

THE UNIVERSITY OF CHICAGO

ESSAYS IN ENVIRONMENTAL ECONOMICS

A DISSERTATION SUBMITTED TO
THE FACULTY OF THE IRVING B. HARRIS
GRADUATE SCHOOL OF PUBLIC POLICY STUDIES
IN CANDIDACY FOR THE DEGREE OF
DOCTOR OF PHILOSOPHY

BY
CLAIRE QING FAN

CHICAGO, ILLINOIS

JUNE 2026

TABLE OF CONTENTS

LIST OF FIGURES	v
LIST OF TABLES	vi
ACKNOWLEDGMENTS	vii
ABSTRACT	viii
1 DAM THY NEIGHBOR: INTERNATIONAL RELATIONS AND THE EXTER- NALITIES OF IMPOUNDING RIVERS	1
1.1 Introduction	1
1.2 Background	7
1.2.1 Dams and their hydrological impacts	7
1.2.2 Theories and measurement of power and propensity to coordinate	9
1.3 Downstream economic effects of dams	12
1.3.1 Empirical method	12
1.3.2 Data	17
1.3.3 Results	21
1.4 The role of international relations	30
1.4.1 Empirical method	30
1.4.2 Data	32
1.4.3 Results	39
1.5 Conclusion	45
2 ENVIRONMENTAL DEGRADATION IN ONE’S OWN BACKYARD: WHO GAINS AND WHO LOSES FROM SAND MINING IN INDIA (WITH SUSHANT BAN- JARA AND VARUN K)	46
2.1 Introduction	46
2.2 Background and Institutional Setting	52
2.2.1 Sand mining in India	53
2.2.2 Sand mining leases	55
2.2.3 Benefits and losses from sand mining	55
2.3 Data and Empirical Strategy	57
2.3.1 Data	57
2.3.2 Identification strategy	61
2.3.3 Support for parallel trends assumption	63
2.4 Results	66
2.4.1 Effects on flooding	66
2.4.2 Effects on village-level mean nightlights	69
2.4.3 Effects on Agriculture	72
2.4.4 Heterogeneity by income and caste	75
2.5 Conclusion	79

3	RURAL HOUSEHOLD WATER ACCESS IN INDIA (WITH DEVIKA LAKHOTE)	82
3.1	Introduction	82
3.2	Setting and Data	84
3.3	Research Design	86
3.4	Results	88
3.5	Discussion and next steps	90
3.6	Figures	92
3.7	Tables	95
APPENDIX A	APPENDIX TO CHAPTER 1	96
A.1	Additional methodological description	96
A.1.1	Drought and wetness sensitivity	96
A.2	Additional Tables and Figures	99
A.2.1	Tables	99
A.2.2	Figures	108
APPENDIX B	APPENDIX TO CHAPTER 2	115
B.1	Additional Results and Checks	115
B.1.1	Descriptive data	115
B.1.2	Raw Data	117
B.1.3	Balance Checks	120
B.1.4	Robustness	122
REFERENCES		123

LIST OF FIGURES

1.1	Flow share from dammed area (red bar) along downstream river stretches	14
1.2	Geolocated dams with construction finished in 2001-2013 (GDAT)	18
1.3	Dam completion by purpose and year	19
1.4	Hydroelectric dams: Dynamic effects of flow share on nightlights	27
1.5	Effects on nightlights of hydroelectric dams, by flow share bin	28
1.6	Effects of flow share from domestic vs foreign hydroelectric dams on nightlights	29
1.7	Implied effects of domestic and foreign flow share from hydroelectric dams: heterogeneity by joint IGO membership	42
1.8	Distributed lag regression: cumulative effects of flow share from foreign hydro dams, by joint IGO membership	44
2.1	Sand excavator and trucks at a sand mine in Patna	55
2.2	Centroids of existing and proposed sand mines	64
2.3	Balance in Observable Characteristics	66
2.4	Dynamic effects of Sand mining on Flooding	68
2.5	Village-level dynamic effects of sand mining on nightlights	71
2.6	Dynamic effects of sand mining on vegetation	74
2.7	Dynamic effects of sand mining on economic inequality	77
3.1	Screenshot of IMIS platform	92
3.2	Treatment timing across years and villages	93
3.3	Effect of HWA on total enrollment	93
3.4	Effect of HWA on total exam-takers in grades 5-8	94
3.5	Effect of HWA on share of girls' in total enrollment	94
A1	Non-hydroelectric dams: Dynamic effects of flow share on nightlights	108
A2	Dynamic effects of flow share from hydroelectric dams above county-specific median	110
A3	Cumulative effects of flow share from hydroelectric dams on PM2.5	111
A4	Implied effects of domestic and foreign flow share from hydroelectric dams: heterogeneity by GDP imbalance	112
A5	Implied effects of domestic and foreign flow share from hydroelectric dams: heterogeneity by voting similarity in the UN General Assembly	113
A6	Implied effects of domestic and foreign flow share from hydroelectric dams: heterogeneity by regime type similarity	114
B1	Example of mine details in a District Survey Report	116
B2	Sand being transported on boats	117
B3	Mean Inundation over time	118
B4	Mean Nightlights and EVI over time	119
B5	Mine level effects of sand mining on vegetation - Using Sun and Abraham [2021]	122

LIST OF TABLES

1.1	Average height and reservoir capacity of dams built 2001-2013	19
1.2	Static TWFE estimates of effects of flow share from dams on nightlights, by dam purpose	23
1.3	Effects on nightlights, by pre-dam land use	24
1.4	Effects of domestic vs foreign dams on nightlights	26
1.5	Examples of country pairs along IR measure distributions. Format: upstream, downstream (IR value)	37
1.6	International relations and the effects of foreign hydroelectric dams on nightlights	41
2.1	Random checks with Google Maps satellite imagery	59
2.2	Effect of mining on Flooding	67
2.3	Effects of sand mining on village-level mean nightlights	70
2.4	Effects of sand mining on mine-level vegetation	73
2.5	Effects of sand mining on economic inequality	76
2.6	Effect of Sand Mining on Household Assets	79
3.1	Summary statistics	95
A1	Some costs and benefits of dams	99
A2	Effects of flow share from dams on PM2.5, by dam purpose	100
A3	Effect on nightlights of flow share from dams, by buffer width used to construct sample	101
A4	Effects on nightlights from domestic vs foreign hydroelectric dams, by trade relations	102
A5	Effects on nightlights from domestic vs foreign hydroelectric dams, by GDP imbalance	103
A6	Effects on nightlights from domestic vs foreign hydroelectric dams, by UN General Assembly voting similarity	104
A7	Effects on nightlights from domestic vs foreign hydroelectric dams, by regime type similarity	105
A8	Effects on nightlights from domestic vs foreign hydroelectric dams, by joint membership in IGOs	106
A9	Controlling for country-specific drought and wetness sensitivity when estimating IR interaction term: IGOs with joint membership	107
A10	Effects on nightlights using within country pair, time-varying bilateral engagement	109
B1	Correlations between treatment status or timing and assembly election outcomes	121
B2	Effect of Sand Mining on Household Assets	122

ACKNOWLEDGMENTS

I am immensely grateful to my advisors, Koichiro Ito, Amir Jina, Oeindrila Dube, and James Robinson, for helping me articulate my research interests and then teaching me how to pursue them. I am likewise grateful to my coauthors, Sushant Banjara, Varun K, Devika Lakhote, and Katie Zhang. Working with you substantially increased both the quality of my dissertation and the utility I derived from producing it, and those are the experiences that make me want to continue in research.

Thank you to those who hosted me and traveled with me in India for your generosity and wisdom: Anjani ji, Murari ji, the staff of Gram Gaurav Sansthan and Arpan Seva Sansthan, and the many people who hosted me in their courtyards and shared about their lives. I hope that over the course of a career, I can do some work that will mean something to you.

Finally, thank you to all the friends, peers, and faculty at Harris and in the UChicago EEE group. Research has ups and downs, but to be in a community with you, work with you and learn from you made the PhD a good gig throughout. Thank you.

ABSTRACT

This dissertation uses quasi-experimental methods to study how politics and governance determine the allocation of natural resources and the consequences for economic development. The first chapter, in the context of dams around the globe, combines a novel hydrology-based measure of dam exposure with measures of bilateral relations to quantify the downstream externalities of dams, within and across borders, and how the transboundary externalities are related to international relations. The second chapter, in the context of Bihar, India, provides the first quantitative causal evidence on the local environmental and economic impacts of sand mining, which constitutes 85% of global mineral extraction. To inform how resource access policy might be designed to be both welfare-improving and politically enforceable, we focus on how the costs and benefits are distributed among socially dominant versus marginal groups. The third chapter studies the public provision of water infrastructure at the national scale in India, assessing whether meeting government water provision targets achieves the commonly stated goal of educational gains, especially for girls.

CHAPTER 1

DAM THY NEIGHBOR: INTERNATIONAL RELATIONS AND THE EXTERNALITIES OF IMPOUNDING RIVERS

1.1 Introduction

Policies are made and enforced within countries. Yet, environmental externalities, including air pollution, water pollution, dust and desertification, common pool resource depletion, species invasion, and, of course, greenhouse gas emissions, are transboundary in nature, propagating outside their country of origin [Early et al., 2016, Heo et al., 2024, McWhinnie, 2009, Middleton, 2017, Sigman, 2002]. This means that around the world, key inputs to health and economic activity are potentially impacted by free-riding on the part of policymakers and economic agents in foreign countries.¹

What are the economic costs of transboundary environmental externalities? And, in the absence of an international regulatory authority, what can be done to avert or mitigate them? This paper studies these questions in the global context of dams on transboundary rivers, which elicit controversy by generating fears of disruption to water supply and ecological functions in downstream countries. I begin by measuring the causal impact of dams on downstream economic activity both in the same country as the dam and in foreign downstream countries. Then, I determine the extent to which the variation in externalities depends on international relations between riparian countries.

To estimate the causal effects of dams, including the far downstream effects, I leverage the spatial tributary structure of rivers to construct a novel continuous measure of exposure to an upstream dam. As a river flows downstream from a dammed location, it converges with the undammed flow of numerous tributaries. This means that as one moves downstream

1. In addition to my advisors, Koichiro Ito, Amir Jina, Oeindrila Dube, and James Robinson, many thanks go to Shaoda Wang, Eyal Frank, Ashton Pallottini, Paul Poast, Michael Tiboris, and Manasi Bose for formative discussions and comments. This paper has greatly benefited from the feedback of participants at IPWSD, AERE Summer Conference, and the University of Chicago Harris PhD Workshop, EEE Student Workshop, Development Lunch, and EPIC Lunch.

along the river, the share of the river discharge (that is, m^3/s of flow) originating from the dammed location decreases, diluting any potential hydrological impacts of the dam. For each location downstream of a dam and each year, I compute the location's "flow share" measure of dam exposure as the fraction of the pre-dam local river discharge that originates from the now-dammed location. Assuming that economic activity near rivers is adapted to the local pre-dam river discharge, flow share provides a continuous measure of hydrological exposure to dams that varies between locations along the same river, downstream of the same dam. Given the density of river tributary networks in much of the world, there is variation in flow share even among locations near each other. This allows me to identify the causal downstream effects of dams by comparing cells near each other that experience different levels of exposure to the dam, using difference-in-differences with the flow share measure as treatment.

My findings are summarized as follows. First, hydroelectric dams, which form the bulk of dams built in recent years, have precisely estimated negative effects on downstream nightlights. These effects are concentrated on irrigated cropland, suggesting that agricultural impacts are the primary channel. Second, these downstream economic costs accrue both within and across country borders. While the domestic costs may be offset by the direct benefits of dams or domestic policy mechanisms for compensation, the cross-border externalities are at least as large. Third, in the absence of a central international authority, upstream-downstream country pairs are nevertheless able to mitigate the potential externalities when they enjoy more cooperative international relations. The negative transboundary externalities of dams are concentrated in country pairs that face high coordination costs or broader non-alignment on international issues, with joint membership in intergovernmental organizations being the most predictive of realized externalities. For country pairs with median or better levels of coordination costs, I find small and insignificant transboundary externalities to nightlights growth.

Dams provide a suitable empirical setting to study transboundary externalities because

their locations and years of construction are well-defined, and it is straightforward to identify the countries that built them as well as the downstream countries receiving potential externalities. The externalities of dams - potential and realized - are sources of discord in many parts of the world. Globally, 276 river basins cross national borders, together spanning 145 countries and encompassing 60% of Earth’s freshwater supplies (UN Water). Out of about 31,779 geolocated dams in one database, 25% are upstream of foreign countries. While a dam can generate substantial benefits in the form of hydropower, irrigation, or flood control that may be deemed to outweigh the local environmental and human displacement costs, dam-building social planners may accord little weight to the potential consequences for drinking water supply, agricultural water supply and soil fertility, riverine fish supply, electricity, and flood and drought risk accruing to downstream neighboring countries. In fact, even when a dam is meant to support global social welfare (e.g. for hydropower generation to replace fossil fuels and meet the country’s Paris Agreement commitment), it may be built and operated in a way that imposes negative or ambiguous externalities on regional neighbors. According to the UN, formal international coordination is commonly lacking: about 2/3 of transboundary rivers do not have any cooperative management framework. Many countries explicitly keep river flow and dam inflow and outflow data secret.

Although the overall pace of dam-building has slowed in recent years, large, high-profile, and controversial hydroelectric dams continue to be planned and built. In the 2010s, construction of the Grand Ethiopian Renaissance Dam (GERD), the largest hydropower dam in Africa, led to talk of sabotage and war between Ethiopia and downstream Egypt [eth, October 22 2019, Tadesse, 2013]. Most recently, China approved plans to build what would be the world’s largest hydropower dam on the headwaters of the Brahmaputra River, drawing concern from downstream India and Bangladesh [May et al., 2025]. Their concern is potentially warranted: for example, water withholding by hydroelectric dams in China and Laos is suspected to have changed the quantity and seasonality of Mekong flows, threatening the supply of fish, a staple food in Southeast Asia [Fawthrop, 2022, Ziv et al., 2012], and

exacerbating the effects of the 2019 drought in that region [Basist and Williams, 2020].

Yet, although conflicts and negative externalities generate attention, it is not always the case that upstream countries operate dams solely in the manner of self-interest. For example, Kyrgyzstan’s Toktogul Dam on the Naryn River provides 40% of the country’s electricity. When drought strikes, electricity generation would require withholding river flow to maintain a certain capacity in the reservoir; however, downstream Uzbekistan and Kazakhstan rely on the flow for irrigation. During a recent drought, the riparian countries reached a deal in which Uzbekistan and Kazakhstan would sell electricity from non-hydroelectric sources cheaply to Kyrgyzstan in exchange for allowing the river to flow [kyr, March 25 2021]. The fact that the Central Asian countries achieved such a Coasean solution, while the Mekong countries did not, demonstrates a wide variation in the realized externalities of dams and suggests that international politics plays a significant role in shaping the outcome. Moreover, to the extent that some downstream flow impacts are difficult to negotiate away, it seems possible that better communication and coordination between countries can facilitate on-the-ground adaptation: e.g. when the downstream country has information about how the dam will be operated in the next 1, 5, or 10 years, people can shift their economic activities accordingly to align with the expected quantity and seasonality of river flow.

The countries involved in the examples above are geographically representative of the fact that new dams, since the 1980s, have primarily been built in Asia, Africa, and South America [Zhang and Gu, 2023]. Thus, the potential economic effects of dams, and the ability of governments and economies to avert or adapt to these effects, have direct consequences for economic development in low- and middle-income countries that either build dams or are dependent on rivers that have been dammed by their upstream neighbors.

This paper makes three contributions to the literature. First, this paper provides the first global-scale estimates of the international transboundary effects of dams. It therefore adds to our limited body of evidence on the economic costs of transboundary externalities. Existing evidence suggests that countries strategically locate economic and policy activities

so as to offload negative externalities beyond their borders.² Most pertinent to this paper, Olmstead and Sigman [2015] show that upstream countries free-ride in dam location decisions: conditional on geographical suitability for dam-building, a river basin is more likely to be the site of a dam if it is upstream of another country. These studies invite the question of the economic costs of the resulting transboundary externalities. So far, a small body of evidence³ suggest that the economic costs are large and deserve further study across more contexts. Most closely related to this paper, a recent paper by Lei [2025] measures the effects of Chinese dams on the Mekong in downstream Southeast Asian areas. He finds that the externalities for agricultural production can be either positive or negative depending on climate conditions. Whereas Lei [2025] provides a detailed profile of the externalities from dams on the Mekong, this paper is global in scope, calculating average causal treatment effects across all dams built between 2001-2013 for which location and construction year are available. A global average can be useful because the effects of dams are likely to differ across river basins based on factors such as climate, baseline hydrological dynamics, and downstream land use.⁴ In addition, rather than using agricultural productivity as the outcome, this paper measures externalities in terms of changes in economic activity as proxied by nighttime lights. The latter is intended to capture total economic effects net of adaptation, accounting for agricultural, urban, health, and industrial mechanisms.

Second, to my knowledge, this is the first paper to empirically quantify whether positive international relations can mitigate negative transboundary environmental externalities. As such, it addresses the gap in our empirical understanding of how to mitigate transboundary environmental externalities. The empirical literature has studied mitigation of inter-jurisdictional spillovers in subnational settings. However, the solutions there⁵ all require

2. For example, in the contexts of water pollution [Sigman, 2002] and air pollution [Heo et al., 2024]

3. Most notably, on the effects of China’s air pollution and East Asia’s regional dust on mortality in South Korea [Heo et al., 2024, Jia and Ku, 2019]

4. For example, the global analysis of Olmstead and Sigman [2025] finds no evidence that dams negatively impact resilience to local droughts downstream, contrary to the results of Lei [2025].

5. Such as establishing centralized or integrated resource management [Lipscomb and Mobarak, 2016,

the authority of a central government. In international settings, which lack such a central authority, studies of how to mitigate transboundary externalities have primarily been theoretical.⁶ Keohane and Ostrom [1995] consider countries as analogous to decentralized users of small-scale common pool resources (CPR) to whom the CPR design principles of Ostrom [1990] apply. In line with both Ostrom’s principles and the theory of Coasean bargaining, Libecap [2014] proposes differences in transaction costs as a key source of variation in the international community’s success at addressing different global environmental externalities. Yet, we lack empirical evidence on the extent to which transaction costs and CPR design principles alter externalities in practice, as well as their underlying determinants among countries. By quantifying the role of international relations in mediating dam externalities, this paper addresses that empirical gap.

Finally, this paper adds to our understanding of the economic impacts of dams, especially hydroelectric dams, an issue of policy relevance as many countries seek to expand renewable energy. The existing literature on the impacts of dams primarily focuses on the local effects around the dam or relatively close downstream.⁷ Most closely related to this paper, using the same global rivers and dams datasets, Du and Zhang [2025] find that hydroelectric dams induce a variety of environmental changes and net losses to agriculture and aquaculture within 100km downstream of dams. These results empirically motivate, while leaving open,

Sigman, 2005, Wang and Wang, 2021], altering bureaucratic incentives [Dipoppa and Gulzar, 2024, Kahn et al., 2015], or mandating compensation between jurisdictions [Bao, 2012, Chen et al., 2022]

6. Within political science, a literature on hydropolitics has empirically established correlations between the existence of formal treaties over shared rivers and various dimensions of politics and coordination costs. For example, Tir and Ackerman [2009] find that formal treaties are more likely in river basins with greater power imbalance, trade, common democratic regime type, and water scarcity. Yet, formal agreements vary in how they (are perceived to) distribute the costs and benefits of resource use between countries. Then, given the terms of agreement, compliance is ultimately up to the signatory countries, and countries sometimes engage in protracted disputes over whether an action is in compliance with an existing agreement. Thus, the hydropolitics literature has left open the question of how international relations affect the ultimate economic consequences along shared rivers, whether through treaties or other mechanisms.

7. For example, Duflo and Pande [2007] use a river gradient instrumental variable to study the agricultural effects of Indian irrigation dams in their own districts and directly neighboring districts. Strobl and Strobl [2011] use a similar IV to study the effects of African dams up to two river sub-basins downstream. Zhang [2018] measures the costs of displacement from the area flooded by the reservoir of a hydroelectric dam.

the question of whether such negative impacts propagate farther downstream and hence whether the concern of downstream riparians such as Egypt, India, and Bangladesh are justified. The flow share measure of dam exposure allows me to generate evidence on what those far downstream impacts are. There is also a need for more evidence on the impacts of dams across economic sectors. Jeuland [2020] notes that a key reason why decisions to build dams are rarely informed by economic evidence is that existing economic evidence on dam impacts do not account for multi-sector impacts. Evidence is especially scarce on channels other than the direct impacts of local dam construction and irrigation access [Dillon and Fishman, 2019].⁸ In conducting a global study with nighttime lights - a measure of economic activity - as the outcome, this paper contributes evidence on the effects of dams across economic sectors, accounting for inter-sectoral reallocation and adaptation.

The rest of this paper proceeds as follows. Section 1.2 provides background information on dams and theories of international cooperation. Section 1.3 presents the methodology, data, and results for the downstream impacts of dams. Section 1.4 presents the methodology, data, and results for adding international relations to the analysis. Finally, Section 1.5 concludes.

1.2 Background

1.2.1 Dams and their hydrological impacts

Around the world, there are at least 62,000 large dams.⁹ The benefits of dams are typically the irrigation, hydropower, urban and industrial water supply, or flood control that the dams were constructed to provide [International Commission on Large Dams, 2025]. On the costs side, in addition to upstream costs of displacement [Zhang, 2018] and soil quality [Duflo and Pande, 2007], known downstream economic costs of dams include losses to agriculture and

8. The lack of conclusive evidence is reflected, for example, in the World Bank’s flip-flopping over the past decades on whether it finances dams. Most recently, in 2024, it again changed course as it approved financing for multi-billion dollar hydropower projects in Africa and Central Asia [Leslie, 2024].

9. Defined by the International Commission on Large Dams as those with a minimum height of 15m or impounding a reservoir of a minimum volume of 3 million m³

aquaculture [Du and Zhang, 2025], fisheries [Ziv et al., 2012], and drought resilience [Lei, 2025].

What are the downstream hydrological impacts of dams that lead to these costs? Appendix Table A1 lists a selection of these impacts and how they have translated into economic effects. First, dams alter the quantity of water that flows downstream. Irrigation and water supply dams do this by allowing for water withdrawal from the river. Although hydropower generation does not directly consume water, the impoundment of a large reservoir leads to higher rates of evaporation. Second, dams alter the timing of flow to suit the purposes of the dam operator. Irrigation and water supply dams store up water during wet or non-growing seasons, then release it during dry seasons (when rainfall and the natural flow of the river are insufficient) or growing seasons depending on local downstream agricultural needs. Hydropower dams rely on maintaining a minimum water level within the reservoir to ensure a ready supply of water to power the generation turbine. To achieve this storage level, dam operators withhold flow during dry periods, potentially exacerbating downstream water scarcity during dry seasons and droughts [Richter and Thomas, 2007]. Thus, different types of dams generate different timing impacts, with hydropower dams in particular causing changes in direct conflict with the needs of downstream agriculture. Third, dams alter the quality and contents of downstream flow. The dam structure generally traps sediment and species. Downstream water temperature changes when the dam only releases water from a certain depth, and a reduction in flow velocity leads to a reduction in water nutrients. These hydrological impacts lead to reductions in downstream soil fertility, biodiversity, and water quality [He et al., 2024].

Yet, even conditional on the extensive margin decision to build a dam, on the intensive margin, policy levers are available to reduce the realized extent of hydrological and economic effects. Measures to mitigate potential downstream impacts are available to dam builders

in the design stage¹⁰ and operation stage.¹¹ Importantly, however, such mitigation measures come at a cost of decreased capacity and flexibility for electricity generation and/or increased construction expense. Thus, increased weight on downstream welfare in the dam builder’s objective function, which can be achieved through downstream political influence or upstream-downstream cooperation, can play a critical role in determining downstream externalities.

This paper will separately analyze the effects of hydroelectric dams and other types of dams, for two reasons. First, hydroelectric dams are the most policy-relevant type of dam today. Although irrigation has historically been the most common purpose of dams, Figure 1.3 illustrates that in recent years, new dam construction has been primarily for hydropower development. Second, hydroelectric dams are built and operated differently from other dams, likely with larger detrimental downstream impacts. As discussed above, the water storage and release needs of hydropower generation can be at odds with downstream water needs. In addition, Table 1.1 shows that hydroelectric dams are by far the largest in terms of both dam size and reservoir impounded. This gives hydroelectric dams greater capacity than other dams to store water and control the flow of the river.

1.2.2 Theories and measurement of power and propensity to coordinate

What determines the propensity of countries to internalize transboundary externalities in the absence of meaningful international authorities? Within the international relations (IR) literature to date, rather than a consensus regarding what induces countries to coordinate or how to measure coordination, multiple theories prevail.

10. For example, a hydroelectric dam builder may choose to construct a “run-of-the-river” dam, which does not have a reservoir, rather than a storage-based dam. Run-of-the-river dams rely on the natural movement of water to generate electricity. Although they still cause some degree of flow timing alteration and other impacts [Kuriqi et al., 2021], they are typically considered to have less potential for downstream impacts than storage-based dams. A dam builder can also choose to install fish passages, fish-friendly turbines, sediment bypass tunnels, and other mechanisms to reduce the impacts on the quality and contents of river flow [He et al., 2024].

11. The dam operator may choose a water release schedule that better mimics the natural flow regime [He et al., 2024].

One prevailing school of thought is realism, which is founded on the assumption that countries are self-interested agents seeking to maximize security. This assumption implies that countries are likely to prioritize relative gains over absolute gains, reducing the likelihood of a country engaging in interstate cooperation that benefits other countries, even if cooperation generates absolute gains for the country itself [Waltz, 1979]. However, cooperation can occur under certain circumstances. In the context of upstream and downstream riparian states, realists would predict that, first, power imbalance in favor of the downstream country, which puts the downstream country in a position to threaten the security of the upstream country, may induce the upstream country to internalize externalities. Second, realists would predict that common strategic interests in other realms may increase cooperation over river-sharing [Tir and Ackerman, 2009].

Another prevailing school of thought is liberalism. The liberal perspective emphasizes that institutions, shared norms, and economic interdependence can induce potential gains from cooperation and reduce the transaction costs of cooperation. This leads to cooperation towards mutual long-term gains even without power politics. For example, democratic peace theorists posit that domestic politics can affect international cooperation: two countries are more likely to cooperate if both are democracies. Among other reasons, democratic regimes share common norms, are more transparent about their aims and activities, and face domestic pressure to avoid costly conflict [Lipson, 2003, Maoz and Russett, 1993, Neumayer, 2002].¹² Another liberalist theory is liberal institutionalism, which stresses the role of inter-governmental organizations (IGOs) such as the United Nations, World Bank, and European Union in reducing the transaction costs of coordination and cooperation [Keohane, 1984, Keohane and Martin, 1995]. IGOs perform this role by providing third-party mediation, monitoring, and dispute arbitration, fostering economic interdependence, and promoting norms of cooperation.

12. A smaller number of studies posit that two autocracies are also likely to cooperate, for example, because they have longer time horizons and face fewer domestic political constraints when searching for mutually beneficial arrangements [Garriga, 2009].

Anecdotal evidence lends credence to each of these theories' applicability in the realm of transboundary river management. For example, China, the most upstream and most powerful of the Mekong Basin countries, has declined to join the Mekong River Commission, which facilitates joint river management between the Lower Mekong countries of Southeast Asia. Realists might attribute this to China's lack of strategic incentives for coordinating with downstream neighbors and the relative inability of those neighbors to retaliate against China's use of the river, owing to China's position as the upstream hegemon. Regarding the heatedness of the dispute over the GERD between non-democratic Ethiopia and Egypt, democratic peace theory might predict that the dispute would not have been so heated, or perhaps would have been averted from the start, if the countries involved had instead been democracies that trusted each other and whose leaders would have been held accountable by displeased domestic constituencies over threats of armed conflict.

As for liberal institutionalism, several notable instances of successful coordination over shared waters illustrate the roles that IGOs can play. One such role is the provision of mediation. For example, the World Bank was a key mediator in negotiating the Indus Waters Treaty between India and Pakistan, which is widely regarded to have successfully minimized water-related conflict and ensured the flow of waters to downstream Pakistan from 1960 until it was suspended in 2025. As a signatory to the treaty alongside the riparian countries, the Bank continued to be involved in the treaty's implementation. In 2007, a Bank-appointed neutral expert was crucial to resolving a dispute over India's proposed hydropower dam. Likewise, the negotiation of the 1995 Mekong Agreement between Cambodia, Laos, Thailand, and Vietnam required these states to overcome histories of rivalry and conflict. The efforts of an official mediator appointed by the United Nations Development Programme were critical to this achievement [Dinar et al., 2013].

Another channel through which IGOs may facilitate coordination is by creating norms of cooperation. When the IGO is a provider of economic aid, it has leverage with which to enforce these norms. In the previously mentioned Central Asian example, the Soviets

initiated the practice of using compensatory side payments of fossil fuel energy to ensure the flow of the river from the Kyrgyz dam during dry periods. Yet, the persistence of such coordination was tenuous after the collapse of the central Soviet authority. Ultimately, the continuation of the arrangement was due in large part to the insistence of IGOs such as the World Bank on the formation of inter-state cooperative institutions as a condition for aid [Weinthal, 2002].

These three theories each motivate a different set of empirical measures of bilateral relations between upstream dam-building countries and downstream countries. First, realism motivates the use of trade dependence and GDP imbalance as measures of power dynamics, and the use of voting similarity in the United Nations General Assembly as an indicator of strategic alignment. Second, democratic peace theory motivates the use of regime type similarity. Third, liberal institutionalism motivates the use of joint membership in IGOs. The use of these measures as proxies of relative power and coordination costs echoes previous work in the hydropolitics literature, such as Tir and Ackerman [2009] and Zawahri and Mitchell [2011], and in the geoeconomics literature, such as Kleinman et al. [2024]. I describe the compilation of these quantitative measures in Section 1.4.2.

1.3 Downstream economic effects of dams

1.3.1 Empirical method

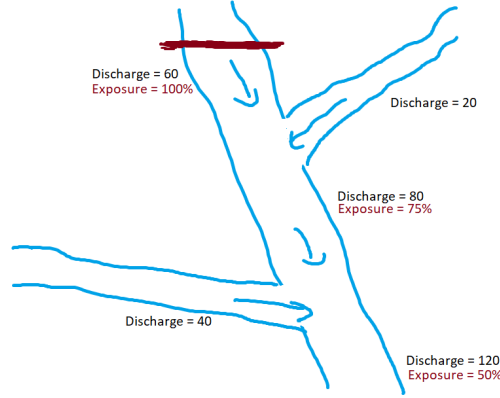
Estimating the causal effects of dams using flow share

To causally identify the effects of dams, including on regions far downstream, the main challenge is finding a comparable control group. Possible “naive” approaches might be to compare places near rivers with places farther away, places near dammed rivers with places near undammed rivers, or places upstream versus downstream of a dam. However, areas in these pairs may not be comparable: for example, historical development has been concentrated near large rivers. And empirically, in my sample which will be described in the next

section, neither balance nor parallel trends is satisfied when comparing places near rivers downstream of dams with places near undammed rivers, even in the same level-2 administrative region. Existing work, primarily focused on estimating local impacts, has often used a river gradient IV for local dam placement [Duflo and Pande, 2007, Hansen et al., 2011, Strobl and Strobl, 2011]. For estimating impacts on far downstream areas, such an IV is unlikely to have a strong first-stage.

Instead, I construct a novel measure of dam exposure and identify the causal effects of dams under two assumptions. The first assumption is that local populations and economies near rivers are adapted to the pre-dam long-term river discharge (that is, the volume of water flowing through in a given interval of time) of the nearest river reach. Under this assumption, I leverage the tributary network of rivers to generate spatial variation in exposure to the dam *along the same river*. Restricting the sample to locations near rivers, let i denote location and d denote dams. Then, for each i that is near a river reach downstream of d , I calculate the *flow share* from d to i as the pre-dam river discharge of the branch that was dammed as a fraction of the pre-dam total river discharge at cell i if i is downstream of d . For example, consider the river network in Figure 1.1. The black text indicates pre-dam river discharge (e.g. in m^3/s). For cells just downstream of the dam, 100% of the river flow that the area is used to having comes from the stretch of the river that was dammed. However, downstream of the first tributary, only $60/80 = 75\%$ of the traditional flow is affected by the dam, because the other 25% comes from the undammed tributary. Similarly, further downstream, below the second tributary, only $75\% * 80/120 = 50\%$ of the traditional flow is affected by the dam. Thus, the share of baseline local river flow that is now dammed provides a continuous measure for exposure to a dam among locations along the same river.

