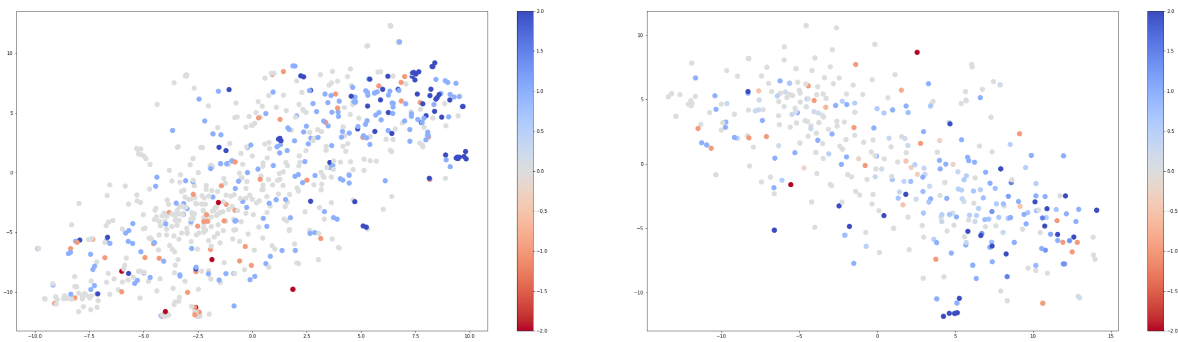
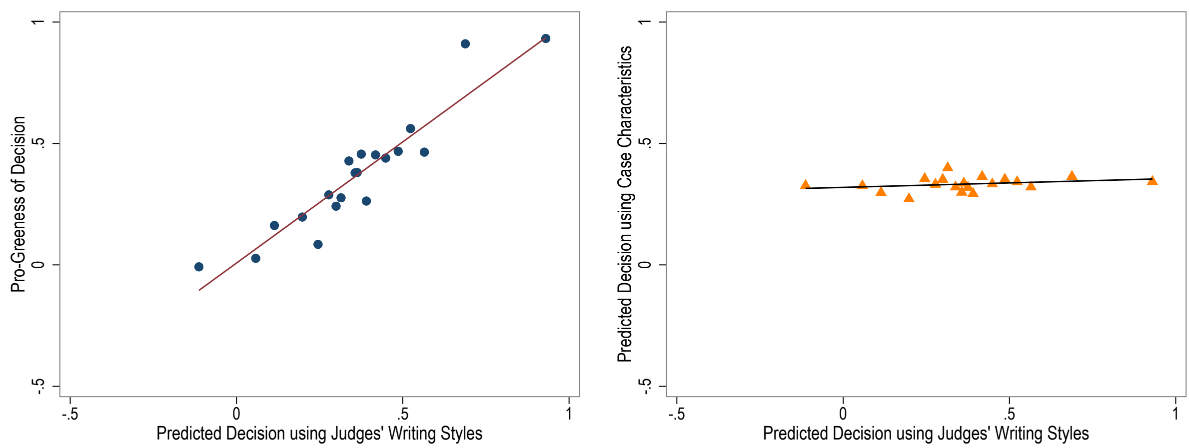


Figure 3: Visual Illustration of Judges' Writing Styles

Note: Each order in our corpus is represented as a 25 dimensional vector that was constructed using the doc2vec algorithm. In this figure, the x-axis and y-axis of each panel are chosen by t-SNE, a statistical method for visualizing high-dimensional data that maximizes the dispersion of the data when presented in two dimensions. The left panel presents a two dimensional visualization of the vectors that represent environmental cases' writing style. The colors represent the cases' hand-labeled median impact score. The figure shows that cases that are labeled as being pro-environmental are generally clustered in a similar space in this two-dimensional representation. The right panel presents the judge-level embedding of judges assigned to environmental cases. The judge-level embedding is a summary of the judges' writing across all cases (not including environmental cases in our sample). The colors represent the mean impact score of the environmental cases the judge has adjudicated. Judges who tend to write in a manner similar as noted by the physical distance in the top-right panel to other judges on non-environmental cases also tend to decide on environmental orders in a similar way as noted by the colors.

A. Order-Level



B. District-Year-Level: With Orders

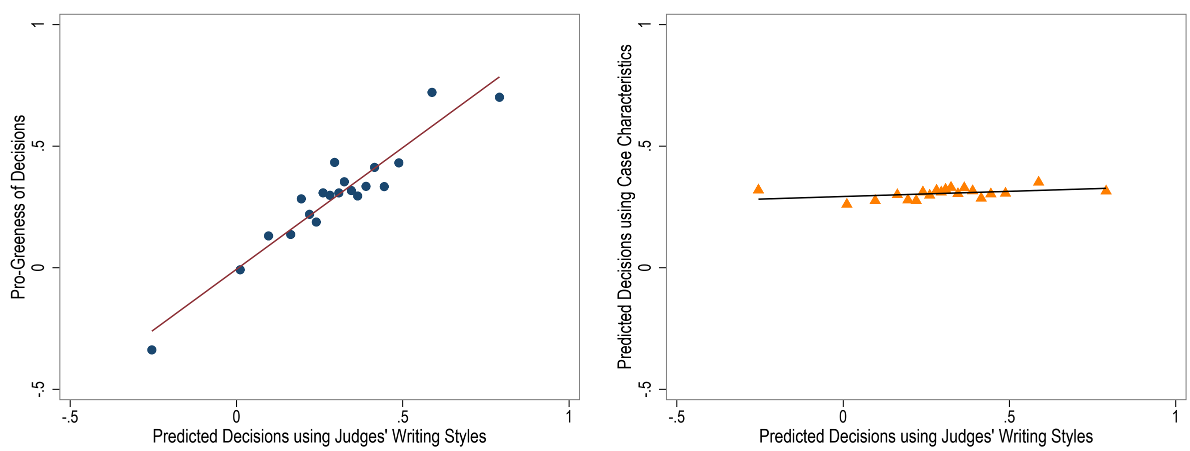


Figure 4: Graphical First Stage

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).

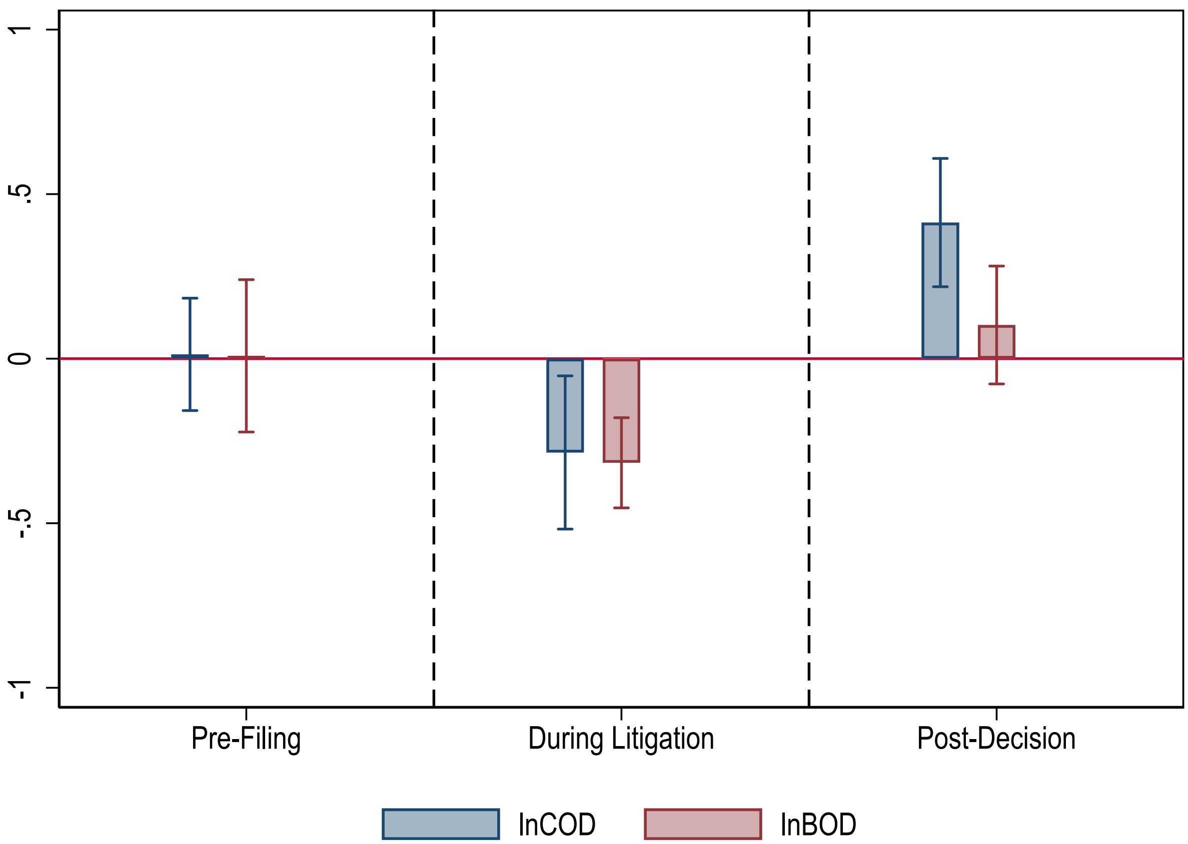


Figure 5: Dynamic Impacts of Green Orders on Pollution

Note: This figure presents estimation results of the impact of pro-environmental rulings on (time shifted) pollution outcomes. Every estimate is an independent regression. Outcomes are the log of the maximum value of BOD or COD 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. "Pre-filing" regressions include district-years 4 to 1 prior to the filing year of an order. "During Litigation" regressions include all district-years between the filing and the decision date of an order. "Post-Decision" regressions include years 1 to 5 post the decision year of an order. 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.

