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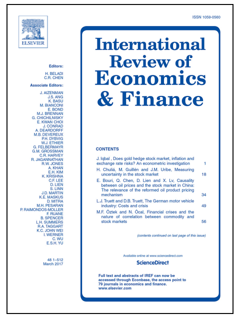

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Undisclosed Pollution: Environmental Information Disclosure and Transboundary Pollution

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Undisclosed Pollution: Environmental Information Disclosure and Transboundary Pollution

Abstract

This paper examines the impact of China's environmental information disclosure (EID) on transboundary pollution using a panel dataset covering 180 counties along 20 major rivers. The results show that EID exacerbates transboundary pollution. After its implementation, downstream counties experience a significant increase in water-polluting firms, as well as higher emissions of industrial wastewater and chemical oxygen demand, while non-downstream counties see a notable reduction in water pollution. Mechanism analysis shows that EID enhances environmental information exposure and prompts a strategic enforcement response by local governments. This is evidenced by an increase in environmental enforcement intensity in non-downstream counties, while enforcement in downstream counties either remains statistically unchanged or even weakens. We also find that the observed rise in downstream pollution is primarily driven by the relocation of water-polluting firms from upstream to downstream counties and an increase in newly established firms, rather than by more pollution emissions from incumbent firms. This paper highlights an unintended consequence of EID: it reshapes the spatial distribution of pollution by promoting the relocation of polluting activities to geographically and institutionally vulnerable downstream regions.

Keywords: Environmental information disclosure; Transboundary pollution; Environmental enforcement; Difference-in-differences

JEL CLASSIFICATION: D62, Q53, Q58

1. Introduction

Under a decentralized management system, environmental policies formulated by the central government are often carried out by local governments. However, the actions of one jurisdiction may have negative externalities on neighboring regions, leading to unintended consequences of environmental regulations (Lipscomb and Mobarak, 2017). Transboundary water pollution serves as a prime example, where upstream provinces strategically locate polluting firms downstream of rivers and export pollution across provincial borders (Cai et al., 2016). This practice allows these provinces to capitalize economic benefits (such as employment and tax revenue) within their own jurisdictions, while shifting the environmental and health costs to neighboring provinces (Monogan et al., 2017; Fu et al., 2022).

Environmental Information Disclosure (EID) policies have gained significant attention for their potential to enhance environmental governance by increasing transparency and public oversight. By requiring local governments to disclose environmental data, EID aims to raise public awareness and incentivize high-polluting firms to control pollution in response to heightened scrutiny. Existing literature highlights that EID is an effective tool for improving environmental outcomes, as it fosters better governance by incentivizing transparency and promoting compliance through social and market pressures (Shi et al., 2021; Zhang et al., 2022). However, these positive outcomes are not always guaranteed, especially in decentralized systems where the central government's environmental policies are implemented by local authorities. In such settings, local governments may respond strategically to centrally-mandated policies, adjusting their implementation in ways that generate unintended consequences. One particularly concerning issue is the relocation of polluting activities across borders, which can exacerbate environmental problems in neighboring regions. This is especially prevalent in federal systems, where jurisdictional boundaries are often not aligned with environmental flows, leading to spillovers of pollution that can undermine the effectiveness of local environmental regulations (Lipscomb and Mobarak, 2017). While extensive research has documented the positive effects of EID on environmental outcomes, there is a notable gap regarding its potential negative spillovers resulting from strategic responses by local governments.

This paper aims to fill this gap by investigating how EID in China, which was introduced in 2007, might inadvertently exacerbate transboundary pollution. The Ministry of Ecology and Environment of China introduced the EID measures on February 8, 2007, which assigned the responsibility of publishing local environmental quality information to local governments and encouraged local firms to proactively release pollution data. The initiative marked China's first proposition for environmental information disclosure. As part of this proposition, the environmental conditions of 113 Chinese cities have been assessed and disclosed since 2008. We focus on China for two key reasons. Firstly, China's EID system is more comprehensive than those in many other countries, covering disclosures from both the corporate sector and government (Shi et al., 2021). As a result, empirical evidence from China's EID practices can offer valuable insights for other countries developing comprehensive environmental information disclosure systems (Ren et al., 2024). Secondly, transboundary pollution in river basins is a prominent environmental issue in China. While local water pollution has been improved on average through water pollution control policies, the issues of regional pollution inequality and the misalignment of governance responsibilities remain highly prominent (Jing et al., 2022; Zheng et al., 2022; Zhang et al., 2024). Studying China's transboundary pollution challenges can provide practical insights that may benefit other economies facing similar issues, as the strategic pollution relocation due to transparency-based policies has global relevance, especially for countries with varying environmental enforcement capabilities and growing demands for environmental transparency, such as South Africa, India, Albania, Indonesia, and the European Union.[1]

We identify 20 major rivers in China and compile a panel dataset at the county-year level to examine the pollution activities of water-polluting firms along provincial borders before and after the implementation of EID.

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[1] Source: https://www.gov.za/sites/default/files/gcis_document/201409/a107-98.pdf; https://www.rsrr.in/_files/ugd/286c9c_3a23b52c6eab478e9aef32fc96c4ea3a.pdf; https://ipdcolumbia.org/wp-content/uploads/2024/08/Transparency_in_Env_Governance_Ramkumar_Petkova.pdf; https://www.ufu.de/wp-content/uploads/2022/03/UFU_Aarhus_Broschuere_1_Informieren_EN_barrierefrei_final.pdf.

We present both difference-in-differences (DID) and difference-in-difference-in-differences (DDD) strategy results to enhance the empirical robustness. We provide compelling evidence that EID exacerbates transboundary pollution issues. We observe that the governments adopt more lenient environmental regulations in the counties downstream of rivers. The exacerbation of transboundary pollution is driven by the migration of water-polluting firms from other counties to downstream counties and an increase in the number of newly established firms, rather than higher water pollution emissions from incumbent firms.

To validate our identification strategy, we employ an event study approach to assess the dynamic effects of EID on transboundary pollution outcomes. Our event study supports parallel pre-treatment trends between treated and control cities, with no significant differences observed before EID implementation. Post-implementation, we observe a steady rise in transboundary pollution reinforcing the causal interpretation of our findings. To further strengthen our findings, we conduct a series of robustness checks. First, we address endogeneity concerns of EID by using the ventilation coefficient as an instrumental variable for EID effectively. We control for external factors such as the horizontal ecological compensation policy, the emission reduction targets of the Eleventh Five-Year Plan and the 2008 financial crisis, to exclude the influence of other shocks. We also use a poisson pseudo-maximum likelihood estimator to address the count nature of the variable representing the number of polluting firms. For the placebo tests, we assess whether our identification strategy, which is designed to detect transboundary water pollution, would mistakenly identify significant effects for non-water pollutants. As expected, we find no significant increase in transboundary non-water pollution, supporting the specificity of our approach. Additionally, we perform a permutation test by randomly assigning counties as EID areas and re-estimating the model 1,000 times. The results consistently show no effect, further reinforcing the robustness of our identification strategy.

Our study contributes to three important areas of research. Firstly, it contributes to the literature on the environmental regulation and transboundary pollution by identifying mechanisms that are specific to EID and extending prior evidence largely centered on command-and-control or fiscal instruments. Previous studies have explored the effects of various environmental regulations on transboundary pollution, including the Clean Water Act (Sigman, 2005), the linkage between political promotion and water pollution indicators (Kahn et al., 2015), and ecological compensation (Zheng et al., 2021). However, unlike traditional environmental regulations, EID centers on informational transparency, indirectly influencing behavior through the reputational consequences of non-compliance. Specifically, traditional environmental regulations directly control the pollution behavior of firms through instruments like emission limits, taxes, or permits. These regulations impose legal constraints and are often enforced through mechanisms such as inspections and penalties for non-compliance. Firms might seek to evade compliance by relocating operations to regions with less stringent regulations, a phenomenon that is particularly prevalent in decentralized systems. In contrast, EID does not directly regulate pollution but instead increases transparency by making information about environmental performance publicly available (Sun et al., 2019). It creates reputational risks for local governments and firms, which may prompt them to avoid public scrutiny by relocating polluting activities rather than abating them. Practically, China's EID policy is not merely a variant of environmental regulation, but represents the first large-scale, government-led environmental transparency reform. By investigating EID's cross-jurisdictional effects, our study highlights the need to understand how transparency-based policies may inadvertently contribute to spatial disparities in environmental quality, thereby filling an important gap in the literature on non-traditional environmental governance.

Secondly, our study enriches the literature that examines the impact of environmental information disclosure (EID) on pollution by shifting attention from within-jurisdiction pollution outcomes to cross-jurisdictional spillovers. While previous studies have thoroughly examined the relationship between EID and environmental practices (García et al., 2007; Huang and Chen, 2015; Zhang et al., 2022), our study complements this literature by focusing specifically on EID's effect on transboundary pollution. By analyzing how EID, a tool primarily intended to improve local environmental outcomes, unexpectedly exacerbates pollution in neighboring regions, our study highlights a critical limitation of EID in environmental governance. This finding underscores the need for policymakers to address potential spillover effects when designing and implementing disclosure policies, expanding the understanding of EID's unintended consequences within environmental management frameworks.