Figure 1.1: Flow share from dammed area (red bar) along downstream river stretches



With the flow share measure in hand, the second assumption is parallel trends for continuous treatments: within any level-2 administrative county (e.g. US counties, Indian districts, or Chinese prefectures, henceforth called “county”), for any dammed flow share, locations near the dammed river would see parallel trends in outcomes if all were subject to that same flow share [Callaway et al., 2025]. This motivates a two-way fixed effects (TWFE) approach with county-specific time dummies.¹³ For grid cell i in county j , in year t , near a river subject to dam d , I estimate the TWFE regression

$$Y_{ijt} = \beta \sum_d FS_{id} C_{idt} + \alpha_i + \gamma_{jt} + \varepsilon_{ijt} \quad (1.3.1)$$

where FS_{id} is the pre-dam long-run average flow share from d to i , $C_{idt} = 1$ if dam d was constructed no later than year t and there is no other dam in the sample located downstream

13. The stated parallel trends assumption follows the “strong” parallel trends assumption of Callaway et al. [2025] of no selection-on-gains into treatment *dosage*. Under this assumption, TWFE identifies the weighted average of the marginal effect of an increase in dammed flow share and the effect of some dammed flow share relative to none. The regression weights are non-negative and sum to 1, but are generally not equal to the population distribution of flow share. In this analysis, locations with higher flow share within each county would be given disproportionate weight. An alternative estimator for difference-in-difference with continuous treatment that provides more easily interpretable results is that of de Chaisemartin and d’Haultfoeuille [2024]. However, this estimator would require variation within counties in the timing of first dam exposure. Hence, it would restrict the estimation sample to counties containing dams and counties with multiple rivers that have upstream dams. Since such a sample restriction severely reduces the ability of this analysis to answer the research question of far downstream impacts and foreign externalities, I continue with TWFE.

of d and upstream of i in year t .

Similarly, I can estimate heterogeneous effects of dams satisfying different criteria, such as dams in the same country as i or in a foreign upstream country, by estimating separate coefficients on the flow share affected by dams falling in different subsets:

$$Y_{ijt} = \beta \sum_d FS_{id} C_{idt} X_{idt} + \phi \sum_d FS_{id} C_{idt} (1 - X_{idt}) + \alpha_i + \gamma_{jt} + \varepsilon_{ijt} \quad (1.3.2)$$

where X_{idt} is a binary indicator that could vary at the dam-, dam by cell-, or dam by cell by year-level. For example, to separately estimate the effects of domestic and foreign dams, I define $X_{id} = 1$ if dam d is in the same country as cell i and $X_{id} = 0$ otherwise.

Note that the flow share measure combined with two-way fixed effects will identify the effects of dams *via changes in river flow only*. Dams may generate costs or benefits through other channels such as electricity provision, but within a downstream county, these are likely to affect areas equally, and will be absorbed by the county time trends γ_{jt} .

Estimating pre-period and dynamic effects

Since the flow share measure is continuous and changes multiple times during the sample period for cells with multiple upstream dams, I use two methods to estimate dynamic effects and assess pre-period parallel trends. First, following Suárez Serrato and Zidar [2016] and Fuest et al. [2018], I estimate the following distributed lag regression:

$$Y_{ijt} - Y_{ij,t-1} = \sum_{\tau \neq -1} \phi^\tau \sum_d FS_{id} (C_{id,t-\tau} - C_{id,t-\tau-1}) + \gamma_{jt} + \varepsilon_{ijt} \quad (1.3.3)$$

where, as in Equation (1.3.1), $C_{idt} = 1$ if dam d was constructed by year $t - \tau$ and there is no other dam in the sample located downstream of d and upstream of i in year t . Since Equation (1.3.1) posits a relationship between contemporaneous flow share and outcome Y , this implies a relationship between change in flow share and ΔY , hence the annual change on

the left-hand side of Equation (1.3.3). Cell fixed effects are differenced out. For event time τ , the coefficient ϕ^τ provides the effect of an increase in dammed flow share that occurred τ years earlier. If the strong parallel trends assumption holds, then $\phi^\tau = 0$ for $\tau < 0$. That is, within-county variation in the annual change in nightlights in any year should be uncorrelated with variation in how much flow share was dammed in a future year.

Second, I transform the continuous flow share measure into a binary measure and estimate a standard event study. To construct the binary measure, for each county j , I begin by identifying the year T_j in which any cell in j was first subjected to any upstream dam constructed after 2000. For each cell i in county j , I then determine whether the cell's flow share from all dams in year T_j is above or below the county-specific median in that year:

$$HighFS_i = \mathbf{1}[FS_{i,T_j} > MedianFS_{j,T_j}].$$

In addition, I define county-level binary event-time treatment dummies $D_{rt}^\tau = \mathbf{1}[t - \tau = T_j]$. These quantities allow me to estimate the event study

$$Y_{ijt} = \sum_{\tau \neq -1} \psi^\tau HighFS_i \times D_{it}^\tau + \alpha_i + \delta_{jt} + \varepsilon_{irt} \quad (1.3.4)$$

where ψ^τ represents the effect of having above-median flow share, τ years after dam exposure in the county began. With a binary treatment, the identification assumption becomes the more standard parallel trends assumption, of which a placebo test is whether $\psi^\tau = 0$ for $\tau < 0$. For robustness, I repeat this analysis with $HighFS_i$ defined based on the county-specific median flow share in 2013 (end of sample period).

1.3.2 Data

Dams

I obtain dams information from the Global Dam Tracker (GDAT). Out of the 35k dams around the world recorded in GDAT, 31,780 are geolocated, and most dams have non-missing data for year that construction finished, main purpose, and other attributes. Although GDAT does not capture close to the universe of dams in the world, it is significantly more comprehensive than other freely available dam databases [Zhang and Gu, 2023], and excluded dams tend to be smaller structures.¹⁴

There are 1525 dams with geolocation in GDAT that were finished between 2001-2013. Of these, 1410 were matched to downstream populated cells (cells discussed below). Dynamic event studies are estimated on panels of cells balanced in event-time, which received at least one upstream dam no later than 2009. There are 1200 dams built between 2001-2009. Out of the 1525 dams, 668 (44%) are known to be hydroelectric dams, 506 (33%) are known to be irrigation or water supply dams, and 82 (5%) are known to be flood control dams. The rest have unknown purpose (17%) or serve recreation or fisheries (1%). Although some dams are multipurpose, I use the “main purpose” variable in GDAT to classify dams into a single purpose category. Based on this categorization, almost all dams known to produce electricity are classified as hydroelectric dams.

The 1525 dams finished between 2001-2013 are distributed across 63 countries. Among them, 543 (39%) are upstream of one or more foreign countries, and are hence in a position to potentially impose transboundary externalities. Figure 1.2 shows the geographical spread of the dams, with blue dots indicating that the dam is upstream of one or more foreign countries. Although many dams exist in North America and Europe, since the 1980s, new

14. For instance, there are over 91,000 dams in the US alone by the US government’s count, but only 7% of these, or 6370, are considered “large” dams according to the definition of the International Commission on Large Dams [National Inventory of Dams]. GDAT records 7012 dams in the US, of which 5999 are “large” dams. Thus, if coverage in the US is comparable to in the rest of the world, then GDAT would have an inclusion rate of over 90% for “large” dams.

dams have primarily been built in Asia, Africa, and South America [Zhang and Gu, 2023]. Figure 1.2 reflects the predominance of dams in low- and middle-income countries in those regions. Of the 1525 dams, only 5% are in countries classified as high-income by the World Bank in 2024.

Figure 1.2: Geolocated dams with construction finished in 2001-2013 (GDAT)

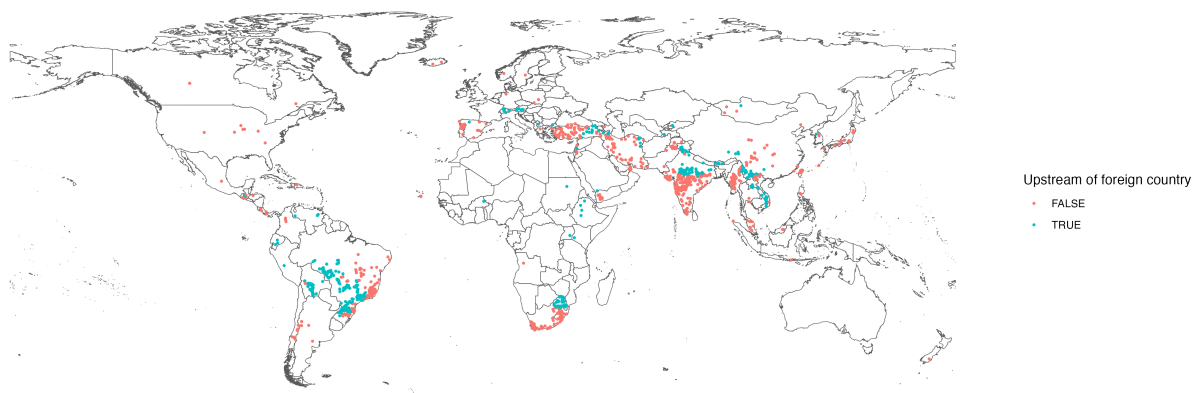


Table 1.1 shows the prevalence and size of different types of dams constructed between 2001-2013. Out of the dams for which the main purpose is known, hydroelectric dams are by far the largest in terms of both dam height and reservoir capacity. Moreover, Figure 1.3 shows that although the number of dams constructed has declined over time, the decline is mainly driven by non-hydroelectric dams. Although my sample ends in 2013, the fact that new dams in recent years have been almost exclusively hydroelectric makes hydropower the most policy-relevant type of dam today.

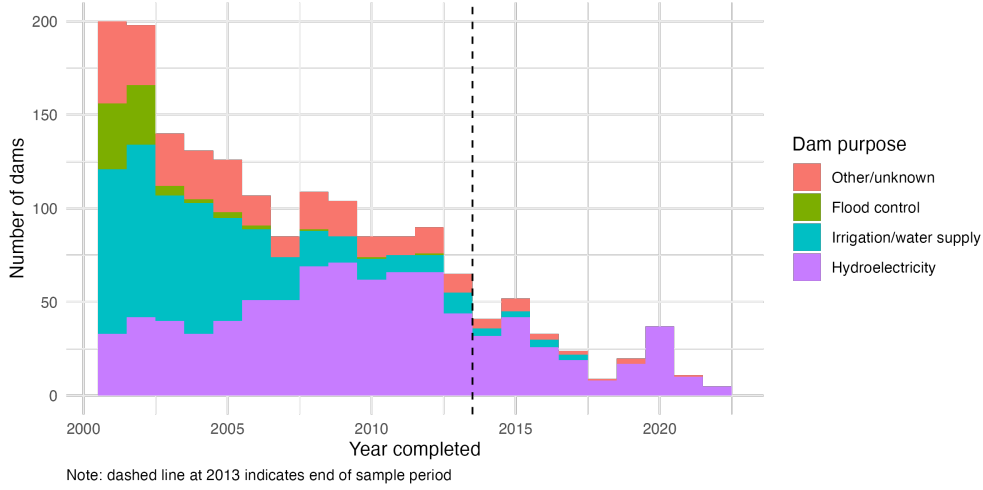
Rivers and discharge

I obtain geospatial data on river courses and tributary networks from HydroRIVERS. To measure pre-dam discharge, I use the discharge attribute included in HydroRIVERS, which represents the average across 1971-2000 as estimated from the WaterGAP integrated water balance model. Therefore, I restrict the sample of dams to those with recorded year built

Table 1.1: Average height and reservoir capacity of dams built 2001-2013

Dam purpose	N	Height (m)		Reservoir volume (millions m ³)	
		Mean	Median	Mean	Median
Hydroelectricity	668	52.5	35	1689.1	58.8
Irrigation/water supply	506	31.4	23.9	26.0	0.8
Other/unknown	269	20.8	12	72.8	0.3
Flood control	82	14.7	8.8	41.3	0.1
All	1525	35.8	21.2	442.4	0.6

Figure 1.3: Dam completion by purpose and year



of 2001 or later. Furthermore, because small streams are ubiquitous in much of the world, I sparsify the river network by restricting the sample to river reaches at or above the 80th percentile of 1971-2000 average discharge rates, which is $2.17 \text{ m}^3/\text{s}$. For reference, the discharge rate of the Chicago River soon after branching out from Lake Michigan, averaged over 2000-2006, was $3.9 \text{ m}^3/\text{s}$. I make this restriction because (1) a dam on a very small stream may not amount to the same treatment as a dam on a large river, and (2) small streams are so ubiquitous that the spatial resolution of analysis would need to be very fine to avoid having multiple streams/ivers in the average cell.¹⁵

15. Although it would be ideal for this study, to my knowledge, there is no data product that would allow me to measure *changes* in river discharge caused by dams at a global scale. River gauge networks (e.g. as maintained by the GRDC) are spatially sparse, and data in recent decades are not available for most of Africa and Asia. While reanalysis products such as WaterGAP and the GloFAS are spatially and temporally

Dependent variables

Satellite-derived nighttime lights data are a widely-used proxy for economic activity, with approximately unit elasticity with respect to GDP in developing countries [Henderson et al., 2012], which describes most dam-building and dam-affected countries in recent decades. I use the DMSP nightlights product, available from NOAA for 1992-2013. I aggregate nightlights in each year to the 0.05 degree resolution. Following Burlig and Preonas [2024], I do so by taking the maximum rather than the mean across small cells. The nightlights index ranges from 0 to 63, with 0 indicating complete darkness. Nighttime lights, especially the older DMSP product relatively to the more recent VIIRS, have known shortcomings, including top-coding, satellite sensor sensitivity, capturing extensive margin more than intensive margin changes, and capturing urban growth better than rural growth. However, they remain the best option available for analyzing economic activity at a local level globally.

As a robustness check, I also use PM2.5 air pollution concentrations as an outcome. Gridded satellite-based PM2.5 air pollution data for the globe is available for each year from 1998-2021 [Shen et al., 2024], and I obtain the 1998-2013 data. Since PM2.5 concentrations are partly determined by factors such as pollution regulations that do not strictly track with economic activity, the use of PM2.5 as a rough proxy for economic activity relies on the assumption that those factors are either time-invariant or change in similar ways for all cells within each county. If that is the case, then effects on PM2.5 capture a combination of effects on population, traffic, industry, and agricultural burning - all components of economic activity.

Other data

I obtain gridded population estimates for the year 2000 from WorldPop, and aggregate to the 0.05 degree resolution by summing. I obtain gridded land cover classifications, also for the

complete, they only incorporate dams via basic modeling that does not account for how each dam is actually operated.

year 2000, from the ESA Climate Change Initiative. I aggregate the 10 arc-second resolution land cover data to the 0.05 degree resolution by taking the population-weighted mode. For both variables, I use 2000 data so as to capture pre-dam baselines.

Final sample

The unit of analysis is 0.05 x 0.05 degree grid cells, which have area of roughly 30 km², or 1/20 the area of the city of Chicago. The main sample consists of cells within 25km of river reaches that are downstream of at least one of the 1525 dams constructed between 2001-2013. I further subset to cells that had population of at least 100 people in the year 2000. This yields approximately 75,000 cells, spanning 95 countries. For each cell, nightlights data are available from 1992-2013, giving a panel of 1.8 million cell x year observations.

The 1525 dams of which the cells are downstream span 63 countries. In addition to cells within the same countries as the dams, there are 106 pairs of foreign upstream dam country/downstream cell country.

1.3.3 Results

Overall effects of dams on downstream economic activity

Given that different types of dams vary greatly in their physical scale and typical impacts on the river's quantity and seasonality of flow, I separately estimate the effects of hydroelectric and other types of dams. Table 1.2 presents the estimates of the static TWFE specification of Equation (1.3.1), with dams divided by purpose and nightlights as the outcome. The largest negative impact comes from hydroelectric dams (Column 1), consistent with the large size of hydroelectric dams relative to other dams. The average cell in the sample had about 15.5% of its pre-2001 flow share impounded by hydroelectric dams by the end of the sample period in 2013. Scaled by this factor, the estimate in Column (1) implies that the hydrological effects of hydroelectric dams caused a reduction in nightlights of 0.06 during the sample period,

which is 2% of the average growth in nightlights of 2.79 among sample cells from 2001-2013. Panel (a) of Figure 1.4 shows the distributed lag estimates for the cumulative effects of flow share from hydroelectric dams. Consistent with the parallel trends assumption, there are no significant cumulative effects throughout the pre-period. Reductions to growth begin to accumulate following dam construction, becoming statistically significant at the 95% level two years post-construction, with no indication of recovery to pre-dam growth trends up to four years after dam construction.

Column (1) of Table 1.2 and Appendix Figure A1 show that non-hydroelectric dams, by contrast, have small and insignificant effects on average. While Column (3) of Table 1.2 finds that dams primarily operated for flood control have a large positive marginal effect, such dams constitute only 5% of the dams constructed between 2001-2013. Going forward, I will focus on hydroelectric dams.

To understand the mechanisms driving the downstream growth reductions from hydroelectric dams, I estimate the effects separately for subsamples of cells with different pre-dam land use. Table 1.3 shows that cells classified as irrigated cropland in 2000 experience the largest and most precisely estimated decreases to economic growth following the construction of upstream dams, suggesting agriculture as the primary channel for dam impacts. Relative to the average increase of 3.93 in nightlights over 2001-2013 experienced by this subsample, the effect at the mean 2013 flow share represents a 4% reduction in potential economic growth. Panel (b) of Figure 1.4 displays the cumulative effects estimated from a distributed lag regression over irrigated cropland cells. In the subsample, the parallel trends assumption continues to hold, while the post-period reductions accumulate more quickly and steeply. The more severe economic cost over irrigated cropland is consistent with the fact that a majority (60%) of irrigated land globally was irrigated by surface water sources, such as rivers, in the 2000s [Siebert et al., 2013], and would hence be vulnerable to changes in surface water.

As a robustness check for the distributed lag specification, Appendix Figure A2 shows event study estimates following Equation (1.3.4) for the effect of above-median within-county

Table 1.2: Static TWFE estimates of effects of flow share from dams on nightlights, by dam purpose

	(1)	(2)	(3)
Flow share from hydroelectric dams	-0.395*** (0.124)		
Flow share from non-hydroelectric	-0.0350 (0.108)		
Flow share from irrigation dams		-0.268 (0.178)	
Flow share from non-irrigation		-0.151* (0.0907)	
Flow share from flood control dams			2.507*** (0.802)
Flow share from non-flood control			-0.192** (0.0831)
Observations	1773618	1773618	1773618
Mean 2013 flow share	0.155	0.0435	0.00288
Effect at mean 2013 flow share	-0.0615	-0.0117	0.00722

Notes: Mean 2013 flow share is the mean of flow share from dams of the dam type of interest in 2013, the end of the sample period. Effect at mean 2013 flow share is the product of that mean and the coefficient on flow share from the dam type of interest. For comparison, average change in nightlights from 2001-2013 in the sample was 2.79. All specifications include cell and county x year fixed effects. Standard errors in parentheses, clustered by river reach. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

flow share from hydroelectric dams. They are qualitatively similar to the results in Panel (a) of Figure 1.4. In addition, as a robustness check for nightlights as a measure of economic activity, Appendix Table A2 and Appendix Figure A3 show that the effects on PM2.5, though noisier, are consistent with the effects on nightlights. Finally, whereas the main specifications are estimated on the sample of cells within a 25km buffer from rivers, Appendix Table A3 shows that the results are robust to the buffer width from which cells are included in the sample.

One advantage of the flow share measure of dam exposure is that it allows for the identification of dam effects far downstream from the dam. To test whether the negative economic effects of hydroelectric dams are concentrated near the dam or propagate far downstream, I estimate a version of Equation (1.3.1) that includes a separate term for flow share from

Table 1.3: Effects on nightlights, by pre-dam land use

	(1) Rainfed crop	(2) Irrigated crop	(3) Urban	(4) Vegetation	(5) Sparse or barren
FS from hydroelectric dams	-0.249 (0.212)	-0.936*** (0.253)	0.283 (1.960)	0.0397 (0.176)	2.558*** (0.967)
FS from non-hydroelectric	0.0187 (0.158)	-0.483* (0.254)	-1.711* (1.027)	0.0203 (0.182)	-0.348 (0.493)
Observations	669086	230494	21252	480788	167530
Mean 2013 flow share	0.124	0.174	0.138	0.208	0.118
Effect at mean 2013 flow share	-0.0309	-0.163	0.0391	0.00825	0.302
Mean change in nightlights, 2001-13	3.430	3.930	2.930	1.700	2.090

Notes: Mean 2013 flow share is the mean of flow share from hydroelectric dams in 2013, the end of the sample period. Effect at mean 2013 flow share is the product of that mean and the coefficient on flow share. The mean change in nightlights from 2001-2013 among cells in the sample of each land cover type is provided for comparison. All specifications include cell and county x year fixed effects. Standard errors in parentheses, clustered by river reach. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

hydroelectric dams within each of the intervals $[0, 0.1)$, $[0.1, 0.2)$, $\dots$, $[0.9, 1]$. Figure 1.5 plots the results. As one travels downstream from a hydroelectric dam, the marginal effect on nightlights of additional flow share from the dam is negative and consistent in magnitude until flow share reaches 0.3. In the $[0.2, 0.3)$ interval, it remains negative and may increase in magnitude. This indicates that the hydrological impacts of hydroelectric dams indeed propagate far downstream. For example, the Lancang River, which is the headwaters of the Mekong in China, contributes 16% of the Mekong's total annual flows. The results in Figure 1.5 suggest that China's series of hydroelectric dams on the Lancang would be expected to have a measurable negative impact on economic activity in most of the river basin upstream of the Mekong River Delta [Mekong River Commission]. Moreover, the consistency of the marginal effect across most of the flow share distribution lends support to the assumption that impounded flow share has a linear relationship with nightlights.

Cross-border externalities

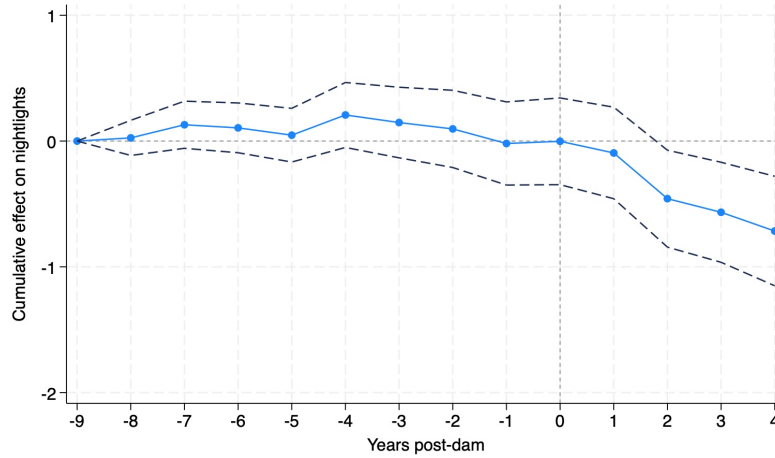
Since dams impose downstream economic costs, including far downstream, I now turn to explicitly estimating the cross-border effects. Table 1.4 displays the results of estimating separate effects of hydroelectric dams in the same country, and in foreign upstream countries, as the grid cell, over all cells and subsamples by pre-dam land use. Column (1) shows that even though the average flow share exposure to foreign dams (5.17%) is smaller than that to domestic dams (10.4%), the marginal effect of flow share from foreign dams is more than twice as large. Consequently, the implied magnitude of the externality at average flow share levels is higher across the border than within the dam's country. Columns (2)-(6) suggest that in foreign downstream countries, again, the primary channel is agriculture. Cumulative dynamic effects of both domestic and foreign flow share are plotted in Figure 1.6.

Table 1.4: Effects of domestic vs foreign dams on nightlights

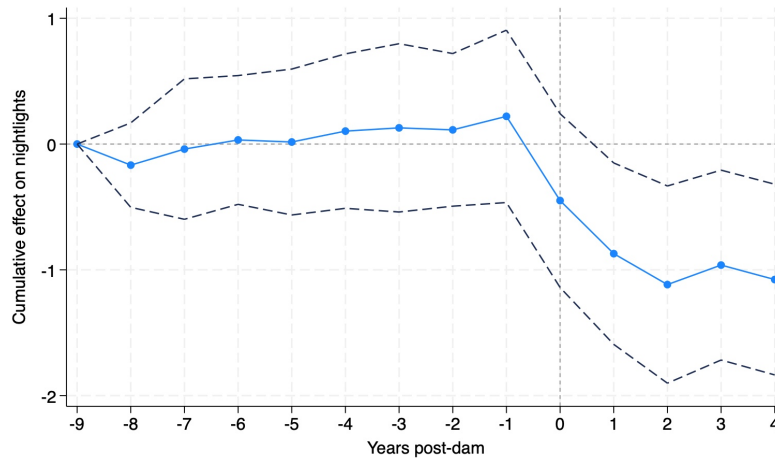
	(1) All	(2) Rainfed crop	(3) Irrigated crop	(4) Urban	(5) Vegetation	(6) Sparse or barren
FS from domestic hydro	-0.291** (0.135)	-0.175 (0.216)	-0.556 (0.414)	0.331 (1.996)	0.0624 (0.184)	2.449** (1.069)
FS from foreign hydro	-0.814*** (0.308)	-1.084 (0.856)	-1.249*** (0.320)	-2.315 (3.364)	-0.255 (0.496)	2.872 (2.272)
FS from non-hydroelectric	-0.0511 (0.108)	0.00938 (0.159)	-0.526** (0.255)	-1.712* (1.027)	0.0189 (0.183)	-0.346 (0.491)
Observations	1773618	669086	230494	21252	480788	167530
Mean 2013 domestic FS	0.104	0.104	0.0630	0.0893	0.156	0.0383
Effect at mean 2013 domestic FS	-0.0302	-0.0182	-0.0351	0.0295	0.00973	0.0937
Mean 2013 foreign FS	0.0517	0.0200	0.111	0.0489	0.0521	0.0797
Effect at mean 2013 foreign FS	-0.0421	-0.0217	-0.139	-0.113	-0.0133	0.229
Mean change in nightlights, 2001-13	2.790	3.430	3.930	2.930	1.700	2.090

Notes: Mean 2013 flow share is the average flow share from hydroelectric dams in 2013, the end of the sample period. Effect at mean 2013 flow share is the product of that mean and the coefficient on flow share. The mean change in nightlights from 2001-2013 among cells in the sample of each land cover type is provided for comparison. All specifications include cell and county x year fixed effects. Standard errors in parentheses, clustered by river reach. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure 1.4: Hydroelectric dams: Dynamic effects of flow share on nightlights



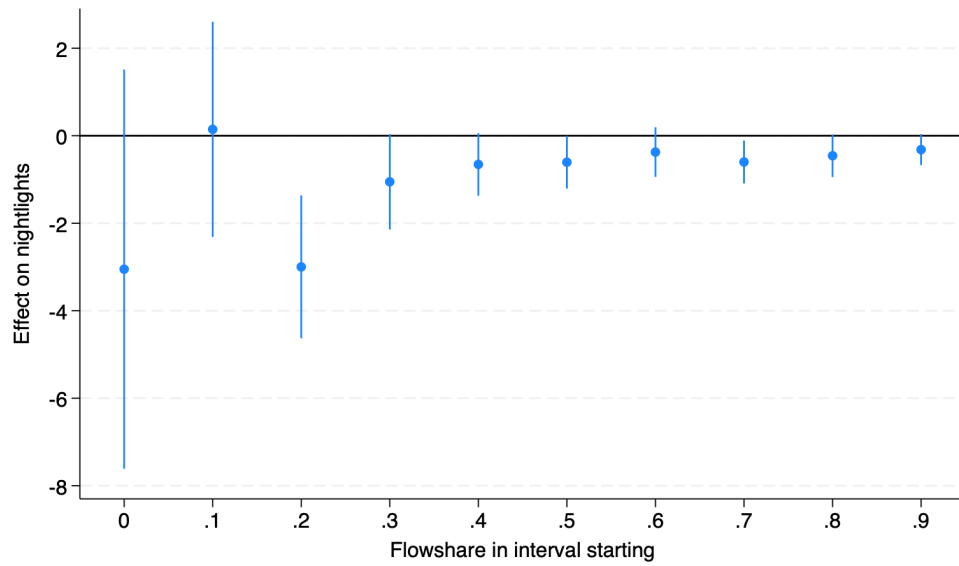
(a) All land use



(b) Irrigated cropland

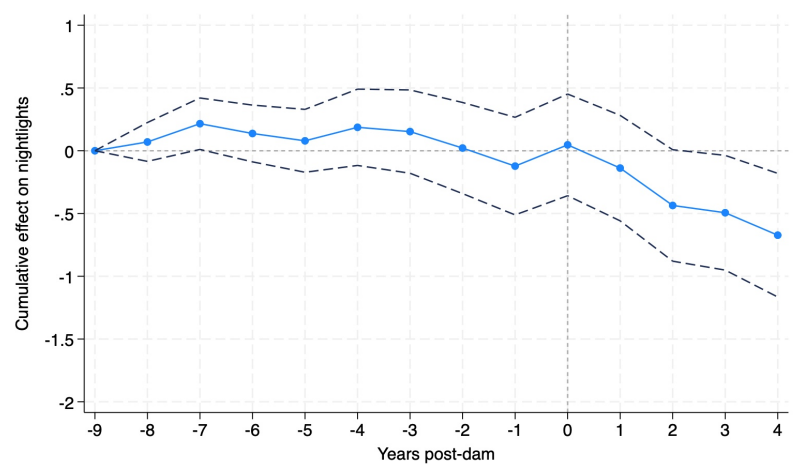
Note: This figure plots distributed lag regression coefficients and 95% confidence intervals for flow share from non-hydroelectric dams, obtained by estimating Equation (1.3.3) with separate terms for flow share from hydroelectric dams only and flow share from all non-hydroelectric dams. The figure plots the cumulative effects on nightlights relative to 9 years prior to dam construction, that is, $\sum_{k=-9}^t \phi^k$. Panel (a) displays cumulative effects over the entire sample, and Panel (b) displays cumulative effects estimated over the subsample of cells classified as irrigated cropland in 2000. The coefficient on non-hydroelectric dams is omitted. The regression includes county x year fixed effects. Standard errors clustered by river reach.

Figure 1.5: Effects on nightlights of hydroelectric dams, by flow share bin

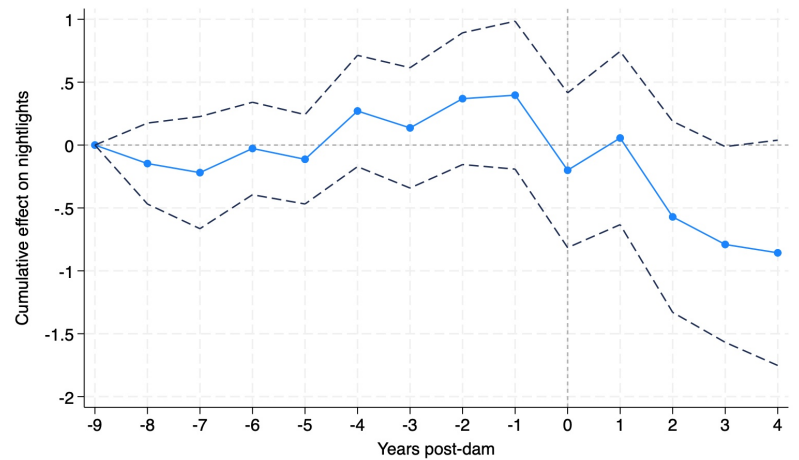


Notes: This figure plots the estimates and 95% confidence intervals from a regression that includes a separate term for flow share from hydroelectric dams within each of the intervals $[0, 0.1)$, $[0.1, 0.2)$, $\dots$, $[0.9, 1]$. Each plotted coefficient represents the marginal effect of additional flow share impounded by hydroelectric dams when that flow share is within the specified interval. The specification further includes flow share from non-hydroelectric dams, cell fixed effects, and county x year fixed effects. Standard errors clustered by river reach.

Figure 1.6: Effects of flow share from domestic vs foreign hydroelectric dams on nightlights



(a) Domestic



(b) Foreign

1.4 The role of international relations

1.4.1 Empirical method

Estimating the role of international politics

To estimate how the downstream effects of dams varies by bilateral relations between the dam's country and the downstream cell's country, I assume that, after location fixed effects have controlled for country-level baseline characteristics, the baseline *pairwise difference or relationship* in any characteristic between the upstream and downstream countries is orthogonal to the potential effects of a dam on cells in the downstream country. For example, a downstream country's GDP or total volume of trade with other countries may well influence how insulated local areas are to having the river flow altered, through access to capital or other mechanisms. However, after controlling for the downstream country's baseline GDP or total trade volume, the baseline difference in GDP between the downstream country and upstream dam-building country is plausibly exogenous to the dam effects.