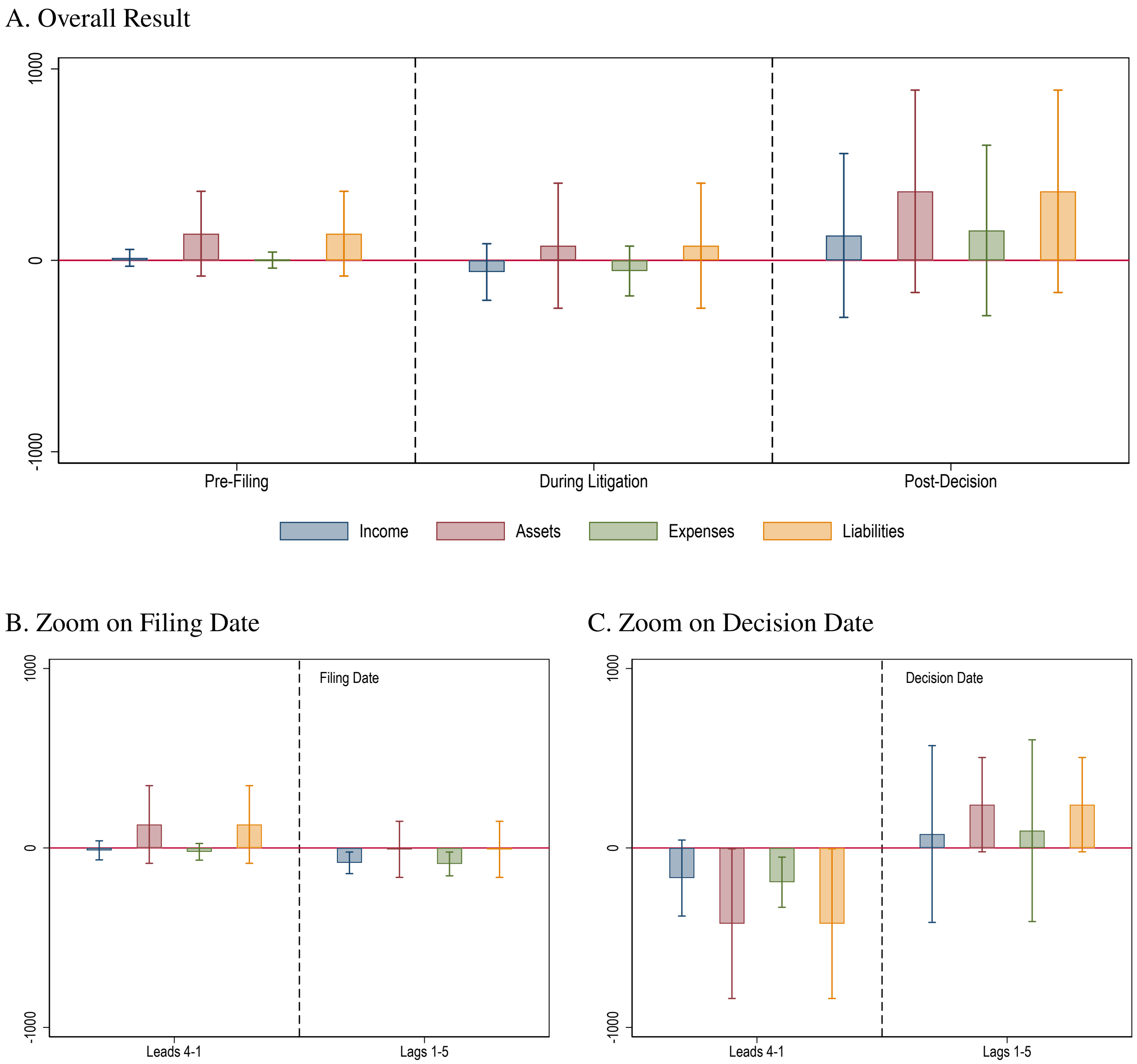


Figure 6: Impact of Green Orders on Firm Financials

Note: This figure presents estimation results of Equation 6.2. Especially, it displays the impact of a green order on firm financial outcomes of firms mentioned in a green order relative to firms mentioned in non-green orders. Income, assets, expenses and liabilities are measured in million USD from the Prowess database, which curates data from annual financial reports of all listed and a set of large unlisted companies. "Pre-filing" regressions include district-years 4 to 1 prior to the filing year of an order. "During Litigation" regressions include all district-years between the filing and the decision date of an order. "Post-Decision" regressions include years 1 to 5 post the decision year of an order. The variable $FracGreenOrders$ is instrumented for by a 25 dimensional vector summarizing judges writing styles and the fraction of Judges with a postgraduate degree on the order associated with a firm. Confidence intervals are at the 95%-level.

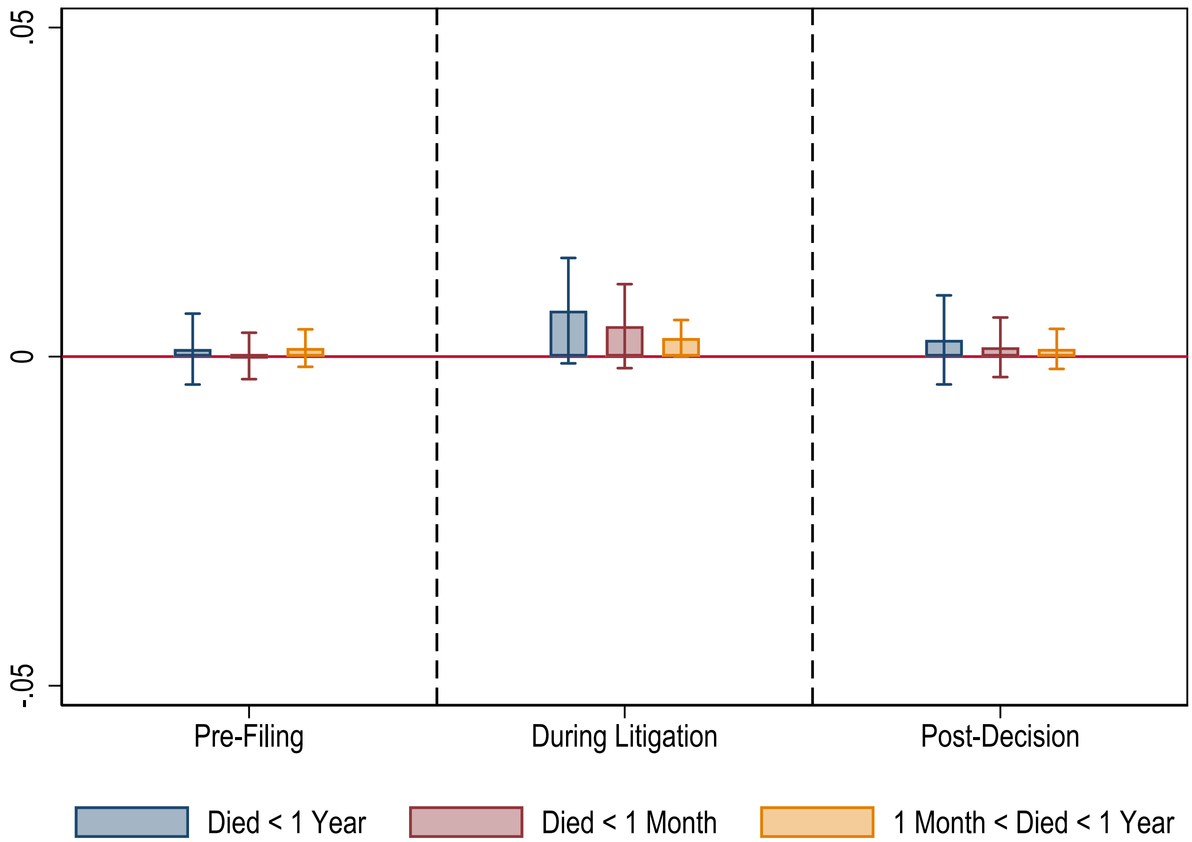


Figure 7: Dynamic Impacts of Green Orders on Infant Mortality

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 are, respectively, the share of infants in a district and year 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 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. 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.

Table 1: Summary Statistics for each source of data

	N	Mean	SD	Min	Max
Pollution (Monitor-Year)					
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 (BOD)					
Appeal	339	0.26	0.44	0.0	1.0
Constitutional	339	0.21	0.41	0.0	1.0
Government is Respondent	339	0.81	0.40	0.0	1.0
Government is Petitioner	339	0.15	0.36	0.0	1.0
Number of Judges	339	1.72	0.75	1.0	3.0
Environmental Impact (Median Coding)	339	0.34	0.73	-1.0	2.0
Average Forest Cover in Location (%)	185	10.30	6.82	2.7	36.0
Average Nightlights in Location (%)	127	11.40	12.80	0.9	62.6
Judge Level Data - Pollution Merge (BOD)					
Male	212	0.98	0.14	0.0	1.0
Graduate Level Education	212	0.43	0.50	0.0	1.0
Post-Graduate Level Education	212	0.16	0.37	0.0	1.0

Table 2: Summary Statistics of the Pollution Working 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

Note: The observations are at the district-year level.

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: 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 6: 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 5 apply.

Table 7: Summary Statistics of Financial Indicators for Firms Mentioned in Judicial Orders

	N	Mean	SD	Min	Max
Panel A - Sample around Filing Date					
Income	343	309.88	949.36	0.0	6,909.8
Assets	351	589.52	1,887.87	2.4	13,812.6
Expenses	345	302.19	930.43	0.0	6,744.9
Liabilities	351	589.52	1,887.87	2.4	13,812.6
Panel B - Sample around Decision Date					
Income	457	458.19	1,025.83	0.0	6,909.8
Assets	480	916.43	2,205.54	0.1	13,812.6
Expenses	464	434.59	975.92	0.0	6,744.9
Liabilities	480	916.43	2,205.54	0.1	13,812.6

Note: This table presents summary statistics of firm financial variables for firms mentioned in the judicial orders. Each firm is mentioned at least once. The data here pertain to four years before and five years after judicial decisions. Observations are at the firm-financial year level, and outcomes are measured in million USD.

Table 8: Summary Statistics of the Mortality Data

	N	Mean	SD	Min	Max
Case Level Data - Mortality Merge					
Appeal	411	0.29	0.46	0.0	1.0
Constitutional	411	0.22	0.41	0.0	1.0
Government is Respondent	411	0.82	0.38	0.0	1.0
Government is Petitioner	411	0.14	0.35	0.0	1.0
Number of Judges	411	1.83	0.75	1.0	3.0
Environmental Impact (Median Coding)	411	0.44	0.77	-2.0	2.0
Average PM2.5 (µg/m3)	322	47.48	32.14	8.6	228.7
Judge Level Data - Mortality Merge					
Male	226	0.99	0.11	0.0	1.0
Graduate Level Education	226	0.38	0.49	0.0	1.0
Post-Graduate Level Education	226	0.13	0.34	0.0	1.0
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 9: Contemporaneous Impacts on Infant Mortality (Monthly)

	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	0.00198	-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.

A Appendix

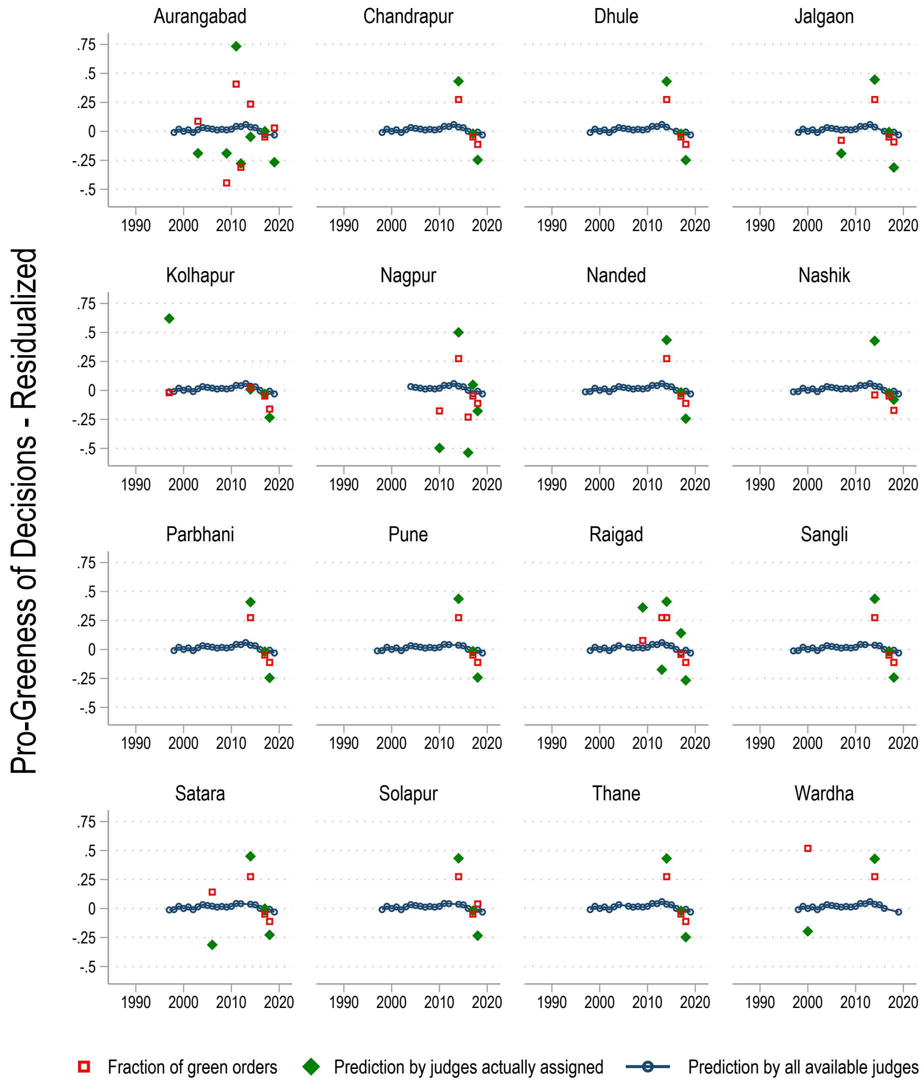


Figure A1: Random Variation in Judge assignment under Bombay HC

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 A1: Balance Check: Do pre-filing pollution levels predict pro-greeness of judges?