Finally, our study provides new evidence for the Pollution Haven Effect (PHE) by demonstrating how EID influences firm relocation decisions in a manner consistent with this hypothesis. The PHE suggests that firms facing stricter environmental regulations tend to move to areas with laxer standards (Copeland and Taylor, 1994). Our findings show that EID, by increasing scrutiny and local accountability, inadvertently incentivizes firms to migrate to downstream counties, where regulations may be less stringent. This finding provides fresh support for the PHE, adding a nuanced understanding of how informational transparency, even when intended to improve environmental outcomes, can drive firms to relocate, potentially worsening pollution in less regulated areas.

2. Policy Background and Research Hypothesis

2.1 Policy Background

In February 2007, The Ministry of Ecology and Environment of China approved the *Measures for the Disclosure of Environmental Information (Trial)*, which came into effect in May 2008. This regulation marked China's first large-scale legislative initiative aimed at enhancing transparency in environmental governance. It required government agencies and major industrial polluters to disclose a wide range of environmental information, including environmental laws and policies, pollution emissions, environmental quality, and emergency response measures. It also established accountability and penalty mechanisms for non-compliance. Since its implementation, environmental conditions in 113 cities, primarily national environmental protection priority cities, have been regularly assessed and made publicly available.

China, with one of the most extensive divisions of labor globally, has become an international hub for pollution concentration (Wang et al., 2019). The EID represents a unique approach to public involvement in governance by enhancing access to environmental information. It is China's first large-scale legislative effort to disclose environmental data, implementing regulations through public supervision and advocating for cleaner production at the lowest possible cost (Liu et al., 2021; Shi et al., 2021; Wang and Shao, 2024).

The EID measures require Chinese governmental authorities and major industrial polluters to disclose environmental information to the public. Provincial Environmental Protection Bureaus (EPBs) must provide information in four key categories: environmental laws and regulations, environmental quality, environmental management and supervision, and environmental accidents and emergency responses. Serious polluting firms must disclose details about pollutant concentrations and volumes, the operation of environmental facilities, and their emergency response plans. The primary aim of the Chinese EID is to involve new actors in environmental governance, including the public, NGOs, and the media, codifying informational developments in China since the early 2000s.

EID facilitates pollution reduction by compelling polluting firms to disclose environmental information, often triggering complaints from NGOs and local communities and forcing firms to invest in pollution reduction (Lan et al., 2025). Market responses to environmental disclosures also incentivize firms to cut emissions to avoid negative reactions, such as stock price drops observed in the U.S. (Konar and Cohen, 1997). In 2007, China's Ministry of Ecology and Environment and the Central Bank of China issued opinions to enforce environmental laws and mitigate credit risks, requiring commercial banks to reduce loans to environmental violators. Furthermore, international companies increasingly prioritize 'green' supply chains and may terminate partnerships with polluting suppliers.

Environmental disclosure reduces information asymmetry between China's Ministry of Ecology and Environment, local governments, and the public, enhancing traditional environmental regulation (Zhao et al., 2023). By increasing public awareness of local environmental issues, the EID program creates bottom-up pressure on local governments to enforce regulations more actively. Additionally, it may lead to changes in resource reallocation among firms and industries (Liu et al., 2021).

2.2 Transmission Mechanisms of Transboundary Pollution

Water pollution remains a significant and pressing issue in many countries, often exacerbated by transboundary effects of pollution and the geographical distribution of polluting firms. Understanding the spillover effect of pollution in cross-border rivers is a crucial research focus in environmental economics, as the negative externalities of pollution are amplified by the flow of water. Jurisdictional boundaries, serving as spatial edges, frequently bear the burden of these detrimental externalities, leading to significantly higher pollution levels near borders compared to interior regions. This pattern is observable in various countries, including the United States, Canada, Brazil, China, and across Southeast Asia (Helland and Whitford, 2003; Gray and Shadbegian, 2004; Kahn et al., 2015; Lipscomb and Mobarak, 2017; Monogan et al., 2017; Nguyen et al., 2022). The transmission mechanisms of transboundary pollution can be understood through the lens of the "pollution haven theory".

Following the implementation of the "Tenth Five-Year Plan for National Environmental Protection" in 2001, which emphasized sustainable development, local governments have faced mounting pressure to strike a balance between economic growth and environmental preservation. Government officials are keen to reap economic benefits like job creation and increased tax revenue, while simultaneously minimizing environmental impacts within their respective jurisdictions. This dynamic creates a strong incentive for local officials to externalize pollution (Hutchinson and Kennedy, 2008). As a result, provincial governments allocate fewer enforcement efforts to downstream counties, i.e., strategic environmental regulation, because the perceived benefits of water pollution control diminish along the river within a given province.

The pollution haven effect posits that firms, particularly high-polluting ones, tend to establish operations in regions with lax environmental regulations to the costs associated with pollution control (Copeland et al., 2004). Consequently, the government's strategic environmental regulation has inadvertently contributed to transboundary pollution. Research by Duvivier and Xiong (2013) reveals that polluting firms often favor border regions due to the more relaxed environmental regulations prevalent in those regions.

2.3 Environmental Information Disclosure and Transboundary Pollution

The ecological environment is characterized by intrinsic externalities, such as non-competitiveness and non-exclusivity, which often lead to "tragedy of the commons" scenarios in the consumption of ecological resource. Environmental governance is further complicated by "free-rider" challenges, where the decentralized governance structure in China enables local governments to adopt varied environmental regulation strategies. Environmental Information Disclosure (EID) is widely recognized as a decentralized management strategy. It has emerged as a complement to command-and-control and market-based environmental regulation tools (Feng and He, 2020; Pien, 2020; Zhang et al., 2022). However, the impact of EID on transboundary pollution may produce contrasting outcomes. This section presents two competing hypotheses regarding the effects of EID on transboundary pollution: the governance effect and the pollution haven effect.

2.3.1 Governance Effect: EID as a Tool for Managing Transboundary Pollution

A significant body of literature has highlighted the promising role of EID in environmental governance (Shi et al., 2021; Chen and Duan, 2025). The first hypothesis suggests that EID functions as a governance tool that improves environmental management and reduces transboundary pollution. By making environmental data publicly accessible, EID increases the reputational and market exposure of local governments and firms. This transparency incentivizes firms to reduce emissions and adopt cleaner production technologies due to heightened public scrutiny and the desire to maintain a positive image (Ding et al., 2022). In this scenario, EID acts as a complementary regulatory tool that encourages compliance with environmental standards and fosters better pollution management across jurisdictions. EID would have a "governance effect" on transboundary pollution, as it encourages local governments to address pollution more effectively within their jurisdictions and prevent the offloading of pollution to neighboring areas (Shi and Xu, 2018; Zhang et al., 2022). Under this hypothesis, EID is expected to have a governance effect that mitigates transboundary pollution.

2.3.2 Pollution Haven Effect: EID Leading to Strategic Pollution Relocation

On the other hand, the increased environmental assessment pressure resulting from EID can lead to unintended consequences that may exacerbate strategic polluting behavior. Local governments and firms, under pressure to meet environmental standards and avoid negative publicity, might shifting polluting activities to nearby regions with weaker regulations or enforcement, rather than adopt more sustainable practices (Chen et al., 2018; Cai et al., 2016). For instance, firms might relocate their most polluting operations to regions with less stringent regulations or to neighboring areas with weaker enforcement (Shi and Xu, 2018). This phenomenon, known as the pollution haven effect, undermines efforts to effectively manage transboundary pollution. Geographically, this has been observed as a “downstream effect”, where water-polluting industries concentrate in downstream counties of each province (Cai et al., 2016). This dynamic suggests that EID may serve as a catalyst for transboundary pollution, particularly when pollution is shifted to neighboring counties downstream, rather than retained and managed locally.

The second hypothesis posits that EID could exacerbate transboundary pollution through strategic pollution relocation by local governments and firms. By mandating the disclosure of average environmental data of prefectures, EID policies overlook pollution imbalances, particularly those between the central and border areas within a prefecture. Local governments are compelled to present an appealing environmental image within their jurisdictions, which may drive them to transfer pollution to downstream neighbors. As such, EID could unintentionally fuel strategic polluting behaviors, exacerbating transboundary pollution rather than alleviating it. Based on the above reasoning, this paper proposes two competing hypotheses:

Hypothesis 1: Environmental Information Disclosure reduces transboundary pollution through the governance effect.

Hypothesis 2: Environmental Information Disclosure exacerbates transboundary pollution through the pollution haven effect.

3. Empirical Strategy

3.1 Specification for identifying transboundary pollution effect

Our initial goal is to identify the transboundary pollution effect, specifically the downstream effect. We expect to see higher pollution levels in the most downstream county of a province. However, it is not appropriate to accurately capture this downstream effect by using the difference in pollution between the most downstream counties and other counties, because the downstream counties differ from others in various characteristics.

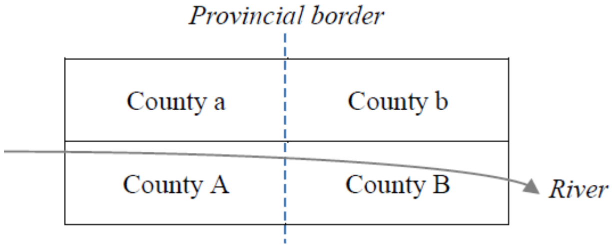


Figure 1. County map at the provincial border

To address this issue, we draw on the approach of Cai et al. (2016) and select three adjacent counties to the northeast of the most downstream counties as control counties. Let us use the heuristic map in Figure 1 to illustrate our strategy in detail. Suppose a river flows from the west to the east, crossing the most downstream county A in an upstream province, and then entering the most upstream county B in a downstream province. We refer to counties A and counties B as riverside counties. Counties A and counties a share the same provincial characteristics and are likely to have similar geographic features, the same is true for counties B and b. We refer to counties A and counties a as down counties. In this context, county A is the downstream county, while the others serve as comparable control counties.