To implement this, I simply estimate Equations (1.3.2) with an additional interaction term between flow share from each dam and the upstream and downstream countries' baseline bilateral relations. That is, for each downstream location i , let D denote the downstream country that i belongs to, let U index foreign countries upstream of D , and let R_{UD} denote a measure of baseline pre-dam relations between countries U and D . I estimate:

$$Y_{ijt} = \beta \sum_{d \in D} FS_{id} C_{idt} + \phi_1 \sum_U \sum_{d \in U} FS_{id} C_{idt} + \phi_2 \sum_U \sum_{d \in U} FS_{id} C_{idt} IR_{UD} + \alpha_i + \gamma_{jt} + \varepsilon_{ijt} \quad (1.4.1)$$

I interpret β as the effect of river impoundment by domestic dams, ϕ_1 as the effect of river impoundment by foreign dams given the lowest baseline level of the international relations measure IR , and ϕ_2 as the change to the cross-border externality ϕ_2 that is associated with an increase in IR . While flow share is assigned by river reach, IR measures are assigned by country pair. To be conservative, I cluster standard errors by country in regressions

containing IR interaction terms.

Addressing confounders for international relations

In the absence of an instrument for the IR measures, one may be hesitant to interpret the coefficients of interaction terms between flow share and these measures as the causal effect of IR. I address this concern with two pieces of analysis.

First, I address the specific possibility that more favorable relations with one's neighbors could be correlated with domestic political, economic, or other factors that makes a country more resilient to environmental shocks in general. For example, if countries with more inclusive and responsive political institutions also tend to seek more cooperative foreign relations, then the interaction term coefficients could be capturing the effects of more effective domestic aid rather than international coordination. Or, wealthier countries that tend to get their way over their neighbors may also have private sectors better equipped to adapt to shocks.

To alleviate such concerns, for each country in the sample, I estimate the pre-period (1992-2000) sensitivity of nightlights to domestic drought and wetness shocks. I describe the estimation of these sensitivity parameters in Appendix A.1.1. Then, I re-estimate Equation (1.4.1) with additional interaction terms between flow share and the drought and wetness sensitivities:

$$\begin{aligned}
Y_{ijt} = & \beta \sum_{d \in D} FS_{id} C_{idt} + \phi_1 \sum_U \sum_{d \in U} FS_{id} C_{idt} + \phi_2 \sum_U \sum_{d \in U} FS_{id} C_{idt} IR_{UD} \\
& + \phi_3 \sum_U \sum_{d \in U} FS_{id} C_{idt} DroughtSens_D + \phi_4 \sum_U \sum_{d \in U} FS_{id} C_{idt} WetSens_D + \alpha_i + \gamma_{jt} + \varepsilon_{ijt}
\end{aligned} \tag{1.4.2}$$

The interaction terms with the sensitivities control for the downstream country's ability to deal with water-related shocks in general, without needing to specify the determinants of that ability, which may differ across countries.

Second, I use an alternative identification strategy that leverages within country-pair, over time variation in IR. The Integrated Crisis Early Warning System (ICEWS) has, since 1995, coded media reports of interactions between states, organizations, and citizens of different countries. This provides over-time variation in bilateral engagement between pairs of countries. Using counts of cooperative and hostile engagement events, as well as ICEWS-coded intensity scores of events, as measures of IR, I use a cell x dam country x year panel to estimate

$$Y_{ijUDt} = \beta \sum_{d \in D} FS_{id} C_{idt} \mathbf{1}[U = D] + \phi_1 \sum_{d \in U} FS_{id} C_{idt} \mathbf{1}[U \neq D] \\ + \phi_2 \sum_{d \in U} FS_{id} C_{idt} IR_{UDt} + \phi_3 \sum_{d \notin U} FS_{id} C_{idt} + \alpha_i + \psi_{UD} + \gamma_{jt} + \varepsilon_{ijUDt} \quad (1.4.3)$$

where β is the effect of flow share from domestic dams, ϕ_1 is the effect of foreign upstream dams in country U when $IR_{UDt} = 0$, and ϕ_2 , the coefficient of interest, is the additional effect of dams in country U when IR_{UDt} increases by one unit. The ϕ_3 term is a control for flow share from all dams in countries other than U . The inclusion of country-pair fixed effects ψ_{UD} accounts for any time-invariant factors that may be correlated with IR.

With time-varying IR measures, one may be concerned about reverse causality: that once a dam has been built and downstream economic impacts realized, bilateral engagement will shift in the following years in response. To alleviate this concern, I use 1-year lags of the bilateral engagement measures. In Section 1.4.2, I discuss the ICEWS dataset in greater detail.

1.4.2 Data

Power asymmetry

I compile two measures that proxy for power asymmetry, which realists would predict to be a determinant of propensity to cooperate. The first measure of political power is trade

dependence. I obtain annual bilateral trade flows from the Correlates of War Project [Barbieri and Keshk, 2016]. For each downstream cell x upstream dam pair, let U denote the upstream dam-building country, and D denote the downstream country containing the cell. I construct four measures of bilateral trade relations between U and D . The first three are measures of trade dependence: (1) the share of U 's imports that come from D , (2) the share of the U 's exports that go to D , and (3) the difference between D 's share of U 's imports and U 's share of D 's imports. A higher value of any of these indicates that U is more trade dependent on D , and hence, D has more leverage over U . The fourth measure of bilateral trade relations is (4) the undirected total trade volume between U and D , adjusted by the combined sizes of the two countries' GDPs. All trade flows and GDPs are measured at pre-dam baseline with the average value over 1990-2000.

Although trade dependence is a commonly used measure of power in the geoeconomics literature [Mohr and Trebesch, 2025], one disadvantage of the trade measure is that the direction of the effects of trade on political cooperation has been found to be contingent on other incentives and circumstances [Brooks, 2024, Martin et al., 2008]. Thus, I use GDP imbalance as a second measure of power relations. To calculate GDP imbalance, I obtain country-level annual GDP data from the World Bank. I average across the baseline years of 1990-2000 for each country, and construct two binary measures for whether D 's baseline GDP is at least 20% larger, or at least 20% smaller, than U 's.

Strategic alliances

Power and cooperation can be influenced by geopolitical alliances or positions that trade flows and economic might may not capture.¹⁶ To capture political alignment, also a realist measure of propensity to cooperate, existing economic and political science literature has used and validated measures of how similarly two countries vote in the United Nations

16. Although China and the United States are not a country pair that shares rivers, for illustrative purposes, consider that China was the source of the largest share of American imports as recently as 2022. Their poor relations would not be captured by trade, but would be by UNGA voting similarity.

General Assembly (UNGA) [Becko et al., 2025, Kleinman et al., 2024]. Three measures of bilateral voting similarity, the S -, π -, and κ -scores, all begin with the sum across vote calls of the difference between two countries' votes. The S -score scales this difference measure by the squared maximum possible difference (Signorino & Ritter, 1999). The π and κ scores use slightly different methods to further adjust for the distribution of each country's votes, to account for the probability that two countries cast the same vote by chance [Cohen, 1960, Scott, 1955]. A fourth measure, ideal point distance, seeks to account for the fact that year-to-year changes in voting similarity are partially due to changes in the content of the measures being voted on, rather than true changes in the relative positions of countries. It begins with each country's ideal point, which captures its political positions relative to the US-led liberal order. The ideal point distance is then the absolute difference between two countries' ideal points [Bailey et al., 2017, Kleinman et al., 2024]. A larger value of the S -, π -, or κ -score indicates more similar votes, whereas a smaller value of ideal point distance indicates the same. For all four measures, I obtain pre-dam baselines by averaging each measure over 1993-2000, hence excluding Soviet years during which the measures were not available for former Soviet states.¹⁷

Regime type similarity

For regime type similarity, I begin with the democracy index and the autocracy index created by the Polity Project, version 5. Each index takes on integer values ranging from 0 to 10. A higher value of the democracy index indicates presence of more aspects of competitive, open elections, constraints on the executive, and rights to political participation. Likewise, a higher value of the autocracy index indicates the presence of more aspects of suppressed

17. UNGA voting similarity provides an intuitive measure of political alignment in the context of great power politics. For example, Becko et al. [2025] and Kleinman et al. [2024] use it to measure countries' alignment with China vs the US. On the other hand, one drawback is that it may be somewhat less informative about bilateral relations concerning regional issues. For example, the S -, π -, and κ -scores between India and Pakistan averaged over 1993-2000 were each above the 50th percentile among in-sample country pairs. Yet, the two countries were in strong disagreement over bilateral security issues and engaged in armed conflict during the same period.

political participation and unconstrained authority of the executive. For example, at the extremes, the United States and many European countries have a democracy index of 10 and autocracy index of 0, and North Korea has a democracy index of 0 and autocracy index of 10, throughout the 1992-2013 sample period. China, where the executive is chosen from multiple candidates and does not have unlimited authority to the extent of North Korea's, has a democracy index of 0 and autocracy index of 7 throughout the sample period.

The indices move as the terms of executive constraints or political participation shift. For example, Myanmar's autocracy index increased from 5 to 6 following the hardening of military rule in 2004, then decreased to 3 in 2011 with the transition to civilian government led by Aung San Suu Kyi. Given the potential for significant and sudden fluctuations in the democracy and autocracy indices, and because the indices reflect a country's fundamental political institutions that are unlikely to be endogenous with the operation or recent impacts of dams, I use time-varying contemporaneous measures instead of the pre-period average.

I categorize a country pair as both democratic if both countries have democracy index above 5, and likewise for both autocratic. I then categorize the pair as having the "same" regime type if the countries are either both democratic or both autocratic. Of the 2207 country pair x year observations within my sample for which Polity data is available, 53% are categorized as having the same regime type. As alternative measures, I also categorize a country pair as having a large difference in democracy index or autocracy index if the magnitude of the difference is above the 75th percentile in the distribution of country pairs in my sample. By this method, for example, Thailand and China have large differences in both indices, while Ukraine and Austria do not.

Joint membership in intergovernmental organizations

A key challenge in using joint membership in IGOs as a proxy of propensity to coordinate is that there is a wide variety of IGOs with substantial variation in both purpose and clout. For example, the Correlates of War Project provides data on the membership of countries in

over 500 IGOs, some of which are very niche. I construct two measures of joint membership in IGOs that targets the most relevant IGOs in different ways. For both measures, to obtain pre-dam baseline values, I use the values from the year 2000, as averaging across multiple years would necessitate accounting for the formation of new IGOs over time.

First, I subset to 51 organizations that are significant enough to be profiled in the Political Handbook of the World 2020-2021 (PHW). These include 13 organizations and agencies within the UN system, 5 regional development banks, and 31 other IGOs (plus the predecessors for two of them that went through renaming and rechartering during my sample period). The latter include global organizations such as the World Bank and World Trade Organization as well as regional ones such as the African Union and European Union. Out of these 51 IGOs, I count how many each upstream-downstream country pair is jointly member to.

Second, I use data from the Diplometrics Program at the Pardee Institute at the University of Denver. For each of 405 IGOs, this dataset assigns time-varying weights based on the frequency of media mentions as a proxy for the importance of the IGO in international affairs. For each country pair-year, it sums up the weights of the joint IGOs. These weighted sums are approximately normally distributed. I center and scale them based on the distribution of weighted sums across all country pairs (not just river-sharing ones) over 1992-2013.

Examples of country pairs along the distributions of international relations values

For one representative measure for each of power asymmetry, strategic alliance, regime type similarity, and IGO membership, Table 1.5 provides country pairs at the minimum, median, and maximum values along the distribution of the 106 in-sample country pairs. For all four measures, a higher value indicates a greater theoretical propensity for the upstream country to bear the downstream country's interests in mind when constructing and operating dams.

Table 1.5: Examples of country pairs along IR measure distributions. Format: upstream, downstream (IR value)

	Min	Median	Max
GDP % difference 1990-2000	China, Laos (-100%)	Burkina Faso, Benin (-17%)	Bhutan, India (1181%)
UNGA <i>S</i> -score 1993-2000	Syria, Israel (-0.18)	Guatemala, Mexico (0.87)	Spain, Portugal (0.98)
Same regime type Time-varying	South Africa, Eswatini (0)		Austria, Netherlands (1)
# Joint IGOs 2000	North Korea, South Korea (10)	Turkey, Georgia (18)	Austria, Netherlands (26)

Note: GDP % difference is the downstream country's GDP minus the upstream country's GDP, as a percentage of the upstream country's GDP. The count of IGOs with joint membership is out of the 51 IGOs, regional development banks, and UN agencies profiled in the Political Handbook of the World 2020-2021 for which country membership data is available through the Correlates of War Project.

In the top row, the IR measure of interest is the difference between the two countries' GDP as a percentage of the upstream country's GDP, averaged over 1990-2000. Realism would predict that Laos, which had an economy less than 1% the size of upstream China's, would have had little leverage over China's dam construction and operation decisions. On the other hand, India, which enjoys the opposite asymmetry relative to upstream Bhutan, may be able to credibly threaten meaningful retaliation if Bhutanese dams were to impose negative externalities on India.

The second row illustrates how voting similarity in the UN General Assembly serves as a proxy for international friendship. At one extreme, it captures the enmity between Syria and Israel, which have longstanding territorial disputes and a history of armed conflict, regarding bilateral and broader regional issues. At the other extreme, it captures the close bilateral accord and alignment on global issues between Spain and Portugal. Alliance and cooperation on other issues may be expected to mitigate transboundary externalities by giving downstream countries such as Portugal greater leverage on river-sharing issues, or by providing existing norms and channels for coordination.

Although the analysis uses time-varying regime type measures, in the third row, for simplicity of illustration, I give examples of country pairs that had either the same regime

type or different regime types throughout 1992-2013. During this period, South Africa was a democracy with democracy index of 9, whereas Eswatini has been an absolute monarchy with autocracy index of 7. Democratic peace theory would therefore predict that all else equal, South Africa and Eswatini are less likely to cooperate on their shared rivers than Austria and the Netherlands, which, like several other European country pairs in the sample, were both democracies with democratic index of 10.

In the bottom row, the IR measure of interest is the number of IGOs listed in the PHW that two countries are jointly member to. The country pair in the sample that is jointly in the fewest IGOs is North Korea and South Korea, as expected from North Korea's isolation. At the other end of the distribution, European country pairs such as Austria and the Netherlands are in more than twice as many notable IGOs as the two Koreas. According to the theory of liberal institutionalism, the lesser availability of third-party mediation and monitoring afforded to North and South Korea by IGOs makes these countries less likely to cooperate on their shared rivers than the European countries.

Time-varying bilateral engagement

Finally, I use the Integrated Crisis Early Warning System (ICEWS) dataset as a source of high-frequency variation in IR. The ICEWS dataset, available from 1995-2023, records media mentions of interactions between socio-political actors of different countries, including government administrations, political parties, public figures, and citizens. The interactions range from the very hostile (e.g. armed conflict) to everyday diplomacy (e.g. hosting visits, giving praise or making accusations) to significant cooperative events (e.g. signing formal agreements, or providing economic or military assistance). Each interaction is assigned an intensity score ranging from -10 (very hostile) to +10 (very cooperative). From this dataset, I calculate three country pair x year level measures of bilateral engagement: the number of cooperative interactions (events with positive intensity score), the number of hostile interactions (events with negative intensity score), and the sum of the intensity scores

across interactions.

I do not use the ICEWS bilateral engagement measures in the main specifications estimated with Equation (1.4.1) because cross-sectional comparison of bilateral engagement between country pairs is not a reliable metric for the extent of cooperation or hostility. For example, North and South Korea not only have a high number of hostile interactions, but also one of the highest numbers of cooperative interactions among country pairs in the sample, when the measures are averaged across the pre-period years of 1995-2000. On the other hand, as discussed by Liu and Yang [2025], bilateral engagement spikes during periods of major geopolitical shifts, such that *changes* in bilateral engagement over time do reflect *changes* in relations. This makes it an ideal source of high-frequency, over-time variation within country pairs that can be used in estimating Equation (1.4.3). For example, over-time variation in bilateral engagement between North and South Korea during the late 1990s and 2000s well captures the relative detente of the Sunshine Policy initiated in 1998 and the renewed decline in relations following nuclear and military tensions beginning in 2006.

In addition, part of the over-time variation in recorded interactions between country pairs may be due to differences in their media landscapes or other factors unrelated to true differences in IR. Thus, following Liu and Yang [2025], I standardize the annual observation of each measure by taking the z-score within the country-pair-specific distribution.

Other data

For estimating country-level pre-period drought and wetness sensitivities, I use SPEI data over 1992-2000 at the 0.5 degree resolution from the Global SPEI Database [Vicente-Serrano et al., 2010].

1.4.3 Results

Given that dams impose substantial transboundary externalities, are countries with cooperative international relations able to coordinate or bargain their way out of the potential

costs?

In Table 1.6, Columns (1)-(4) display estimates of Equation (1.4.1). The regressors are flow share from domestic hydroelectric dams, flow share from foreign hydroelectric dams, and the interaction between the latter and one measure of IR from each of the theories of international cooperation described in Sections 1.2.2 and 1.4.2. For all four IR measures in the table, a higher value indicates greater propensity for coordination between upstream and downstream countries according to IR theory. Across IR measures, I find that when the propensity to coordinate is low, flow share from foreign dams has a precisely estimated negative effect. And for all IR measures except one, the coefficient on foreign flow share is larger in magnitude than, and statistically distinguishable from, the coefficient on domestic flow share. This suggests that when bilateral coordination is poor, country borders do matter, with more harm caused by dams in foreign upstream countries than by dams in one's own country. The average flow share from foreign hydroelectric dams, which are farther upstream, is necessarily lower than the average flow share from domestic dams (0.05 vs 0.10 in 2013). Nonetheless, the bottom panel of Table 1.6 shows that due to the difference in marginal impacts, under the scenario of minimum propensity to coordinate as proxied by the IR measures, the effect of the average foreign flow share level is still greater than the effect of average domestic flow share.

Yet, the positive coefficients on all four IR interaction terms indicate that as bilateral relations improve, or as the downstream country wields greater power over the upstream country, the negative transboundary externalities are mitigated. Figure 1.7 and Appendix Figures A5 and A6 plot the implied magnitudes of the coefficients in Columns (1)-(4), which are also listed in the bottom panel. At the median or better values of any of the IR measures except GDP difference, the implied magnitude of the effect of average flow share from foreign hydroelectric dams is close to and statistically indistinguishable from zero. This suggests that, whether through side payments like those of the Central Asian countries or through more indirect leverage or diplomacy, many country pairs are able to mediate away much of

Table 1.6: International relations and the effects of foreign hydroelectric dams on nightlights

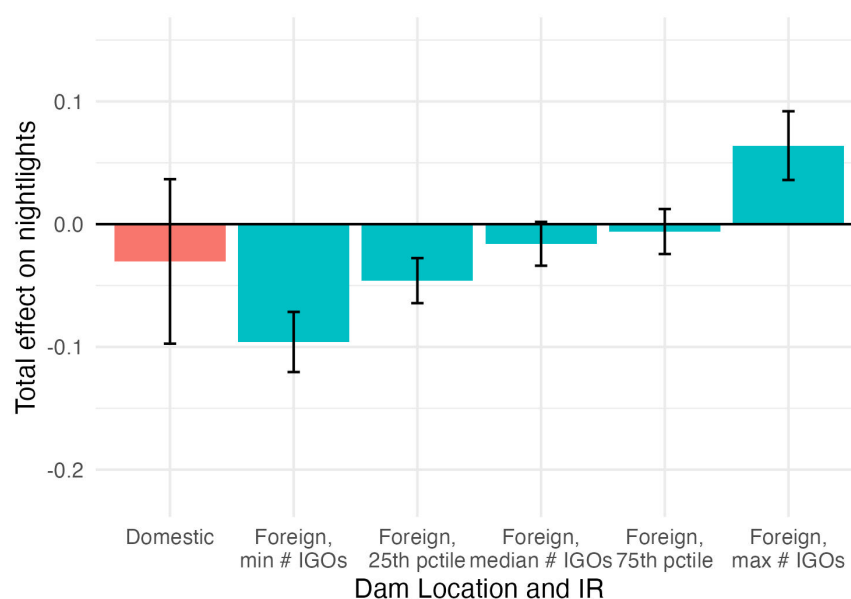
	(1)	(2)	(3)	(4)	(5)
FS from domestic hydro dams	-0.291 (0.324)	-0.281 (0.326)	-0.288 (0.324)	-0.293 (0.325)	-0.297 (0.326)
FS from foreign hydro dams	-0.806*** (0.255)	-3.772*** (0.382)	-2.429*** (0.474)	-3.789*** (0.436)	-3.792*** (0.355)
x GDP % diff	0.000908*** (0.000274)				0.00788 (0.0322)
x UNGA <i>S</i> score		3.815*** (0.193)			-1.812 (2.562)
x Same regime type			2.235*** (0.386)		0.513 (0.652)
x # IGOs with joint membership				0.193*** (0.0235)	0.253** (0.118)
FS from non-hydroelectric dams	-0.0510 (0.176)	-0.101 (0.173)	-0.0949 (0.167)	-0.0902 (0.174)	-0.101 (0.173)
Observations	1740442	1752747	1713226	1773618	1690996
<i>Effect of flow share at 2013 means:</i>					
Domestic FS	-0.0307	-0.0300	-0.0313	-0.0303	-0.0328
Foreign FS, min IR	-0.0347	-0.180	-0.0902	-0.0960	
Foreign FS, median IR	-0.0347	-0.0187	-0.00722	-0.0160	
Foreign FS, max IR	0.0115	-0.00103	-0.00722	0.0640	

Notes: Effect of domestic flow share at 2013 mean is the product of the coefficient on domestic flow share and the mean flow share from domestic hydroelectric dams in 2013, the end of the sample period, which was .10. In Columns (1)-(4), the effect of foreign flow share at the minimum, median, or maximum value of the IR measure is the sum of (a) the coefficient on foreign flow share times the mean flow share from foreign hydroelectric dams in 2013, which was .05, and (b) the coefficient on the IR interaction term times the mean foreign flow share in 2013 times the minimum, median, or maximum value of the IR measure of interest among country-pairs in the sample. For comparison, average change in nightlights from 2001-2013 in the sample was 2.79. All specifications include cell and county x year fixed effects. Standard errors in parentheses, clustered by country. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

the potential negative transboundary externalities of dams in upper riparian countries.

Since there are multiple ways of quantifying GDP imbalance, UNGA voting similarity, regime type similarity, and joint IGO membership, Appendix Tables A5, A6, A7, and A8 show robustness of the results in Columns (1)-(4) to alternative measures discussed in Section 1.4.2. All results are qualitatively consistent with the narrative that hydroelectric dams have the potential to impose substantial negative transboundary externalities, and IR more favorable to the downstream country mitigates these externalities. In addition, Appendix Table A4 shows the results of using trade dependence as an alternative to GDP imbalance as a

Figure 1.7: Implied effects of domestic and foreign flow share from hydroelectric dams: heterogeneity by joint IGO membership



Notes: This figure plots the magnitudes and 95% confidence intervals of flow share effects implied by Column (4) of Table 1.6 at mean values of domestic and foreign flow share from hydroelectric dams in 2013, which were 0.12 and 0.05, respectively. For the implied effect of foreign flow share, the figure shows heterogeneity by the number among the 51 IGOs profiled in the Political Handbook of the World, 2020-2021, that a country pair is jointly member to. Among the 106 country pairs in the sample, the minimum, 25th percentile, median, 75th percentile, and maximum values of the number of joint IGOs were 10, 15, 18, 19, and 26.

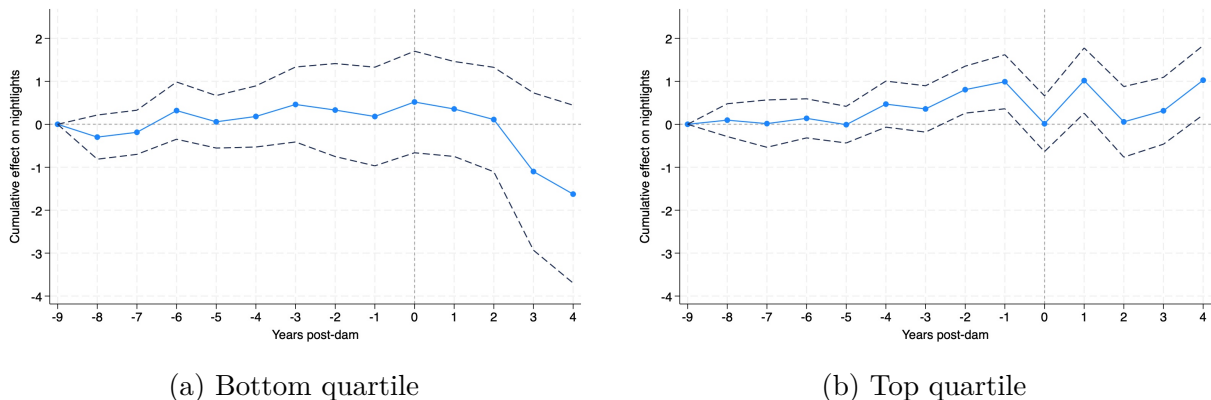
measures of power. For the most part, these results tell the same story when there is sufficient statistical power. The one exception is using the ideal point distance metric of UNGA voting similarity: as greater ideal point distance indicates less agreement on international issues, the positive coefficient on the interaction term here suggests that geopolitical alliance exacerbates dam externalities. However, this counterintuitive result is driven by a positive correlation between ideal point distance and other measures of voting similarity, and is imprecisely estimated.

Since there can be correlation between IR measures, to determine whether each IR measure has explanatory power on transboundary externalities conditional on the others, in Column (5) of Table 1.6, I include interactions with all four measures from Columns (1)-(4) in one regression. Only joint IGO membership retains its precision. Moreover, scaling each interaction term coefficient by the mean value of the IR variable suggests that joint IGO membership has the greatest power to mitigate the potential negative externalities of foreign hydroelectric dams. This is consistent with anecdotal evidence on how riparian countries with formal cooperative river management frameworks were able to achieve them: for example, pivotal roles in negotiation were played by the UNDP for the 1995 Mekong Agreement, the World Bank for the Indus Waters Treaty of 1960, and the UN for the 1977 Ganges Water Sharing Treaty between India and Bangladesh [Dinar et al., 2013].

Figure 1.8 shows the distributed lag estimates of the cumulative dynamic impacts of flow share from foreign hydroelectric dams, estimated with separate coefficients for when joint IGO membership between dam country and cell country are in the bottom and top quartiles. The results again indicate that the negative transboundary externalities of flow share are concentrated in country pairs with high coordination costs, that is, in the bottom quartile of joint IGO membership.

Finally, I conduct two exercises to lend credence to the interpretation of the IR interaction coefficients as capturing the effects of IR rather than of potential confounding variables. First, to control for potential confounders that affect downstream countries' ability

Figure 1.8: Distributed lag regression: cumulative effects of flow share from foreign hydro dams, by joint IGO membership



to cope with environmental shocks, Appendix Table A9 presents results of estimating Equation (1.4.2) with joint IGO membership as the IR measure. Across all specifications, I find that controlling for the interactions between flow share and country-specific sensitivities to drought and wetness does not qualitatively alter the result that foreign hydroelectric dams impose significant negative transboundary externalities, and that joint membership in more, or more influential, IGOs mitigates these externalities.

Second, Appendix Table A10 presents results of estimating Equation (1.4.3), using time-varying measures of bilateral engagement from ICEWS with country-pair fixed effects to account for any time-invariant correlates of IR. Qualitatively, this analysis tell the same story as the main results: as IR becomes more cooperative (more cooperative events, fewer hostile events, or a greater cooperative intensity of engagement across all events), the negative effects of hydroelectric dams in foreign upstream countries are mitigated. For the most part, the effects less precisely estimated than the main results using time-invariant IR measures. This could be because some of the effects of a dam are “locked-in” once the dam has been designed, sited, and built, and there is only partial flexibility to change the downstream effects over time on the intensive margin alone.

1.5 Conclusion

Many of today's most pressing environmental issues are transboundary in nature. This paper uses the context of dams around the world to generate evidence on the economic implications of transboundary externalities and on the determinants of countries' abilities to mitigate them. It is the first to conduct a causal analysis of the transboundary effects of dams at a global scale, as well as the first to measure how international relations shape transboundary environmental externalities of any kind.

I find that hydroelectric dams have far-reaching effects that translate into reductions in economic growth in foreign downstream countries. But despite the lack of a central international authority, bilateral international relations that reduce the transaction costs of coordination, particularly joint membership in intergovernmental organizations, are associated with a full mitigation of the transboundary externalities.

These findings hold two implications. First, given that new dams in recent decades have primarily been built by low- and middle-income countries, transboundary externalities and international relations matter for economic development. Second, international institutions play a significant role in facilitating transboundary resource management, alleviating the potential impacts of externalities on development. These implications motivate a rich agenda for future research on the international political economy of the environment, including on the mechanisms through which international institutions affect coordination, the strategic use of environmental externalities as leverage on other international political issues, and the potential efficiency gains of facilitating international cooperation over natural resources.

CHAPTER 2

ENVIRONMENTAL DEGRADATION IN ONE’S OWN BACKYARD: WHO GAINS AND WHO LOSES FROM SAND MINING IN INDIA (WITH SUSHANT BANJARA AND VARUN K)

2.1 Introduction

Economic growth and urbanization have spurred a decades-long global construction boom. Revenue in the construction market quadrupled from 2001 to 2020 by one measure, and the market size is projected to increase by another 25% in the span of only four years from 2023 to 2027 [AECOM, 2023, Statista, 2021]. Physically, this development is built on sand. As a primary input for concrete, asphalt, and glass, sand sourced from rivers and beaches accounts for 85% of global mineral extraction, making it the second most-used natural resource after water.¹ Unlike higher-value mined resources, sand is both costly to transport and consumed at a massive scale. Annually, up to 50 billion tonnes of sand—equivalent to 14,500 pounds per person—are extracted from fragile ecosystems near human populations and economic activity, causing significant environmental disruption [Beiser, 2018]. Sand mining is most prevalent and least regulated in developing countries undergoing construction booms. This activity is estimated to have caused a 90% reduction in sediment levels in major Asian rivers, potentially triggering severe environmental and social consequences, including increased flooding, aquifer depletion, salinization, ecosystem degradation, infrastructure damage, and more [Koehnken, 2018].

As environmental concerns have mounted, governments have responded with regulation. However, the combination of high economic rewards of sand mining, logistical difficulties, and

1. Desert sand is not used for these construction and industrial purposes because sand grains created by wind erosion are too rounded to bind together. River and marine sand grains, eroded by the stronger force of water, are angular and better suited to be a building material. Since marine sand requires cleaning to filter out salt, river sand is the most preferred for construction and industry.

political incentives has led to poor enforcement of these restrictions in developing countries, with large-scale illegal sand mining existing in at least 70 countries globally [Koehnken, 2018]. Thus, a key policy challenge is to identify regulations that are both welfare-improving and enforceable by being incentive-compatible within local political economies.

Currently, however, there is a vacuum of rigorous evidence that would inform such policymaking. Sand mining in developing countries is a data-poor industry due to high rates of informality and illegality. As a result, quantitative research on sand mining is scarce, and basic questions remain open: how big exactly are the environmental impacts? Given these costs, why do so many river-adjacent communities seem to participate in the mining of sand in their own backyards? What are the net economic outcomes for local communities?

In this paper, we aim to begin filling that knowledge gap by providing what is, to our knowledge, the first data-driven accounting of sand mining’s causal local costs and benefits and to whom they accrue. We do so in the context of India, where the construction sector accounts for 8% of GDP and the sand mining industry thrives [Baijal and Awasthi, 2023, Mouterde, 2022]. While sand mining is widespread across several states in India, we focus our analysis on Bihar, which is one of the most flood-prone states in the country and where the Sone river is known as a source of high-quality construction-grade sand. We address three key questions: (i) What are the local environmental externalities of sand mining, particularly through effects on flooding and agricultural productivity? (ii) What are the local economic benefits of sand mining? and (iii) How are these economic benefits, if any, distributed among the local population?

To answer these questions, we combine satellite imagery with newly digitized administrative data, applying a staggered difference-in-differences framework. In India, sand mining operations require environmental clearance and permitting by both district and state governments, as mandated by the National Green Tribunal. Each district is also required to publish a District Survey Report (DSR), which lists currently permitted sand mines as well as proposed sites likely to be auctioned in the future.