	Predicted pro-greeness of order(s)					
	Order level			District-year level		
	(1)	(2)	(3)	(4)	(5)	(6)
BOD 1 year pre-filing	-0.000137		0.00178	0.000288		0.000591
	(0.000510)		(0.00252)	(0.000156)		(0.000905)
BOD 2 years pre-filing	0.00000568		-0.0181*	-0.00000589		-0.00103
	(0.000558)		(0.00724)	(0.000184)		(0.000713)
BOD 3 years pre-filing	-0.0000848		0.0107	-0.000101		-0.000286
	(0.000617)		(0.00690)	(0.000167)		(0.000824)
COD 1 year pre-filing		0.000384	0.0000239		0.0000162	-0.0000609
		(0.000553)	(0.00119)		(0.000162)	(0.000251)
COD 2 years pre-filing		-0.000678	0.00421		-0.0000602	0.0000887
		(0.000584)	(0.00239)		(0.000152)	(0.000199)
COD 3 years pre-filing		0.00206**	-0.000876		-0.000444*	-0.000404*
		(0.000663)	(0.00185)		(0.000175)	(0.000192)
District + year FEs	Yes	Yes	Yes	Yes	Yes	
Mean Dep. Var.	0.285	0.341	0.341	-0.101	0.138	0.139
Joint significance p-value	0.98	0.00	0.00	0.30	0.08	0.22
R2	0.001	0.186	0.316	0.001	0.003	0.004
Observations	210	112	112	4,755	2,309	2,261

Note: This table presents regression results of the predicted pro-greeness of orders on pre-filing pollution levels. Columns (1) - (3) are at the order level. The dependent variable is the pro-greeness of an order predicted by a 25 dimensional vector, capturing the order's judge(s)' writing style, and the order's district and year. Orders relevant to multiple districts are assigned the first district in an alphabetical order. Columns (4) - (6) are at the district-year level. The dependent variable is the average pro-greeness of all orders in a district-year predicted by 25 dimensional vector, capturing the average over all orders's judges' writing style, and district and year fixed effects. In all columns (1) - (6) the regressions include district and year fixed effects. BOD measures the annual maximum biochemical oxygen demand (mg/l) in the district. BOD measures the annual maximum chemical oxygen demand (mg/l) in the district.

Table A2: Balance check: Do pre-filing pollution levels predict case characteristics?

	COD Sample		BOD Sample	
	Mean	COD t-1	Mean	COD t-1
At least one order	.1149689	.0154844	.1529328	.0068728
		(.0079659)		(.0054845)
Number of orders	.1372421	.0284444*	.1936913	.0106402
		(.0121528)		(.0080888)
Number of green orders	.0566656	-.0048657	.047138	.0026881
		(.0046597)		(.0043607)
Fraction of green orders	.0506223	-.006733	.0396851	-.0006966
		(.0038907)		(.0034467)
Average number of judges per order	.2088765	.0220925	.273442	.0097315
		(.0159505)		(.0107095)
% of orders with at least one female judge	.000928	.001596	.0034851	-.0006769
		(.0011864)		(.0008054)
% of orders with a majority of post-graduate judges	.0233268	-.0002389	.0195168	.0017757
		(.0039071)		(.0026265)
% of orders with government as petitioner	.0215962	.0143241***	.0143718	.0023488
		(.0043148)		(.0018188)
% of orders with government as respondent	.0874659	.000122	.1307136	.0065406
		(.0069049)		(.0051186)
% of appeal cases	.0314499	.016482***	.0356329	.003172
		(.0046695)		(.0033034)
% of constitutional cases	.0391746	.0016444	.0575078	.0033373
		(.0036341)		(.0022159)

Note: This table presents estimated coefficients from regressing case characteristics on pre-filing pollution levels. Each row represents results from two independent regressions, each regressing the variable in the left column on the pre-filing levels of chemical oxygen demand (COD) and bichemical oxygen demand (BOD), respectively. All regressions inlcude district and year fixed effects. Robust standard errors 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 in parentheses. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent levels, respectively.

Table A3: 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 A4: Contemporaneous Impacts on Water Pollution (Yearly)

	(1) ln(Max BOD)	(2) ln(Max BOD)	(3) ln(Mean BOD)	(4) 1(Mean BOD ¿ 3)
Fraction of Green Orders	-0.241**	-0.181*	-0.0424	-0.144***
	(0.103)	(0.102)	(0.0961)	(0.0449)
Dummy for Presence of an Order	0.0619	0.134	0.0872	0.0798*
	(0.118)	(0.129)	(0.126)	(0.0481)
District-years with no orders	Dummied	Dummied	Dummied	Dummied
Year and District FEs	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes
Clustering	IOC	IOC	IOC	IOC
Eff First Stage F	8.857	8.400	8.400	8.400
N	5649	4670	4670	4670

Note: All notes from Table 3 apply.

Table A5: Contemporaneous Impacts on Water Pollution (Yearly) Heterogeneity

	Cases with Government as			Constitutional Cases		Appeal Cases	
	Petitioner (1)	Respondent (2)	Any (3)	Only (4)	Excluded (5)	Only (6)	Excluded (7)
Panel A:	Dependent variable: ln(BOD)						
Fraction of Green Orders	0.0486	-0.252***	-0.212**	0.0496	-0.243**	-0.0473	-0.339***
	(0.198)	(0.0972)	(0.106)	(0.171)	(0.107)	(0.162)	(0.116)
Dummy for Presence of an Order	0.0922	0.0949	0.157	0.00819	0.120	0.0349	0.0853
	(0.219)	(0.0585)	(0.156)	(0.0941)	(0.142)	(0.136)	(0.119)
Unique orders	31	234	265	67	209	62	214
Eff First Stage F	19.88	8.405	8.268	3.767	11.31	4.444	6.721
N	5649	5649	5649	5649	5649	5649	5649
Panel B:	Dependent variable: ln(COD)						
Fraction of Green Orders	-0.146	-0.326***	-0.226*	0.142	-0.216	-0.172	-0.171
	(0.212)	(0.126)	(0.120)	(0.295)	(0.134)	(0.197)	(0.149)
Dummy for Presence of an Order	0.288	0.0591	0.357**	0.179	0.250*	0.486**	0.234*
	(0.228)	(0.110)	(0.176)	(0.159)	(0.143)	(0.229)	(0.139)
Unique orders	14	45	54	12	48	15	45
Eff First Stage F		6.473	7.420		9.681		9.357
N	3053	3053	3053	3053	3053	3053	3053
District-years with no orders	Dummied	Dummied	Dummied	Dummied	Dummied	Dummied	Dummied
Year and District FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	IOC	IOC	IOC	IOC	IOC	IOC	IOC

Note: All notes from Table 3 apply.

Table A6: 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.

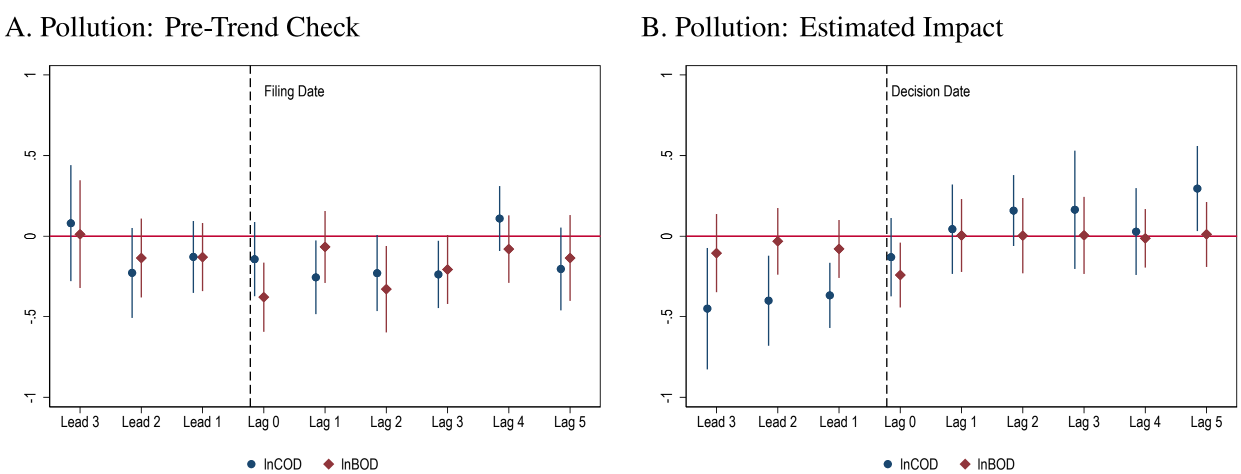
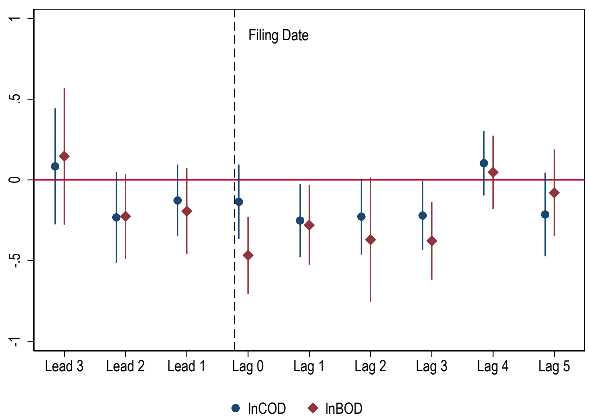


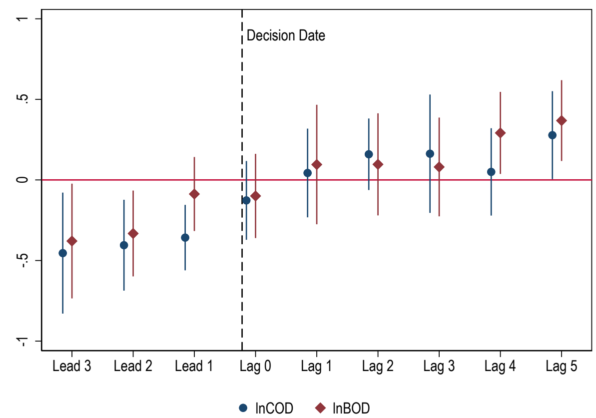
Figure A2: Dynamic Impacts of Green Orders on Pollution

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.

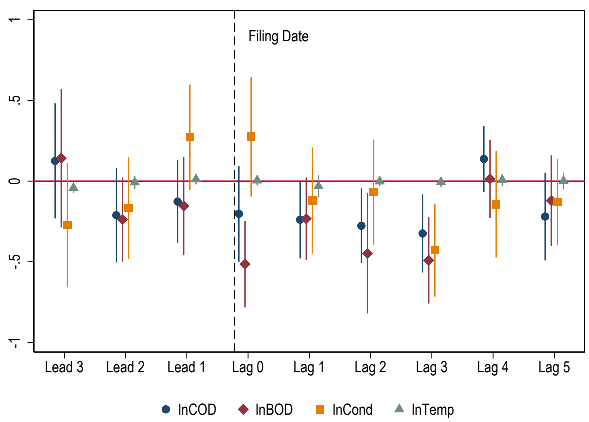
A. Common Support BOD + COD: Pre-Trend Check



B. Common Support BOD + COD: Estimated Impact



C. Common Support All: Pre-Trend Check



D. Common Support All: Estimated Impact

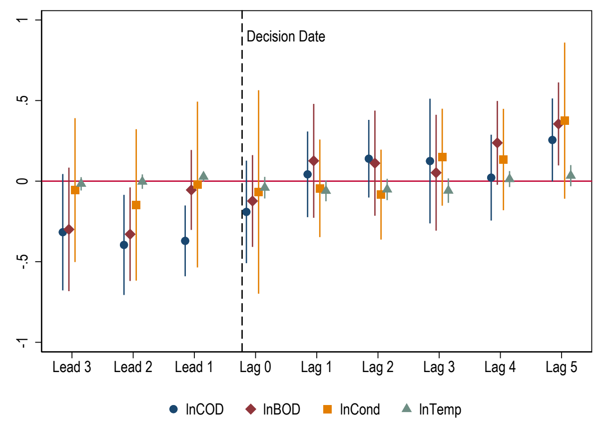


Figure A3: Dynamic Impacts of Green Orders on Pollution with Common Support

Note: All notes from Figure A2 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.

Table A7: 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 5 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.

Table A8: 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 A6 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 A9: Yearly Mortality Regressions

	Baseline Regressions			With Air Pollution Controls			With Air Pollution + Shrug Controls		
	(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	0.000607	-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 A6 apply. Additionally, (ii) The time-period of the mortality sample spans 1989-2017 (columns 1 to 6) and 1997-2017 (columns 7-9).