Nevertheless, one potential concern arises: downstream counties may systematically differ from other counties in aspects such as geographic features, industrial structure, economic development level, etc. To mitigate this risk, we conduct a balance test utilizing a T-test to examine whether downstream counties and the selected control counties differ significantly across these key attributes. The results of Appendix Table A1 confirm that there are no significant differences between the two groups, thus alleviating concerns regarding potential selection bias.

We implement the following regression to examine downstream effect:

$$Y_{it} = \alpha + \beta_1 Downstream_i + X_{it}\phi + Down_i + River_i + \delta_t + \varepsilon_{it} \tag{1}$$

where i and t indicate county and year, respectively. Y_{it} is the number of water-polluting firms, industrial wastewater emissions and COD emissions in county i in year t. We use water pollution as the outcomes because it is easier to monitor and its flow direction is relatively stable compared to air pollution (Pan and Chen, 2021). $Down_i$ is a geographical dummy, setting to 1 if a county belongs to the set of down counties within its province (i.e. county A and county a), and 0 otherwise. $River_i$ is also a geographical dummy, setting to 1 if a county is located along a river (i.e. county A and county B), and 0 otherwise. $Downstream_i$ is the interaction term of the above two dummy variables, setting to 1 if a county is located along a river and is the most downstream county within its province (i.e. county A), and 0 otherwise. X_{it} is a set of control variables that represent county i's socioeconomic characteristics in year t, including GDP per capita, total population, the proportion of industrial GDP, and the ratio of government expenditure to GDP. δ_t represents year fixed effects. The coefficient of interest, β_1, represents the difference in water pollution between the downstream county and its neighboring non-downstream counties, which is referred to as the downstream effect.

3.2 Specification for identifying the impact of EID on transboundary pollution

3.2.1 Main specification strategies

This study focuses on the question of how EID affects the downstream effect. We employ a difference-in-differences (DID) analysis by leveraging geographical and year variations in EID implementation. Specifically, we estimate:

$$Y_{ict} = \alpha + \beta_2 EID_c \times Post_t + X_{ict}\phi + \lambda_i + \delta_t + \varepsilon_{ict} \tag{2}$$

where i denotes downstream counties, c denotes the corresponding prefecture-level cities (administratively above the county level), and t denotes years.[2] For the difference-in-differences (DID) estimation, we restrict the sample to downstream counties, which are defined as counties situated along a river and identified as the most down county within their province. EID_c is a dummy variable that indicates whether county i in its corresponding city c disclosed environmental information. $Post_t$ is a dummy variable that indicates whether the year is 2008 or later. We also include county fixed effects and year fixed effects. The standard errors are clustered by county to allow for correlation within county. The coefficient of interest, β_2, quantifies the increment of downstream effect following the implementation of EID. If β_2 is positive, it means that EID makes the transboundary water pollution problem more serious.

3.2.2 Validity of the identification strategies

To ensure that the Difference-in-Differences (DID) estimates are credible, it is essential to satisfy the parallel trends assumption. This assumption requires that, in the absence of environmental information disclosure (EID), the treated and control cities would have exhibited similar trends in pollution outcomes. However, the non-random selection of EID cities poses a potential challenge to the validity of this assumption. We employ a three-pronged approach to address these endogeneity concerns.

First, we adjust for potential selection bias by incorporating city-level baseline characteristics and flexible year trends. Following Lu and Yu (2015) and Boustan et al. (2020), we introduce the interaction terms between year-fixed effects and predetermined city-level controls. This allows us to capture differential trends across cities based on their initial conditions. Specifically, the 113 EID cities were designated as *National Key Environmental Protection Cities* under China's Eleventh Five-Year Plan. These cities were typically sub-provincial cities, provincial capitals, municipalities directly under the central government, and cities with severe pollution problems. To capture this policy selection mechanism, we construct three geographical dummy variables indicating whether the city is a directly administered municipality, a sub-provincial city, or a provincial capital. We also control for industrial wastewater discharge, SO_2 emissions, and smoke dust emissions in 2007. By incorporating these predetermined controls and their interactions with year fixed effects into the specification (2), we mitigate the omitted variable bias arising from systematic differences in pollution

[2] We use downstream counties as the unit of analysis rather than downstream cities because only downstream counties possess the geographical conditions necessary for pollution transfer. In contrast, using downstream cities as the analytical unit would result in a higher level of spatial aggregation, potentially masking cross-border pollution flows and leading to identification challenges.

trends across regions.

Second, we estimate nonparametric event study models. Specifically, we estimate the following equation:

$$Y_{ict} = \alpha + \gamma_k \sum_{k=-7,k\neq-1}^{7} EID_c \times I(t-2008=k) + X_{ict}\phi + \lambda_i + \delta_t + \varepsilon_{ict} \tag{3}$$

where i denotes downstream counties, c denotes the corresponding prefecture-level cities (administratively above the county level), and t denotes years. Indicator variables $I(t-2008=k)$ measure the year relative to the implementation year (2008). The event periods range from −7 to 7. Following the standard practice in the existing literature (Ren et al., 2024; Wu et al., 2025; Chen et al., 2024), the omitted category is $k=-1$, the year immediately preceding the implementation of EID. This choice ensures that all estimated coefficients are interpreted relative to a clean pre-treatment baseline. Each estimate of γ_k provides the change in transboundary pollution in EID cities relative to non-EID cities during year k, as measured from the year immediately prior to EID implementation.

This specification offers two main advantages. It allows us to test the parallel trends assumption underlying our DID strategy by examining the pattern of γ_k coefficients for $k<-1$. Our event study results suggest no similar trends in pollution outcomes prior to EID implementation, supporting the validity of the parallel trends (details are discussed in Section 5.3). This specification also enables us to trace out the dynamic effects of the policy, revealing whether the impact of EID is immediate, gradual, or potentially non-monotonic over time.

Third, to further mitigate concerns about the non-random selection of EID cities, we employ the air circulation coefficient as an instrumental variable for EID. This approach helps isolate the exogenous variation in EID that is driven by natural factors rather than policy decisions or regional characteristics (details are discussed in Section 5.4.1).

Another potential threat arises from the possibility of confounding effects from concurrent policies and factors. In our robustness checks, we exclude the impact of the horizontal ecological compensation policy, the Eleventh Five-Year Plan and the Global financial crisis.

3.2.3 Additional specification strategies

Due to the issue of limited sample size in our main specification (2), we further employ a difference-in-difference-in-differences (DDD) model. This model also allows us to directly capture the heterogeneous impacts of the EID policy across non-downstream and downstream counties.

$$Y_{ict} = \alpha + \beta_3 Downstream_i \times EID_c \times Post_t + \beta_4 EID_c \times Post_t + \beta_5 Downstream_i \times Post_t + X_{ict}\phi + \lambda_i + \delta_t + \varepsilon_{ict} \tag{4}$$

In Model (4), the main parameter of interest is β_3, which measures the difference in the pollution increase between downstream counties and non-downstream counties after the implementation of EID. The meanings of the variables and the fixed effects setup are identical to those in Model (2). This coefficient captures the key heterogeneity in the treatment effect across jurisdictions located downstream versus non-downstream, providing additional insights into whether EID results in more pollution increases in counties located downstream of major rivers.

4. Data

Our analysis utilizes a county-year panel dataset encompassing 180 counties from 2001 to 2015.[3] This study draws on multiple datasets, including the Annual Survey of Above-Scale Industrial Firms Database, which provide data only up to 2015. Nonetheless, the study period is sufficient for capturing the medium-term effects of EID implementation, which informs the theoretical understanding of transboundary pollution dynamics. Each observation represents a county in a given year and includes data on the number of water-polluting firms, water pollutant emissions, and other county economic characteristics. The data for this study comprises four sources.

County location data

We focus on China's 20 major inter-provincial rivers, which account for 90% of the country's annual river runoff. Along these rivers, we first identify 90 counties situated at provincial borders (e.g., counties A and B), as depicted in Figure 1. Subsequently, for each of these counties, we select a neighboring county within the same province that is also situated at the provincial border (e.g., counties a and b).

Industrial firm data

To examine the pollution activities of firms, we aggregate micro-firm data at the county-year level based on firms' location. We calculate the number of water-polluting firms in each county-year using micro-firm data. Industries are classified as water-polluting according to the definition provided by Cai et al. (2016). Such information is sourced from the *Annual Survey of Above-Scale Industrial Firms Database*, collected by the National Bureau of Statistics. This survey covers all state-owned industrial firms and non-state-owned firms above a certain scale.

Pollution data

Given the variations in emission intensities among different firms, the number of water-polluting firms cannot fully represent the intensity of water pollution activities in counties. Unfortunately, the Chinese Environmental Statistics Yearbook does not disclose data on pollutant emissions at the county level. We obtain the county pollution emissions by summing up the pollutant emissions from industrial firms, using the *Chinese Environmental Statistics Database* (*CESD*) provided by the Ministry of Environmental Protection of China. Industrial firms included in the survey are required to report their emissions of major pollutants, treatment conditions, and other relevant information for the previous year. The monitoring system covers a significant proportion of polluting industrial firms, accounting for approximately 85% of China's total major pollutants. The *CESD* is widely recognized as the most comprehensive and reliable firm pollution database in China (Zhang et al., 2018).