We digitize these DSRs to identify the location and timing of sand mining activity. This yields a sample of 584 existing sand mines, with permit dates ranging from March 2016 to April 27, 2021, and 585 proposed sites that remain untreated during our study period. Our identification strategy assumes that, within the same district and along the same river, areas near sites permitted earlier, later, or not yet permitted would have followed similar trends in outcomes absent treatment. This allows us to use staggered difference-in-differences estimators to isolate the causal effects of sand mining on environmental and economic outcomes.

Given concerns in recent econometric literature about the traditional two-way fixed effects (TWFE) estimator under treatment heterogeneity and staggered adoption [Callaway and Sant’Anna, 2020, de Chaisemartin and D’Haultfœuille, 2020], we use the estimator proposed by Borusyak et al. [2024] as our main specification. We also show that our results are robust to alternative estimators that account for these issues.

To measure the environmental consequences of sand mining, we focus on flooding, an oft-cited outcome of the gouging of the riverbank. Matching monthly gridded satellite data on inundation to active and potential sand mines, we find that sand mining leads to a significant increase of 1.5 p.p. in inundation rate and 2.1 p.p. in flooding incidents around active mining locations after the start of mining operations, compared to locations identified as potential mining sites where operations have not yet begun. This represents a 15% increase over the baseline inundation rate of 10% in areas around active mines, or a 21% increase over the baseline flood frequency of 10.0%. Although the increase in flooding provides only a partial measure of the environmental costs of sand mining, it is already economically significant.

How does sand mining affect agriculture—by shifting land and labor, reducing productivity through flooding, or enhancing it through mechanization, irrigation, or investment? To measure its net impact, we use vegetation index as the outcome variable. Our analysis shows that sand mining causes a 5% decline in vegetation near mining sites. Part of this decline is likely mechanical, as mining operations clear land for truck access and transportation.

On the other hand, anecdotal evidence suggests that sand mines also present economic opportunities for locals, such as employment in mining or transport of sand or collection of tolls on land that sand-transporting trucks must pass through. To measure the local net economic effects, we obtain Black Marble gridded satellite-based nightlights data [Román et al., 2018] and aggregate it to villages containing the sand mines. We find that sand mining increases nightlights in the villages containing the mines relative to not-yet-treated and never-treated villages. The positive effect begins about one year following the granting of a sand mine permit, and grows to a medium-run effect of 1.2 units after 3 years. This result is robust to removing the grid cells overlapping with the mines themselves as well as a buffer area around the mines, indicating that the nightlights increase represents income growth for local residents rather than simply economic activity directly associated with the mine.

Finally, we explore how the economic benefits are distributed within the village. In Bihar, the layout of the typical village reflects caste-based communities. Higher-caste individuals, who have higher rates of landownership, may bear the brunt of losses to agricultural productivity through flooding and land degradation, but they may be able to compensate for these losses by charging tolls or rents to sand miners. Lower-caste individuals may also lose from decreases in agricultural labor demand as well as suffer direct damages to their homes that are more likely to be built in flood-prone areas. However, they are likely to be the ones benefiting from mining jobs. Whether each group gains or loses on net is therefore an empirical question, and since wealth and political clout are concentrated among high-caste communities, the within-village distribution of net costs or benefits is potentially key to understanding the local political economy that enables sand mining.

To measure the within-village distribution of sand mining’s economic effects, we begin by classifying each populated 0.25 km^2 grid cell within a village as either relatively rich or relatively poor, according to whether its pre-treatment period (2012-2015) nightlights intensity is above or below the 80%ile at the village level. Then, we estimate staggered

difference-in-differences at the grid cell level, with richer cells in all villages as one sample and poorer cells in all villages as a separate sample. We find that sand mining caused nightlights to increase in both richer and poorer cells by $\sim 12\%$ and 18% respectively. The per capita percentage increase in nightlights for both rich and poor cells is $\sim 27\%$ and 36% respectively. This indicates that sand mining generates net economic benefits broadly for the whole village. In addition to analysis along the income distribution, we compare how different caste groups were effected by sand mining using data from NFHS. Our analysis indicates that the benefits of sand mining are concentrated among the upper castes and OBCs, and scheduled castes and tribes do not see positive effects.

In summary, we combine satellite data with novel administrative records from Bihar, India, to provide the first causal, quantitative evidence on the local impacts of sand mining. Consistent with widespread narratives, we find that sand mining causes economically and statistically significant increases in flooding and reductions in agricultural production. At the same time, it also spurs local economic activity, with benefits accruing to both rich and poor households.

These distribution of economic gains help explain why sand mining persists despite its costs. However, the benefits are not evenly distributed within the poor groups. Our analysis shows that positive effects are concentrated among Other Backward Classes (OBCs) and Upper Castes, who make up roughly 79% of Bihar’s population and sit higher in the social hierarchy. Dalit and Tribal communities, comprising the remaining 21%, do not experience gains in household assets. For these groups, especially if they bear the brunt of increased flooding, sand mining is likely welfare-reducing.

Rather than a simple story of outsiders exploiting local communities, our findings suggest that sand mining can represent a rational choice for many local households—benefiting the majority while harming those at the bottom. Though our study focuses on legally permitted mines, the results may help explain why illegal mining persists and why blanket bans, common across Indian states, have largely failed.

Much work remains to understand the long term welfare implications of sand mining. For example, if flooding impacts are persistent, will benefits continue into the longer-run when the local sand supply is exhausted? Do the economic gains from sand mining induce out-migration, human capital gains, or structural transformation, and do these enable the local communities to adapt to long-term environmental changes wrought by sand mining? How do policies that regulate the supply of sand affect macroeconomic outcomes through the costs of construction and urbanization?

Related literature and contributions This paper contributes to the growing body of research at the intersection of the political economy of the environment and the resource extraction literature. Prior work on resource extraction has documented both positive and negative effects of natural resource endowments. Mines and oil production have been shown to generate short-term local labor market benefits while also increasing the likelihood of conflict in contexts with weak governance [Berman et al., 2017, Dube and Vargas, 2013]. The broader welfare implications of resource extraction often depend on local policies and market infrastructure, making them difficult to generalize. However, a recurring theme in the literature is that environmental pollution and its negative consequences disproportionately affect economically disadvantaged and socially marginalized communities [Banzhaf et al., 2019].

Sand mining in India presents a unique case for bridging the resource extraction literature with studies on the political economy of the environment, particularly regarding how governments and institutions attempt—or fail—to regulate externalities [Burgess et al., 2012]. While much of the existing literature on resource extraction focuses on the effects of oil and mining in higher-income countries, particularly in relation to pollution and carbon emissions, it does not typically engage with issues of weak governance and conflict [Boomhower, 2019].

More broadly, this paper contributes to the literature on the environmental impacts of economic development in low- and middle-income countries (for a review, see [Jayachandran,

2022]). To our knowledge, this is the first study to causally estimate the environmental effects of sand mining, the most extracted mineral resource globally. We show that sand mining in Bihar significantly increases flooding in mining areas. At the same time, we find that villages near mining sites experience higher incomes—an outcome that is not obvious given that mining leases are typically awarded to external contractors rather than local actors.

Finally, we add to the literature on the distributional effects of resource extraction by examining why sand mining persists despite its environmental and social costs. Our findings suggest that both wealthy and poor households derive economic benefits from sand mining, which may explain its continued prevalence despite widespread concerns over its negative consequences.

This paper is organized as follows. In Section 2, we describe the background of sand mining and the setting in detail. In Section 3, we give a description of the data we use, our identification strategy and the evidence which supports that strategy. Section 4 focuses on the results of our empirical analysis and Section 5 concludes.

2.2 Background and Institutional Setting

Urbanization driven by economic development has generated an enormous demand for sand, a key input in concrete, which is the primary material of the construction industry. In India, which has thousands of rivers traversing its diverse landscapes, the demand for sand tripled between 2000 and 2017, creating a market worth over two billion USD (Mahadevan [2019]).

This sand is predominantly sourced from rivers and, in some cases, from beaches. Sand mining can be artisanal, where workers manually extract sand using their bare hands, placing it into containers. The extraction process varies depending on the location: near the shore, the sand is typically collected and dumped into piles, while in deeper riverbeds, workers dive into the water to excavate sand from greater depths. However, most large-scale sand mining is carried out using excavators, which extracts sand from river floodplains or artificially created islands formed by obstructing the river’s flow. Figure 2.1 shows excavators at a sand

mine in the rural areas of Patna, India.

2.2.1 Sand mining in India

Sand mining is done by contractors who sell their output to large firms or directly to the market through intermediaries who purchase the product at the mine, transport it to the market in towns where it is sold at a mark up. In many cases, the production process is integrated and the same firm extracts, packages and sells sand. The buyers can buy sand either from depots (which are owned by large firms) or through intermediaries which sell freshly extracted sand straight off the truck at markets in urban areas. The contractors and firms that mine sand do so after leasing the land from the government. Given that the business is extremely lucrative, leases are awarded through a competitive bidding process. Most leases are valid for a period of 5 years.

A significant portion of the sand sold in markets is extracted illegally, meaning it is sourced from areas not leased or authorized by the government. Illegal sand mining takes various forms. In some instances, firms or contractors with legitimate leases extend their operations beyond the allotted mining coordinates. In other cases, local contractors extract sand from unauthorized areas and sell it on the market. These operations are often supported by muscle power sourced from villages near the mining sites. In this paper, we shall focus on the effects of legal sand mining.

Sand extracted from riverbeds is transported either directly to markets for sale or to depots for storage. The final leg of the transportation process is typically handled by trucks, which are often owned by locals from villages near the mining sites, providing economic benefits to the local population. Additionally, local workers are frequently employed to load sand onto the trucks. Since river transport is more cost-effective, boats are commonly used to move sand to intermediate points, from where it is subsequently transported to markets. Figure B2 shows how boat are used to transport sand.

Sand mining can damage the environment Carefully extracting sand from riverbeds within the river’s natural replenishment limits does not necessarily harm the environment. However, excessive sand mining beyond these limits can alter the riverbed’s structure and dynamics. Similarly, the overuse of heavy equipment can exacerbate these effects. Furthermore, certain sand mining practices are inherently damaging. For instance, in many cases, artificial bunds are constructed to partition a section of the river from the main stream for easier mining. While this simplifies operations, it significantly disrupts the river’s natural flow.

Such damage to the riverbed can have far-reaching consequences, including altered river flow patterns, an increased risk of the river overflowing its banks during the monsoon season, and water inundating previously unaffected areas. Recognizing the environmental harm caused by sand mining, the National Green Tribunal (NGT)—a statutory body established by the Indian Parliament to address cases of environmental damage—has issued guidelines for state authorities to follow when granting mining licenses. These guidelines aim to minimize the environmental impact of sand mining activities.

Additionally, the NGT has enacted measures such as banning mining activities during the monsoon season to reduce the risks associated with excessive mining. However, despite these efforts, reports from news outlets indicate that violations of these regulations remain widespread.

Figure 2.1: Sand excavator and trucks at a sand mine in Patna



Note: Photo taken by Varun K in March 2023

2.2.2 Sand mining leases

In India, state governments have the authority to lease land for sand mining. The responsibility for identifying suitable land falls on the *District Commissioner* of each district. As mandated by the NGT, every district must prepare a District Survey Report (DSR), which documents all current mining sites and potential locations for future sand mining.

Once identified, specific tracts of land are designated as mines and leased through an auction process, typically for five years. The DSRs allow us to map existing mines across districts, including Patna. They also list potential future mining sites, which we use as the control group in our analysis.

2.2.3 Benefits and losses from sand mining

Anecdotal evidence and our fieldwork highlight the diverse ways in which villagers can either gain or lose from sand mining activities. In some cases, individuals within the village may act as contractors operating the mine, resulting in direct but concentrated benefits for the community. Additionally, operating a mine often necessitates the construction of an informal road connecting the mine to the main road for sand transportation. Mine owners typically

lease this land or compensate villagers who own it. If mining activities can impose significant costs on the village—such as flooding or reduced agricultural productivity—mine owners may seek to appease affected villagers by providing employment opportunities to those bearing the externalities.

For instance, villagers may be employed to load sand onto trucks, creating jobs for local workers. Furthermore, the sand transported by these trucks is sold at a markup in markets, and the trucks themselves are often owned by villagers, offering additional economic benefits to the community. For these reasons, villagers may prefer to have a sand mine in the village.

The costs of sand mining can be various. Mining can weaken riverbanks, making villages more vulnerable to frequent and severe flooding, especially during the monsoon season (Padmalal and Maya [2014]). The removal of sand destroys habitats for fish, plants, and other aquatic life, reducing biodiversity, which can affect the livelihoods of households which rely on these. Excessive sand removal can lower the water table, reducing the availability of groundwater for irrigation and drinking purposes. Additionally, dust, noise, and pollution from mining operations and truck traffic can contribute to respiratory illnesses and reduced quality of life.

To understand why sand mining persists despite its apparent negative effects, it is critical to know how large the costs and benefits actually are, how they are distributed, and how the costs may be rationalized by villagers. At least the following are possible:

1. **Sand mining is rational:** the benefits exceed the costs for a majority of households in the village.
2. **Cooptation by the powerful:** Costs exceed benefits for a majority of individuals, and benefits are concentrated among a few. The benefits are monopolized by a few with power while the costs are spread among a larger group that faces transaction costs to organizing, or among people who do not have political power within the village.
3. **Time horizon shift:** Sand mining shortens the time horizon over which the villagers

care about local environmental quality, by enabling them to leave agriculture or the village altogether before the costs are fully incurred.

4. **Behavioral:** Locals are not fully internalizing the costs, due to information frictions which prevent them from observing costs or due to their inability to attribute the observable costs to sand mining. For example, even if they experience increased flooding, they may hold incorrect beliefs about how much of it is caused by sand mining.

Each of these explanations holds different implications for sand management policy and the political economy of resource extraction.

2.3 Data and Empirical Strategy

2.3.1 Data

Sand mine locations and permitting dates

We begin by collecting District Survey Reports for districts in the state of Bihar. The DSRs are prepared in accordance with Sustainable Sand Mining Management Guidelines 2016, and contains the exhaustive list of existing and potential mines in a district. ‘Potential mines’, in the context of DSRs are areas with well defined borders which have undergone feasibility studies and identified as future mining sites ready for auctioning in the future. The 2016 guidelines states that the DSR “*Shall contain...District wise detail of existing mining leases of sand and aggregates*” and “*District wise availability of sand or gravel or aggregate resources.*” Furthermore, the guidelines also makes it explicit that “*Mining should be done only in area / stretch identified in the District Level Survey Report suitable for mining*”, giving us confidence that the the DSRs, indeed, contains the exhaustive list of potential and existing mines.

From each DSR, we use optical character recognition to extract the locations of active and proposed sand mining sites, and for the active mines, their dates of lease and dates of

operation. For an example of the format of the data see Appendix Figure B1. Since the quality of DSR PDFs varies between districts, we manually check each coordinate extracted via optical character recognition for accuracy. For some districts, permit lease dates were unavailable from the DSRs. In these cases, we parse publicly available auction documents and use the auction call date as the operations start date. Finally, from the bounding coordinates of each mine as listed on the DSRs, we create mine polygons, each associated with a treatment status (active or proposed sand mine) and, for active mines, a treatment date.

Of Bihar’s 38 districts, 21 contain major rivers. We obtained DSRs with permit leasing dates for 16 of these districts, covering nearly all those south of the Ganga River. This region produces yellow feldspathic sand, highly valued for construction, unlike the less valuable white silica sand found in northern Bihar. As a result, our sample includes nearly all districts where large-scale sand mining is likely to occur.

To validate the location of sand mines, we randomly selected 51 out of 1,200 mine sites and manually checked them using Google Maps satellite imagery. We verified whether an active sand mine exists at the centroid of an identified mine polygon and whether no sand mine is present at the centroid of a proposed mine polygon. Table 2.1 summarizes the results.

For most sites listed as active mines in the DSRs, a sand mine is visible at or near the designated location—where the imagery is clear enough to confirm. Similarly, for the majority of proposed mine sites, we do not see evidence of mining activity. However, four of the 16 proposed mine sites do show signs of mining, possibly because operations began after the DSRs were published in 2021.

Flooding

Our flood measure comes from the JRC Monthly Water History dataset (Pekel et al. [2016]), which provides a monthly binary measure of pixel inundation. To define the area surrounding each mine for assessing flooding impacts, we begin by creating a 500-meter radius buffer

Table 2.1: Random checks with Google Maps satellite imagery

Mining visible at centroid?	% of Existing	% of Proposed
Yes	48.6	6.2
Probably	2.9	6.2
Mining closeby	22.9	12.5
Probably not	8.6	25.0
No	0.0	37.5
Image unclear	17.1	12.5
N	35	16

around the centroid of each mine. However, when mines are located close to one another, their buffers may overlap, leading to potential double counting of affected areas. To prevent this, we merge all contiguous overlapping buffers into a single, unified observation unit. For example, if mines A, B, and C are in proximity and the buffers of A and B as well as A and C overlap, we consolidate all three into a single merged shape, ensuring that each affected area is counted only once.

We use data from 2000 onward to measure flooding in two ways. Within the truncated circle around each potential or existing sand mine, we calculate the percentage of 30m x 30m cells inundated each month. Our first measure, an area-based flooding metric, is the average inundation rate for the months from July to December, as these months are most prone to flooding.

Our second, month-based measure accounts for missing inundation data due to cloud cover, which varies by year. To establish a baseline, we calculate the long-run mean inundation rate for each month from 2004 to 2009. For each month-year combination, we classify a site as flooded if the inundation rate is at least 20% higher than its month-specific long-run mean (Patel [2024]). We then aggregate this binary measure across July-December to capture annual flooding incidents. Our empirical analysis uses panel data at the mine $\times$ year level. To prevent spillover effects from existing mines, we exclude proposed mines located within 500 meters of an active mine from our sample.

Nightlights data

We obtain monthly gridded nightlights data for 2012-2023 at the 15 arc-second (approximately 0.5km) resolution from NASA’s Black Marble product. Black Marble is derived from the satellite imagery collected by the VIIRS instrument, but compared to previous VIIRS nightlight products, it is better-suited for tropical low and middle-income countries like India where cloud cover is persistent and many areas have low nightlight intensity. In particular, it has improved sensitivity to low-intensity lights, better accounts for seasonal variation, and employs “temporal-gap filling” to reduce persistent data gap [Román et al., 2018].

For the village-level nightlights analysis, we exclude cells with centroids inside active sand mines. We then average the remaining cells within each village to create a village $\times$ month panel of nightlights. Finally, we aggregate the data from monthly to yearly values.

For the cell-level nightlights analysis, we remove cells overlapping with active sand mines, as well as cells with estimated baseline 2015 population of less than 10. From the remaining cells, we calculate the village-specific baseline (2012-2015) nightlights value at the 80th percentile, and classify each cell as either relatively rich or relatively poor based on whether its baseline value is above or below this value.

Vegetation Data

To measure agricultural production, we obtain gridded data of the Enhanced Vegetation Index (EVI) at a 16-day, 250m resolution, from 2012-2024, from the MODIS/Terra Vegetation Indices 16-Day L3 Global 250m SIN Grid data product, Version 6.1 (Didan [2021]). Where granular data on agricultural production is not available, vegetation indices are a commonly used proxy (Didan et al. [2015], Burke and Lobell [2017]). Among vegetation indices, the EVI has several advantages over the Normalized Difference Vegetation Index (NDVI), including better differentiating vegetation levels in areas with either high biomass or sparse vegetation, and correcting for the influence of aerosols and haze (Huete et al. [2002]). For the 500m buffer around each mine centroid and each 16-day window, we extract the average

EVI by taking the mean value of all 250m cells overlapping with the buffer. The 16-day values are then aggregated to the annual level.

Other data

Village-level polygons, Census data, and Trivedi elections data were downloaded from the Socioeconomic High-resolution Rural-Urban Geographic Platform for India (Asher et al. [2021]).

For grid cell-level population estimates, we obtain 3 arc-second resolution gridded 2015 (pre-mining) population data from GHS-POP (Schiavina et al. [2023]), a product of the Global Human Settlement Layer, which uses satellite imagery of built-up areas to downscale administrative population data. We aggregate this up to a 15 arc-second resolution to match the Black Marble nightlights data.

2.3.2 Identification strategy

In our analysis, focusing on the state of Bihar, causal inference is made possible by the fact that each district in India is required by the National Green Tribunal to publish a District Survey Report (DSR) listing the locations of both active, permitted sand mines and proposed potential sand mines that are likely to be auctioned for permits in the future. Indeed a sand mine cannot be auctioned without it being identified in the DSR as stipulated by Sustainable Sand Mining Management Guidelines 2016, which is described in Section 2.3.1. Furthermore, Enforcement and Monitoring Guidelines 2020, states the following indicating that the potential mines are not substantially different from existing mines:

“ Sustainable Sand Mining Guidelines, 2016 issued by MoEF & CC requires preparation of District Survey Report (DSR), which is an important initial step before grant of mining lease/LoI. The guidelines emphasize detailed procedure to be followed for the purpose of identification of areas of aggradation/ deposition where mining can be allowed and identification of areas of erosion and proximity to infrastructural structures and installation where mining

should be prohibited.”

Based on these information, our identifying assumption is that, within the same district and along the same river, there would be parallel trends in our outcome variables between areas around sites with active sand mining permits granted earlier versus later, and with areas around “potential” sand mining sites, in the absence of sand mining. In the subsequent subsection we also provide empirical evidence in support of the parallel trends:

We estimate the effect of sand mining on any given outcome Y as follows. For proposed and existing sand mining sites i , on rivers r , in districts d , at year t , we estimate static and dynamic versions of

$$Y_{irdt} = \beta treat_i * post_t + \alpha_i + X_{it}\delta_{rdt} + \varepsilon_{irdt} \quad (2.3.1)$$

where $treat_i = 1$ if the mine becomes operational and $post_t = 1$ after the mine becomes operational.²

Under our parallel trends assumption, β represents the ATT for sites where mining has begun. Our primary specification uses the imputation estimator proposed by Borusyak et al. [2024]. This choice reflects a key feature of our setting: while the DSRs provide the date of lease or auction, the actual start of mining operations is uncertain. In some cases, mining may begin after the lease is granted; in others, it may start beforehand due to irregularities in the permitting process. Given this uncertainty, relying on the period immediately preceding the reported treatment date as a baseline is potentially unreliable. The imputation estimator addresses this by using the average of all pre-treatment periods to construct the counterfactual, providing a more stable reference point. To ensure our findings are not sensitive to this choice, we also test robustness using alternative estimators—specifically those

2. The dynamic version is:

$$Y_{irdt} = \sum_{\tau=-4}^{\tau=4} \beta_{\tau} D_{it}^{\tau} * treat_i + \alpha_i + \delta_{rdt} + \varepsilon_{irdt} \quad (2.3.2)$$

where D_{it}^{τ} is a dummy variable that indicates that whether a mine i started operating τ periods earlier or will start operating τ periods after.

of Sun and Abraham [2021] and Callaway and Sant’Anna [2020]—which rely on the last pre-treatment period as the comparison baseline.

Since flooding is a physical phenomenon, our flooding analysis uses truncated circles with a 500m radius around the centroid of each mining site as the unit of analysis (i), as described in Section 2.3.1. This approach isolates the geographical area most likely to be affected by increased flooding, if it occurs. We apply a similar method when analyzing effects on vegetation. Our sample includes mines which started operations between 2016 and 2020.

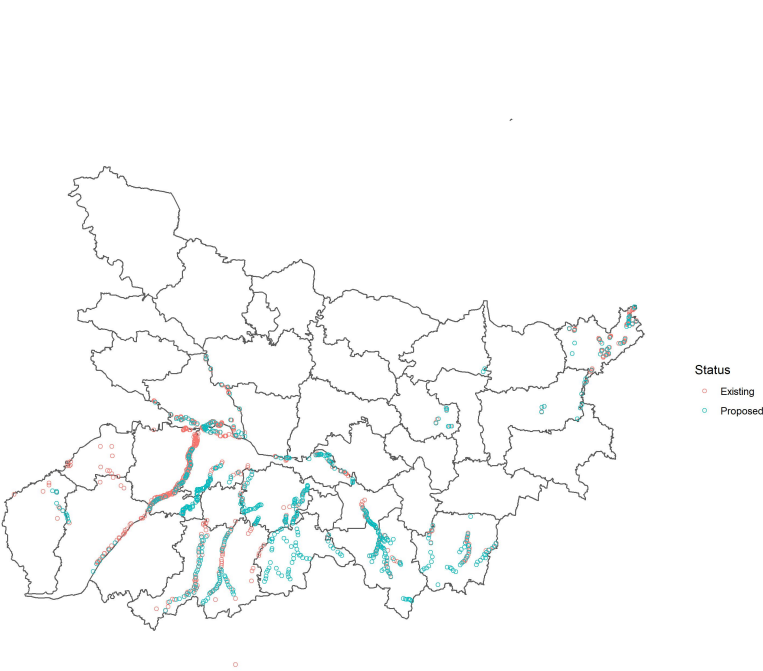
For the nightlights analysis, however, we aggregate data at the village level (i = village). Since rivers rarely run through the center of villages, sand mines are often located at their edges. Aggregating at the village level allows us to capture changes in residential and commercial areas, even if they are not adjacent to a sand mine. Finally, for our analysis of distributional effects, we use grid cells as the unit of analysis (i = grid cell).

2.3.3 *Support for parallel trends assumption*

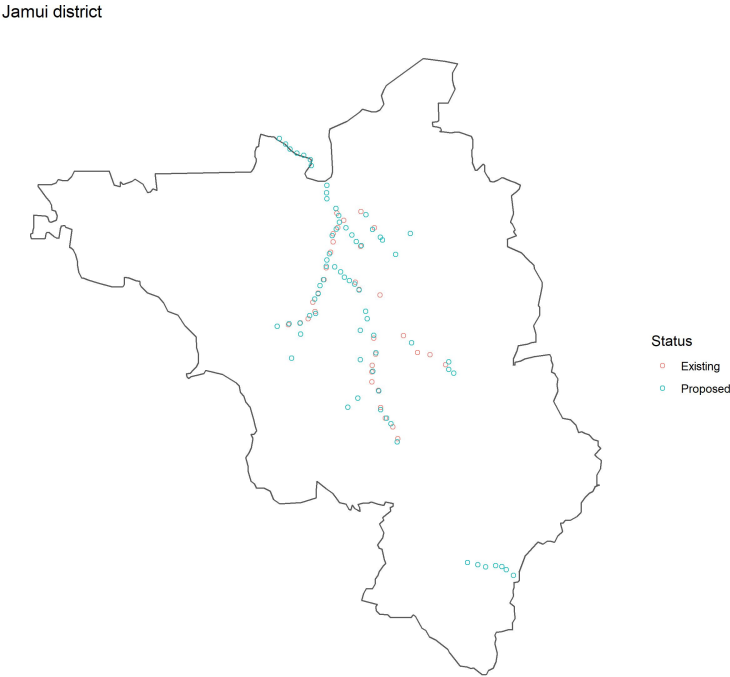
To empirically assess the plausibility of the parallel trends assumption, we begin by mapping the sites with existing and proposed leases. Figure 2.2a maps the centroids of existing and proposed sand mines in Bihar, and Figure 2.2b zooms into one district. Within any given district, the existing and proposed mines are well-interspersed, so it does not appear to be the case that timing of leases correlates with potential confounders such as being more up- or downstream along the river or distance from markets or urban areas.

Next, we check for pre-trends in economic and demographic variables in the villages around existing and proposed mines. We use the Socioeconomic High-resolution Rural-Urban Geographic Platform for India (Asher et al. [2021]) to access village-level Population Census Abstract data from the 1991, 2001, and 2011 Censuses. For different demographic and public goods variables at the village level we perform two kinds of comparisons between villages which had an operational mine by 2020 and those which had a potential mine. First, we compare the cross-sectional differences on these variables in 2011 (see Figure 2.3a).

Figure 2.2: Centroids of existing and proposed sand mines



(a) Mine locations in Bihar



(b) Mine locations in Jamui district

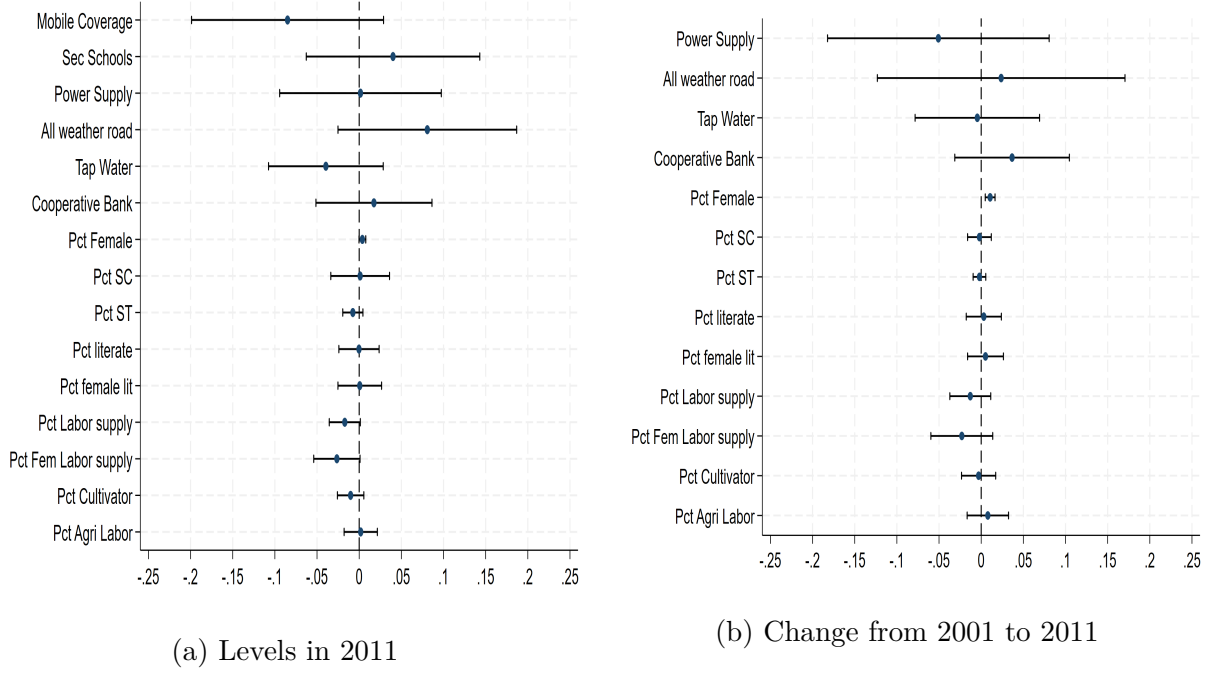
The treated and control villages are similar across most variables. Then in Figure 2.3b, we compare the change in these variables between 2001 and 2011 across the two types of villages. The figure clearly illustrates that the trend in change for the decade was not different between the treatment and control village.

Finally, one may be concerned that the timing of when a sand mining permit is granted in a village could be related to the village's political connections, posing a threat to the parallel trends assumption. Although we cannot test for balance in a comprehensive way - for example, we do not know of any publicly available data on district government officials' villages of origin, we can check for balance on state assembly election outcomes. Although sand mining sites are chosen and auctioned off by the district government rather than the legislative assembly, it is possible that members of the legislative assembly (MLAs) hold some informal influence over these decisions.

Bihar held state assembly elections in 2015 and 2020. In our sample of existing and proposed mines, 96% of existing mines received their permit in 2016-2020, so we check for balance based on 2015 election results. In that election, the parties winning the most assembly constituency (AC) seats were the RJD, JD(U), and BJP, in that order. The RJD, JD(U), and INC formed the ruling coalition that held a majority in the assembly. In July 2017, that coalition fell apart and a new ruling coalition formed between the JD(U), BJP, and LJP.

Appendix Table B1a shows mine-level correlations between the party of the elected MLA and sand mine permit status. There is no significant correlation between MLA party affiliation and either the probability of having been treated (i.e. granted a permit) by 2021, when our DSR data was published, or the year in which treated mines were granted their permits. In Appendix Table B1b, we aggregate the mines to the AC level. We find that among the 78 ACs containing any existing or proposed mines, the party of the elected MLA is not significantly correlated with the total number of existing and proposed mines, the share of existing mines in that total, or the timing of existing mines' permits. Although the

Figure 2.3: Balance in Observable Characteristics



Notes: This figure studies differences between villages closest to treated and potential mines control group in an array of observable characteristics, prior to treatment. Panel A presents the coefficient obtained from a regression of each variable on a dummy that equals 1 if the village is close to a treated mine. The regression includes fixed effects for district * river. Panel B replicates the analysis but replaces the dependent variable with its first difference between 2011 and 2001.

coefficient on RJD in Column (1) is large, this is to be expected as the RJD's support base is primarily cultivators who tend to live near rivers, where sand mining is more prominent for purely geographical reasons. As such, many of the prime locations for sand mining happen to be in RJD ACs. There is also no significant or consistent correlation between the number of sand mine permits an AC receives in a given year and whether the MLA's party is in the ruling coalition during that year.