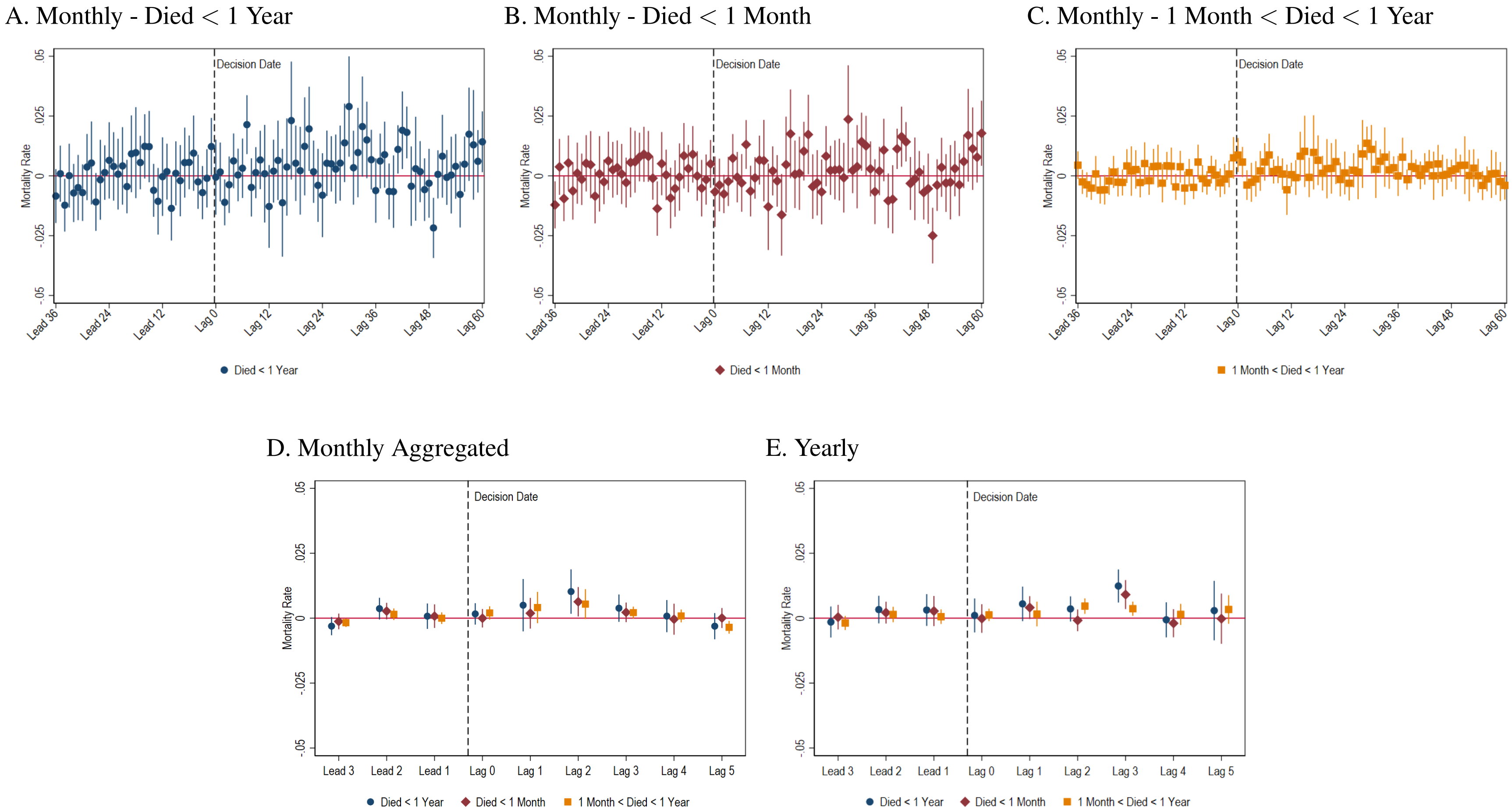


Figure A4: Dynamic Impacts of Green Orders on Infant Mortality (With Air Pollution Control)

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.

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

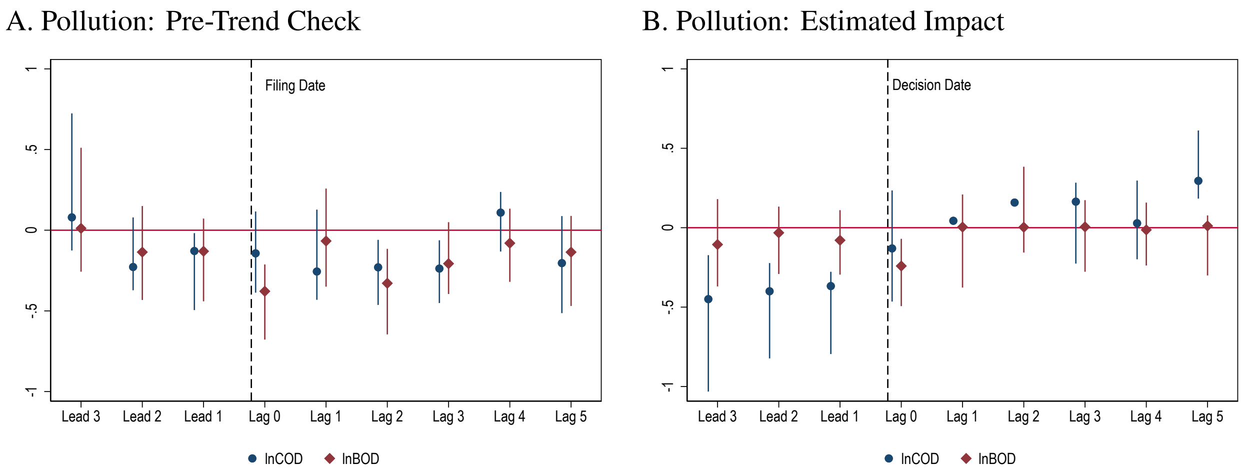


Figure OA1: Dynamic Impacts of Green Orders on Pollution

Note: All notes from Figure A2 apply. Additionally, confidence intervals are robust to weak inference.

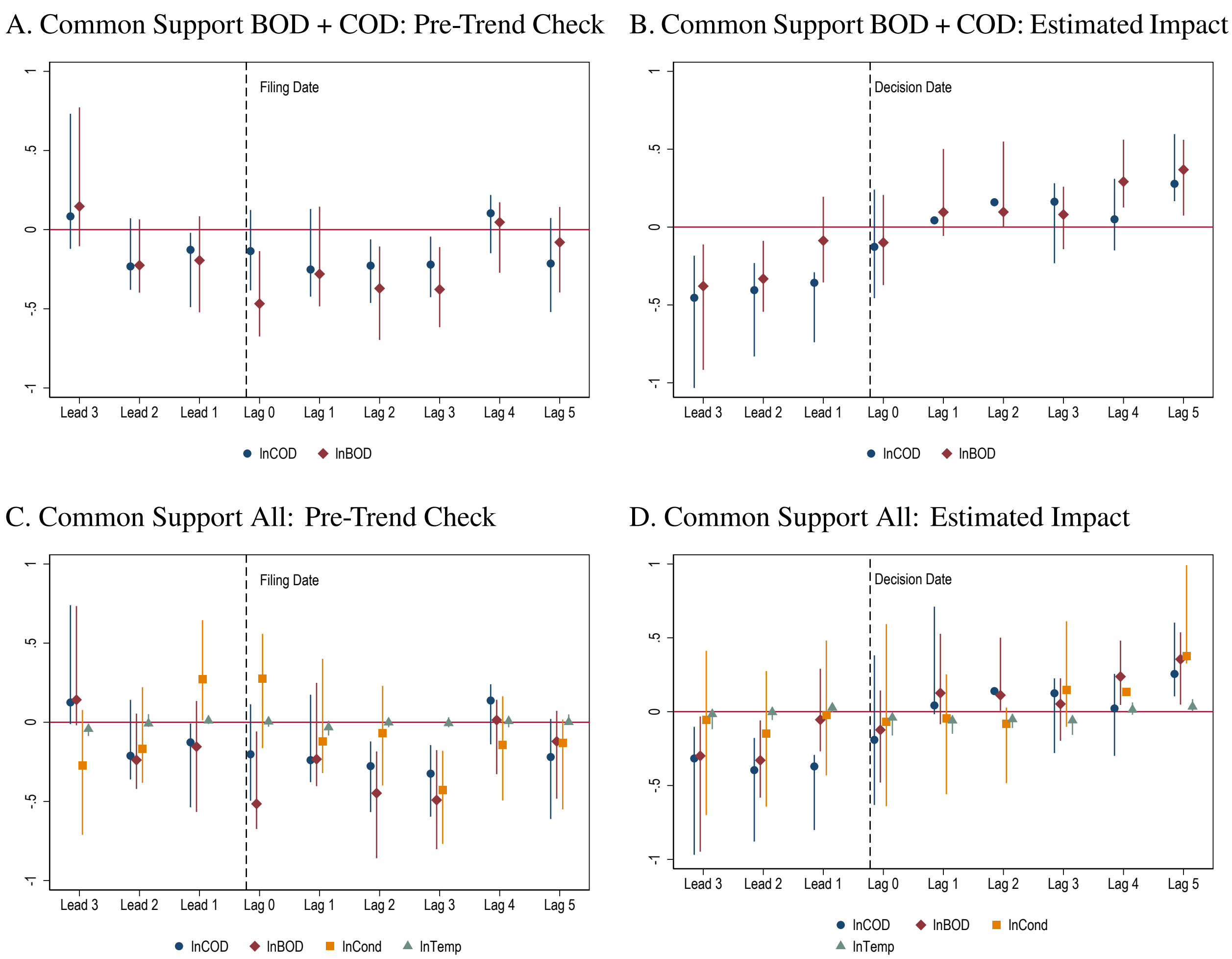


Figure OA2: Dynamic Impacts of Green Orders on Pollution with Common Support

Note: All notes from Figure A3 apply. Additionally, confidence intervals are robust to weak inference.

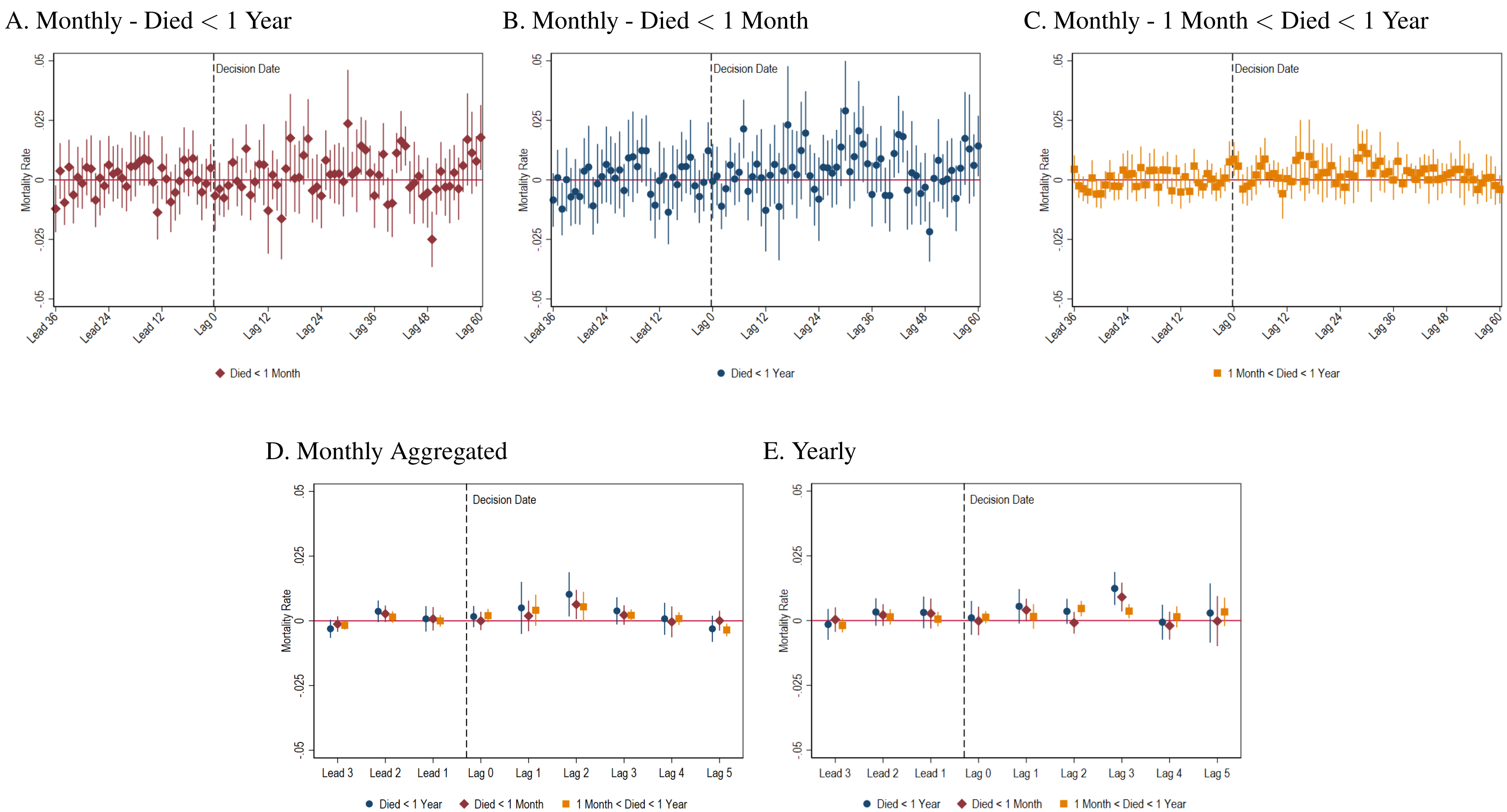


Figure OA3: Dynamic Impacts of Green Orders on Infant Mortality (With Air Pollution Control)

Note: All notes from Figure A4 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 9 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) 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	0.000607	-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) 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
	[.; .]	[-0.0135; 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) 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
	[-0.0224; 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.