[3] Considering the emphasis on pollution control during "Tenth Five-Year Plan" in China in 2001, we choose 2001 as the starting year for our sample.

It is worth noting that the pollution emissions calculated in this study are not the complete, but rather a slight underestimation, as we did not consider the pollution from small-scale firms. However, this underestimation is unlikely to significantly affect the conclusions since large-scale industrial firms account for the majority of total pollution.

Other county characteristics

County economic variables are constructed using data obtained from the *China County Statistical Yearbook*, including GDP per capita (*lnpgdp*), total population (*lnpopulation*), the proportion of industrial GDP (*Ind_gdp*), and the ratio of government expenditure to GDP (*Gov*). These variables, used as county-level controls, help control for the influence of time-varying economic characteristics on pollution outcomes.

Finally, we obtain a sample with 2700 observations, covering 180 counties over a span of 15 years (2001-2015). Table 1 provides summary statistics for the variables used in our analysis. There are on average 2.5 water-polluting firms per county per year, generating 2.518 million tons wastewater and 0.034 million tons COD. Approximately 38% of the sample implements environmental information disclosure.

Table 1. Summary statistics

	Observations	Mean	Std. Dev.	Min	Max
Dependent variables					
Number of water-polluting firms	2700	2.490	4.587	0	58
Wastewater emissions (Million tons)	2700	2.154	3.110	0	33.031
COD emissions (Million tons)	2700	0.034	0.045	0	0.471
Independent variables					
Downstream	2700	0.250	0.433	0	1
EID	2700	0.383	0.486	0	1
Post	2700	0.533	0.499	0	1
Controls					
lnpgdp	2700	9.551	0.915	7.443	11.446
lnpopulation	2700	3.574	0.840	0.693	5.112
Ind_gdp (%)	2700	34.862	17.241	1.723	58.999
Gov	2700	0.178	0.149	0.018	0.723

Notes: The table presents summary statistics for key variables from 180 Chinese counties between 2001 and 2015. GDP are deflated to 2001 yuan using GDP deflators.

5. Empirical Results

5.1 Results for identifying transboundary pollution effect

The regression results presented in Table 2, based on the specification (1), examine whether there is a cross-provincial border pollution effect by comparing downstream counties (Counties A) with non-downstream counties (Counties a, B and b). Columns (1) to (3) show the results without controlling for additional factors, while columns (4) to (6) include control variables.

Columns (1) and (4) show that downstream counties host more water-polluting firms than non-downstream counties. After controlling for covariates, counties located downstream have approximately 0.736 more firms compared to other counties—equivalent to about 30 percent of the sample mean. Columns (2) and (5) focus on wastewater emissions. The coefficients for *Downstream* in these columns are 0.509 and 0.351, respectively. This indicates that downstream counties have higher wastewater emissions by approximately 0.4 million tons, equivalent to about 19 percent of the sample mean. Similarly, in columns (3) and (6), the results indicate a persistent downstream effect on COD emissions. Specifically, the downstream counties have higher COD emissions by approximately 0.006 million tons, accounting for roughly 18 percent of the sample mean. Taken together, the results demonstrate that downstream counties experience more industrial activities and associated water pollution.

Table 2. Examination for downstream effect

	Number of w.p. firms	Wastewater emissions	COD emissions	Number of w.p. firms	Wastewater emissions	COD emissions
	(1)	(2)	(3)	(4)	(5)	(6)
Downstream	0.905***	0.509**	0.007**	0.736**	0.351	0.005*
	(0.343)	(0.229)	(0.003)	(0.322)	(0.217)	(0.003)
Controls	N	N	N	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Down FE	Y	Y	Y	Y	Y	Y
River FE	Y	Y	Y	Y	Y	Y
Observations	2700	2700	2700	2700	2700	2700
R^2	0.060	0.087	0.023	0.069	0.105	0.043

Notes: This table reports the estimated impact of the *Downstream* dummy variable on pollution outcomes to examine the downstream effect. The sample includes 180 Chinese counties located near provincial boundaries from 2001 to 2015. Each observation is a county–year combination. Controls include county-level GDP per capita (lnpgdp), total population (lnpopulation), the proportion of industrial GDP (Ind_gdp), and the ratio of government expenditure to GDP (Gov). Standard errors clustered at county level are reported in parentheses. ***, **, and * denotes significance at the 1, 5, and 10 percent levels, respectively.

5.2 Results for identifying the impact of EID on transboundary pollution

After identifying the presence of transboundary pollution effects, we proceed to our core analysis by empirically examining the impact of EID on transboundary pollution. Table 3, Panel A presents the baseline results from our main specification in Equation (2), using the subsample of downstream counties. Strikingly, the coefficients of the double interaction term *EID*×*Post* are positive and statistically significant across all columns, indicating that the implementation of environmental information disclosure (EID) has intensified pollution activities in downstream regions. Specifically, EID leads to an average increase of 2.3 water-polluting firms in downstream counties relative to the pre-EID period. These firms are associated with an increase of approximately 0.7 million tons of industrial wastewater and 0.01 million tons of chemical oxygen demand (COD). These magnitudes are not only statistically significant but also economically large, underscoring the profound impact of EID on pollution relocation dynamics. These results support Hypothesis 2, which posits that EID may unintentionally exacerbate transboundary pollution in geographically vulnerable downstream areas. The evidence is also consistent with the pollution haven hypothesis, suggesting that pollution-intensive firms may relocate to regions where enforcement externalities are more likely, such as counties located downstream from regulatory jurisdictions. In short, when transparency rises, pollution doesn't disappear—it moves.

To highlight this geographical heterogeneity, Panel B provides a compelling contrast. For non-downstream counties those without the natural conditions to transfer pollution, the coefficients of *EID* × *Post* are negative and statistically significant across most specifications. In these areas, EID appears to function as intended: the number of polluting firms, as well as emissions of wastewater and COD, all decline. The policy thus proves effective only where firms cannot exploit geographic loopholes.

Table 3. The impact of EID on transboundary pollution using DID specification

	Number of w.p. firms (1)	Wastewater emissions (2)	COD emissions (3)	Number of w.p. firms (4)	Wastewater emissions (5)	COD emissions (6)
Panel A：Sample for downstream counties						
EID×*Post*	2.330***	0.776**	0.010**	2.226***	0.613*	0.009**
	(0.647)	(0.375)	(0.004)	(0.618)	(0.358)	(0.004)
Observations	675	675	675	675	675	675
R^2	0.539	0.627	0.641	0.547	0.633	0.644
Panel B：Sample for non-downstream counties						
EID×*Post*	-0.514**	-0.355**	-0.002	-0.574**	-0.434**	-0.004*
	(0.248)	(0.172)	(0.002)	(0.263)	(0.178)	(0.002)
Observations	2025	2025	2025	2025	2025	2025
R^2	0.623	0.644	0.647	0.626	0.649	0.650
Controls	N	N	N	Y	Y	Y
County FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y

Notes: This table reports the impact of environmental information disclosure (EID) on transboundary pollution using a DID specification (Equation 2). The sample includes 45 downstream counties (Panel A) and 135 non-downstream counties (Panel B) from 2001 to 2015. Each observation is a county–year combination. Controls include county-level GDP per capita (lnpgdp), total population (lnpopulation), the proportion of industrial GDP (Ind_gdp), the ratio of government expenditure to GDP (Gov), and interactions between city-level predetermined characteristics and year fixed effects. Standard errors clustered at county level are reported in parentheses. ***, **, and * denotes significance at the 1, 5, and 10 percent levels, respectively.

Table 4 presents the results from the difference-in-difference-in-differences (DDD) specification. The results highlight both the intended and unintended consequences of EID, demonstrating how it influences pollution outcomes differently in downstream and non-downstream counties. The coefficient for the *EID×Post* term is negative across all columns, indicating that EID contributes to a reduction in pollution in non-downstream counties. Specifically, EID reduces the number of water-polluting firms and wastewater emissions in these counties. In contrast, the coefficient for the *Downstream×EID×Post* interaction term is positive and statistically significant across all models, indicating that, relative to non-downstream counties, pollution levels significantly increase in downstream counties after the implementation of EID.

Overall, the results in Table 3 and Table 4 support hypothesis 2 that while EID improves transparency and encourages pollution reduction in non-downstream counties, it also creates strategic avoidance behavior, where polluting firms shift their operations to downstream counties. This geographic spillover effect highlights the need for careful consideration of inter-jurisdictional dynamics in the design of environmental policies. EID, while improving transparency, may inadvertently increase the spatial reallocation of pollution, exacerbating transboundary pollution issues.