2.4 Results

2.4.1 Effects on flooding

In this section we present static and dynamic difference-in-differences estimates on flooding. In Table 2.2, our static results indicate that within 500m of a sand mine, mining increases

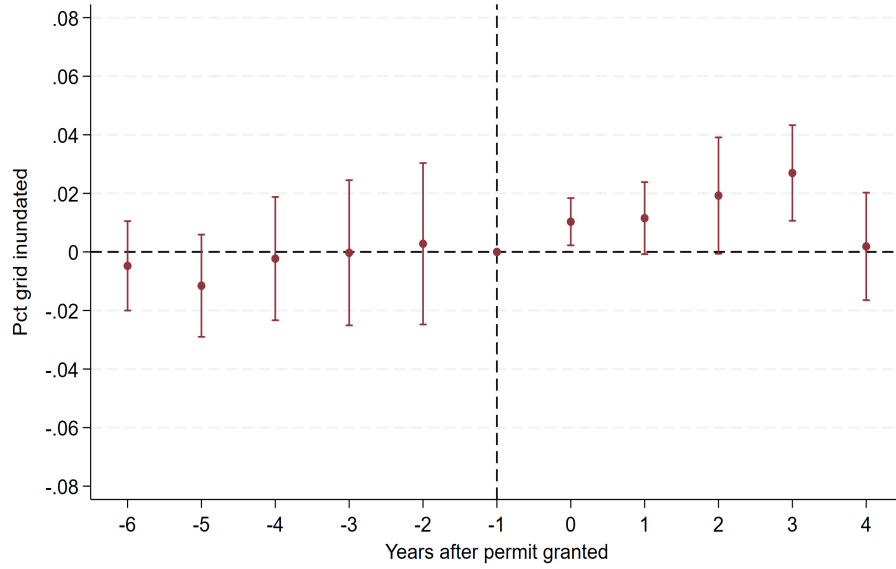
inundation rates by 1.5 p.p., which represents a 15 % increase over the pre-mining baseline of 10% in areas around active mines. For our second, month-based flooding measure, within 500m of sand mines, there is a 2.1 p.p. increase in the proportion of months with an incident of flooding, which represents a 21 % increase over the baseline of 10 %. Figure 2.4 show the event study coefficients from dynamic imputation estimator. The results from the event study are consistent with the static estimates. They show that the increase in flooding persists at least four years following the opening of a sand mine.

Table 2.2: Effect of mining on Flooding

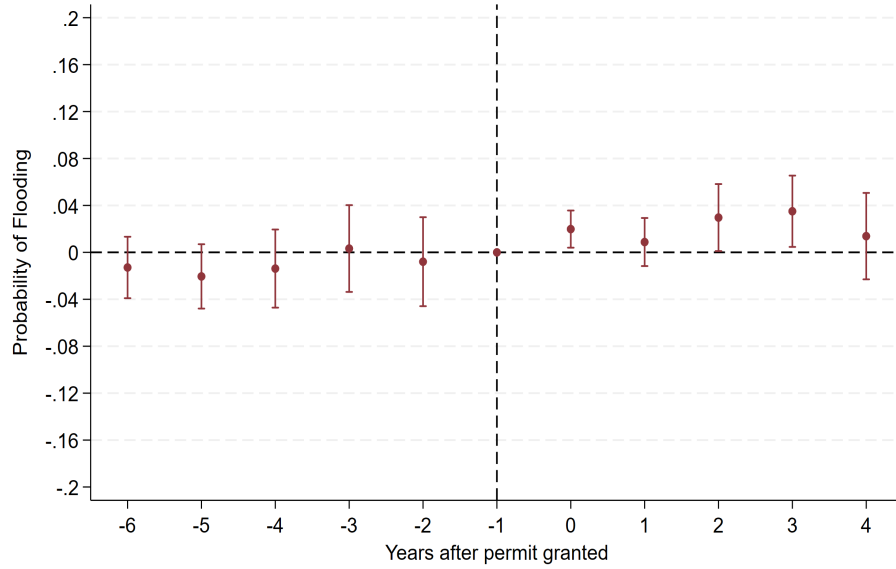
	Percent Grid Inundated				Probability of Flooding			
Treated mines	0.015*** (0.005)	0.016*** (0.006)	0.016** (0.007)	0.013** (0.006)	0.021*** (0.007)	0.022*** (0.007)	0.023** (0.009)	0.019** (0.008)
Observations	5,725	6,196	6,101	6,310	5,725	6,196	6,101	6,310
Mean Dep variable	0.098	0.098	0.098	0.098	0.098	0.098	0.098	0.098
Method	Imputation	Imputation	SAB	SAB	Imputation	Imputation	SAB	SAB
Fixed Effect	Dist*River	District	Dist*River	District	Dist*River	District	Dist*River	District

Notes: This table presents the impact of sand mining on flooding, as measured by mean inundation and flooding incidents in an a buffer area of 500 meter radius around the mine. Estimates are from the staggered difference-in-differences specification in Equation 2.3.1. The empirical analysis uses yearly panel data on inundation and includes year-by-district-by-river/year-by-district and mine fixed effects, as well as controls for temperature and precipitation in the year. We focus on a time window 4 years before and 4 years after a mine started operations. For each treated mine, we determine a control group which hasn't received a mine within the geographic unit. Column (1)-(4) shows estimates for mean inundation using either the Imputation estimator (Borusyak et al. [2024]) or the Sun and Abraham [2021] estimator. Column (5)-(8) shows estimates for flooding incidents using either the Imputation estimator (Borusyak et al. [2024]) or the Sun and Abraham [2021] estimator. SAB indicates that the columns shows results for the Sun and Abraham [2021] estimator. The mean dependent variable is computed for ever treated in the years before treatment. Standard errors are displayed in parentheses and clustered at mine level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 2.4: Dynamic effects of Sand mining on Flooding



(a) Percent grid inundated with water



(b) Flooding

Notes: This figure presents event study evidence of the effect of sand mining on flooding following Equation 2.3.2 estimated using the imputation procedure of Borusyak et al. [2024]. Panel a) shows the estimates for mean inundation at the mine level, and panel b) shows the estimates for probability of an incident of flooding at the mine level. The empirical analysis uses yearly panel data on inundation and includes year-by-district-by-river and mine fixed effects, as well as controls for temperature and precipitation in the year. We focus on a time window 4 years before and 4 years after a mine started operations. Each dot corresponds to an estimated coefficient, and vertical lines indicate the corresponding 95% confidence intervals. The dashed line represents the omitted coefficient. Standard errors are clustered at mine level.

2.4.2 Effects on village-level mean nightlights

In our main nightlights specification, we exclude towns and cities with populations over 15,000, as larger urban areas are unlikely to be affected by nearby sand mines in the same way as rural villages. We limit the sample to the four years before and after the year a mine is allotted.

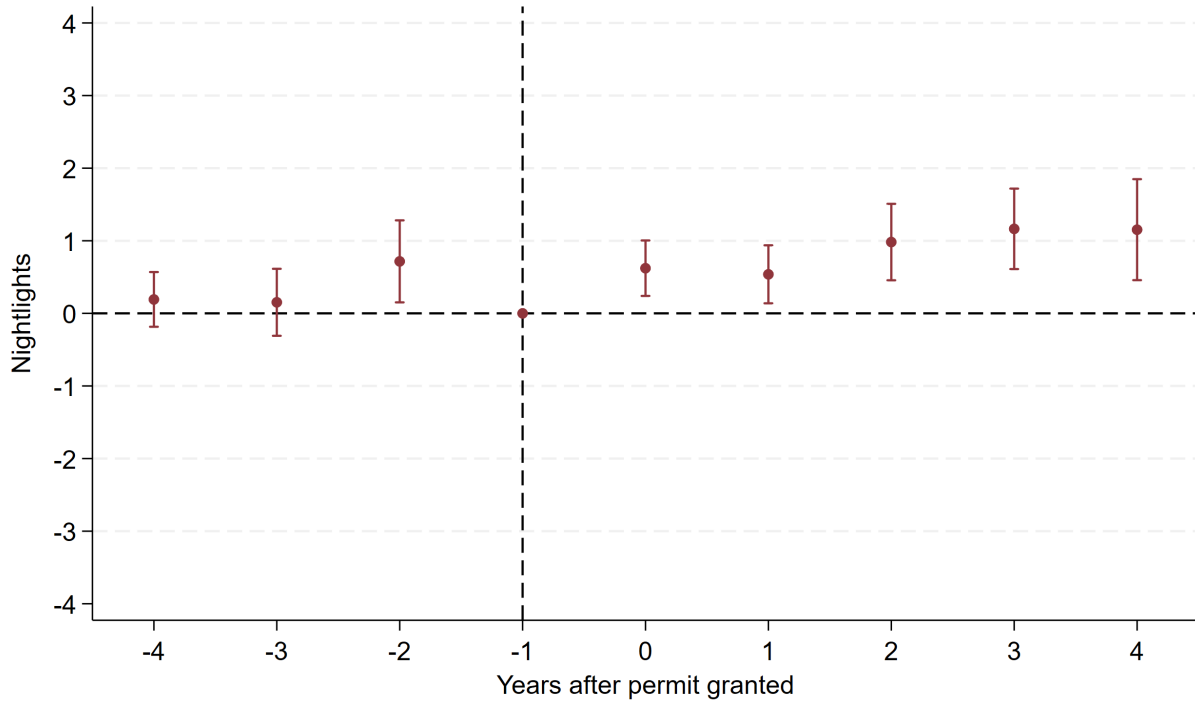
Table 2.3 reports static estimates for villages with populations below 15,000. We find that nightlights increased by 11.2% relative to a baseline mean of 6.42 in treated villages. Figure 2.5 presents the dynamic effects, showing that nightlights rise steadily in mining villages compared to not-yet-treated and never-treated villages. The effect grows over time, reaching 1.2 units four years after treatment—about a 20% increase over the pre-treatment baseline.

Table 2.3: Effects of sand mining on village-level mean nightlights

	Nightlights			
Treated mines	0.782*** (0.210)	0.735*** (0.232)	0.949*** (0.250)	0.735*** (0.232)
Observations	4,534	4,679	4,617	4,679
Mean Dep variable	6.34	6.34	6.34	6.34
Method	Imputation	SAB	Imputation	SAB
Fixed Effect	Dist*River	Dist*River	District	District

Notes: This table presents the impact of sand mining on economic activity, as measured by nightlights in a village close to the mine. Estimates are from the staggered difference-in-differences specification in Equation 2.3.1. The empirical analysis uses yearly panel data on nightlights and includes year-by-district-by-river/year-by-district and village fixed effects, as well as controls for temperature and precipitation in the year. We focus on a time window 4 years before and 4 years after a mine started operations. For each treated mine, we determine a control group which hasn't received a mine within the geographic unit. Column (1)-(2) shows estimates for nightlights using either the Imputation estimator (Borusyak et al. [2024]) or the Sun and Abraham [2021] estimator with year-by-district-by-river and village fixed effects. Column (3)-(4) shows estimates for nightlights using either the Imputation estimator (Borusyak et al. [2024]) or the Sun and Abraham [2021] estimator with year-by-district and village fixed effects. SAB indicates that the columns shows results for the Sun and Abraham [2021] estimator. The mean dependent variable is computed for ever treated in the years before treatment. Standard errors are displayed in parentheses and clustered at village level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 2.5: Village-level dynamic effects of sand mining on nightlights



Notes: This figure presents event study evidence of the effect of sand mining on nightlights following Equation 2.3.2 estimated using the imputation procedure of Borusyak et al. [2024]. The empirical analysis uses yearly panel data on nightlights and includes year-by-district-by-river and mine fixed effects, as well as controls for temperature and precipitation in the year. We focus on a time window 4 years before and 4 years after a mine started operations. Each dot corresponds to an estimated coefficient, and vertical lines indicate the corresponding 95% confidence intervals. The dashed line represents the omitted coefficient. Standard errors are clustered at mine level.

2.4.3 *Effects on Agriculture*

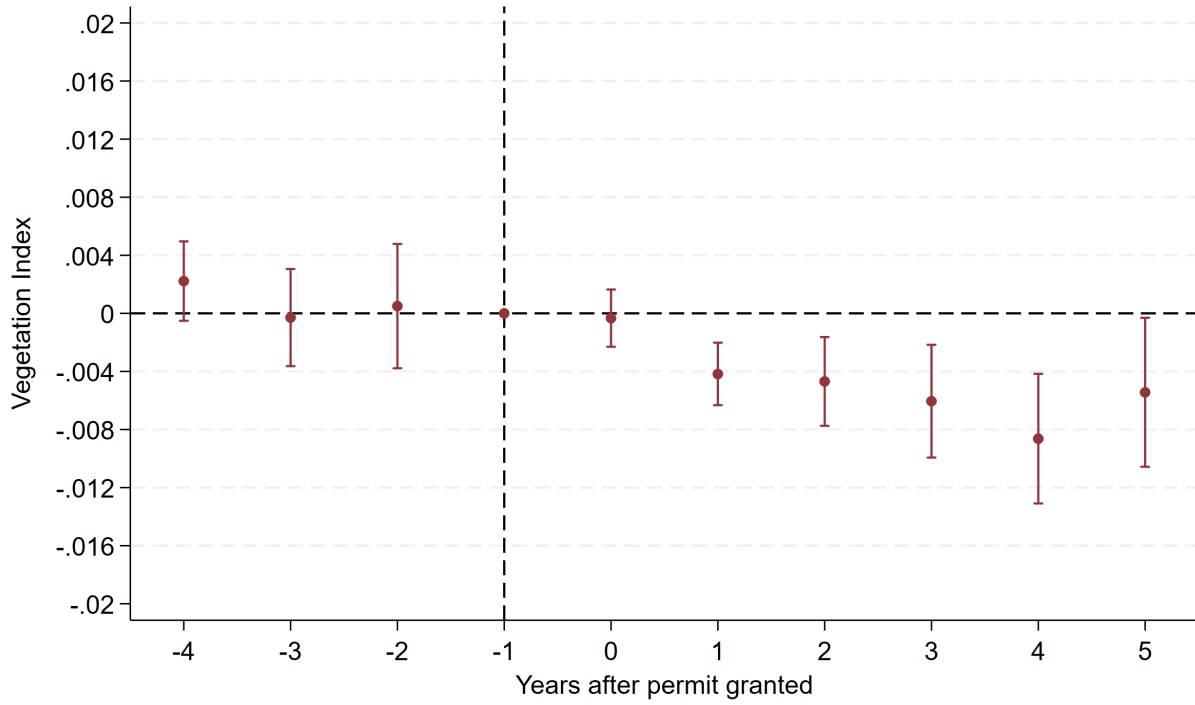
Sand mining may affect agricultural production through several possible channels, such as substitution of land or labor from agriculture to sand mining, decreased productivity due to flooding, or increased productivity due to mechanization, irrigation, or other investments funded with sand mining-derived capital. To measure the net effect of sand mining on agricultural production, we use EVI as an outcome variable. Table 2.4 shows that within 500m of mine centroids, sand mining has a precise but small effect on EVI, equivalent to 2% of the pre-mining mean among treated mine areas. The magnitude is consistent across specifications. Figure 2.6 plots the dynamic effects using our main specification of the imputation method with district x river time dummies. The largest post-period effect occurs in the medium-run of 3-4 years, and amounts to about 5% of the pre-mining baseline. We interpret these results as indicating that there is most likely a mechanical effect of sand mining on vegetation at the mine itself.

Table 2.4: Effects of sand mining on mine-level vegetation

	Vegetation Index			
Treated mines	-0.005*** (0.001)	-0.003* (0.002)	-0.005*** (0.001)	-0.003* (0.002)
Observations	7,177	7,449	7,177	7,449
Mean Dep variable	0.21	0.21	0.21	0.21
Method	Imputation	SAB	Imputation	SAB
Fixed Effect	Dist*River	Dist*River	District	District

Notes: This table presents the impact of sand mining on agricultural production, as measured by vegetation index in an a buffer area of 500 meter radius around the mine. Estimates are from the staggered difference-in-differences specification in Equation 2.3.1. The empirical analysis uses yearly panel data on EVI and includes year-by-district-by-river/year-by-district and mine fixed effects, as well as controls for temperature and precipitation in the year. We focus on a time window 4 years before and 4 years after a mine started operations. For each treated mine, we determine a control group which hasn't received a mine within the geographic unit (either district or district-by-river). Column (1)-(4) shows estimates for mean inundation using either the Imputation estimator (Borusyak et al. [2024]) or the Sun and Abraham [2021] estimator. Column (1)-(2) shows estimates for nightlights using either the Imputation estimator (Borusyak et al. [2024]) or the Sun and Abraham [2021] estimator with year-by-district-by-river and mine fixed effects. Column (3)-(4) shows estimates for nightlights using either the Imputation estimator (Borusyak et al. [2024]) or the Sun and Abraham [2021] estimator with year-by-district and mine fixed effects. SAB indicates that the columns shows results for the Sun and Abraham [2021] estimator. The mean dependent variable is computed for ever treated in the years before treatment. Standard errors are displayed in parentheses and clustered at mine level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 2.6: Dynamic effects of sand mining on vegetation



Notes: This figure presents event study evidence of the effect of sand mining on vegetation following Equation 2.3.2 estimated using the imputation procedure of Borusyak et al. (2024). The empirical analysis uses yearly panel data on vegetation and includes year-by-district-by-river and mine fixed effects, as well as controls for temperature and precipitation in the year. We focus on a time window 4 years before and 4 years after a mine started operations. Each dot corresponds to an estimated coefficient, and vertical lines indicate the corresponding 95% confidence intervals. The dashed line represents the omitted coefficient. Standard errors are clustered at mine level.

2.4.4 *Heterogeneity by income and caste*

In this subsection, we examine the distributional effects of sand mining using two approaches.

First, we analyze the economic impact separately for relatively rich and poor cells, where “rich” refers to areas with baseline nightlight values above the 80th percentile at the village level, and “poor” refers to areas at or below this threshold. Second, we assess the effects of sand mining on household assets using NFHS data, disaggregated by caste. Together, these methods allow us to evaluate how sand mining shapes outcomes across different economic and social strata.

Impacts along the income hierarchy In our main cell-level specification, we limit the sample to cells with an estimated baseline 2015 population between 20 and 10,000, within villages with a total population of less than 15,000.

In our analysis of impacts along the income distribution (see Table 2.5), we find that sand mining caused nightlights in richer cells in mine-containing villages to rise by 1.6 units and nightlights in poorer cells to rise by 1.25 units on average over a period of four years after treatment. Compared to the pre-treatment of baselines of 12.71 and 6.8, this is an increase of 12.5% and 18.8% respectively (also see Figure 2.7a). This indicates that sand mining generates net economic benefits broadly for the whole village.

One potential concern with using baseline nightlights to identify relatively richer and poorer areas is that higher nightlights may reflect population density rather than income per capita. To address this, as a robustness check, we repeat the cell-level analysis using nightlights divided by cell-level estimated 2015 population instead of raw nightlights, both for the classification of rich and poor cells and as the outcome variable. Weidmann [2021] has shown that in African countries, inequality as measured by nightlights per capita tracks with that measured by DHS surveys. Our results shown in Table 2.5 and Figure 2.7b, indicate the nightlights per capita increased by 27% and 36% for rich and poor cells respectively.

The take away from these results is that both formerly rich and poor areas benefit

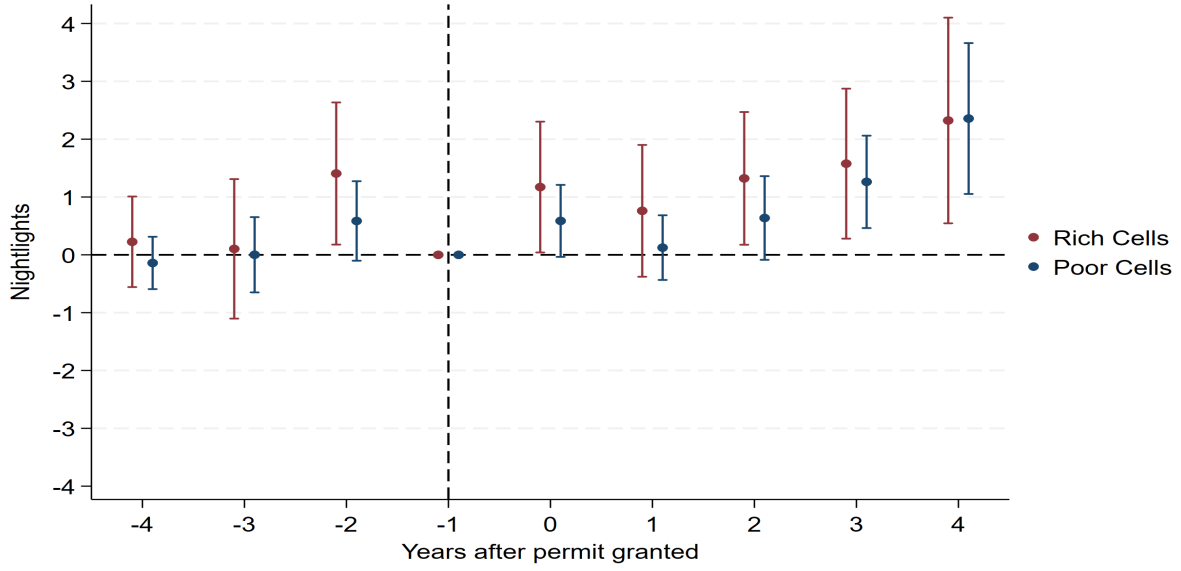
economically from sand mining. Percentage increase is larger for areas which were poor at baseline, but the absolute increase, particularly in per capita values, is much larger for areas which were rich at baseline.

Table 2.5: Effects of sand mining on economic inequality

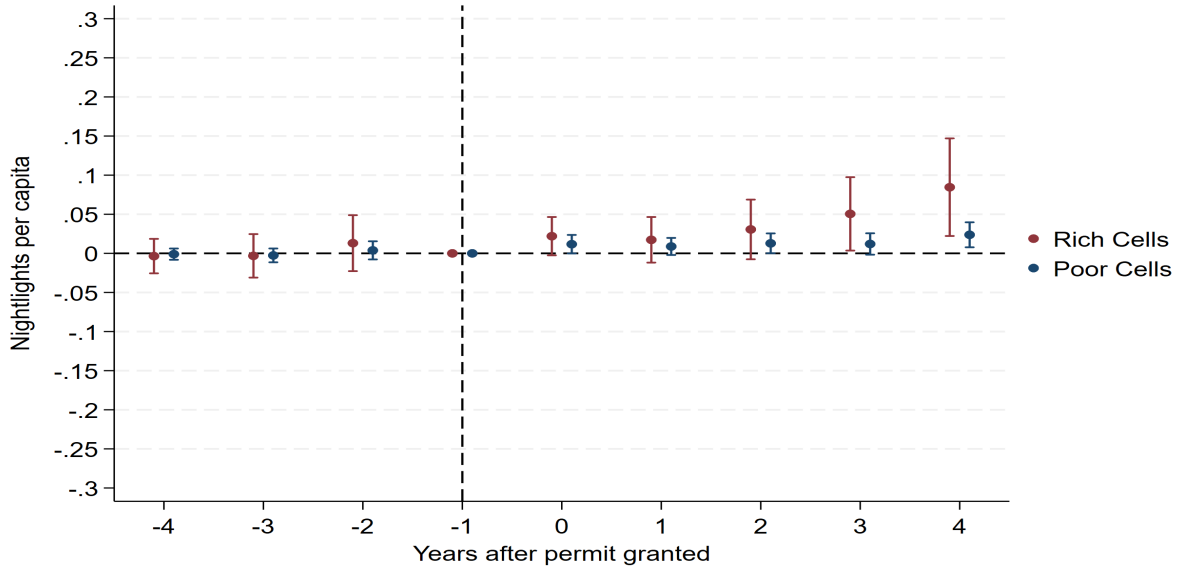
	Nightlights				Nightlights per capita			
	Rich		Poor		Rich		Poor	
Treated mines	1.330*** (0.488)	1.221** (0.507)	0.912*** (0.321)	0.791** (0.326)	0.040** (0.016)	0.045*** (0.016)	0.015** (0.006)	0.011** (0.005)
Observations	8,214	8,491	26,697	27,596	8,214	8,491	31,376	27,596
Mean Dep variable	12.74	12.74	6.80	6.80	0.24	0.24	0.05	0.05
Method	Imputation	SAB	Imputation	SAB	Imputation	SAB	Imputation	SAB
Fixed Effect	Dist*River	Dist*River	Dist*River	Dist*River	Dist*River	Dist*River	Dist*River	Dist*River

Notes: This table presents the impact of sand mining on economic activity for rich and poor areas in a nearby village (defined at baseline), as measured by nightlights. Estimates are from the staggered difference-in-differences specification in Equation 2.3.1 estimated separately for the rich and poor sample. The empirical analysis uses yearly panel data on nightlights and includes year-by-district-by-river and village fixed effects. We focus on a time window 4 years before and 4 years after a mine started operations. For each treated mine, we determine a control group which hasn't received a mine within the geographic unit. Column (1)-(4) shows estimates for nightlights for rich and poor areas using either the Imputation estimator (Borusyak et al. [2024]) or the Sun and Abraham [2021] estimator. Column (5)-(9) shows estimates for nightlights per capita using either the Imputation estimator (Borusyak et al. [2024]) or the Sun and Abraham [2021] estimator with year-by-district and village fixed effects. SAB indicates that the columns shows results for the Sun and Abraham [2021] estimator. The mean dependent variable is computed for ever treated in the years before treatment. Standard errors are displayed in parentheses and clustered at village level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 2.7: Dynamic effects of sand mining on economic inequality



(a) Nightlights



(b) Nightlights per capita

Notes: This figure presents event study evidence of the effect of sand mining on economic inequality using nightlights data. We follow Equation 2.3.2 which is estimated using the imputation procedure of Borusyak et al. [2024]. The empirical analysis uses yearly panel data on nightlights separately for areas which were below the 80thile of nightlights within the village between 2012-15 (poor) and those which were above (rich). Analysis includes year-by-district-by-river and mine fixed effects. Panel a) shows the estimates for nightlights at the grid level, and panel b) shows the estimates for nightlights per capita at the grid level. We focus on a time window 4 years before and 4 years after a mine started operations. Each dot corresponds to an estimated coefficient, and vertical lines indicate the corresponding 95% confidence intervals. The dashed line represents the omitted coefficient. Standard errors are clustered at mine level.

Impacts along the social hierarchy In Table 2.6, we analyse the effects of sand mining on household assets using data from the National Family Health Survey of 2014 and 2019. The outcome variable is a normalized value of assets at the state level. As we have data for only 2 years, we are restricted to a static analysis. Our analysis is at the NFHS cluster level, and a cluster which is within 2 km of a mine which became operational between 2016 and 2018 is considered as treated, and a cluster which lies between 2 to 5 km of a mine treated in that period is control. Additionally, we consider clusters within 0 to 5 km of a potential mine as control.

In Columns 1 to 3, we compare overall assets and by caste at baseline in 2014. We find that assets in 2014 are similar across caste groups and on average. In 2019, after mines become operational, the assets in treated areas are higher than in control areas. Importantly, these positive effects are concentrated among the Upper castes and the other backwards castes (OBCs), and Scheduled Castes and Tribes do not see any positive effects on assets. It is worth keeping in mind that backward castes is a term used for caste groups which are heterogeneous. Around 40% of these groups consists of the Yadavs, Kurmis and Koeris, who are the dominant OBCs, and parties which have Kurmis and Yadavs as their base have won power in Bihar for the last 35 years. Thus, even though we do not observe assets by sub castes in the NFHS data, this analysis suggests that benefits are concentrated among the dominant caste groups.

While the overall results in Table 2.6 show asset gains for all households combined, this aggregate effect is driven almost entirely by UC and OBC households, who make up the numerical majority in the sample. Scheduled Castes and Scheduled Tribes, by contrast, do not experience measurable improvements. This divergence highlights that average household gains mask substantial heterogeneity, with dominant caste groups capturing the bulk of the benefits.

The distributional effects of sand mining look very different when examined by income versus caste. Along income lines, both richer and poorer areas experience economic gains,

Table 2.6: Effect of Sand Mining on Household Assets

	Assets in 2014			Assets in 2019					
	All	UC + OBC	SC/ST	All	UC + OBC	SC/ST			
<i>Treated HH</i>	-0.074 (0.150)	-0.115 (0.171)	0.045 (0.146)	0.227** (0.106)	0.212** (0.100)	0.300** (0.131)	0.292** (0.116)	0.059 (0.152)	-0.059 (0.158)
Observations	2,945	2,134	807	2,923	2,923	2,005	2,005	905	904
Control group mean	.11	.283	-.369	.145	.145	.313	.313	-.222	-.222
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
River FE	Yes	Yes	Yes	No	Yes	No	Yes	No	Yes

Notes: This table presents the impact of sand mining on household assets in mining areas disaggregated by caste groups. The dependent variable is a normalized index of (rural) household assets for the state of Bihar and is taken from NFHS-IV and V. The sample includes households which were within 5 kilometers of a mine which was operational by 2018 or a potential mine. Within this sample, if a household lies within 2 km of a treated mine then it is considered to be treated and otherwise it is considered to be part of the control sample. We use data from districts which have both a treated and control mine. We control for distance to mine in all specifications. Standard errors are clustered at the NFHS cluster level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

though richer areas see larger absolute increases, reinforcing existing advantages. By contrast, the caste-based analysis reveals a sharper divide: asset growth is concentrated among Upper Castes and dominant Other Backward Castes (OBCs), while Scheduled Castes and Scheduled Tribes show no measurable improvements. These two perspectives are not contradictory. The gains observed in poorer areas are largely driven by OBC households, who, despite being poorer than UCs, remain socially and politically dominant relative to SC/STs. Once we disaggregate by caste, it becomes clear that SC/ST households are excluded from these gains. This suggests that historical social hierarchies, rather than income alone, play a decisive role in determining who is able to capture the benefits of sand mining.

2.5 Conclusion

Economic growth and urbanization have fueled a global construction boom, sharply increasing demand for sand—a key input in construction materials. This surge has driven widespread sand mining, especially in developing countries where regulation tends to be weak or poorly enforced. While sand mining creates economic opportunities, it also brings serious environmental risks, including flooding, aquifer depletion, and ecosystem damage.

Understanding the local tradeoffs is essential for designing effective and enforceable policy.

This study provides the first causal, quantitative evidence of sand mining’s local effects, using Bihar, India as a case study. We find that sand mining leads to a significant rise in flooding: inundation rates increase by 1.5 percentage points, or about 15% over baseline levels. Agricultural production falls by 5%, likely due to physical disruptions from mining. These results highlight the environmental costs of extraction, especially in a flood-prone region like Bihar.

At the same time, we find that sand mining generates net economic benefits for nearby villages. Using satellite-based nightlights as a proxy for income, we observe a sustained rise in economic activity beginning about a year after mining starts. These gains are not confined to a single income group—both relatively rich and poor households experience improvements. This broad distribution of benefits likely contributes to the persistence of mining despite the environmental harms we document. However, disaggregating by social group reveals that the economic gains are concentrated among castes higher in the social hierarchy. Dalit and tribal households, who are fewer in number and have less political and economic influence, do not share in these benefits. Given their exposure to increased flooding, their overall welfare is likely negative.

Overall, our findings suggest that sand mining brings gains to local households and cannot be dismissed as purely exploitative. But the unequal distribution of benefits at the social group level and environmental costs points to the need for more targeted regulation. Policymakers should consider measures to mitigate flooding, promote sustainable mining, and compensate communities—especially socially marginalized groups—for environmental harm.

Future research should examine the long-term impacts of sand mining on migration, structural transformation, and human capital. Understanding how communities perceive and adapt to mining-related environmental change will be critical for crafting policies that are both effective and politically viable. Additional work should also evaluate how sand

mining regulations affect broader economic outcomes, including construction costs and urban development.