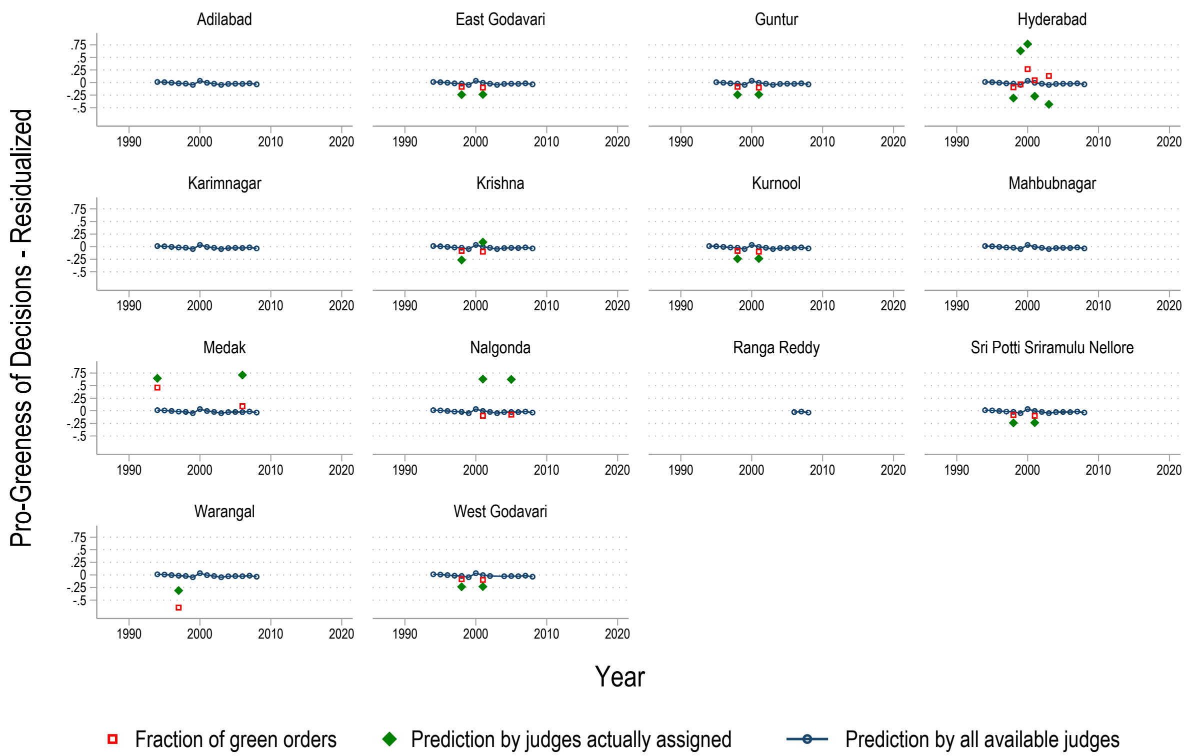


Figure OA4: Random Variation in Judge assignment in Andhra Pradesh

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.