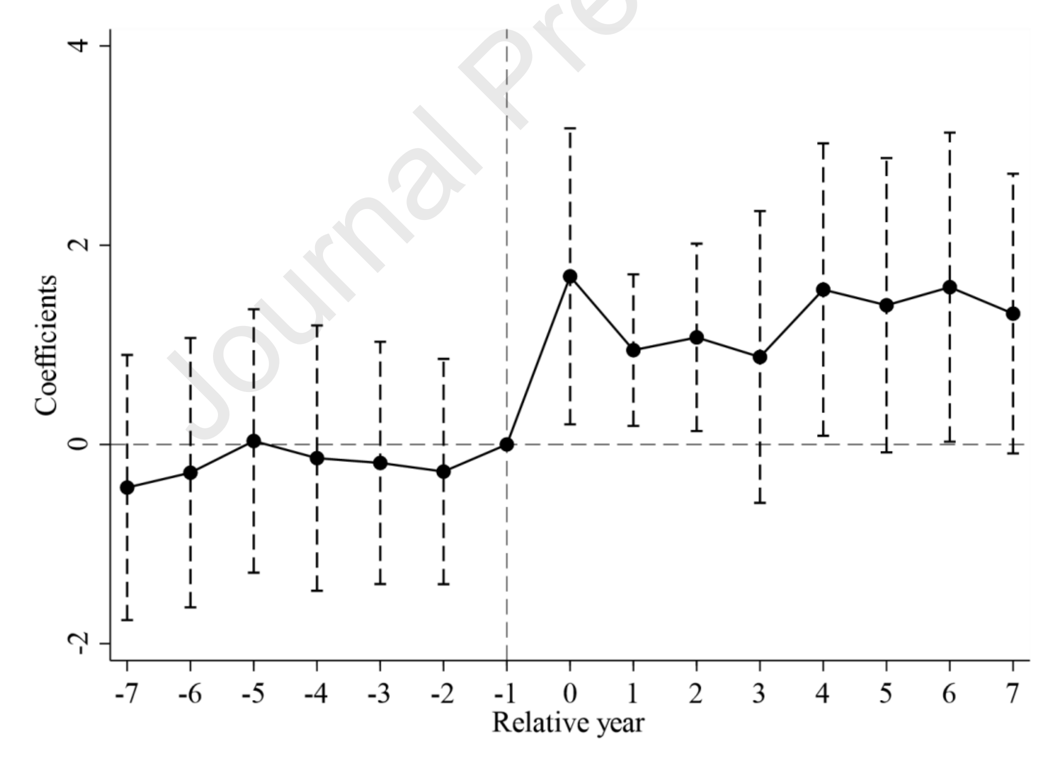
Table 4. The impact of EID on transboundary pollution using DDD specification

	Number of w.p. firms (1)	Wastewater emissions (2)	COD emissions (3)	Number of w.p. firms (4)	Wastewater emissions (5)	COD emissions (6)
Downstream×EID×Post	2.844***	1.131***	0.012**	3.023***	1.237***	0.014***
	(0.690)	(0.410)	(0.005)	(0.699)	(0.417)	(0.005)
EID×Post	-0.514**	-0.355**	-0.002	-0.601**	-0.410**	-0.003
	(0.248)	(0.172)	(0.003)	(0.258)	(0.176)	(0.003)
Downstream×Post	-0.337	0.199	0.008***	-0.448	0.114	0.008**
	(0.276)	(0.193)	(0.003)	(0.290)	(0.203)	(0.003)
Observations	2700	2700	2700	2700	2700	2700
R^2	0.598	0.639	0.645	0.599	0.640	0.647
Controls	N	N	N	Y	Y	Y
County FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y

Notes: This table reports the impact of environmental information disclosure (EID) on transboundary pollution using a DDD specification (Equation 4). The sample includes 180 counties from 2001 to 2015. Each observation is a county–year combination. Controls include county-level GDP per capita (lnpgdp), total population (lnpopulation), the proportion of industrial GDP (Ind_gdp), the ratio of government expenditure to GDP (Gov), and interactions between city-level predetermined characteristics and year fixed effects. Standard errors clustered at county level are reported in parentheses. ***, **, and * denotes significance at the 1, 5, and 10 percent levels, respectively.

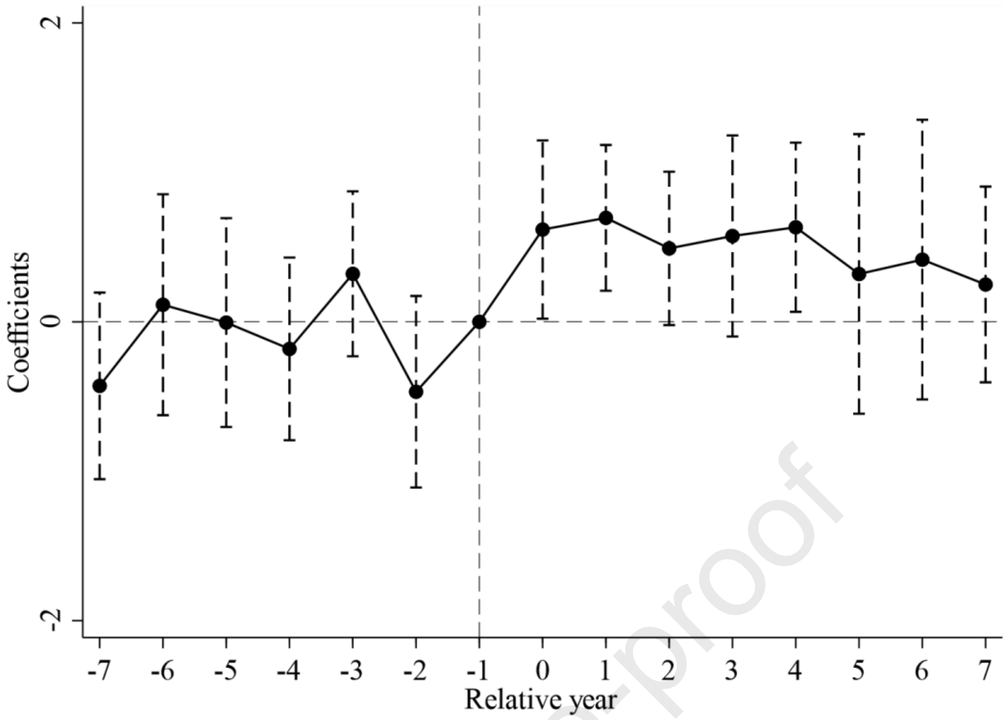
5.3 Parallel trends

To address potential concerns about pre-existing trends and to examine the dynamic effects of environmental information disclosure (EID), we adopt an event study framework based on the specification in Equation (3). Figure 2 plots the estimated coefficients of γ_k, along with their 90% confidence intervals. A pronounced increase in downstream pollution effects is observed following the implementation of EID, consistent with the baseline estimates reported in Table 3. Importantly, we find no evidence of differential pre-treatment trends in pollution outcomes between EID and non-EID cities prior to the policy, lending support to the validity of the parallel trends assumption. In addition, after the implementation of EID, the post-treatment coefficients are generally positive in magnitude, even if a small number of coefficients are not statistically significant.[4] These patterns are fully consistent with our central finding that EID exacerbates transboundary pollution. We also report the full set of event-study estimation results, including coefficient estimates and standard errors, in Appendix Table A2.

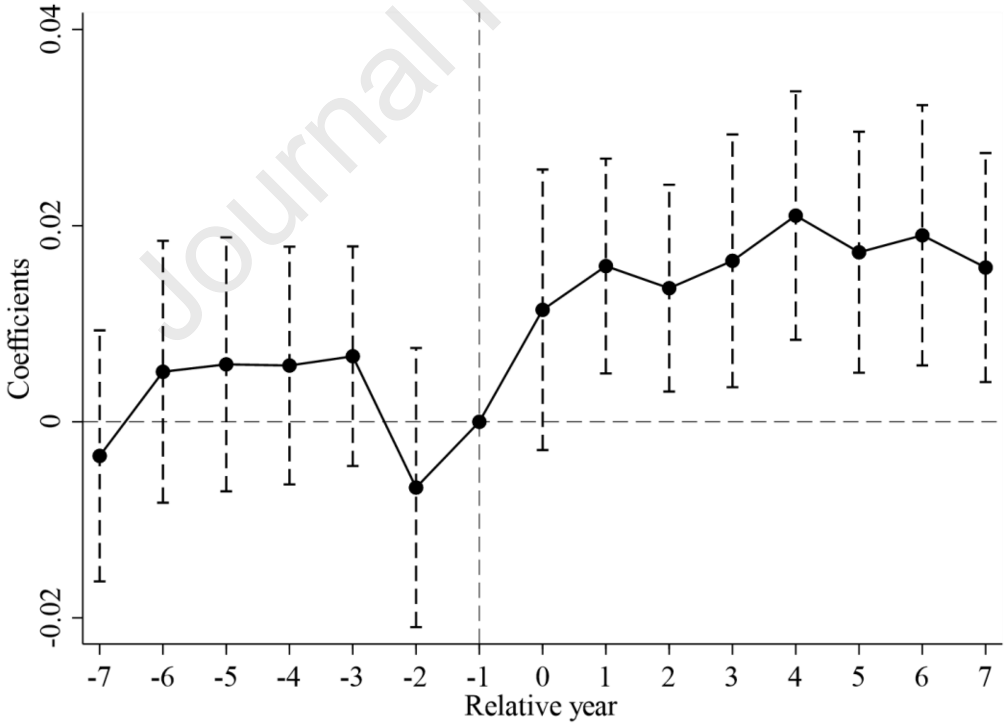


(a) Number of water-polluting firms

[4] The presence of statistically insignificant coefficients in certain post-treatment periods is not uncommon in event-study designs and may reflect increased estimation variance, or heterogeneous adjustment paths over time (Borusyak et al., 2024).



(b) Wastewater Emissions



(c) COD Emissions

Figure 2. Event-Study estimates: Impacts of EID on transboundary pollution

Notes: The figures plot the estimated coefficients and 90% confidence intervals of Equation (3). *X* axis is the year relative to the EID implementation, and relative year = −1 serves as the reference group. *Y* axis is the estimated coefficients. The sample includes

45 downstream counties from 2001 to 2015. Each observation is a county–year combination. Standard errors are clustered at county level.