CHAPTER 3

RURAL HOUSEHOLD WATER ACCESS IN INDIA (WITH DEVIKA LAKHOTE)

3.1 Introduction

As aquifers are drawn down and climate change is expected to exacerbate water scarcity in many parts of the world, applied microeconomists have directed a sizable amount of attention to the welfare consequences of access to and allocation of water for agriculture [Blakeslee et al., 2020, Duflo and Pande, 2007, Hornbeck and Keskin, 2014, Ryan and Sudarshan, 2022, Sekhri, 2014]. But equally jeopardized, and arguably even more important than irrigation, is access to adequate and clean water for drinking and household needs, which 2 billion people currently lack [World Bank, 2021].

The consequences of changes to household water access (hereon referred to as, HWA) are borne disproportionately by women. In India (the situation is similar or worse in much of sub-Saharan Africa), in cases where water is not piped into the home, it is women and girls who fetch it from outside 80% of the time, spending on average 35 minutes per day, equivalent to the loss of 27 days over a year [UNICEF]. Accordingly, drinking water is a much more salient issue to women than to men [Chattopadhyay and Duflo, 2004]. In fact, decreased HWA may be costly to women even if the cause is water competition from irrigation itself [Karim et al., 2012]. Agriculture and industry stake large politically and financially backed claims to water supplies, and policymakers must make increasingly constrained water allocation decisions between places and industries. Thus, it is crucial that our accounting of the costs and benefits of various kinds of water use reflect those borne by both men and women, those with and without political and intra-household bargaining power.

Existing causal evidence has shown that HWA can have important consequences for health and overall welfare. It has begun to establish the relevance of girls' schooling, women's time use, and market participation as further outcomes [Ashraf et al., 2021, Devoto et al.,

2012]. However, these studies have largely been confined to local urban RCTs or historical settings, with uncertain generalizability to the people across continents, especially in rural areas, facing water access challenges today.¹

Our analysis focuses on the breadth of rural households in India - where the scarcity of water infrastructure continues to be a pressing concern. Scarcity of water infrastructure, in turn, affects household access to clean, potable water. This has direct effects on health. Several demand-side solutions have been created to address the symptoms of low HWA - such as deworming, bottled water, water purifying kits, etc. [Ahuja et al., 2010]. In this paper, we focus our attention on the supply-side problem - lack of water access points - that the government of India is trying to address at a large-scale through the nationwide roll-out of piped drinking water, tubewells, handpumps and open wells.

We use village-level HWA data from the entirety of rural India to provide large-scale, spatially granular causal evidence on the familiar first-order questions of the effects of HWA infrastructure on girls' schooling. We do this by leveraging timing of treatment in an event study design. We find that improved HWA has positive and significant effects on children's enrollment in school as well as year-end exam attendance. However, contrary to our hypothesis, we see a very small differential effect on girls' outcomes. We discuss reasons as to why that may be the case.

Section 3.2 describes the setting of our study, the data construction process, and outcomes of interest. Section 3.3 describes the event study design we employ to estimate the main result of our paper. Section 3.4 discusses the results and our interpretation of the results. Section 3.5 concludes and provides direction for future work.

1. The exception is Gamper-Rabindran et al. [2010], which looks at the effect of piped water rollout across Brazil on infant mortality.

3.2 Setting and Data

We have acquired India’s Integrated Management Information System (IMIS) database, which contains the universe of government-funded rural water access points, including pumps, wells, and piped water services, nation-wide. For each of these water access points, the database contains its location at the sub-village level, dates of commissioning and construction, water source, population covered, liters per capita per day (LPCS) provided, contamination status, and more. IMIS is likely unparalleled among all countries, including developed ones, for providing a comprehensive database of local water access systems in a country ([Wescoat et al., 2016](#)). However, it has not (to our knowledge) previously been used at scale in social science research, likely because the database structure makes it costly to download large portions of the data. We suspect that a chief reason for the relative paucity of large-scale empirical evidence on supply-side effects of HWA is the difficulty of obtaining large-scale access points data. By taking on the one-time cost, we hope to open up unique research opportunities beyond this project as well.

Figure 3.1 shows an example of the webpage that stores the IMIS data. The scraping procedure involved two main steps: building a point-and-click algorithm to click through the webpages and arrive at the page for each access point, and extracting relevant information from that page. First, the algorithm clicks through several administrative levels (state, district, sub-district, gram panchayat, village) to get to a list of habitations. A habitation is defined as the catchment area within a village where an access point is located. A habitation can have one or more access points. Each habitation page has a unique URL that we store so that we can access each habitation page independently. Then, the algorithm opens up each habitation page and stores a list of unique access point URLs. Each access point has its own webpage with information the construction date, funds required for construction, volume of water to be supplied by the access point, total target population for the access point, and so on. Using a combination of scraping techniques, we extract this information for each access point and save it in an accessible format for further analysis.

Since the 1970s, India has been gradually expanding rural HWA, and this intertemporal variation is captured by IMIS. Each water access point provides certain liters per capita per day (LPCD) of water to population covered by that access point. As a summary measure of HWA, for each village i and year t with set of access points S_{it} , we calculate:

$$\text{HWA}_{it} = \frac{\sum_{s \in S_{it}} (p_s \times \text{LPCD}_s)}{P_i} \quad (3.2.1)$$

The unit of measurement for HWA is LPCD. p_s gives the population covered by access point s . This is an estimate provided by the government as part of the database. We take it at face value, i.e. we cannot determine if this is the actual number of people in the village who use this access point. Instead, we think of it as the intended coverage of the access point. LPCD_s is the liters per capita per day that can be provided by access point s . Again, this is an estimate provided by the government based on water availability, engineering calculations, etc. and we take it as given. We calculate the total liters per day provided to village i by access point s by multiplying p_s with LPCD_s . We calculate this quantity for every access point available to the village and sum over all access points. Note that a single village can have multiple access points that cover different parts of the village as well as different sub-populations. To get our final HWA_{it} , we divide the total liters per day provided to the village by the number of people who live in the village. This gives us an average of the volume of water each person in the village has access to, daily.

To measure outcomes, we use schooling outcomes data from the annual survey of schools in India (U-DISE). The survey is conducted at the school-level, we aggregate it to the village-level and match it to our water access points dataset using a fuzzy matching algorithm. We use student enrollment as our primary outcome, and in addition, we also look at share of girls' in total enrollment and year-end exam attendance.

Therefore, our final data for analysis is unique at the village-year level and contains information on annual HWA and schooling outcomes for each village in our sample. Table

3.1 present summary statistics of our sample. It contains 150,060 villages between 2005-2017 across 27 states in India. An average village in the sample has a population of 1792, has about 368 households, 396 students enrolled in school and 177 LPCD of water supply.

3.3 Research Design

Since this is a nationwide policy roll-out with a sizeable amount of funding being directed to it, we want to estimate the effect of this rollout on certain outcomes of interest, the main one being student enrollment in schools. We hypothesize that an increase in HWA through this policy will, in turn, increase the number of students enrolling in school through multiple channels that we shall discuss later in the paper.

In order to do this, we construct a measure of household water access (HWA) that captures the liters per capita per day (LPCD) of water that is intended to be supplied to a given village through the policy roll-out. In an ideal setting, a random assignment of access points to each village would allow us to get an unbiased estimate the effect of HWA on enrollment. However, that is not a feasible strategy in our setting because the roll-out across the country is not random: allocation of federal funding between states is determined partly by existing access points, while funding allocation within states does not always follow any set criteria - for example, in Odisha [van der Kerk, 2017].

In lieu of an ideal experiment, our strategy is to use an event study design. We construct a binary and absorbing treatment status, defined as 1 when the combination of all HWA infrastructure recorded for a village has total water-giving capacity of at least 40 LPCD, which the Indian government stated as its first-order goal when launching the Accelerated Rural Water Supply Programme in 1972. The government considered 40 LPCD to be the minimum amount of water needed to complete basic daily chores in addition to drinking and eating. For context, the WHO names 50 LPCD as the water needed “to ensure that most basic needs are met while keeping public health risks at a low level” [UN Water], so from the perspective of development policymakers and organizations, the marginal benefits

of reaching 40 LPCD should be sizable. Further, Figure 3.2b shows that this treatment definition induces substantial variation in treatment status and timing across villages. The 75th percentile village has already reached the 40 LPCD goal at the beginning of our analysis period. The median village reaches the goal in 2011. The 25th percentile village does not reach the goal by the end of the analysis period in 2017.

We can estimate the event study using a dynamic two-way fixed effects (DTWFE) model,

$$Y_{it} = \gamma_i + \eta_t + \sum_k \beta_k D_{it}^k + \varepsilon_{it} \quad (3.3.1)$$

In the above specification, Y_{it} is the outcome of interest for village i in year t . γ_i and η_t are the village and year fixed-effects, respectively. D_{it}^k is dummy that takes value 1 if, village i first reached 40 LPCD in year $t - k$, and 0 otherwise. The parameters of interest, β_k , are meant to be interpreted as the ATT k years after first receiving 40 LPCD. The identifying assumption here is that villages reaching 40 LPCD at different times (or not at all) would have parallel trends in Y in the counterfactual where no village is ever treated. More precisely, define $G_i = g$ if village i belongs to the cohort of villages first treated in year g , and denote $Y_{i,t}(g)$ as the potential outcome for i in year t if $G_i = g$. Then, using notation from Roth et al. [2023], we are assuming that for any village i and years $t, t' \neq t$,

$$E[Y_{i,t}(\infty) - Y_{i,t'}(\infty) | G_i = g] = E[Y_{i,t}(\infty) - Y_{i,t'}(\infty) | G_i = g'] \quad (3.3.2)$$

However, according to Callaway and Sant'Anna [2021], even if the parallel trends assumption holds in the staggered treatment setting, the estimates from the DTWFE model may be biased if different cohorts (villages treated in different years) have heterogeneous trajectories of treatment effects. In the case of our sample, this may be the case if, for example, treatment timing and treatment effects both depend on villages' pre-existing water access. Then, due to negative weighting issues, the $\hat{\beta}_k$ estimates from the DTWFE regression no longer provide the ATT. Therefore, to derive interpretable estimates under heterogeneous

treatment effects, we estimate the event studies using the Callaway Sant’Anna estimator, with a combination of never-treated villages and not-yet-treated villages as control groups when estimating each cohort-year treatment effect. The parallel trends assumption is modified to only allow comparison to never-treated and not-yet-treated villages. If C denotes the never-treated group, then the parallel trends assumption for comparing treated villages to never-treated villages is as follows,

$$E[Y_t(0) - Y_{t-1}(0)|G = g] = E[Y_t(0) - Y_{t-1}(0)|C = 1] \quad (3.3.3)$$

To compare to the not-yet-treated villages, the parallel trends assumption is as follows, For all $g = 2, \dots, \tau, s, t = 2, \dots, \tau$ with $t \geq g$ and $s \geq t$,

$$E[Y_t(0) - Y_{t-1}(0)|G = g] = E[Y_t(0) - Y_{t-1}(0)|D_s = 0, G \neq g] \quad (3.3.4)$$

The Callaway Sant’Anna estimates are our preferred estimates and our results present an aggregate of those cohort-wise treatment effects.

A common threat to the parallel trends assumption is events other than the treatment coinciding with the treatment. We examine treatment timing in Figure 3.2a. 30% of the villages do not reach the 40 LPCD goal by the end of the analysis period in 2017. 30% of the villages have already reached the goal by 2005. The remaining 40% of the villages reach the goal, almost evenly between 2005 and 2017. There is no spike in any given year. The lack of bunching of treatment in any particular year reduces the likelihood of treatment coinciding with other policies that could affect our outcomes.

3.4 Results

Our main outcomes of interest are the number of students enrolled in school and the number taking year-end exams, both overall and by gender. Since we expect improved HWA to reduce

the time that girls would spend on fetching water, we hypothesize that they would spend that time on things that are more useful for them. We can think of change in school enrollment as one of the ways to measure time substitution between water-fetching and schooling. We provide evidence from 60% of rural India about whether rural HWA infrastructure actually improves development outcomes. Under the assumption of parallel trends between villages that reach 40 LPCD at different times, our event study results indicate that improving HWA does have a persistent positive effect on school enrollment, suggesting that reduced water collection duties could be freeing up time for children to attend school.

In Figures 3.3, 3.4 and 3.5, we present estimates for our main outcomes on the y-axis: total enrollment, total exam-takers, and share of girls enrolled. The x-axis shows leads and lags from the year of treatment year. We use a panel balanced in event-time i.e. we use the same sample and measure the effect of treatment upto 4 years before and after treatment.

Panel (a) of Figure 3.3 shows the estimates from the dynamic two-way fixed effects model. There is an increase in enrollment by 33 in the year of treatment. A year after treatment, enrollment increases by 13, by 15 two years after treatment, by 22 three years after treatment, and by 25 four years after treatment. The Callaway Sant’Anna group-time averages presented in panel (b) of Figure 3.3 are smaller and less precise but trend similarly. There is a increase in enrollment of 23 in the year of treatment, and a consistent increase of approximately 10 every year after treatment. The baseline enrollment in a control village pre-treatment is 350. This implies that improved water infrastructure has a positive, significant and lasting effect of 6.5% on the number of students enrolling in school.

To measure actual attendance beyond enrollment, we look at the effects on the numbers of students taking end-of-year exams from grades 5-8. This allows us to measure if the enrolled students continue to stay in school and progress. Panel (a) of Figure 3.4 shows that the number of students who take end-of-year exams increases significantly in year of treatment by 2 students. It continues to increase by 2.5 a year or two after treatment, by 4 students three years after treatment, and by 6 students four years after treatment. In panel

(b), we see muted effects on exam-takers. There is an increase of 1 in the year of treatment and of 2.5 a year after treatment. However, the effects are imprecise in the following years. The increase immediately after treatment is an increase of 11% on the base of 21.

In panels (a) and (b) of Figure 3.5, we see that the share of female students enrolled in the school does not change immediately after treatment. But there is a slight increase of 0.002 3-4 years after treatment. The baseline share of girls in total students enrolled is 0.49. Thus, the change in share is only an increase of 0.4%. Given that the baseline share is already close to equal and there is a lack of a large effect, we infer that enrollment is perhaps not the margin on which HWA has gendered effects. It is also possible that the health benefits of having HWA disproportionately improve boys' outcomes and nullify the time-use effect on girls. We have some evidence from South Asia that suggests this might be the case given the strong preference for boys [Jayachandran, 2015]. We interpret these results cautiously, however, as nominal enrollment is not the same as daily school attendance, studying, and learning.

3.5 Discussion and next steps

If taken at face value, our results indicate that HWA investments do not generate the educational returns commonly expected by policymakers and development organizations, either overall or for girls specifically. A few explanations for this underwhelming conclusion are possible and deserve further study. One is that water quantity may not be so beneficial if water quality is not ensured. Another possibility is that HWA infrastructure does not remain functional for long, due to seasonal or permanent water depletion, or lack of maintenance. Although infrastructure construction is primarily funded by central and state governments, operation and maintenance are up to local panchayats, which may face budget constraints or expertise limitations, or may not prioritize the maintenance of infrastructure that do not benefit men as much as women. Moreover, without regular monitoring of existing HWA infrastructure, it is possible that state governments looking to fulfill nominal water availabil-

ity targets could lack incentives to invest in the infrastructure’s potential lifespan or ease of maintenance. Although India’s IMIS database is already unparalleled for granularity and depth of rural HWA information, these two classes of possibilities point to the potential need for even more data and continuous monitoring (e.g. of water quality and continued water levels and operational status) if we are to fully realize the benefits of HWA infrastructure.

A third possible explanation for our findings so far is that at the village level, rollout of HWA coincides with improved water access in the village’s schools, and students from neighboring villages not yet receiving HWA enroll at the treated villages’ schools instead. If neighboring villages receiving HWA at different times differ in levels of development (but not in time trends absent treatment, per the event study assumption), this could explain both the positive effect on enrollment numbers and the attenuated effect on learning outcomes. To explore this possibility, in the future, we will compare HWA rollout with the rollout of water access in schools, as recorded in the DISE panel data.

3.6 Figures

Figure 3.1: Screenshot of IMIS platform



National Rural Drinking Water Programme

Department of Drinking Water & Sanitation

Ministry of Jal Shakti

About JJM

Other WebApps

Data Entry

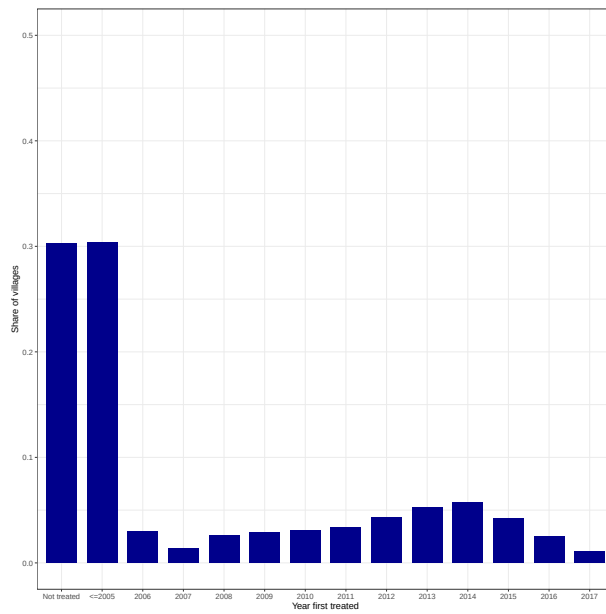
Download JJM App

Dashboard

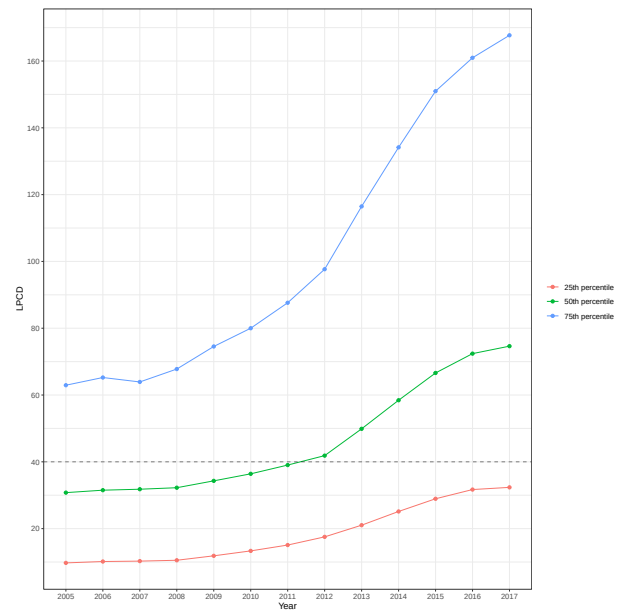


S.No.	State	Population & Habitation Having PWS As on 01/04/2018												Target Population & Habitation By		
		Number of Habitation			% of Habitation			Population(Lakhs)			% of Population			Number of Habitation	% of Habitation	Populat
		Total	FC	PC+QA	Total	FC	PC+QA	Total	FC	PC+QA	Total	FC	PC+QA			
1	2	3										4		5		
	Total	7,21,277	5,42,584	1,78,693	41.79	31.44	10.35	4,967.51	3,484.63	1,482.88	54.08	37.93	16.14	21,398	1.24	
1	Andaman & Nicobar Islands	254	242	12	63.50	60.50	3.00	2.42	2.19	0.23	91.36	82.85	8.52	0	0.00	
2	Andhra Pradesh	39,514	28,241	11,273	80.81	57.76	23.06	348.46	223.14	125.31	94.61	60.59	34.02	1,130	2.31	
3	Arunachal Pradesh	3,675	2,359	1,316	48.84	31.35	17.49	7.80	5.00	2.80	62.84	40.27	22.57	157	2.09	
4	Assam	35,147	25,219	9,928	39.91	28.63	11.27	137.75	95.64	42.11	46.50	32.28	14.21	1,651	1.87	
5	Bihar	7,552	4,803	2,749	6.85	4.36	2.49	116.46	64.12	52.34	11.71	6.45	5.26	0	0.00	
6	Chandigarh	0	0	0	0.00	0.00	0.00	0	0	0	0.00	0.00	0.00	0	0.00	

Figure 3.2: Treatment timing across years and villages

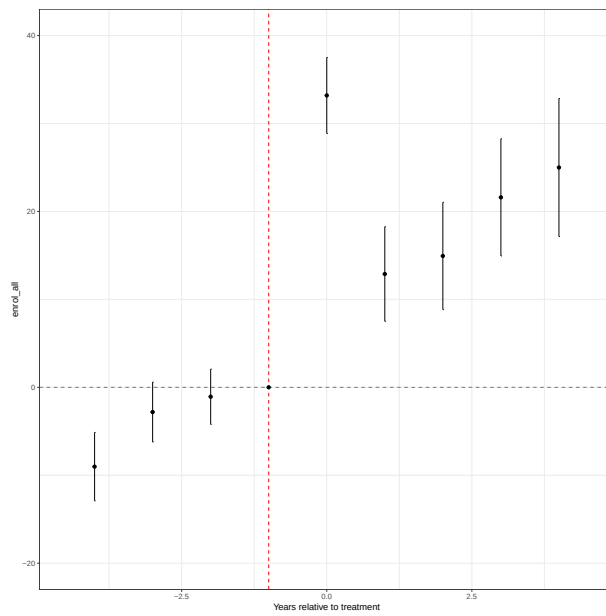


(a) Timing of treatment event across years

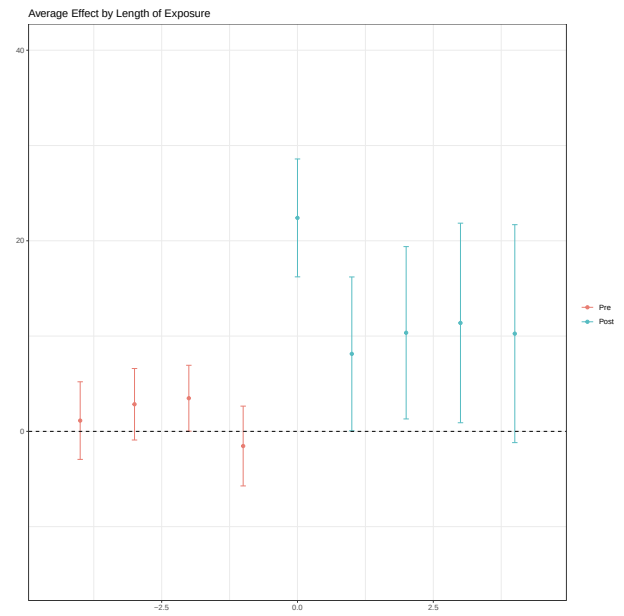


(b) Variation in treatment across years

Figure 3.3: Effect of HWA on total enrollment



(a) Dynamic two-way fixed effects



(b) Callaway Sant'Anna

Figure 3.4: Effect of HWA on total exam-takers in grades 5-8

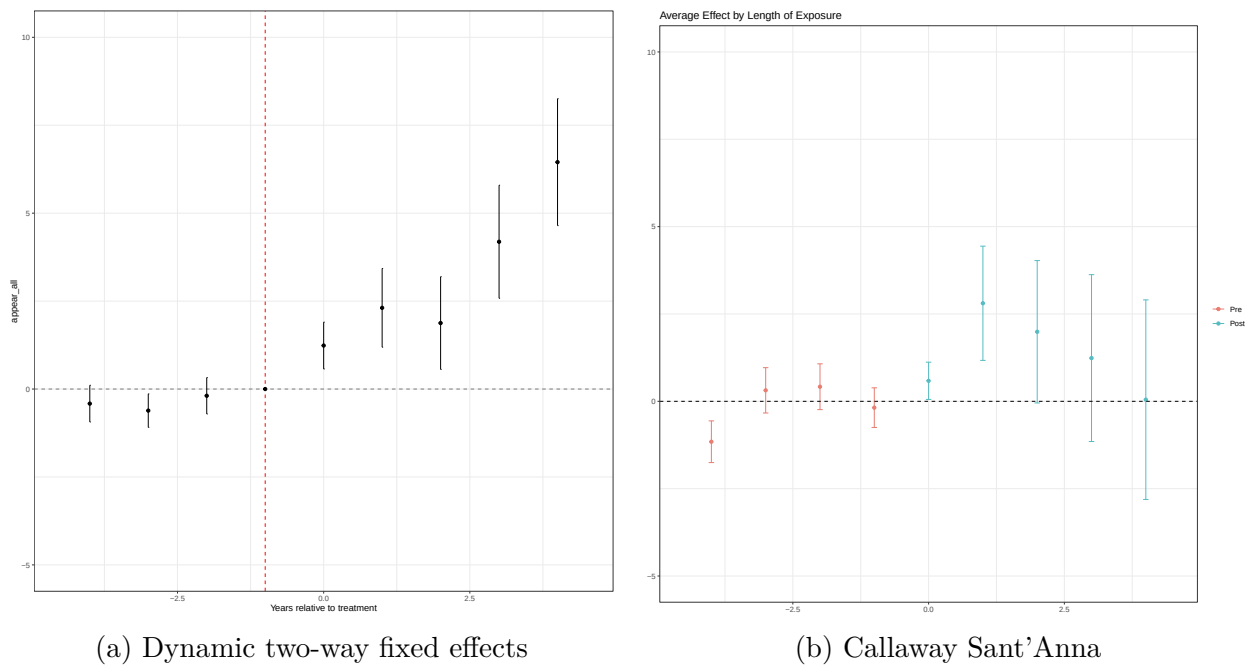
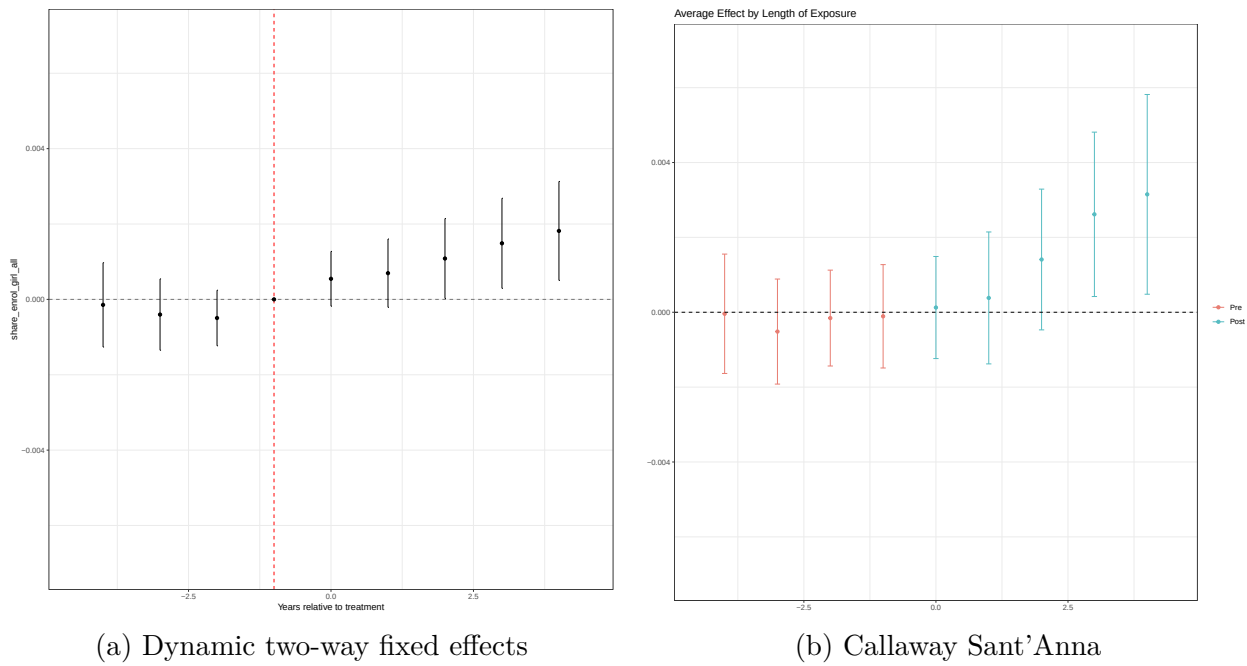


Figure 3.5: Effect of HWA on share of girls' in total enrollment



3.7 Tables

Table 3.1: Summary statistics

Statistic	N	Mean	St. Dev.	Min	Median	Max
Population	150,060	1,791.882	2,782.451	1	1,020	223,929
Number of HHs	150,060	367.594	601.959	1	210	42,848
Enrolment	150,060	396.248	824.219	0.000	182.667	52,479.580
LPCD	150,060	176.697	7,415.409	0.000	50.800	2,511,407.000

APPENDIX A

APPENDIX TO CHAPTER 1

A.1 Additional methodological description

A.1.1 Drought and wetness sensitivity

Measuring drought and wetness

To measure abnormal drought and wetness conditions, I use the Standardized Precipitation-Evapotranspiration Index (SPEI), available for the globe at the 0.5 x 0.5 degree resolution (about 3025 km² per cell) from the Global SPEI Database (Vicente-Serrano et al., 2010). Unlike commonly used measures of dryness and wetness that are based solely on precipitation (i.e. the “supply” of moisture), the SPEI is a measure of water surplus (negative values indicating deficit), as it also incorporates several other variables such as temperature, pressure, and wind speed that determine the potential evapotranspiration (i.e. the atmospheric “demand” for moisture). Thus, the SPEI better captures anomalies in the amount of moisture left available in the earth and water bodies for human use. For each cell and time, the SPEI measures this anomaly in units of standard deviations from the cell-specific long-run distribution.

I use two different methods to convert monthly SPEI data into annual measures. In the first method, I begin with 1-month timescale SPEI for each month of a given year, then average across the 12 months. For example, suppose the 1-month timescale SPEI for June 1995 in cell i equals -1. This means the water balance in cell i in June 1995 was one standard deviation below the mean water balance experienced in cell i across June of every year since 1901. This measure, for each month in 1995, is averaged to obtain the 1995 SPEI measure. As the mean of 12 standard normal variables that are positively correlated, the annual measure has a standard deviation of about 0.4. In the second method, I simply take the 12-month timescale SPEI calculated for December of each year. For example, a

12-month SPEI value of -1 in December 1995 indicates that the total water balance over January-December 1995 was one standard deviation below the mean of the distribution of total water balance over every January-December period since 1901. By construction, this measure has standard deviation of 1.

Finally, for each of these annual SPEI measures, I classify a cell as experiencing drought in a given year if $\text{SPEI} < -1$ standard deviation and wet if $\text{SPEI} > 1$ standard deviation. I further break down drought into severe drought, $\text{SPEI} < -2$ standard deviations, and mild drought, SPEI between -1 and -2 standard deviations, and similarly for mild and severe wetness.

Estimating sensitivity to drought and wetness

For each country separately, over the pre-period years 1992-2000, I estimate

$$Y_{irt} = \sigma_1 \text{Drought}_{it} + \sigma_2 \text{Wet}_{it} + \alpha_i + \delta_{rt} + \varepsilon_{irt} \quad (\text{A1})$$

and

$$Y_{irt} = \sigma_3 \text{DroughtSev}_{it} + \sigma_4 \text{DroughtMild}_{it} + \sigma_5 \text{WetMild}_{it} + \sigma_6 \text{WetSev}_{it} + \alpha_i + \delta_{rt} + \varepsilon_{irt} \quad (\text{A2})$$

where i indexes 0.05 degree cells, r indexes administrative regions, and t indexes years. Since administrative regions of any given level vary in size across countries, for each country, I choose the smallest level r with average jurisdiction area of at least 6050 km², i.e. likely to contain two 0.5 degree cells to generate within-jurisdiction variation in SPEI. For example, the regressions for Brazil, India, and the United States are estimated with state-year fixed effects (level 1 administrative regions), and the regressions for China are estimated with prefecture-year fixed effects (level 2 administrative regions). For countries such as Uganda and Vietnam where subnational jurisdictions of any level tend to be small, as well as smaller

countries, the regressions are estimated with a single set of year fixed effects for the whole country. Standard errors are clustered by the 0.5 degree SPEI cell to which 0.05 degree cells i are assigned.

Results

Appendix Table A9 presents results of estimating Equation (1.4.2) with joint IGO membership as the IR measure. In Columns (2) and (4), the drought and wetness sensitivity parameters are the estimates of σ_1 and σ_2 from Equation (A1). In Columns (3) and (5), the severe drought and severe wet sensitivity parameters are the estimates of σ_3 and σ_6 from Equation (A2). Across all specifications, I find that controlling for the interactions between flow share and country-specific sensitivities to drought and wetness does not qualitatively alter the result that foreign hydroelectric dams impose significant negative transboundary externalities, and that joint membership in more, or more influential, IGOs mitigates these externalities. This lends credence to the interpretation of the IR interaction coefficients as capturing the effects of IR rather than of other confounding variables that affect a downstream country's ability to cope with environmental shocks.