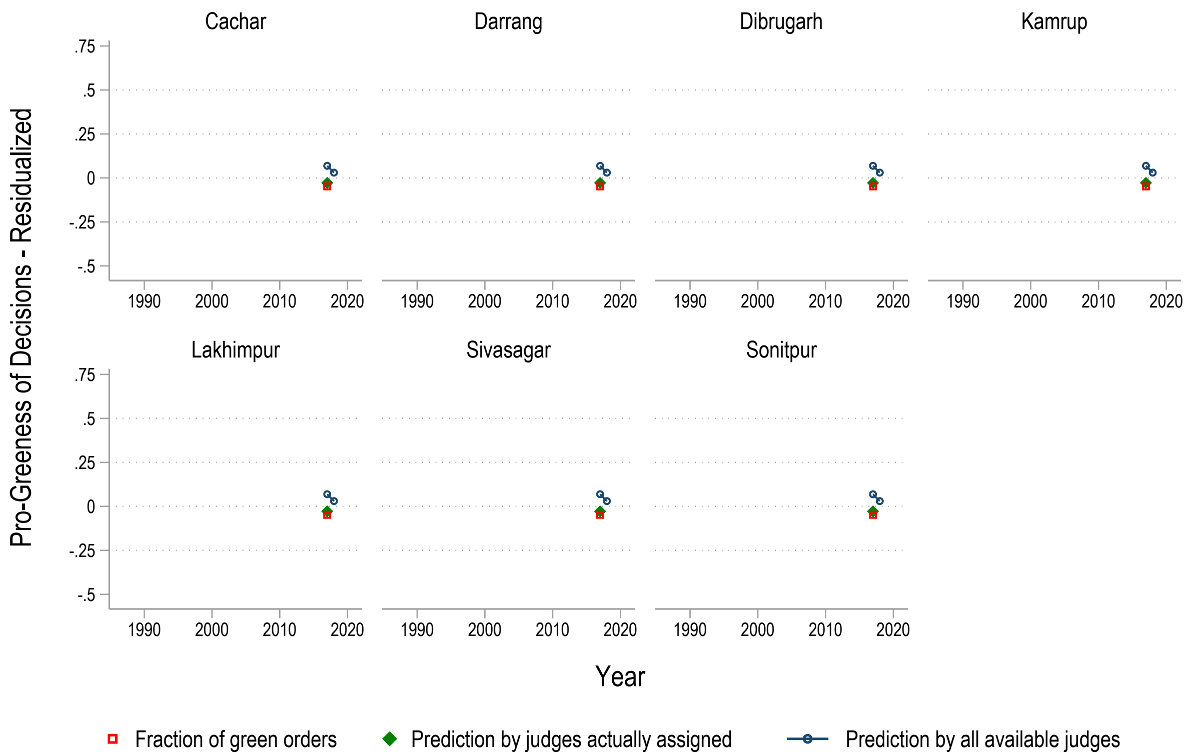


Figure OA5: Random Variation in Judge assignment in Assam

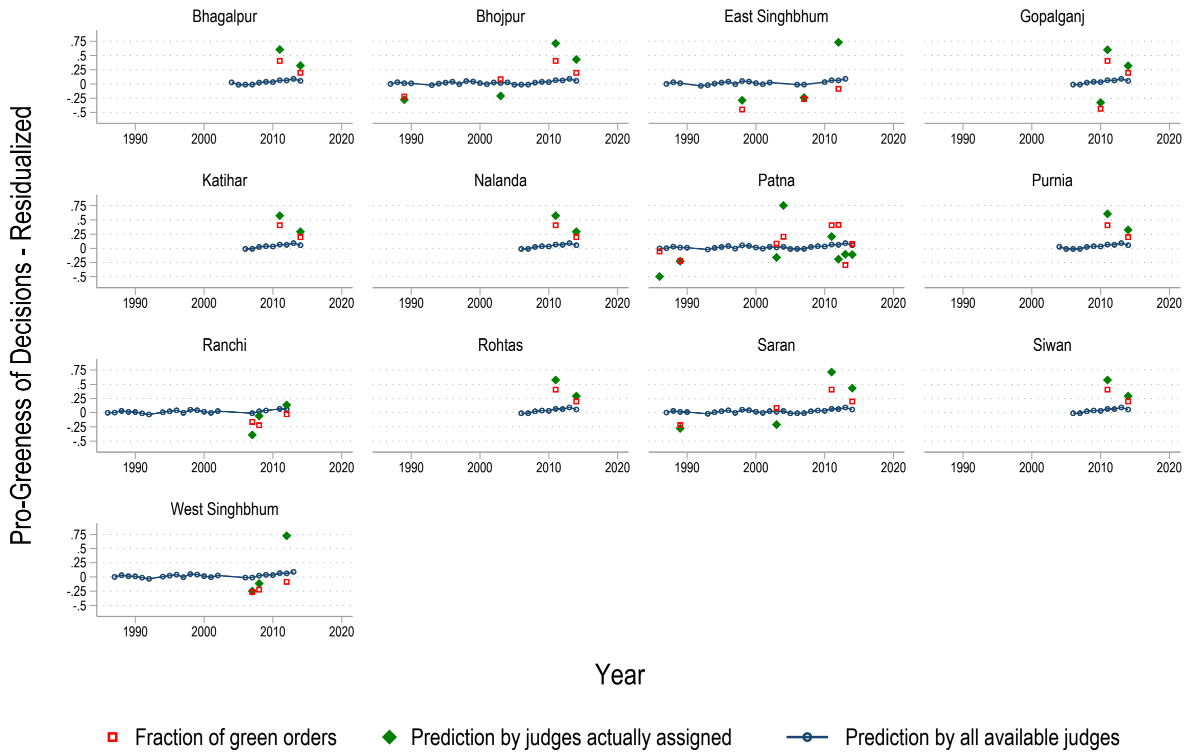


Figure OA6: Random Variation in Judge assignment in Bihar

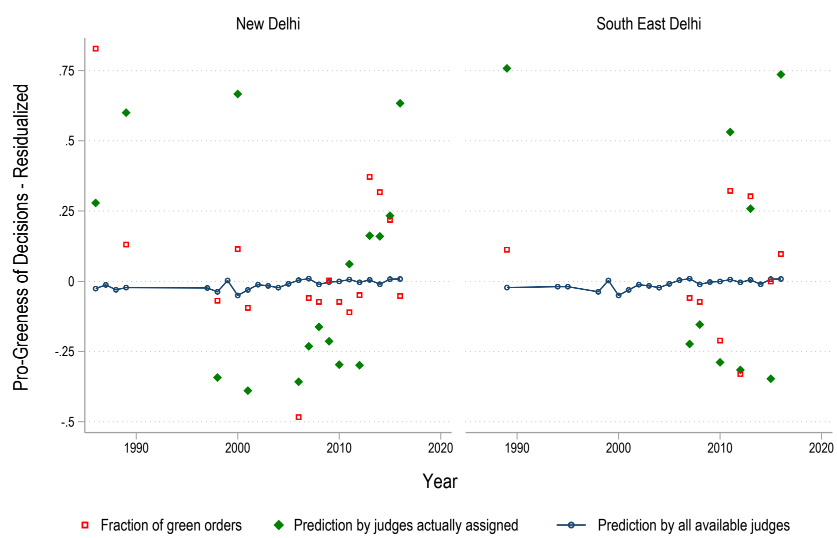


Figure OA7: Random Variation in Judge assignment in Delhi

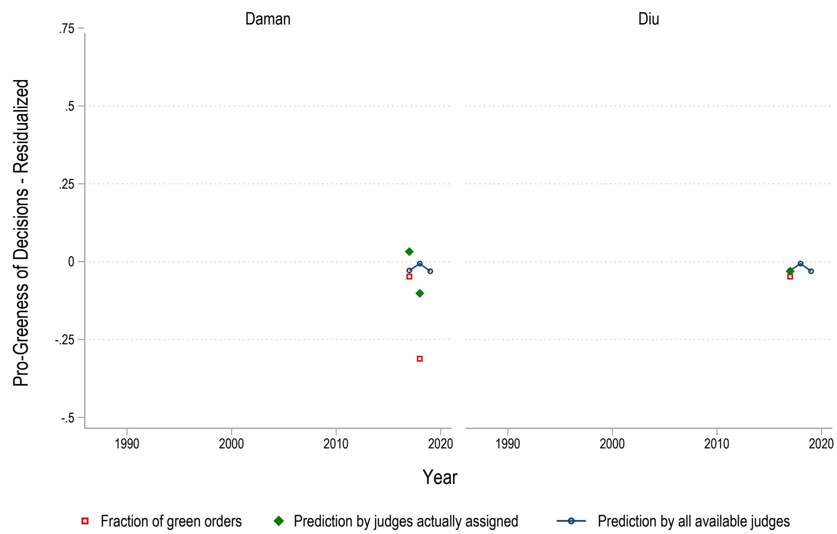


Figure OA8: Random Variation in Judge assignment in Goa

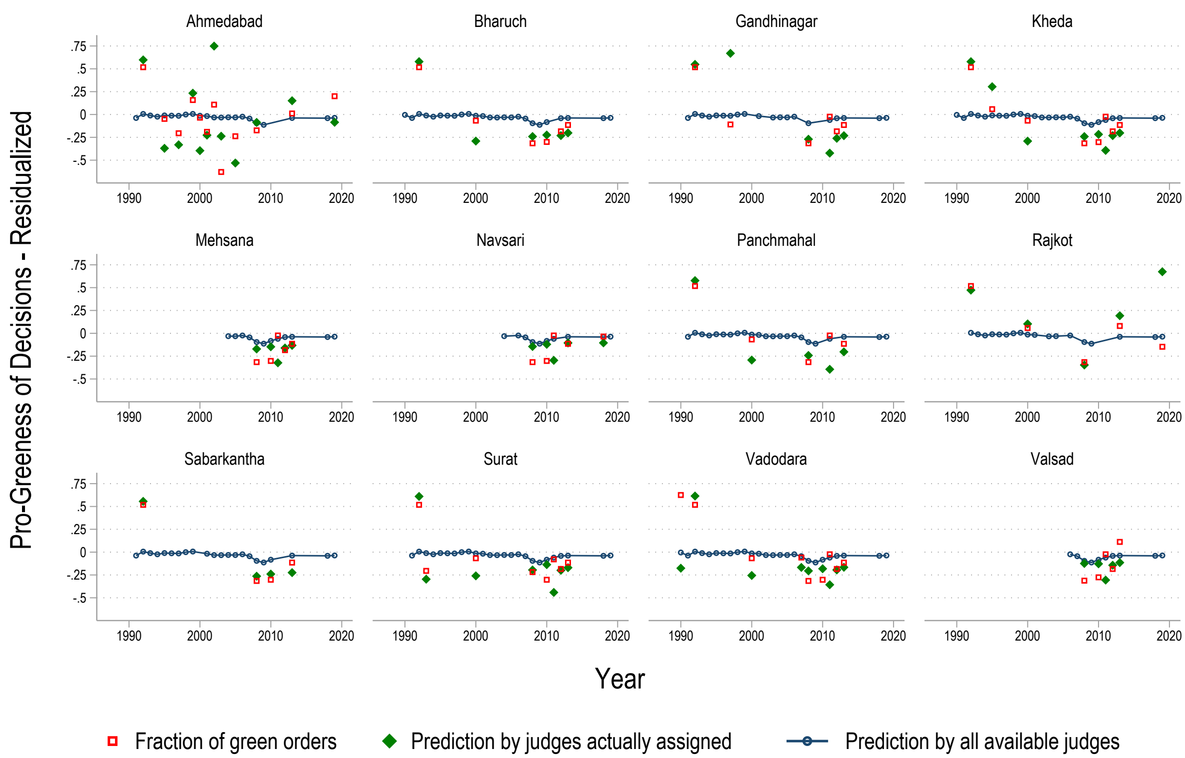


Figure OA9: Random Variation in Judge assignment in Gujarat

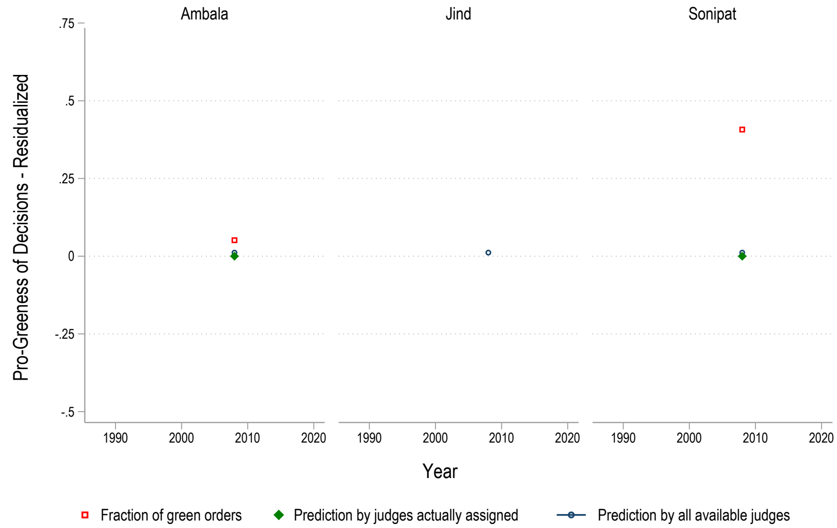


Figure OA10: Random Variation in Judge assignment in Haryana

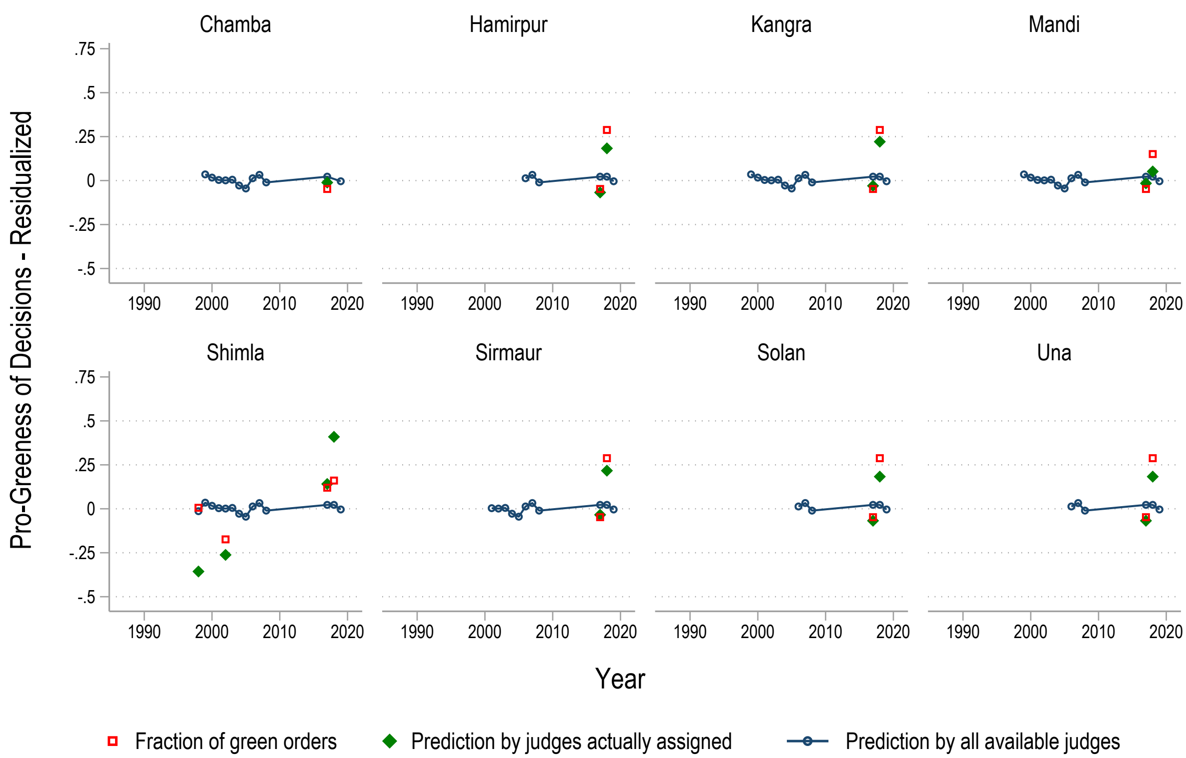


Figure OA11: Random Variation in Judge assignment in Himachal Pradesh

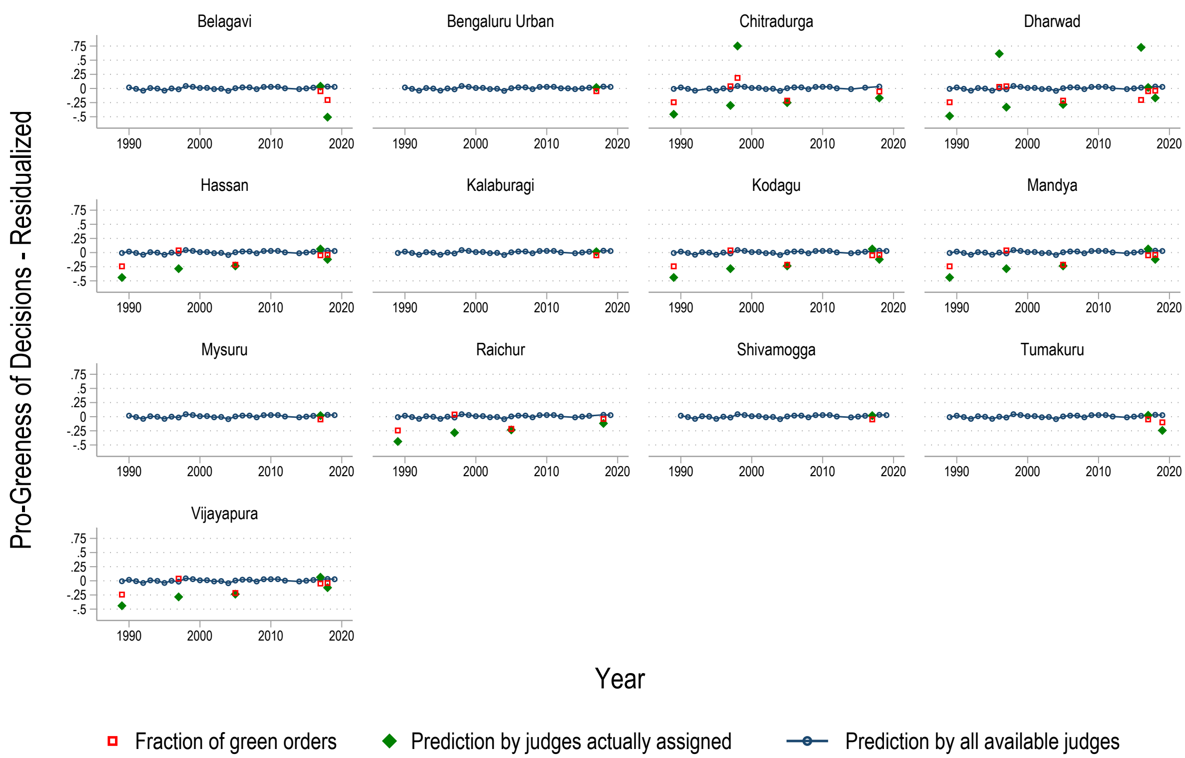


Figure OA12: Random Variation in Judge assignment in Karnataka

Note: Notes of Figure OA4 apply.