5.4 Robustness checks

In this section, we conduct a series of robustness checks to validate the main results. The results remain robust and are presented in Table A3, Table A4, Figure A1 and Figure A2.

5.4.1 Instrumental variable estimation

Since 2008, environmental information has been publicly disclosed in 113 cities. The occurrence of EID events is not entirely exogenous. One key endogeneity issue with EID as the core independent variable may arise from the reverse causality between environmental quality and the choice to disclose environmental information. As environmental performance becomes a promotion criteria for local government officials, cities with better environmental quality might be more inclined to disclose environmental information to gain recognition from higher-level governments (Wu and Cao, 2021). Additionally, regions with better environmental quality are more likely to meet public demands for information disclosure, reduce public pressure, and attract human capital and financial inflows (Tian et al., 2016). If these dynamics hold, reverse causality may exist.

Another endogeneity issue may stem from the institutional nature of EID. As an informal environmental regulation policy, the effectiveness of EID in pollution control depends on the administrative governance strength of local governments. The impact of EID on transboundary pollution may be correlated with governance strength. On one hand, cities with stronger governance are more likely to disclose environmental information; on the other hand, governance strength also influences transboundary pollution outcomes. Since it is challenging to accurately measure and fully control for government strength, estimation results may be biased. There may be other omitted variables, such as the environmental awareness of government officials.

Following Hering and Poncet (2014), we adopt the ventilation coefficient as an instrumental variable (IV) for EID. The ventilation coefficient reflects the ability of air circulation to disperse pollutants, with higher ventilation leading to better dispersion and potentially reducing the concentration of local pollution. This geographic advantage is positively correlated with local environmental information disclosure. Moreover, the ventilation coefficient is exogenous to the implementation of EID policies. It is primarily determined by geographical and meteorological factors, such as topography, wind patterns, and climate, all of which are naturally occurring and independent of human activity or policy decisions (Shi and Xu, 2018). These factors are outside the control of local governments and are not influenced by political or economic considerations that typically drive EID implementation. The ventilation coefficient (VC) is defined as the product of wind speed (WS) and the height of the atmospheric boundary layer (BLH), calculated as follows:

$$VC_{c,2007} = WS_{c,2007} \times BLH_{c,2007} \tag{5}$$

The raw data is sourced from the ERA-INTERIM gridded meteorological data published by the European Centre for Medium-Range Weather Forecasts (ECMWF). Using ArcGIS software, we process this data and average it at the county level to obtain the ventilation coefficient. We use data from 2007 as it predates the implementation of EID. To construct a year-varying feature, we interact the ventilation coefficient with a dummy variable *Post* indicating whether the year is after 2008. This interaction variable is used as an instrumental variable for EID.

Table A3 reports the 2SLS results. The first-stage regression results show that the coefficient of *lnVC*× *Post* is significantly positive. The Klieibergen-Paap F statistic is 18.187, exceeding the critical value (16.38) at the 10% bias level, ruling out the weak instrument problem. Additionally, the Kleibergen-Paap rk LM statistic is 20.484, which allows us to reject the null hypothesis of under-identification. In columns (2) to (4) of Table A3, the second-stage regressions for the number of water-polluting firms, wastewater emissions, and COD emissions are presented. The coefficient of *EID*×*Post* remains positive and statistically significant. In conclusion, our findings are not severely affected by endogeneity issues.

5.4.2 Exclude the impact of other shocks

Horizontal ecological compensation policy: Horizontal ecological compensation policy refers to a collaborative approach between local governments within river basins to share the costs and benefits of ecological protection, especially for transboundary water quality management. This policy is implemented to address the challenges posed by cross-border water pollution, as it encourages cooperation among upstream and downstream regions to jointly fund and manage ecological restoration efforts. By promoting fairness and reducing negative externalities, horizontal compensation enhances the effectiveness of water quality improvements across regions, thus mitigating the adverse impacts of pollution (Ren et al., 2021). Following the approach of Yu et al. (2024), we define a dummy variable: if a city has implemented the horizontal ecological compensation policy in a given year, the variable is assigned a value of 1; otherwise, it is assigned a value of 0. After controlling for this important policy, the results can be seen in Appendix Figure A1, Panel B.

The Eleventh Five-Year Plan: The "National Total Emission Control Plan for Major Pollutants during the Eleventh Five-Year Plan" (referred to as the "Plan") proposed emission reduction targets for COD and SO_2 pollutants for each province by 2010. Local governments may strengthen environmental regulations during this period, thereby restricting the entry and pollution discharge of polluting firms. Following Pan and Fan (2021), this study incorporates the target emission reduction rates for COD and SO_2 for each province as control variables. Specifically, we include the interaction terms between the target reduction rates and year fixed effects in specification (2). The results are shown in Appendix Figure A1, Panel C.

The Global financial crisis: The 2008 global financial crisis led to instability in capital markets, disrupting business activities. To account for this, we exclude data from 2008 and 2009. The results are shown in Appendix Figure A1, Panel D. Although the magnitude of the coefficients changes slightly, the qualitative patterns of these alternative specifications remain consistent.

5.4.3 Change the estimator

One of the dependent variables—the number of water-polluting firms—contains a nontrivial number of zero values, raising concerns about potential bias in standard linear estimation. To address this, we re-estimate our baseline model using the Poisson pseudo-maximum likelihood (PPML) estimator. As shown in Appendix Figure A1 (a), Panel E, the results are qualitatively robust to this alternative estimation method.

5.4.4 Placebo test

As this study focuses on transboundary water pollution, the sample counties are defined based on rivers as geographical markers. In contrast, non-water pollutants do not propagate through rivers and therefore should not exhibit similar cross-boundary spillover effects. Consequently, if our identification strategy is valid, we should not observe any significant increase in non-water transboundary pollution following the implementation of EID. This forms the basis of a placebo test for our empirical design. Appendix Table A4 reports the estimated effects of EID on non-water transboundary pollution. The results show no significant change in the number of non-water-polluting firms in downstream counties after EID implementation. This null effect reinforces the credibility of our identification strategy.

We provide further evidence here by performing a permutation test as one of the placebo tests, following the approach of Liu et al. (2025). Our sample for identifying the impact of EID on transboundary pollution includes 45 downstream counties, each located in a distinct city. In the baseline specification (2), 17 out of these 45 cities were designated as EID pilot cities (i.e., the treatment group). To mimic this empirical setup, we randomly assign 17 cities as treated and re-estimate our baseline specification 1,000 times. If there are no differential trends in water pollution outcomes, the estimated coefficients of "*EID×Post*" should follow an approximate normal distribution centered around 0. The results, shown in Appendix Figure A2, consistently indicate no evidence of an effect in the placebo programs, further strengthening the identification assumption.

5.5 Mechanism analysis

5.5.1 Information exposure mechanism

EID differs from command-and-control and market-based instruments in both effects and mechanism. Whereas traditional regulations alter firms' feasible set through binding standards, taxes, or permits, EID alters the information environment, that is raising reputational and market exposure for local officials and firms. To empirically substantiate this mechanism, we provide evidence supporting the idea that information exposure increases the likelihood of transboundary pollution. Specifically, we argue that the effect of EID on transboundary pollution should be more pronounced in areas where information exposure is higher, such as regions with greater public environmental concerns or higher internet penetration. In these regions, the reputational risk associated with pollution within a jurisdiction is more likely to drive firms to relocate their activities across borders. We measure information exposure through three key indicators: (1) Internet penetration, which is quantified by the number of internet access subscriptions per 100 people in each county, (2) Public Environmental Concerns (PEC), which are captured using an internet search index for specific environmental keywords (Tao et al., 2023), with the detailed system of keywords available in Appendix Table A5, and (3) the presence of an environmental complaint hotline, which is measured as a binary variable indicating whether a county had an operational environmental complaint hotline in a given year (Zhou et al., 2024).[5] By utilizing these measures of information exposure, we can assess whether higher reputational visibility in certain areas amplifies the effects of EID on the relocation of polluting firms to downstream counties, thereby intensifying transboundary pollution.

Table 5 presents the results from the mechanism analysis, which tests the information exposure mechanism by incorporating interaction terms between *EID*×*Post* and various proxies for information exposure. The interaction terms *EID* × *Post* × *Internet*, *EID* × *Post* × *PEC*, and *EID* × *Post* × *Hotline* all show positive and significant coefficients in most cases, indicating that regions with higher internet penetration, greater public environmental concern, and the presence of environmental complaint hotlines experience stronger EID effects in increased pollution in downstream counties. These findings highlight in regions where reputational risks are more pronounced due to higher visibility through media, public concerns, or easily accessible complaint platforms, firms may relocate pollution to downstream areas to avoid scrutiny. Thus, higher levels of information exposure may inadvertently intensify the unintended consequences of EID, leading to cross-jurisdictional pollution displacement.