A.2 Additional Tables and Figures

A.2.1 Tables

Table A1: Some costs and benefits of dams

	Economic Benefits	Environmental Changes	Economic Costs
Upstream & Reservoir Area	Hydropower	Inundation Waterlogging Salinity Seismicity	Displacement ↓ Ag soil quality
Downstream	Hydropower Irrigation Water supply Flood control	↓ Flow quantity Δ Flow schedule Δ Temperature ↓ Water nutrients ↓ Sediment load	↓ Ag production ↓ Fisheries, aquaculture ↓ Drought resilience ↓ Water quality
Far downstream	Hydropower Flood control	↓ Fish stocks ↓ Biodiversity	↓ Water supply

Table A2: Effects of flow share from dams on PM2.5, by dam purpose

	(1)	(2)	(3)	(4)
Flow share	-0.387*** (0.0967)			
FS from hydroelectric dams		-0.596*** (0.119)		
FS from non-hydroelectric		-0.191 (0.165)		
FS from irrigation dams			-0.0184 (0.125)	
FS from non-irrigation			-0.474*** (0.112)	
FS from flood control dams				0.733 (1.154)
FS from non-flood control				-0.392*** (0.0963)
Observations	760672	760672	760672	760672

Notes: All specifications include cell and county x year fixed effects. Standard errors in parentheses, clustered by river reach. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A3: Effect on nightlights of flow share from dams, by buffer width used to construct sample

	(1)	(2)	(3)	(4)	(5)
	0km	10km	15km	20km	25km
FS from hydroelectric dams	-0.508 (0.357)	-0.384*** (0.149)	-0.348*** (0.130)	-0.381*** (0.124)	-0.395*** (0.124)
FS from non-hydroelectric	-0.0738 (0.255)	0.149 (0.143)	0.123 (0.128)	0.0388 (0.117)	-0.0350 (0.108)
Observations	282040	1045924	1374164	1604284	1773618

Notes: In Column (1), the sample is restricted to cells that contain rivers. In each of Columns (2)-(5), the sample consist of cells within the specified distance from rivers. All specifications include cell and county x year fixed effects. Standard errors in parentheses, clustered by river reach. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A4: Effects on nightlights from domestic vs foreign hydroelectric dams, by trade relations

	(1)	(2)	(3)	(4)
FS from domestic hydroelectric dams	-0.291 (0.324)	-0.291 (0.324)	-0.292 (0.324)	-0.291 (0.324)
FS from foreign hydroelectric dams	-0.851*** (0.261)	-0.827*** (0.240)	-0.771*** (0.198)	-0.693*** (0.214)
x share of U 's imports coming from D	2.866 (1.815)			
x share of U 's exports going to D		0.877 (3.955)		
x ($D \rightarrow U$ imp share) – ($U \rightarrow D$ imp share)			2.407 (2.224)	
x total trade per ($GDP_U + GDP_D$) (millions USD)				-149.3 (287.9)
FS from non-hydroelectric dams	-0.0530 (0.176)	-0.0518 (0.176)	-0.0498 (0.177)	-0.0464 (0.177)
Observations	1773618	1773618	1773618	1773618

Notes: All specifications include cell FEs and county x year FEs. All trade measures are all calculated as the average over 1990-2000. In Columns (1)-(3), a higher value of the trade measure indicates the upstream dam country U being more trade-dependent on downstream cell country D . In Column (4), a higher value of the trade measure indicates greater bilateral trade in either direction, adjusted by the sizes of the two economies. Standard errors in parentheses, clustered by country. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A5: Effects on nightlights from domestic vs foreign hydroelectric dams, by GDP imbalance

	(1)	(2)	(3)
FS from domestic hydroelectric dams	-0.291 (0.324)	-0.290 (0.323)	-0.291 (0.324)
FS from foreign hydroelectric dams	-0.806*** (0.255)	-0.795*** (0.252)	-0.854*** (0.277)
x GDP % diff	0.000908*** (0.000274)		
x GDP_D much lower than GDP_U		0.0688 (0.950)	
x GDP_U much higher than GDP_D			0.756 (0.906)
FS from non-hydroelectric dams	-0.0510 (0.176)	-0.0505 (0.177)	-0.0537 (0.175)
Observations	1740442	1740442	1740442

Notes: All specifications include cell FEs and county x year FEs. GDP and GDP per capita % differences refer to the difference between the downstream cell country's value and the upstream dam country's value, as a fraction of the upstream dam country's value. They are measured as the average over 1990-2000. Standard errors in parentheses, clustered by country. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A6: Effects on nightlights from domestic vs foreign hydroelectric dams, by UN General Assembly voting similarity

	(1)	(2)	(3)	(4)	(5)	(6)
FS from domestic hydro dams	-0.285 (0.332)	-0.287 (0.332)	-0.287 (0.332)	-0.346 (0.327)	-0.346 (0.326)	-0.340 (0.327)
FS from foreign hydro dams	-3.083*** (0.532)	-3.671*** (0.416)	-2.776*** (0.734)	-2.279*** (0.860)	-3.667*** (0.396)	-3.642*** (0.394)
x κ score	4.585*** (0.797)				-8.350 (21.58)	
x S score		3.727*** (0.209)			8.024 (5.388)	3.073** (1.250)
x π score			4.166*** (1.218)		1.884 (16.87)	
x ideal point distance				5.728 (3.617)	0.746 (4.449)	2.167 (3.679)
FS from non-hydro dams	-0.286 (0.242)	-0.281 (0.244)	-0.288 (0.242)	-0.288 (0.244)	-0.280 (0.244)	-0.279 (0.244)
Observations	1752747	1752747	1752747	1729834	1729834	1729834

Notes: All specifications include cell FEs and county x year FEs. All measures of UN General Assembly voting similarity are all calculated as the average over 1993-2000 for each country pair. A higher value of the κ , S , and π score or a lower value of the ideal point distance indicates greater voting similarity. Standard errors in parentheses, clustered by country. *

$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A7: Effects on nightlights from domestic vs foreign hydroelectric dams, by regime type similarity

	(1)	(2)	(3)	(4)	(5)
FS from domestic hydroelectric dams	-0.308 (0.331)	-0.304 (0.331)	-0.307 (0.331)	-0.298 (0.331)	-0.295 (0.331)
FS from foreign hydroelectric dams	-0.871*** (0.209)	-0.931** (0.359)	-0.776*** (0.216)	-2.234*** (0.358)	-2.374*** (0.524)
x Large difference in democracy index	0.0410 (0.920)				
x Same democracy index		0.434 (0.706)			
x Large difference in autocracy index			-0.706 (1.004)		
x Same autocracy index				2.224*** (0.296)	
x Both democratic					2.124*** (0.363)
x Both autocratic					2.507*** (0.499)
FS from non-hydroelectric dams	-0.323 (0.246)	-0.322 (0.247)	-0.324 (0.246)	-0.308 (0.241)	-0.306 (0.244)
Observations	1706122	1706122	1706122	1706122	1713226

Notes: All specifications include cell FEs and county x year FEs. The democracy index and autocracy index are products of the Polity Project, version 5. Each is provided at the country x year level and ranges from 0 to 10, with a higher score indicating greater democraticness or greater autocratic control, respectively. An upstream-downstream country pair is marked as having a large difference in democracy index in a given year if the difference is at or above four, which is the 75th percentile among foreign country pairs in the sample. Likewise, the country pair is marked as having a large difference in autocracy index in a given year if the difference is at or above five, which is the 75th percentile among foreign country pairs in the sample. The country pair is marked as being both democratic in a given year if both countries have democracy index of at least 5, and likewise for both autocratic. Standard errors in parentheses, clustered by country. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A8: Effects on nightlights from domestic vs foreign hydroelectric dams, by joint membership in IGOs

	(1)	(2)
FS from domestic hydroelectric dams	-0.293 (0.325)	-0.297 (0.324)
FS from foreign hydroelectric dams	-3.789*** (0.436)	-2.714*** (0.625)
x # IGOs with joint membership	0.193*** (0.0235)	
x Diplometrics index		3.137*** (0.573)
FS from non-hydroelectric dams	-0.0902 (0.174)	-0.0650 (0.180)
Observations	1773618	1773618

Notes: All specifications include cell FEs and county x year FEs. The count of IGOs with joint membership is out of the 51 IGOs, regional development banks, and UN agencies profiled in the Political Handbook of the World 2020-2021 for which country membership data is available through the Correlates of War Project. The Diplometrics Program assigns weights to each IGO based on the frequency of its media mentions, then sums the weights of the IGOs that each country pair is jointly member to. The Diplometrics index used in Column (2) is the normalization of this measure. Values in the year 2000 are used for both the number of IGOs and the Diplometrics index. Standard errors in parentheses, clustered by country. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

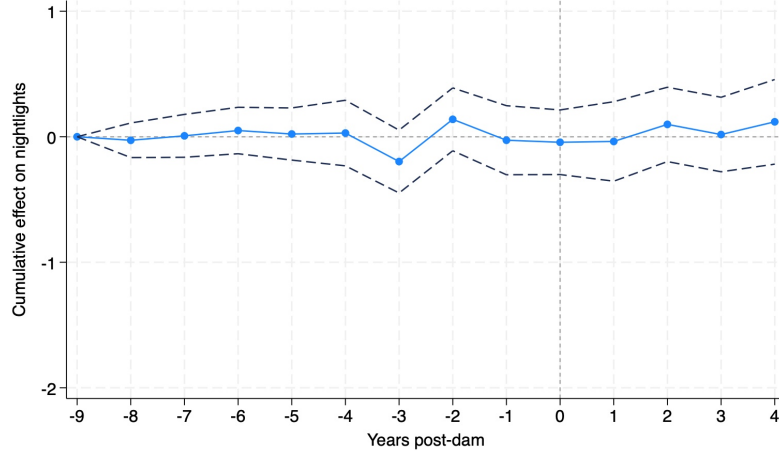
Table A9: Controlling for country-specific drought and wetness sensitivity when estimating IR interaction term: IGOs with joint membership

	(1)	(2)	(3)	(4)	(5)
FS from domestic hydroelectric dams	-0.293 (0.325)	-0.286 (0.327)	-0.354 (0.346)	-0.288 (0.327)	-0.371 (0.337)
FS from foreign hydroelectric dams	-3.789*** (0.436)	-3.938*** (0.716)	-3.267*** (0.605)	-3.899*** (0.585)	-3.737*** (0.605)
x # IGOs with joint membership	0.193*** (0.0235)	0.195*** (0.0234)	0.181*** (0.0145)	0.194*** (0.0241)	0.178*** (0.0140)
x Sensitivity to drought		0.290 (2.913)		0.220 (3.263)	
x Sensitivity to wet		2.235 (1.639)		2.200 (3.053)	
x Sensitivity to severe drought			0.919*** (0.282)		-6.713** (2.723)
x Sensitivity to severe wet			-1.658 (2.947)		-2.304 (2.763)
FS from non-hydroelectric dams	-0.0902 (0.174)	-0.0914 (0.176)	-0.0979 (0.174)	-0.0887 (0.175)	-0.0833 (0.177)
Observations	1773618	1769812	1602018	1770340	1579556
SPEI timescale		1	1	12	12

Notes: All specifications include cell FEs and county x year FEs. The count of IGOs with joint membership is out of the 51 IGOs, regional development banks, and UN agencies profiled in the Political Handbook of the World 2020-2021 for which country membership data is available through the Correlates of War Project. Values in the year 2000 are used for the number of IGOs. For each country, sensitivities to drought and wetness are estimated by regressing nightlights on binary drought and wetness indicators using a cell-level panel spanning 1992-2000. Drought and wet are defined as SPEI below and above one standard deviation, respectively. Severe drought and severe wet are defined as SPEI below and above two standard deviations, respectively. In Columns (2) and (4), the SPEI measure used is the average of 1-month timescale SPEI across months of the year. In Columns (3) and (5), the SPEI measure used is the 12-month SPEI in December of each year. Standard errors in parentheses, clustered by country. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

A.2.2 Figures

Figure A1: Non-hydroelectric dams: Dynamic effects of flow share on nightlights



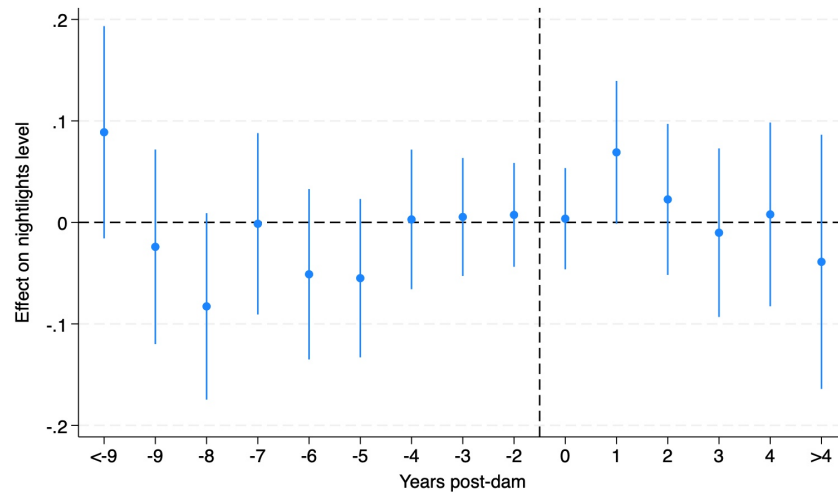
Note: This figure plots distributed lag regression coefficients and 95% confidence intervals for flow share from non-hydroelectric dams, obtained by estimating Equation (1.3.3) with separate terms for flow share from hydroelectric dams only and flow share from all non-hydroelectric dams. The figure plots the cumulative effects on nightlights relative to 9 years prior to dam construction, that is, $\sum_{k=-9}^{\tau} \phi^k$. The coefficient on hydroelectric dams is omitted. The regression includes county x year fixed effects. Standard errors clustered by river reach.

Table A10: Effects on nightlights using within country pair, time-varying bilateral engagement

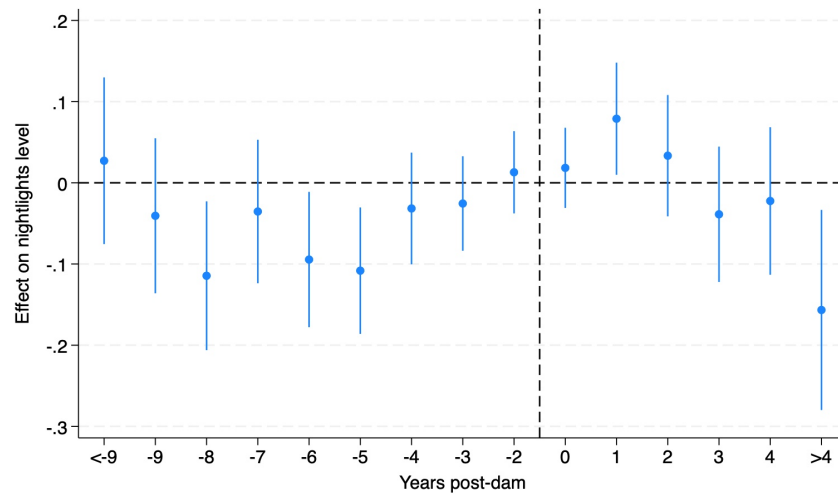
	(1)	(2)	(3)	(4)	(5)	(6)
FS from domestic hydroelectric dams	-0.166 (0.133)	-0.167 (0.133)	-0.166 (0.133)	-0.166 (0.133)	-0.167 (0.133)	-0.165 (0.133)
FS from foreign hydroelectric dams in U	-0.272* (0.152)	-0.248* (0.141)	-0.275* (0.151)	-0.265* (0.150)	-0.245* (0.137)	-0.279* (0.154)
x # cooperative events $_{UD,t-1}$	0.0611 (0.0655)			0.0717 (0.0792)		
x # hostile events $_{UD,t-1}$		-0.00478 (0.0809)			-0.0347 (0.0615)	
x total event intensity $_{UD,t-1}$			0.0589 (0.0538)			0.0752 (0.0687)
FS from hydroelectric dams in other countries	-0.0859 (0.209)	-0.0978 (0.204)	-0.0861 (0.208)	-0.0887 (0.207)	-0.100 (0.205)	-0.0859 (0.207)
FS from non-hydroelectric dams	-0.241 (0.206)	-0.241 (0.206)	-0.241 (0.206)	-0.241 (0.206)	-0.241 (0.206)	-0.241 (0.206)
Observations	1734678	1734678	1734678	1734678	1734678	1734678
Actors involved	Govt	Govt	Govt	All	All	All

Notes: The unit of observation is cell x dam country x year. Flow share from domestic (foreign) hydroelectric dams can be nonzero only when the dam country U is the same as (different from) the cell country D . The interaction terms are interactions between same-year flow share from foreign hydroelectric dams and previous-year z-scores of measures of bilateral engagement from ICEWS. Cooperative events refer to events coded by ICEWS as having a positive intensity score - for example, a diplomatic visit or the signing of a formal agreement. Hostile events refer to events coded by ICEWS as having a negative intensity score - for example, making a threat or reducing economic assistance. Total event intensity is the sum of intensity scores across events in the country pair x year, with a higher value indicating greater cooperation. In Columns (1)-(3), the events counted are those of the country pair x year in which the government of at least one of the countries in the pair was involved. In Columns (4)-(6), all events recorded of the country pair x year are counted. All specifications include cell FEs, country-pair FEs, and county x year FEs. Standard errors in parentheses, clustered by country-pair. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure A2: Dynamic effects of flow share from hydroelectric dams above county-specific median

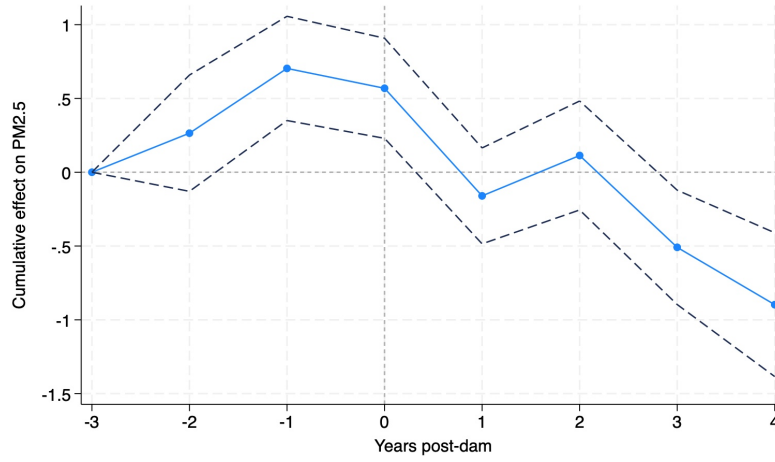


(a) County-specific median defined by first year of dam exposure



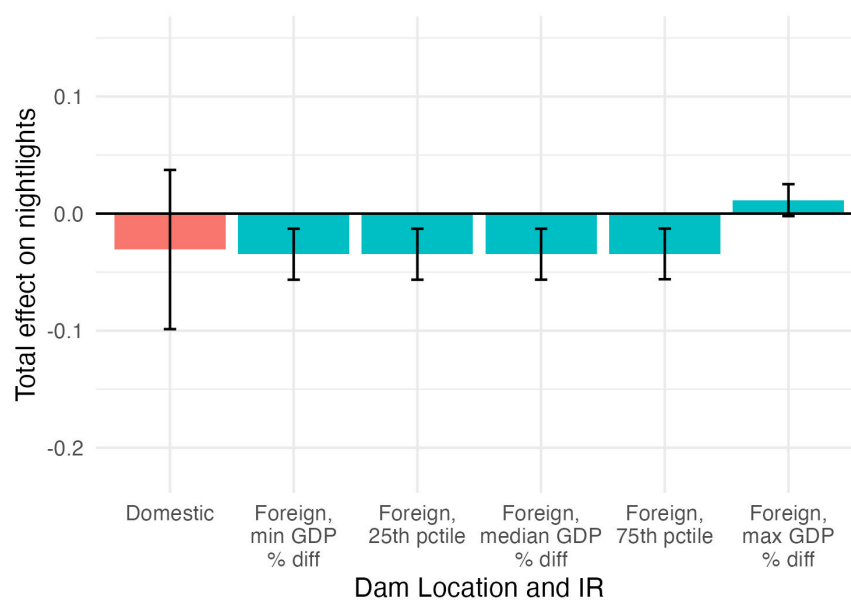
(b) County-specific median defined by 2013

Figure A3: Cumulative effects of flow share from hydroelectric dams on PM2.5



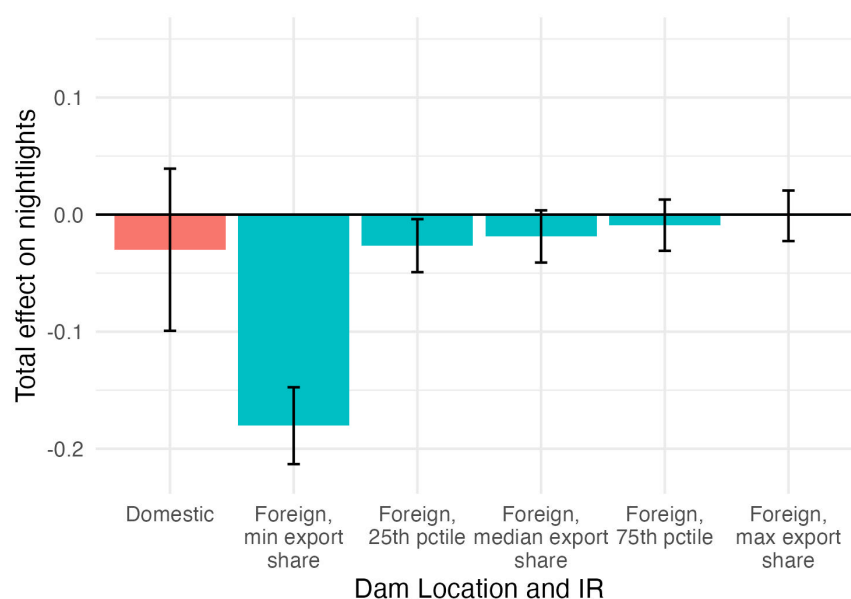
Note: This figure plots distributed lag regression coefficients and 95% confidence intervals from estimating Equation 1.3.3 separate terms for flow share from hydroelectric dams only and flow share from all other dams. Coefficients for flow share from non-hydroelectric dams are not shown. The regression also includes county x year fixed effects. Standard errors clustered by river reach. The figure plots the cumulative effects on PM2.5 relative to 3 years prior to dam construction, that is, $\sum_{k=-3}^{\tau} \phi^k$.

Figure A4: Implied effects of domestic and foreign flow share from hydroelectric dams: heterogeneity by GDP imbalance



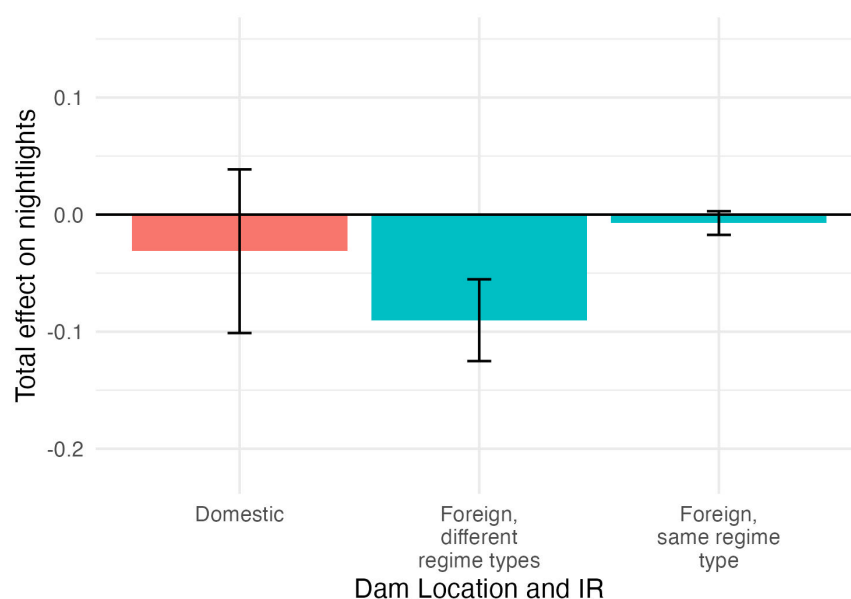
Notes: This figure plots the magnitudes and 95% confidence intervals of flow share effects implied by Column (1) of Table 1.6 at mean values of domestic and foreign flow share from hydroelectric dams in 2013, which were 0.12 and 0.05, respectively. For the implied effect of foreign flow share, the figure shows heterogeneity by the percentage difference in GDPs averaged over 1993-2000. This is calculated as the downstream country's GDP minus the upstream country's GDP, as a fraction of the upstream country's GDP. Among country pairs in the sample, the minimum, 25th percentile, median, 75th percentile, and maximum values of of GDP % difference are -100%, -90%, -17%, 596%, and 1181%.

Figure A5: Implied effects of domestic and foreign flow share from hydroelectric dams: heterogeneity by voting similarity in the UN General Assembly



Notes: This figure plots the magnitudes and 95% confidence intervals of flow share effects implied by Column (2) of Table 1.6 at mean values of domestic and foreign flow share from hydroelectric dams in 2013, which were 0.12 and 0.05, respectively. For the implied effect of foreign flow share, the figure shows heterogeneity by the *S*-score measure of voting similarity in the UN General Assembly averaged over 1993-2000. Among country pairs in the sample, the minimum, 25th percentile, median, 75th percentile, and maximum values of the share of the *S*-score are -0.18, 0.82, 0.87, 0.93, and 0.98.

Figure A6: Implied effects of domestic and foreign flow share from hydroelectric dams: heterogeneity by regime type similarity



Notes: This figure plots the magnitudes and 95% confidence intervals of flow share effects implied by Column (3) of Table 1.6 at mean values of domestic and foreign flow share from hydroelectric dams in 2013, which were 0.12 and 0.05, respectively. For the implied effect of foreign flow share, the figure shows heterogeneity by whether the upstream and downstream countries have the same regime type (either democracy or autocracy) in a given year. Among country pair-year observations in the sample, 53% are classified as having the same regime type.

APPENDIX B

APPENDIX TO CHAPTER 2

B.1 Additional Results and Checks

B.1.1 Descriptive data

Figure B1: Example of mine details in a District Survey Report

अरवल जिलान्तर्गत पयोवरणीय स्वीकृति प्राप्त बालूघाटों की विवरणी

क्र०सं 0	बालूघाट का नाम	पूरा पता	नदी का नाम	रकब A (हे० में)	GPS Cooromates(Latgitide &Longitude)		EC का पत्रांक एवं दिनांक	EC की वैधता की तिथि
					(Latgitide &Longitude)			
1	मुरादपुर हुजरा	मुरादपुर हुजरा थाना— अरवल	सोन नदी	5	A	25° 14' 28.2397" N 84° 37' 55.5743" E	116 dt 16.03.2018	15.03.2024
					B	25° 14' 29.8595" N 84° 38' 1.3338" E		
					C	25° 14' 21.5127" N 84° 38' 3.6433" E		
					D	25° 14' 18.9588" N 84° 37' 57.1714" E		
				5	A	25° 14' 29.9815" N 84° 38' 2.8154" E		
					B	25° 14' 31.5059" N 84° 38' 7.4365" E		
					C	25° 14' 25.6215" N 84° 38' 13.9054" E		
					D	25° 14' 21.7375" N 84° 38' 5.7228" E		
				5	A	25° 14' 20.9216" N 84° 38' 7.9650" E		
					B	25° 14' 24.7778" N 84° 38' 14.7047" E		
					C	25° 14' 19.8157" N 84° 38' 19.7828" E		
					D	25° 14' 15.0806" N 84° 38' 13.5446" E		

Notes: This figure shows an example of a District Survey Report (DSR) from which mines' locations and treatment dates were extracted. This example is taken from the DSR of Arwal district. It contains the following important information: a) the third column is the river name, b) the fifth column contains the coordinates of the mine, separated into latitude and longitude, c) the sixth column is the date the mine received Environmental Clearance (EC), which is required to operate the mine—we take the date of EC as the treatment date, and d) the seventh column is the expiry date of the EC. While the expiry date is redundant in this case, we can, in theory, subtract five years from the expiry date to calculate the treatment date.

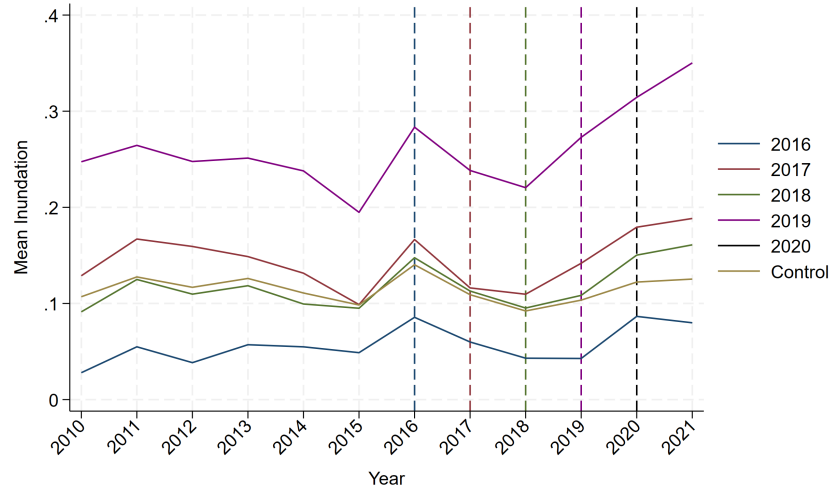
Figure B2: Sand being transported on boats



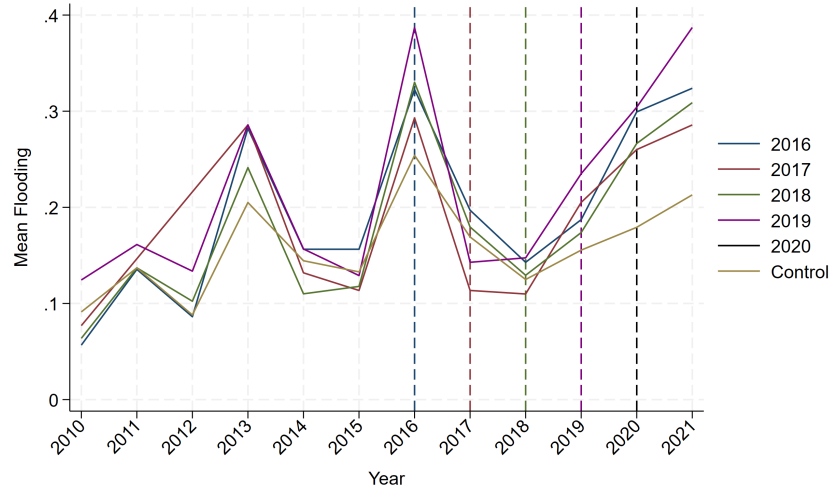
Note: Image was taken by Varun K in March 2023.

B.1.2 Raw Data

Figure B3: Mean Inundation over time



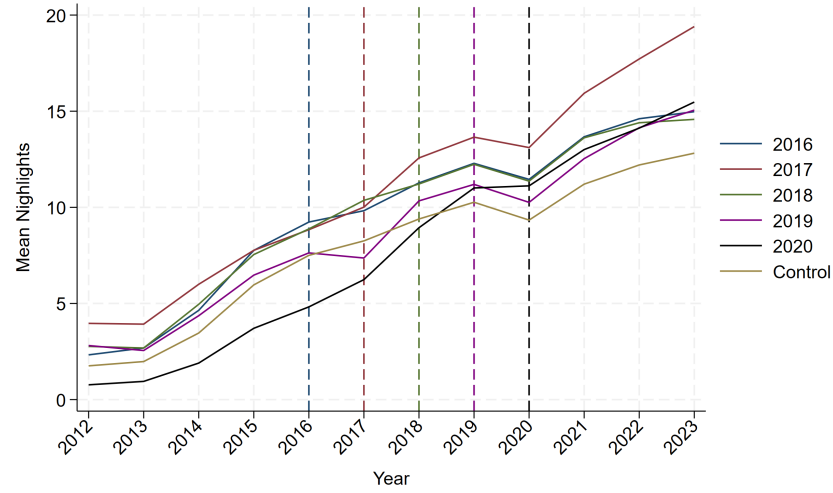
(a) Inundation



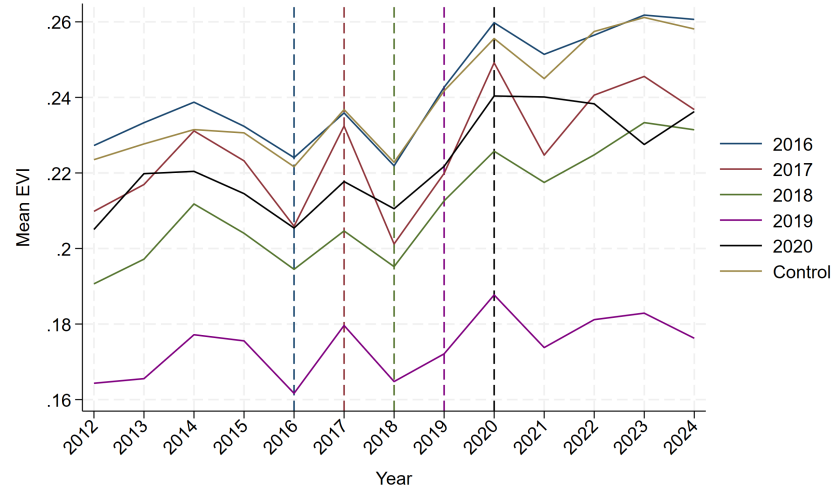
(b) Flood

Notes: This figure plots mean of Inundation (Panel a) and Probability of Flooding (Panel b) for each year grouped by the year of treatment.