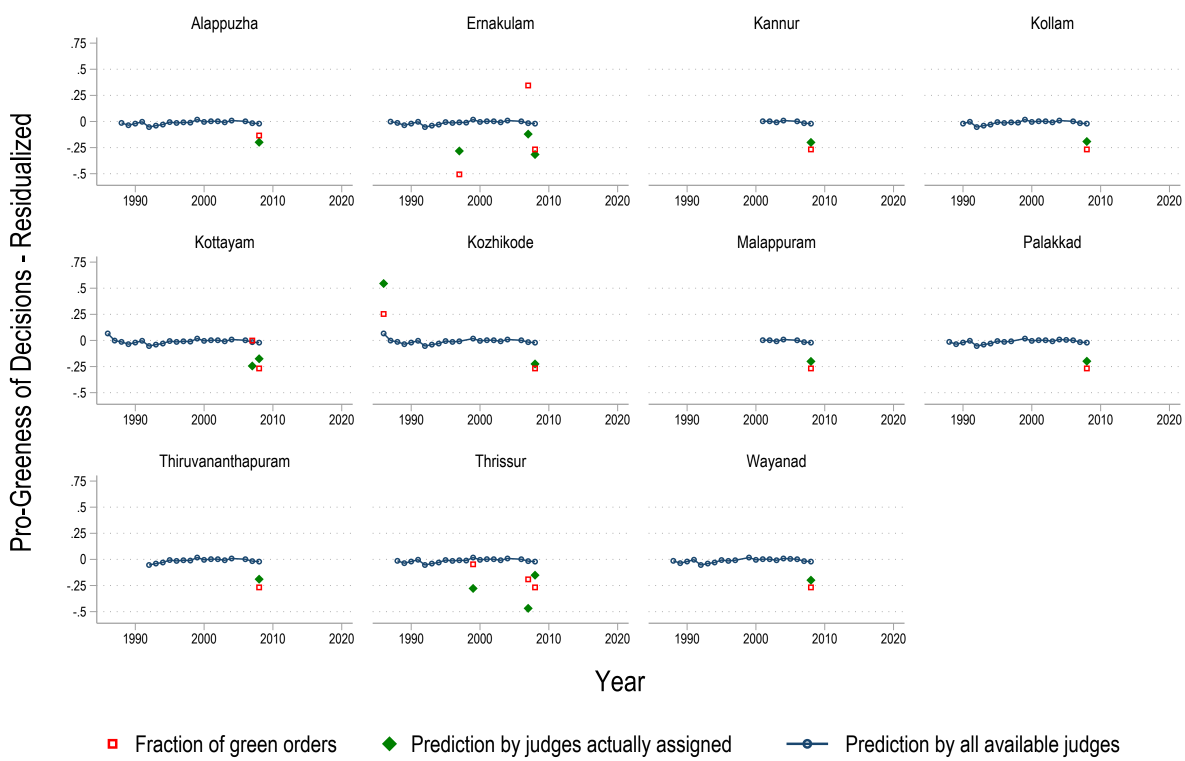


Figure OA13: Random Variation in Judge assignment in Kerala

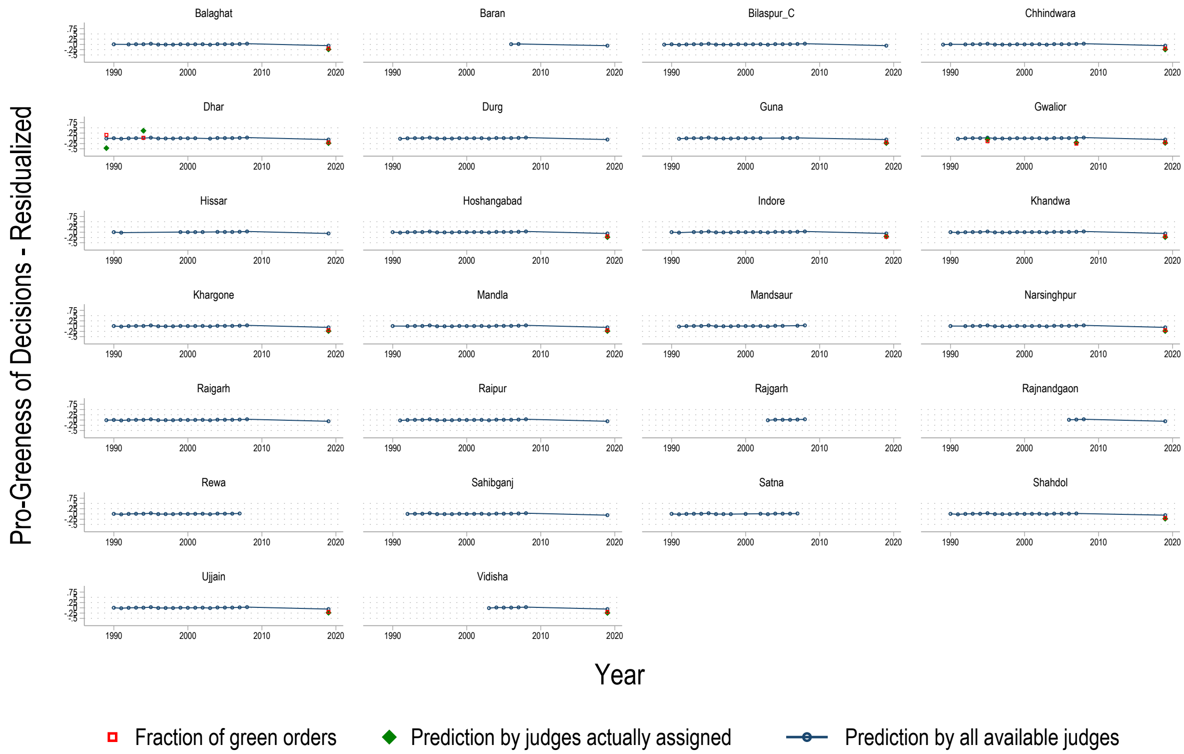


Figure OA14: Random Variation in Judge assignment in Madhya Pradesh

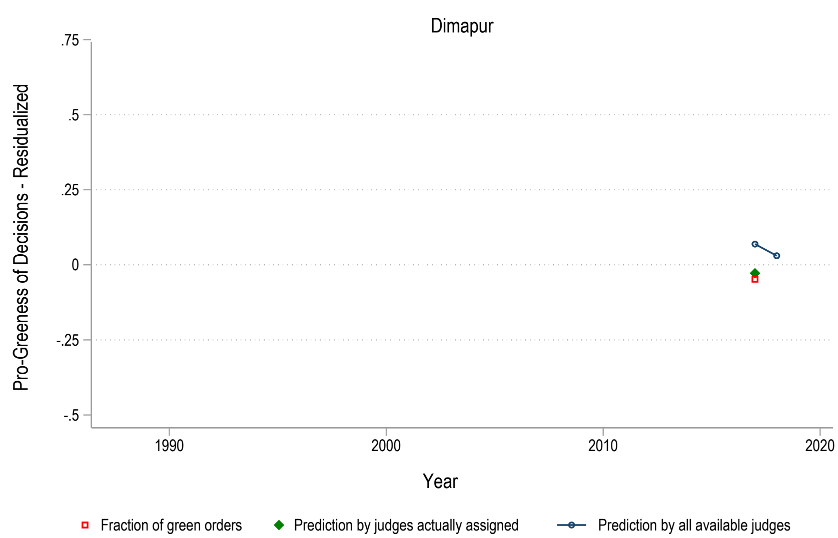


Figure OA15: Random Variation in Judge assignment in Nagaland

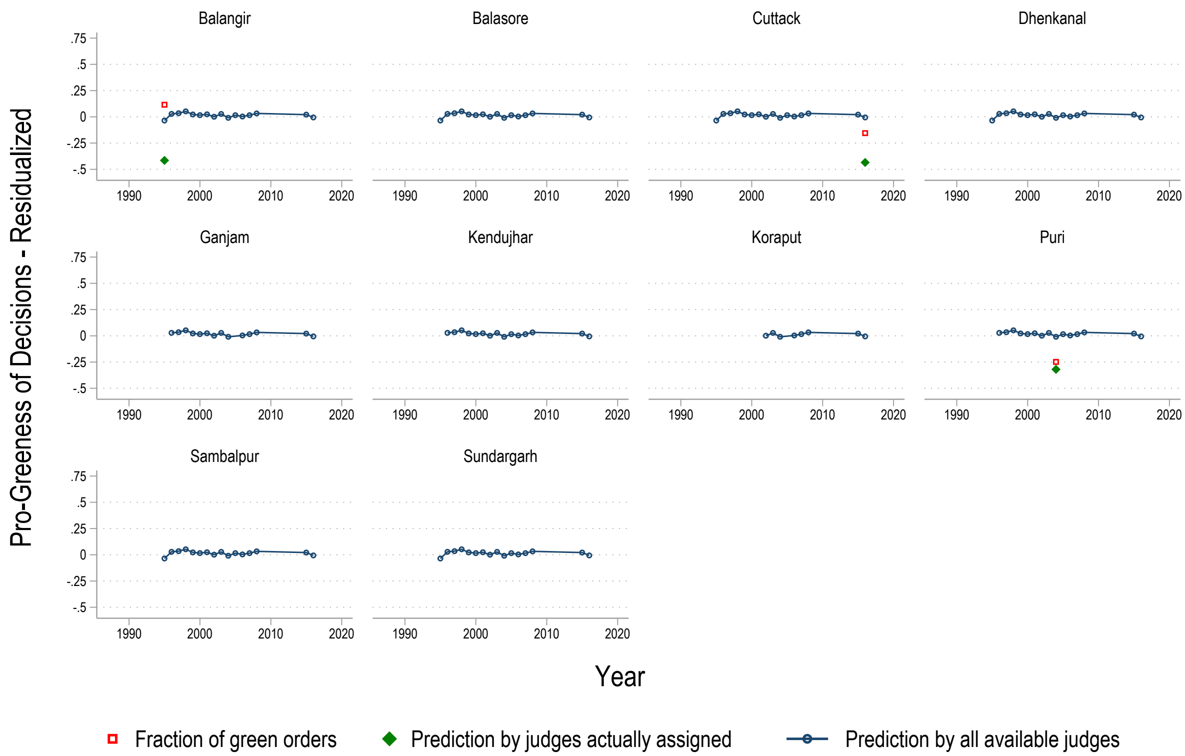


Figure OA16: Random Variation in Judge assignment in Orissa

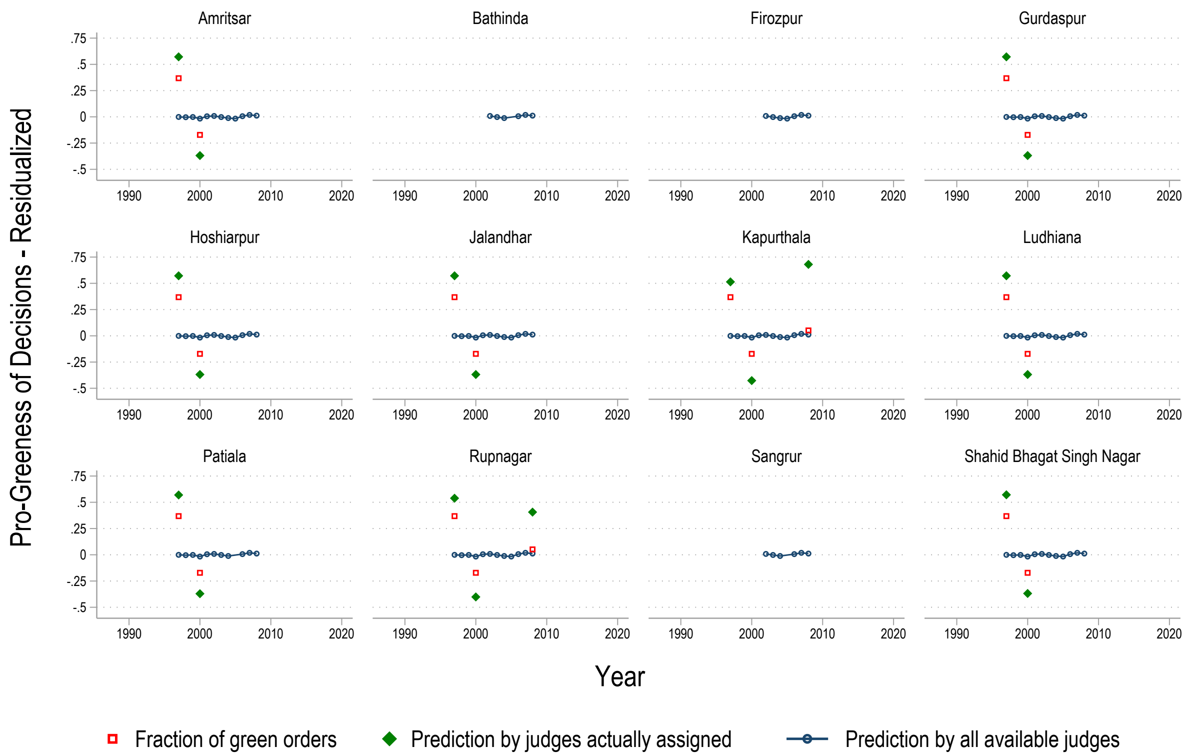