Table 5. Mechanism analysis: Verification of information exposure mechanism

	Number of w.p. firms			Wastewater emissions			COD emissions		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
EID×*Post*	0.343	1.206**	1.563**	-0.336	-0.095	0.267	0.000	0.002	0.007
	(0.799)	(0.553)	(0.738)	(0.431)	(0.341)	(0.447)	(0.005)	(0.005)	(0.005)
EID×*Post*×*Internet*	3.367**			1.691*			0.014*		
	(1.590)			(0.886)			(0.008)		
Internet	-1.246***			-0.654**			-0.010***		
	(0.426)			(0.277)			(0.004)		
EID×*Post*×*PEC*		1.678			1.164*			0.011	
		(1.181)			(0.662)			(0.007)	
EID×*Post*×*Hotline*			2.202**			1.153**			0.007
			(1.067)			(0.524)			(0.007)
Hotline			0.242			0.005			-0.004
			(0.448)			(0.300)			(0.005)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y

[5] The internet search index is based on the search volume of internet users on Baidu, using the keywords listed in Table A5 as the statistical objects, and calculating the weighted sum of the search frequencies for each keyword in Baidu's web search. This data has been publicly available since 2011. We use the 2011 cross-sectional data to measure Public Environmental Concerns.

County FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	675	675	675	675	675	675	675	675	675
R^2	0.558	0.550	0.552	0.639	0.636	0.636	0.648	0.646	0.645

Notes: This table presents test results of information exposure mechanism. The sample includes 45 downstream counties from 2001 to 2015. Each observation is a county–year combination. Controls include county-level GDP per capita (lnpgdp), total population (lnpopulation), the proportion of industrial GDP (Ind_gdp), the ratio of government expenditure to GDP (Gov), and interactions between city-level predetermined characteristics and year fixed effects. Standard errors clustered at county level are reported in parentheses. ***, **, and * denotes significance at the 1, 5, and 10 percent levels, respectively.

5.5.2 Strategic environmental regulation

In this section, we examine the underlying mechanism driving the positive effect of EID on transboundary pollution. Environmental information disclosure (EID) motivates local governments to improve environmental quality within their jurisdictions. However, as EID pressures increase, provincial governments may allocate less enforcement effort to downstream counties and encourage the concentration of polluting activities in these areas, as the perceived benefits of water pollution control diminish downstream within a province. We assess enforcement efforts in each county using the proportion of penalized non-compliant firms by local governments to the total number of industrial firms (Bu and Shi, 2021). This variable captures the stringency of local enforcement and is available for the period 2007–2015. [6]

Table 6 presents the estimated results using specification (2), offering key evidence on regulatory responses across different geographic contexts. For non-downstream counties (Column 2), the coefficient on *EID* × *Post* is positive and statistically significant at the 5% level, indicating that EID strengthens local governments' willingness to punish environmental violations. In contrast, for downstream counties (Column 1), the estimated coefficient is negative, though not statistically significant. This contrast suggests that environmental enforcement efforts do not increase in downstream counties following EID implementation—and may even weaken.

This finding confirms Hypothesis 2: local governments exhibit strategic behavior in environmental enforcement, selectively relaxing regulatory pressure in downstream counties. One plausible explanation is that downstream areas are inherently disadvantaged in inter-jurisdictional water pollution control. Because the environmental consequences of upstream pollution are externalized to downstream regions, provincial-level authorities may have weaker incentives to invest enforcement resources in downstream counties. Additionally, provincial governments might tolerate greater pollution intensity in downstream counties as a way to reconcile environmental goals with economic considerations, concentrating pollution where political or regulatory costs

[6] The list of penalized non-compliant firms is sourced from the national enterprise environmental regulation information database maintained by the Public Environmental Research Center. The total number of industrial firm in each county is obtained from the Annual Survey of Above-Scale Industrial Firms Database.

are perceived to be lower.

Table 6. Mechanism analysis: The Impact of EID on environmental enforcement efforts

	The proportion of penalized firms	
	(1) *downstream*	(2) *non*-downstream
EID×Post	-0.020	0.009**
	(0.015)	(0.005)
Controls	Y	Y
County FE	Y	Y
Year FE	Y	Y
Observations	405	1620
R^2	0.244	0.726

Notes: This table reports the impact of environmental information disclosure (EID) on environmental enforcement efforts using a two-way fixed effects (TWFE) estimator. Column (1) uses a sample of 45 downstream counties from 2007 to 2015, while Column (2) uses the sample to 135 non-downstream counties over the same period. Each observation is a county–year combination. Controls include county-level GDP per capita (lnpgdp), total population (lnpopulation), the proportion of industrial GDP (Ind_gdp), the ratio of government expenditure to GDP (Gov), and interactions between city-level predetermined characteristics and year fixed effects. Standard errors clustered at county level are reported in parentheses. ***, **, and * denotes significance at the 1, 5, and 10 percent levels, respectively.

6 Further Analysis

6.1 Firm Dynamics Analysis: Firm entry, exit, or increase in emissions of incumbent firms

Upon the disclosure of environmental information, downstream counties exhibit a higher number of water-polluting firms. This phenomenon can be effectively analyzed by categorizing firm dynamics into four distinct types: new establishment, migrating-in, migrating-out, and deregistration. Such a classification allows us to dissect firm entry and exit dynamics methodically, thereby providing comprehensive insights into the mechanisms driving the observed changes.

Newly established firms are defined explicitly as firms commencing their operations during the current year, having no prior operational presence. To accurately identify these firms, we use unique industrial firm identifiers from official databases. To mitigate measurement errors arising from potential name changes or multiple facility establishments, each newly identified firm is manually verified using data from the *China Industrial and Commercial Enterprise Registration Database* to ensure authenticity of establishment timing and location.

Migrating firms are identified as firms previously operating in a county that have moved their operations into the other county. Specifically, if a firm's location changed from county *C* in year *t*-1 to county *D* in year *t*, it is categorized as a *migrating-in firm* for county *D* and a *migrating-out firm* for county *C*. Crucially, our identification relies on firms' unique identifiers rather than firm names, thus effectively preventing the misclassification of firms that merely change their names without altering their operational locations.

*Deregistered firm*s constitute the fourth category, referring explicitly to firms that ceased operations and were deregistered in the current year. Similar to the identification of newly established firms, each deregistration is carefully validated through the *China Industrial and Commercial Enterprise Registration Database* to ensure that the firm indeed terminated its operations and is not misclassified due to data inconsistencies or name changes.

By rigorously distinguishing these four types of firm movements, our approach systematically captures the nuances of firm dynamics. To investigate this, we compile data on the annual number of newly established firms, relocation-in firms, relocation-out firms and deregistered firms in each county. Our methodology allows us to identify the specific contribution of each type of firm movement to the overall increase in water pollution in downstream counties. Table 7, columns (1)–(4), present the impact of EID on firm dynamics. We find that, after the introduction of EID, the number of newly established polluting firms in downstream counties increased significantly by 1.282, on average, relative to the pre-policy period. Similarly, the number of migrating-in firms rose by 0.877, indicating a notable influx of firms relocating to downstream counties. These results are both statistically and economically significant, and align with the "pollution haven" hypothesis, suggesting that polluting firms tend to relocate to areas with looser enforcement, particularly those downstream where regulatory incentives are weaker due to transboundary externalities. In contrast, the number of migrating-out firms remains statistically unchanged, and the number of deregistered firms declines, though not significantly. These patterns suggest that downstream counties not only attracted new and relocating firms, but also retained existing ones at higher rates.

To further disentangle the contribution of incumbent firms to pollution outcomes, we examine whether existing firms—those already operating in downstream counties before EID—contributed to the observed rise in emissions. Columns (5) and (6) of Table 7 present the results using aggregate emissions from incumbent firms as the dependent variable. The coefficient of *EID×Post* is statistically insignificant for both industrial wastewater and COD emissions, and its magnitude is substantially smaller compared to the baseline estimates. These results suggest that incumbent firms have not substantially increased their pollution levels following the implementation of EID. In other words, the surge in transboundary pollution is not driven by existing firms becoming dirtier, but rather by the entry and relocation of water-polluting firms into downstream areas, where regulatory stringency is lower due to spatial enforcement asymmetries.

In conclusion, the principal driver of the worsening transboundary pollution following the disclosure of environmental information is the establishment and migration of water-polluting firms into downstream counties.

Table 7. Mechanism analysis: Decomposition of the causes of transboundary pollution

	Number of newly established firms	Number of migrating-in	Number of migrating-out	Number of deregistered firms	Wastewater emissions	COD emissions

	firms	firms			
	(1)	(2)	(3)	(4)	(5)	(6)

	(1)	(2) firms	(3) firms	(4)	(5)	(6)
EID×*Post*	1.282***	0.877***	0.001	-0.067	0.038	0.001
	(0.328)	(0.249)	(0.010)	(0.062)	(0.051)	(0.001)
Controls	Y	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	675	675	675	675	675	675
R^2	0.519	0.598	0.193	0.378	0.467	0.446

Notes: This table reports the impact of environmental information disclosure (EID) on firm location choices using a two-way fixed effects (TWFE) estimator. The sample includes 45 downstream counties from 2001 to 2015. Each observation is a county–year combination. Controls include county-level GDP per capita (lnpgdp), total population (lnpopulation), the proportion of industrial GDP (Ind_gdp), the ratio of government expenditure to GDP (Gov), and interactions between city-level predetermined characteristics and year fixed effects. Standard errors clustered at county level are reported in parentheses. ***, **, and * denotes significance at the 1, 5, and 10 percent levels, respectively.

6.2 Heterogeneity Analysis

The impact of EID may differ between heavily polluting counties and moderately polluting counties. In the former, local governments and firms already face stronger regulatory pressure, possibly from more frequent inspections, greater media attention, and stricter enforcement. In this context, heavily polluted downstream counties are less likely to attract new polluting firms or facilitate the relocation of existing ones, because the visibility of pollution and associated reputational costs are higher. Instead, firms may choose to relocate pollution to moderately polluting counties, where the regulatory environment is comparatively weaker and the reputational risk is lower.