Figure B4: Mean Nightlights and EVI over time



(a) Nightlights



(b) EVI

Notes: This figure plots mean of nightlights (Panel a) and Enhanced Vegetation Index (Panel b) for each year grouped by the year of treatment.

B.1.3 Balance Checks

Table B1: Correlations between treatment status or timing and assembly election outcomes

(a) Mine-level correlations

	(1) Treated (permit)	(2) Treated (permit)	(3) Treated (permit)	(4) Permit year	(5) Permit year	(6) Permit year
RJD	-0.0481 (0.104)	0.00753 (0.0494)	0.0531 (0.0448)	0.0449 (0.469)	0.0875 (0.240)	0.210 (0.305)
JD(U)	-0.185 (0.115)	-0.110 (0.0696)	-0.00654 (0.0706)	0.000497 (0.465)	0.203 (0.362)	1.011* (0.549)
BJP	-0.0593 (0.0974)	0.0619 (0.0529)	0.0577 (0.0712)	0.623 (0.446)	0.262 (0.295)	0.503 (0.501)
Constant	0.664** (0.0870)	0.602** (0.0406)	0.560** (0.0415)	2018.7** (0.394)	2018.7** (0.225)	2018.4** (0.320)
Observations	1421	1421	1383	727	727	715
District FE		Yes			Yes	
District x river FE			Yes			Yes

$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

In Columns (1)-(3), the dependent variable is a binary indicator for whether the mine is existing, i.e. has a permit, rather than proposed. In Columns (4)-(6), the sample is restricted to existing mines, and the dependent variable is the year in which the mine's permit was granted. Standard errors in parentheses, clustered by AC.

(b) AC-level correlations

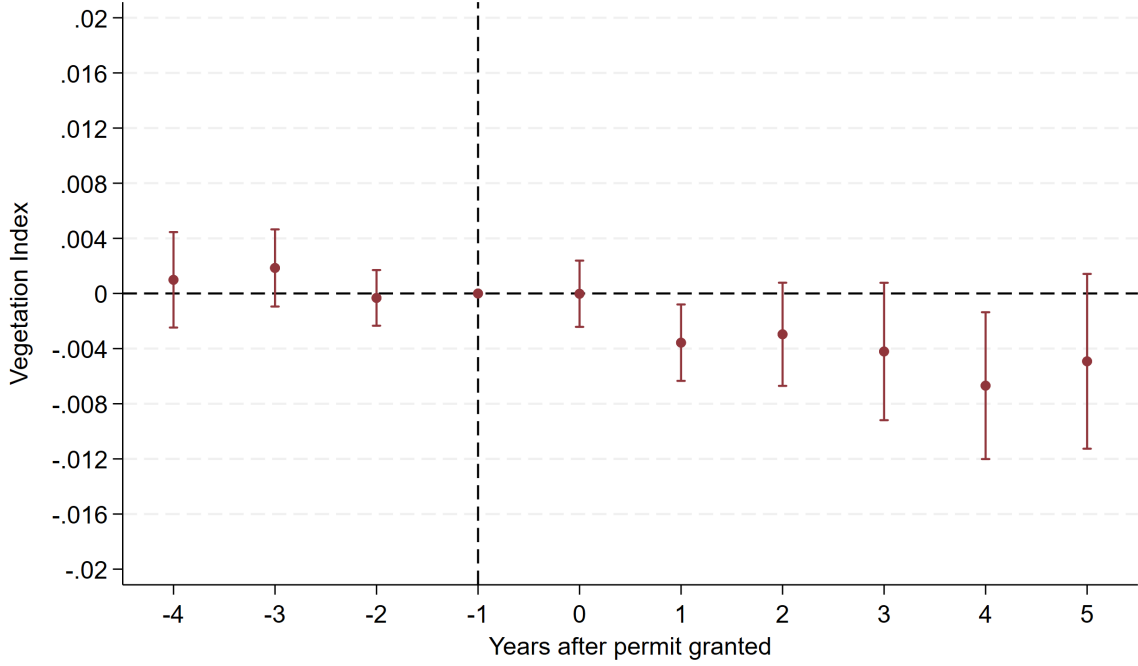
	(1) Total mines	(2) % Existing	(3) Permit year	(4) Permits 2016-17	(5) Permits 2018-20
RJD	3.949 (5.599)	0.0396 (0.105)	-0.381 (0.709)		
JD(U)	-0.0162 (6.070)	-0.0114 (0.114)	-0.928 (0.742)		
BJP	-3.322 (6.297)	-0.0283 (0.118)	0.263 (0.762)		
Ruling coalition 2016-17				3.386 (4.358)	
Ruling coalition 2018-20					-4.282 (3.809)
Constant	17.38** (4.677)	0.577** (0.0878)	2019.1** (0.606)	15.70** (3.758)	20.14** (2.552)
Observations	78	78	52	78	78

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

In Column (1), the dependent variable is the total number of existing and proposed mines. In Column (2), the dependent variable is the share of existing mines in the total. In Column (3), the sample is restricted to ACs with any existing mine, and permit year is the average of the years in which the existing mines received their permits. Column (4) shows the correlation between electing an MLA in the 2016-2017 ruling coalition (RJD, JD(U), INC) and the number of sand mine permits received during those two years. Column (5) shows the correlation between electing an MLA in the 2018-2020 ruling coalition (JD(U), BJP, LJP) and the number of sand mine permits received during those three years. Standard errors in parentheses.

B.1.4 Robustness

Figure B5: Mine level effects of sand mining on vegetation - Using Sun and Abraham [2021]



Notes: This figure presents event study evidence of the effect of sand mining on vegetation following Equation 2.3.2 estimated using the procedure of Sun and Abraham [2021]. The empirical analysis uses yearly panel data on vegetation and includes year-by-district-by-river and mine fixed effects, as well as controls for temperature and precipitation in the year. We focus on a time window 4 years before and 4 years after a mine started operations. Each dot corresponds to an estimated coefficient, and vertical lines indicate the corresponding 95% confidence intervals. The dashed line represents the omitted coefficient. Standard errors are clustered at mine level.

Table B2: Effect of Sand Mining on Household Assets

	Assets in 2014			Assets in 2019					
	All	UC + OBC	SC/ST	All		UC + OBC		SC/ST	
<i>Treated HH</i>	-0.004 (0.245)	-0.135 (0.278)	0.098 (0.197)	0.314 (0.246)	0.472* (0.240)	0.405 (0.301)	0.399 (0.258)	0.188 (0.273)	0.304 (0.245)
Observations	1,054	756	297	851	851	571	571	275	275
Control group mean	-.43	-.27	-.83	-.34	-.34	-.23	-.23	-.57	-.57
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
River FE	Yes	Yes	Yes	No	Yes	No	Yes	No	Yes

Notes: The dependent variable is a normalized index of (rural) household assets for the state of Bihar and is taken from NFHS-IV and V. The sample includes households which were within 2 kilometers of a mine which was operational by 2018 or within 5 km of a potential mine. We use data from districts which have both a treated and control mine. We control for distance to mine in all specifications. Standard errors are clustered at the NFHS cluster level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

REFERENCES

- Kyrgyzstan, Uzbekistan agree on power swap to restore reservoir levels. *Eurasianet*, March 25 2021. URL <https://eurasianet.org/kyrgyzstan-uzbekistan-agree-on-power-swap-to-restore-reservoir-levels>.
- Ethiopia’s Abiy Ahmed issues warning over Renaissance Dam. *Al Jazeera*, October 22 2019. URL <https://www.aljazeera.com/news/2019/10/22/ethiopias-abi-ahmed-issue-s-warning-over-renaissance-dam/>.
- AECOM. Global construction prospects 2024, 2023. URL <https://publications.aecom.com/MEH/report/global-construction-prospects-2024>.
- Amrita Ahuja, Michael Kremer, and Alix Peterson Zwane. Providing safe water: Evidence from randomized evaluations. *Annu. Rev. Resour. Econ.*, 2(1):237–256, 2010.
- Sam Asher, Tobias Lunt, Ryu Matsuura, and Paul Novosad. Development research at high geographic resolution: an analysis of night-lights, firms, and poverty in india using the shrug open data platform. *The World Bank Economic Review*, 35(4), 2021.
- Nava Ashraf, Edward Glaeser, Abraham Holland, and Bryce Millett Steinberg. Water, health and wealth: The impact of piped water outages on disease prevalence and financial transactions in zambia. *Economica*, 88(351):755–781, 2021.
- Shishir Baijal and Ashwani Awasthi. Skilled Employment in Construction Sector in India. *Frank Knight, RICS*, 2023.
- Michael A. Bailey, Anton Strezhnev, and Erik Voeten. Estimating dynamic state preferences from united nations voting data. *Journal of Conflict Resolution*, 61(2):430–456, 2017.
- Spencer Banzhaf, Lala Ma, and Christopher Timmins. Environmental Justice: The Economics of Race, Place, and Pollution. *Journal of Economic Perspectives*, 33(1):185–208, February 2019. ISSN 0895-3309. doi:[10.1257/jep.33.1.185](https://doi.org/10.1257/jep.33.1.185). URL <https://pubs.aeaweb.org/doi/10.1257/jep.33.1.185>.
- Xiaojia Bao. Dams and intergovernmental transfer: Are dam projects pareto improving in China? 2012. URL <http://www.columbia.edu/~xb2112/XiaojiaBaoJMP.pdf>.
- Katherine Barbieri and Omar M.G. Keshk. Correlates of war project trade data set codebook, version 4.0., 2016. URL <https://correlatesofwar.org>.
- A. Basist and C. Williams. Monitoring the quantity of water flowing through the Mekong Basin through natural (unimpeded) conditions, 2020.
- John Sturm Becko, Gene M. Grossman, and Elhanan Helpman. Optimal tariffs with geopolitical alignment. Technical report, Mimeo, 2025.
- Vince Beiser. *The World in a Grain: The Story of Sand and How It Transformed Civilization*. Riverhead Books, 2018.

- Nicolas Berman, Mathieu Couttenier, Dominic Rohner, and Mathias Thoenig. This Mine is Mine! How Minerals Fuel Conflicts in Africa. *American Economic Review*, 107(6):1564–1610, June 2017. ISSN 0002-8282. doi:[10.1257/aer.20150774](https://doi.org/10.1257/aer.20150774). URL <https://pubs.aeaweb.org/doi/10.1257/aer.20150774>.
- David Blakeslee, Ram Fishman, and Veena Srinivasan. Way down in the hole: Adaptation to long-term water loss in rural india. *American Economic Review*, 110(1):200–224, 2020.
- Judson Boomhower. Drilling Like There’s No Tomorrow: Bankruptcy, Insurance, and Environmental Risk. *American Economic Review*, 109(2):391–426, February 2019. ISSN 0002-8282. doi:[10.1257/aer.20160346](https://doi.org/10.1257/aer.20160346). URL <https://www.aeaweb.org/articles?id=10.1257/aer.20160346>.
- Kirill Borusyak, Xavier Jaravel, and Jann Spiess. Revisiting Event-Study Designs: Robust and Efficient Estimation. *The Review of Economic Studies*, page rdae007, February 2024. ISSN 0034-6527. doi:[10.1093/restud/rdae007](https://doi.org/10.1093/restud/rdae007). URL <https://doi.org/10.1093/restud/rdae007>.
- Stephen G. Brooks. The trade truce? *Foreign Affairs*, June 18 2024. URL <https://www.foreignaffairs.com/world/trade-truce-stephen-brooks>. Accessed 2024-06-18.
- Robin Burgess, Matthew Hansen, Benjamin A. Olken, Peter Potapov, and Stefanie Sieber. The Political Economy of Deforestation in the Tropics*. *The Quarterly Journal of Economics*, 127(4):1707–1754, November 2012. ISSN 0033-5533. doi:[10.1093/qje/qjs034](https://doi.org/10.1093/qje/qjs034). URL <https://doi.org/10.1093/qje/qjs034>.
- M Burke and D B Lobell. Satellite-based assessment of yield variation and its determinants in smallholder african systems. *Proceedings of the National Academy of Sciences*, 114(9):2189–2194, 2017.
- Fiona Burlig and Louis Preonas. Out of the darkness and into the light? development effects of rural electrification. *Journal of Political Economy*, 132(9):2937–2971, 2024.
- Brantly Callaway and Pedro HC Sant’Anna. Difference-in-differences with multiple time periods. *Journal of Econometrics*, 225(2):200–230, 2021.
- Brantly Callaway and Pedro H. C. Sant’Anna. Difference-in-Differences with multiple time periods. *Journal of Econometrics*, December 2020. ISSN 0304-4076. doi:[10.1016/j.jeconom.2020.12.001](https://doi.org/10.1016/j.jeconom.2020.12.001). URL <https://www.sciencedirect.com/science/article/pii/S0304407620303948>.
- Brantly Callaway, Andrew Goodman-Bacon, and Pedro H. C. Sant’Anna. Difference-in-differences with a continuous treatment. mimeo. 2025.
- Raghavendra Chattopadhyay and Esther Duflo. Impact of reservation in panchayati raj: Evidence from a nationwide randomised experiment. *Economic and political Weekly*, pages 979–986, 2004.

- Shiyi Chen, Joshua S. Graff Zivin, Huanhuan Wang, and Jiaxin Xiong. Combating cross-border externalities. Technical report, NBER Working Paper 30233, 2022.
- Jacob Cohen. A coefficient of agreement for nominal scales. *Educational and Psychological Measurement*, 20(1):37–46, 1960.
- Clement de Chaisemartin and Xavier d’Haultfoeuille. Difference-in-differences estimators of intertemporal treatment effects. *Review of Economics and Statistics*, 2024. forthcoming.
- Clément de Chaisemartin and Xavier D’Haultfoeuille. Two-Way Fixed Effects Estimators with Heterogeneous Treatment Effects. *American Economic Review*, 110(9):2964–2996, September 2020. ISSN 0002-8282. doi:[10.1257/aer.20181169](https://doi.org/10.1257/aer.20181169). URL <https://www-aeaweb-org.proxy.uchicago.edu/articles?id=10.1257/aer.20181169>.
- Florencia Devoto, Esther Duflo, Pascaline Dupas, William Parienté, and Vincent Pons. Happiness on tap: Piped water adoption in urban morocco. *American Economic Journal: Economic Policy*, 4(4):68–99, 2012.
- K Didan, A B Munoz, R Solano, and A Huete. *MODIS Vegetation Index User’s Guide (MOD13 Series)*. 2015.
- Kamel Didan. MODIS/Terra vegetation indices 16-day L3 global 250m SIN grid V061, 2021.
- Andrew Dillon and Ram Fishman. Dams: Effects of hydrological infrastructure on development. *Annual Review of Resource Economics*, 11(Volume 11, 2019):125–148, 2019. ISSN 1941-1359. doi:<https://doi.org/10.1146/annurev-resource-100518-093913>. URL <https://www.annualreviews.org/content/journals/10.1146/annurev-resource-100518-093913>.
- Ariel Dinar, Shlomi Dinar, Daene C. McKinney, and Stephen C. McCaffrey. *Bridges Over Water: Understanding Transboundary Water Conflict, Negotiation and Cooperation*. World Scientific Publishing Company, 2013.
- Gemma Dipoppa and Saad Gulzar. Bureaucrat incentives reduce crop burning and child mortality in south asia. *Nature*, 634(8036):1125–1131, 2024.
- Xinming Du and Shan Zhang. Requiem for rivers? global dams, environmental impacts, and agricultural adaptation. Technical report, SSRN Working Paper, 2025.
- O. Dube and J. F. Vargas. Commodity Price Shocks and Civil Conflict: Evidence from Colombia. *The Review of Economic Studies*, 80(4):1384–1421, October 2013. ISSN 0034-6527, 1467-937X. doi:[10.1093/restud/rdt009](https://doi.org/10.1093/restud/rdt009). URL <https://academic.oup.com/restud/article-lookup/doi/10.1093/restud/rdt009>.
- Esther Duflo and Rohini Pande. Dams. *The Quarterly Journal of Economics*, 122(2):601–646, 2007.

- Regan Early, Bethany A. Bradley, Jeffrey S. Dukes, Joshua J. Lawler, Julian D. Olden, Dana M. Blumenthal, Patrick Gonzalez, Edwin D. Grosholz, Ines Ibanez, Luke P. Miller, Cascade J. B. Sorte, and Andrew J. Tatem. Global threats from invasive alien species in the twenty-first century and national response capacities. *Nature Communications*, 7: 12485, 2016. doi:[10.1038/ncomms12485](https://doi.org/10.1038/ncomms12485). URL <https://doi.org/10.1038/ncomms12485>.
- Tom Fawthrop. ‘Our Mekong is dying’: Locals reel from fish crisis as dams sprout up from Laos to China. *South China Morning Post*, July 10 2022. URL <https://www.scmp.com/week-asia/people/article/3184578/our-mekong-dying-locals-reel-fish-crisis-dams-sprout-laos-china>.
- Clemens Fuest, Andreas Peichl, and Sebastian Sieglöcher. Do higher corporate taxes reduce wages? micro evidence from germany. *American Economic Review*, 108(2):393–418, 2018.
- Shanti Gamper-Rabindran, Shakeeb Khan, and Christopher Timmins. The impact of piped water provision on infant mortality in brazil: A quantile panel data approach. *Journal of Development Economics*, 92(2):188–200, 2010.
- Ana Carolina Garriga. Regime type and bilateral treaty formalization: Do too many cooks spoil the soup? *Journal of Conflict Resolution*, 53(5):698–726, 2009. doi:[10.1177/0022002709341403](https://doi.org/10.1177/0022002709341403).
- Zeynep K. Hansen, Gary D. Libecap, and Scott E. Lowe. Climate variability and water infrastructure: Historical experience in the western United States. In Gary D. Libecap and Richard H. Steckel, editors, *The economics of climate change: Adaptations past and present*, pages 253–280. University of Chicago Press, 2011.
- Fengzhi He, Christiane Zarfl, Klement Tockner, Julian D. Olden, Zilca Campos, Fábio Muniz, Jens-Christian Svenning, and Sonja C. Jähnig. Hydropower impacts on riverine biodiversity. *Nature Reviews Earth & Environment*, 5(11):755–772, 2024.
- J. Vernon Henderson, Adam Storeygard, and David N. Weil. Measuring economic growth from outer space. *American Economic Review*, 102(2):994–1028, 2012.
- Seonmin Will Heo, Koichiro Ito, and Rao Kotamarthi. International spillover effects of air pollution: Evidence from mortality and health data. Technical report, Working paper, 2024.
- Richard Hornbeck and Pinar Keskin. The historically evolving impact of the ogallala aquifer: Agricultural adaptation to groundwater and drought. *American Economic Journal: Applied Economics*, 6(1):190–219, 2014.
- A Huete, K Didan, T Miura, E P Rodriguez, X Gao, and L G Ferreira. Overview of the radiometric and biophysical performance of the MODIS vegetation indices. *Remote Sensing of Environment*, 83(1-2):195–213, 2002.
- International Commission on Large Dams. General synthesis. https://www.icold-cigb.org/article/GB/world_register/general_synthesis/general-synthesis, 2025. Accessed: 2025-10-28.

- Seema Jayachandran. The roots of gender inequality in developing countries. *economics*, 7(1):63–88, 2015.
- Seema Jayachandran. How Economic Development Influences the Environment. 2022.
- Marc Jeuland. The economics of dams. *Oxford Review of Economic Policy*, 36(1):45–68, 2020.
- Ruixue Jia and Hyejin Ku. Is china’s pollution the culprit for the choking of south korea? evidence from the asian dust. *Economic Journal*, 129:3154–3188, 2019.
- Matthew E Kahn, Pei Li, and Daxuan Zhao. Water pollution progress at borders: the role of changes in china’s political promotion incentives. *American Economic Journal: Economic Policy*, 7(4):223–242, 2015.
- KM Rabiul Karim, Maria Emmelin, Bernadette P Resurreccion, and Sarah Wamala. Water development projects and marital violence: Experiences from rural bangladesh. *Health Care for Women International*, 33(3):200–216, 2012.
- Robert O. Keohane. *After Hegemony: Cooperation and Discord in the World Political Economy*. Princeton University Press, Princeton, NJ, 1984.
- Robert O. Keohane and Lisa L. Martin. The promise of institutionalist theory. *International Security*, 20(1):39–51, 07 1995.
- Robert O. Keohane and Elinor Ostrom. Introduction. In Robert O. Keohane and Elinor Ostrom, editors, *Local Commons and Global Interdependence: Heterogeneity and Cooperation in Two Domains*, pages 1–26. Sage Publications, 1995.
- Benny Kleinman, Ernest Liu, and Stephen J. Redding. International friends and enemies. *American Economic Journal: Macroeconomics*, 16(4):350–385, 2024.
- Lois Koehnken. Impacts of sand mining on ecosystem structure, process and biodiversity in rivers, 2018. URL https://wwfint.awsassets.panda.org/downloads/sand_mining_impacts_on_world_rivers__final_.pdf.
- A. Kuriqi, A. N. Pinheiro, A. Sordo-Ward, M. D. Bejarano, and L. Garrote. Ecological impacts of run-of-river hydropower plants—current status and future prospects on the brink of energy transition. *Renewable and Sustainable Energy Reviews*, 142:110833, 2021.
- Yu-Hsiang Lei. Cross-border spillover effects of dams along international rivers. *Mimeo*, 2025.
- Jacques Leslie. In a major reversal, the World Bank is backing mega dams. *Yale E360*, December 19 2024. URL <https://e360.yale.edu/features/world-bank-hydro-dams>.
- Gary D. Libecap. Addressing global environmental externalities: Transaction costs considerations. *Journal of Economic Literature*, 52(2):424–479, 2014.

- Molly Lipscomb and Ahmed Mushfiq Mobarak. Decentralization and pollution spillovers: evidence from the re-drawing of county borders in Brazil. *The Review of Economic Studies*, 84(1):464–502, 2016.
- Charles Lipson. *Reliable Partners: How Democracies Have Made a Separate Peace*. Princeton University Press, 2003. ISBN 9781400850723. doi:[doi:10.1515/9781400850723](https://doi.org/10.1515/9781400850723). URL <http://doi.org/10.1515/9781400850723>.
- Ernest Liu and David Yang. International power. Technical report, NBER Working Paper 34006, 2025.
- Prem Mahadevan. Sand mafias in india: Disorganized crime in a growing economy. *Global Initiative Against Transnational Organized Crime*, page 27, 2019.
- Zeev Maoz and Bruce Russett. Normative and structural causes of democratic peace, 1946–1986. *American Political Science Review*, 87(3):624–638, 1993. doi:[10.2307/2938740](https://doi.org/10.2307/2938740).
- Philippe Martin, Thierry Mayer, and Mathias Thoenig. Make trade not war? *The Review of Economic Studies*, 75(3):865–900, 2008.
- Tiffany May, Isabelle Qian, and Suhasini Raj. China’s large and mysterious dam project is alarming neighbors and experts. *New York Times*, January 27 2025. URL <https://www.nytimes.com/2025/01/27/world/asia/china-tibet-dam-india.html>.
- Stephanie F. McWhinnie. The tragedy of the commons in international fisheries: An empirical examination. *Journal of Environmental Economics and Management*, 57:321–333, 2009.
- Mekong River Commission. Hydrology. URL <https://www.mrcmekong.org/hydrology/>.
- Nick J Middleton. Desert dust hazards: A global review. *Aeolian research*, 24:53–63, 2017.
- C. Mohr and C. Trebesch. Geoeconomics. 2025.
- Perrine Mouterde. India’s ‘sand mafias have power, money and weapons’. *Le Monde.fr*, September 2022. URL https://www.lemonde.fr/en/environment/article/2022/09/12/in-india-sand-mafias-have-power-money-and-weapons_5996639_114.html.
- National Inventory of Dams. Dam history. <https://nid.sec.usace.army.mil/#/dam-basics/dam-history>. Accessed: 2025-08-17.
- Eric Neumayer. Do democracies exhibit stronger international environmental commitment? a cross-country analysis. *Journal of Peace Research*, 39(2):139–164, 2002. doi:[10.1177/0022343302039002001](https://doi.org/10.1177/0022343302039002001). URL <https://doi.org/10.1177/0022343302039002001>.
- Sheila M. Olmstead and Hilary Sigman. Damming the commons: An empirical analysis of international cooperation and conflict in dam location. *Journal of the Association of Environmental and Resource Economists*, 2(4):497–526, 2015.

- Sheila M. Olmstead and Hilary Sigman. Droughts and economic activity: Do dams and groundwater mediate the impact? Technical report, Mimeo, 2025.
- Elinor Ostrom. *Governing the commons: The evolution of institutions for collective action*. Cambridge University Press, 1990.
- D. Padmalal and K. Maya. *Sand Mining: Environmental Impacts and Selected Case Studies*. Environmental Science and Engineering. Springer Netherlands, Dordrecht, 2014. ISBN 978-94-017-9143-4 978-94-017-9144-1. doi:[10.1007/978-94-017-9144-1](https://doi.org/10.1007/978-94-017-9144-1). URL <https://link.springer.com/10.1007/978-94-017-9144-1>.
- Dev Patel. Floods. 2024.
- Jean-Francois Pekel, Andrew Cottam, Noel Gorelick, and Alan S Belward. High-resolution mapping of global surface water and its long-term changes. *Nature*, 540:418–422, 2016.
- Brian D Richter and Gregory A Thomas. Restoring environmental flows by modifying dam operations. *Ecology and society*, 12(1), 2007.
- Miguel O Román, Zhuosen Wang, Qingsong Sun, Virginia Kalb, Steven D Miller, Andrew Molthan, Lori Schultz, Jordan Bell, Eleanor C Stokes, Bhartendu Pandey, et al. Nasa’s black marble nighttime lights product suite. *Remote Sensing of Environment*, 210:113–143, 2018.
- Jonathan Roth, Pedro HC Sant’Anna, Alyssa Bilinski, and John Poe. What’s trending in difference-in-differences? a synthesis of the recent econometrics literature. *Journal of Econometrics*, 2023.
- Nicholas Ryan and Anant Sudarshan. Rationing the commons. *Journal of Political Economy*, 130(1):210–257, 2022.
- M Schiavina, S Freire, A Carioli, and K Macmanus. GHS-POP R2023A - GHS population grid multitemporal (1975-2030). 2023.
- William A. Scott. Reliability of content analysis: The case of nominal scale coding. *Public Opinion Quarterly*, 19(3):321–325, 1955.
- Sheetal Sekhri. Wells, water, and welfare: the impact of access to groundwater on rural poverty and conflict. *American Economic Journal: Applied Economics*, 6(3):76–102, 2014.
- S. Shen, C. Li, A. van Donkelaar, N. Jacobs, C. Wang, and R. V. Martin. Enhancing global estimation of fine particulate matter concentrations by including geophysical a priori information in deep learning. *ACS EST Air*, 2024. DOI: 10.1021/acsestair.3c00054.
- S. Siebert, V. Henrich, K. Frenken, and J. Burke. Update of the digital global map of irrigation areas to version 5. Rheinische Friedrich-Wilhelms-Universität, Bonn, Germany and Food and Agriculture Organization of the United Nations, Rome, Italy, 2013.
- Hilary Sigman. International spillovers and water quality in rivers: Do countries free ride? *American Economic Review*, 92(4):1152–1159, 2002.

- Hilary Sigman. Transboundary spillovers and decentralization of environmental policies. *Journal of environmental economics and management*, 50(1):82–101, 2005.
- Statista. International revenue of the 250 largest construction contractors worldwide from 2001 to 2021, 2021. URL <https://www.statista.com/statistics/279940/international-construction-contractor-revenue/>.
- Eric Strobl and Robert O. Strobl. The distributional impact of large dams: Evidence from cropland productivity in Africa. *Journal of Development Economics*, 96(2):432–450, 2011.
- Juan Carlos Suárez Serrato and Owen Zidar. Who benefits from state corporate tax cuts? a local labor markets approach with heterogeneous firms. *American Economic Review*, 106(9):2582–2624, 2016.
- Liyang Sun and Sarah Abraham. Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*, 225(2):175–199, December 2021. ISSN 0304-4076. doi:[10.1016/j.jeconom.2020.09.006](https://doi.org/10.1016/j.jeconom.2020.09.006). URL <https://www.sciencedirect.com/science/article/pii/S030440762030378X>.
- K. Tadesse. Ethiopia: Egypt attack proposals 'day dreaming'. *Associated Press*, June 5 2013. URL <https://apnews.com/article/06352dd349814261bbc0cc0202171d8a>.
- Jaroslav Tir and John T. Ackerman. Politics of formalized river cooperation. *Journal of Peace Research*, 46(5):623–640, 2009. doi:[10.1177/0022343309336800](https://doi.org/10.1177/0022343309336800). URL <https://doi.org/10.1177/0022343309336800>.
- UN Water. WASH – Water, Sanitation and Hygiene. <https://www.unwater.org/water-facts/wash-water-sanitation-and-hygiene>. URL <https://www.unwater.org/water-facts/wash-water-sanitation-and-hygiene>.
- UNICEF. Clean drinking water. <https://www.unicef.org/india/what-we-do/clean-drinking-water>. URL <https://www.unicef.org/india/what-we-do/clean-drinking-water>.
- Andrea van der Kerk. Mapping public finance for rural drinking water and sanitation: India, odisha state and ganjam district. Technical report, IRC, 2017.
- Sergio M. Vicente-Serrano, Santiago Beguería, Juan I. López-Moreno, Marta Angulo-Martínez, and Ahmed M. El Kenawy. A new global 0.5° gridded dataset (1901-2006) of a multiscalar drought index: comparison with current drought index datasets based on the palmer drought severity index, 2010.
- Kenneth N. Waltz. *Theory of International Politics*. McGraw-Hill, New York, 1979. ISBN 9780075548529.
- Shaoda Wang and Zenan Wang. The environmental and economic consequences of internalizing border spillovers. mimeo. 2021.

- Nils B. & Gerlinde Theunissen Weidmann. Estimating local inequality from nighttime lights. *Remote Sensing*, 2021.
- Erika Weinthal. *State Making and Environmental Cooperation : Linking Domestic and International Politics in Central Asia*. Global Environmental Accord: Strategies for Sustainability and Institutional Innovation. MIT Press, Cambridge, Mass, 2002.
- World Bank. Global Water Security & Sanitation Partnership: Working with Country Partners for a Resilient Water Future. <https://www.worldbank.org/en/news/feature/2021/11/15/global-water-security-sanitation-partnership-working-with-country-partners-for-a-resilient-water-future>, 2021. URL <https://www.worldbank.org/en/news/feature/2021/11/15/global-water-security-sanitation-partnership-working-with-country-partners-for-a-resilient-water-future>.
- Neda A Zawahri and Sara McLaughlin Mitchell. Fragmented governance of international rivers: Negotiating bilateral versus multilateral treaties. *International Studies Quarterly*, 55(3):835–858, 2011.
- Alice Tianbo Zhang. Within but without: Involuntary displacement and economic development. 2018.
- Alice Tianbo Zhang and Vincent Xinyi Gu. Global dam tracker: A database of more than 35,000 dams with location, catchment, and attribute information. *Scientific Data*, 10(1):111, 2023.
- G. Ziv, E. Baran, S. Nam, I. Rodríguez-Iturbe, and S. A. Levin. Trading-off fish biodiversity, food security, and hydropower in the Mekong River Basin. *Proceedings of the National Academy of Sciences*, 109(15):5609–5614, 2012.