Figure OA17: Random Variation in Judge assignment in Punjab

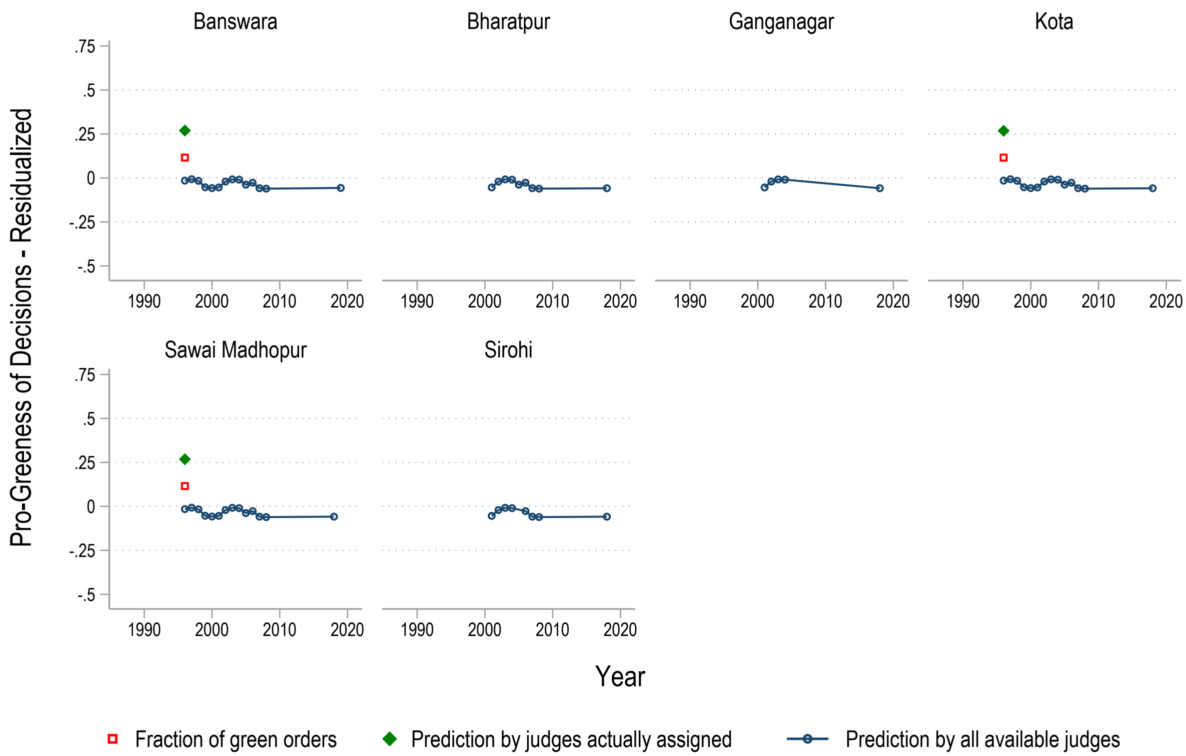


Figure OA18: Random Variation in Judge assignment in Rajasthan

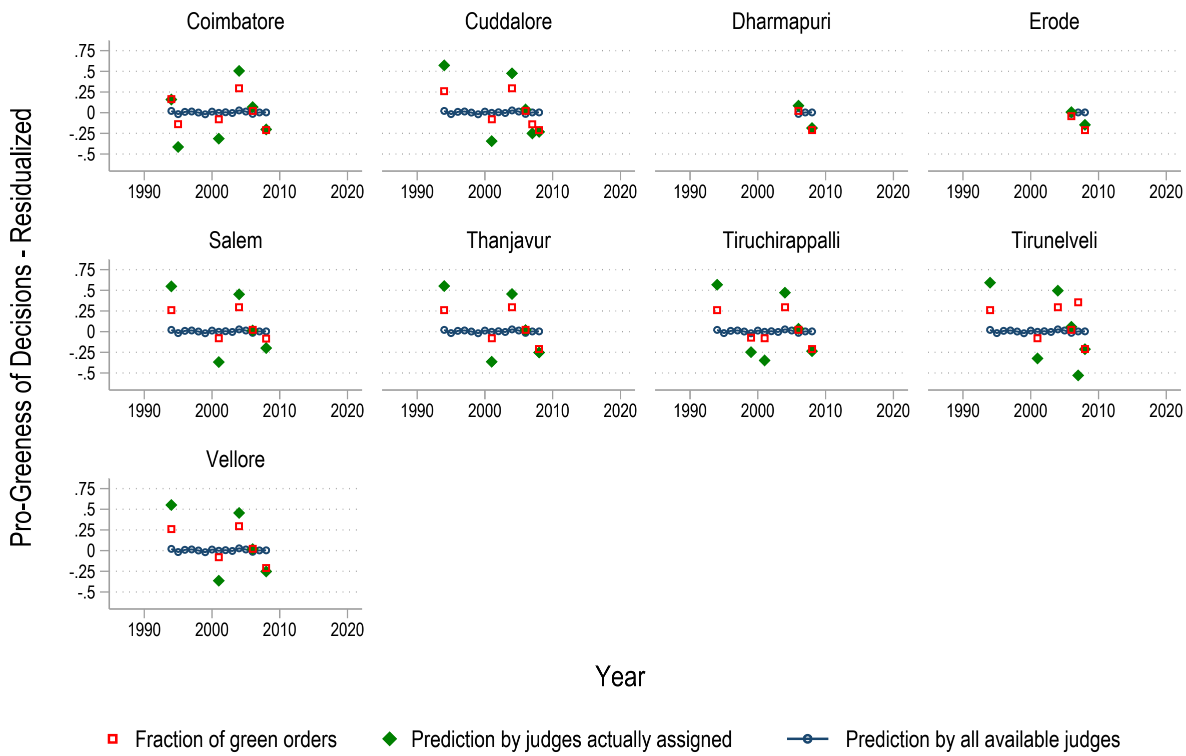


Figure OA19: Random Variation in Judge assignment in Tamil Nadu

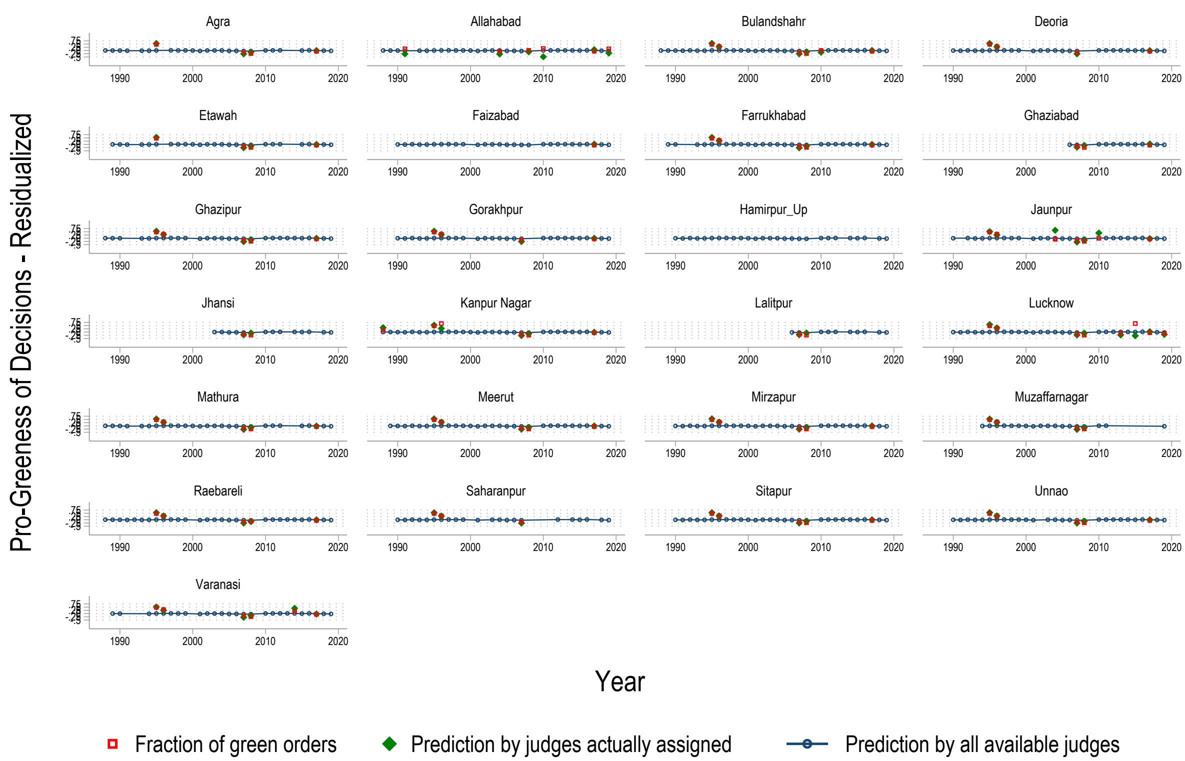


Figure OA20: Random Variation in Judge assignment in Uttar Pradesh

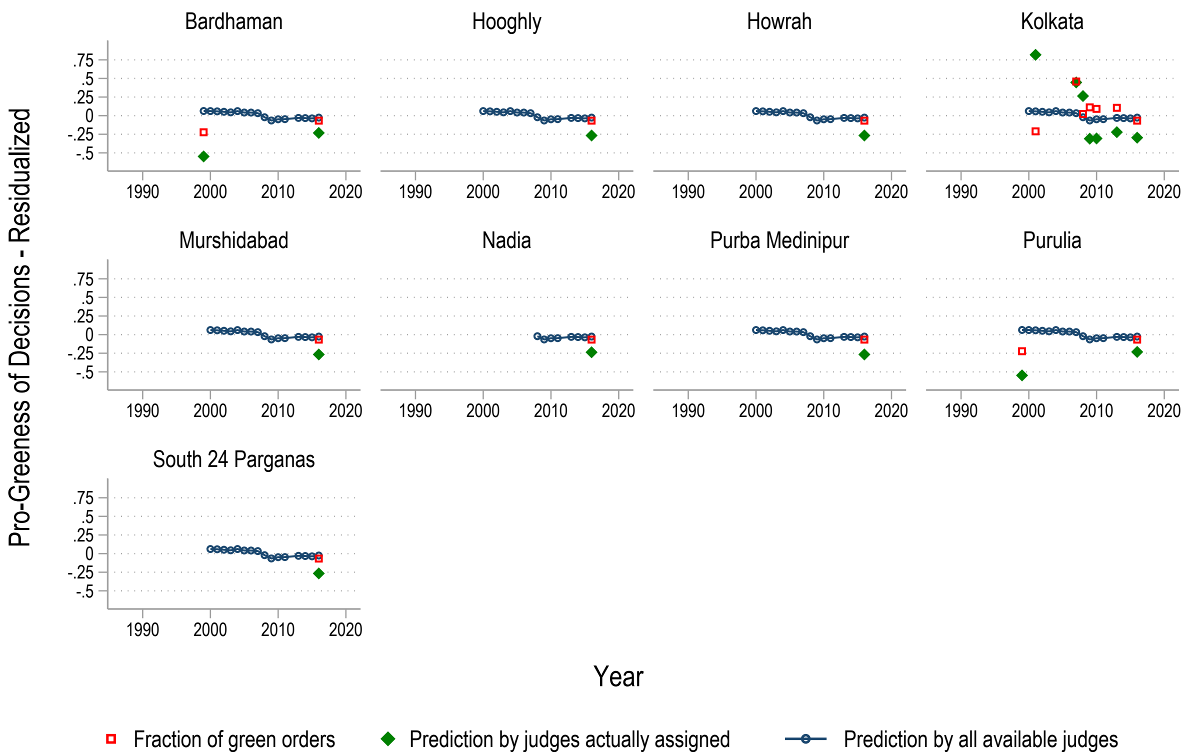


Figure OA21: Random Variation in Judge assignment in West Bengal