To explore this hypothesis, we conduct an additional heterogeneity analysis by dividing the sample of downstream counties into two groups: heavily polluting and moderately polluting counties. Pollution levels are measured using a composite pollution index, which includes industrial wastewater emissions and COD emissions, calculated through the entropy method. We then split the sample based on the median pollution level from the previous year, creating a dummy variable to identify whether a county falls into the heavily polluting group. This dummy variable is incorporated as an interaction term with the core independent variables to test for heterogeneity in the effects of EID. The results, presented in Table 8, show that the coefficient for *EID* × *Post* × *Heavily Polluting* is negative significantly, indicating that the transboundary pollution effects of EID are weaker in heavily polluting counties. In other words, the effects of EID on transboundary pollution are more pronounced in moderately polluting counties.

This finding provides valuable insight into the dynamic relationship between EID and transboundary pollution. It suggests that in regions already under significant pollution-related scrutiny, EID may not exacerbate cross-jurisdictional pollution, as the regulatory pressure and reputational risks limit firms' ability to relocate pollution. Conversely, in moderately polluting counties, the reduced scrutiny and lower regulatory pressure create a context where EID can lead to greater pollution relocation, thereby intensifying the transboundary pollution problem.

Table 8. Heterogeneous effects of EID by pollution levels

	Number of w.p. firms	Wastewater emissions	COD emissions
	(1)	(2)	(3)
EID×Post	4.033***	1.419***	0.017***
	(0.819)	(0.464)	(0.005)
EID×Post×Heavily Polluting	-5.773***	-2.716***	-0.029***
	(1.077)	(0.576)	(0.006)
Controls	Y	Y	Y
County FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	630	630	630
R^2	0.593	0.666	0.687

Notes: This table tests the heterogeneity effect of environmental information disclosure (EID). The sample includes 45 downstream counties from 2002 to 2015. Each observation is a county–year combination. Controls include county-level GDP per capita (lnpgdp), total population (lnpopulation), the proportion of industrial GDP (Ind_gdp), the ratio of government expenditure to GDP (Gov), and interactions between city-level predetermined characteristics and year fixed effects. Standard errors clustered at county level are reported in parentheses. ***, **, and * denotes significance at the 1, 5, and 10 percent levels, respectively.

7. Conclusions and Discussions

Environmental Information Disclosure (EID) has become a vital tool for environmental protection. How governments and firms respond to EID has become a topic of academic attention. This study examines the effects of EID from the perspective of pollution transfer. Using DID and DDD identification strategy, we identify the positive effect of EID on transboundary pollution. Specifically, following the implementation of EID, water-polluting activities notably surge in the most downstream counties of a province. Our evidence reveals strategic pollution behavior, with local governments in downstream counties responding by adopting more lenient environmental regulations, which inadvertently facilitate the relocation of polluting industries. This policy shift has led to an increase in the establishment of new water-polluting firms in these downstream counties, as well as the migration of existing polluting firms from other counties to the downstream areas.

The primary objective of Environmental Information Disclosure (EID) is to promote transparency and reduce pollution. However, our findings reveal a critical unintended consequence: without carefully accounting for local governments' strategic responses, EID may inadvertently distort the spatial distribution of pollution. To address these unintended consequences, particularly the strategic transboundary relocation of pollution, governments should implement the following specific measures: First, leverage comprehensive environmental monitoring and reporting systems to accurately track and disclose pollution movements. Governments should mandate firms to publicly report their pollution activities with spatially detailed data on relocations, expansions, and emission levels across jurisdictions. Enhanced transparency and detailed spatial reporting will deter strategic behavior by making it more difficult for firms to conceal environmentally harmful activities and for local governments to overlook or facilitate such practices. Second, strengthen institutional accountability by conducting periodic environmental performance evaluations specifically targeting local governments. These evaluations should explicitly incorporate metrics related to regional environmental outcomes, particularly pollution displacement effects resulting from strategic responses to EID policies. Linking these performance assessments directly to fiscal transfers or administrative incentives will incentivize local governments to proactively prevent pollution relocation rather than passively permitting it. Third, establish a coordinated inter-regional regulatory framework that incorporates EID practices explicitly focused on cross-boundary pollution monitoring and control. Such coordination would enable unified standards and simultaneous public disclosure of pollution data, effectively limiting the potential for regulatory arbitrage across neighboring regions.

While our study focuses on China’s EID policy, its findings have important implications beyond the Chinese context. The unintended consequence of transboundary pollution due to strategic pollution relocation is a concern for countries with growing efforts to implement transparency-based environmental policies. In particular, emerging economies that are adopting EID-like mechanisms can benefit from our insights on the potential spatial displacement of pollution such as those in Latin America, Africa, and South Asia (Fontaine et al., 2022; Kilincarslan et al., 2020; Tran et al., 2021). Our study highlights the need for comprehensive policy frameworks that combine transparency with direct regulation to avoid unintended cross-border pollution effects and ensure the equitable distribution of environmental benefits across regions.

Our study faces some limitations that should be addressed in future research. Firstly, the wastewater and COD emissions at the county level are estimated by data from micro-industrial firms, potentially underestimating actual emissions. Future research should improve the precision of water pollution emissions data at the county level to mitigate these measurement errors and provide a more accurate picture of the pollution dynamics. Secondly, our study primarily focused on data from large industrial enterprises, overlooking the potential role of smaller firms that may also contribute to transboundary pollution. Future research should adopt a more comprehensive approach that includes a wider range of firms, particularly smaller ones with high pollution potential, to provide a clearer understanding of the relationship between environmental information disclosure and transboundary pollution. Finally, our study focuses on the Chinese context, which may limit the generalizability of the findings to other countries with different governance structures, institutional settings, or levels of industrialization. To address this, future research could conduct comparative studies across countries that have also implemented EID practices.

Declaration of competing interest

No potential conflict of interest was reported by the authors.

Data availability

The data will be made available on request.

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Appendix

Table A1. Balancing test

Variables	Downstream counties (Obs.=45)	Non-downstream counties (Obs.=135)	Statistical Difference
	(1)	(2)	(3)
Administrative region land area (square kilometers)	3860.467	2978.622	881.844
	(829.199)	(569.597)	(1475.592)
Total population (ten thousand people)	49.111	47.378	1.733
	(6.136)	(2.641)	(5.781)
Proportion of value added by the secondary industry (%)	42.471	41.275	1.196
	(1.703)	(2.553)	(3.299)
Proportion of value added by the tertiary industry (%)	37.653	37.923	-0.270
	(2.142)	(2.045)	(3.755)
GDP per capita (CNY)	17303	17754	-450
	(2573)	(1412)	(2861)
Fiscal revenue (ten thousand CNY)	32197	36504	-4306
	(7432)	(5396)	(10291)
Fiscal expenditure (ten thousand CNY)	63527	73178	-9651
	(6138)	(5866)	(10772)
Balance of loans from financial institutions / GDP	0.487	0.421	0.066*
	(0.054)	(0.028)	(0.040)
Number of hospital and health center beds (beds)	939.800	905.682	34.119
	(117.484)	(54.978)	(116.837)
Number of social welfare adoption units (units)	16.644	14.763	1.881
	(3.290)	(1.325)	(2.976)
Average slope (degrees)	11.964	12.193	-0.230
	(0.986)	(0.528)	(1.075)
Terrain undulation degree	1.246	1.041	0.205
	(0.236)	(0.108)	(0.231)

Notes: This table tests whether there are significant differences between downstream counties and the control group. The data represents cross-sectional data for 180 counties from 2007. The choice of 2007 data is because it was the year prior to the EID policy, meeting the predetermined criteria. Values in parentheses in the first two columns represent standard deviations, and those in the third column represent the standard errors from the T-test.

Table A2. Event-Study estimation results

	Number of w.p. firms	Wastewater emissions	COD emissions
	(1)	(2)	(3)
EID×Year2001	-0.433	-0.429	-0.003
	(0.812)	(0.381)	(0.008)
EID×Year2002	-0.284	0.114	0.005
	(0.824)	(0.451)	(0.008)
EID×Year2003	0.035	-0.005	0.006
	(0.806)	(0.426)	(0.008)
EID×Year2004	-0.138	-0.181	0.006
	(0.812)	(0.373)	(0.007)
EID×Year2005	-0.186	0.321	0.007
	(0.742)	(0.337)	(0.007)
EID×Year2006	-0.273	-0.468	-0.007
	(0.690)	(0.391)	(0.009)
EID×Year2008	1.688*	0.618*	0.011
	(0.906)	(0.364)	(0.009)
EID×Year2009	0.947**	0.696**	0.016**
	(0.464)	(0.297)	(0.007)
EID×Year2010	1.075*	0.491	0.014**
	(0.573)	(0.313)	(0.006)
EID×Year2011	0.878	0.574	0.016**
	(0.893)	(0.410)	(0.008)
EID×Year2012	1.554*	0.633*	0.021***
	(0.895)	(0.345)	(0.008)
EID×Year2013	1.397	0.320	0.017**
	(0.901)	(0.569)	(0.007)
EID×Year2014	1.579*	0.416	0.019**
	(0.946)	(0.571)	(0.008)
EID×Year2015	1.313	0.250	0.016**
	(0.856)	(0.399)	(0.007)
Controls	Y	Y	Y
County FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	675	675	675
R^2	0.559	0.637	0.647

Notes: This table reports the dynamic effects of environmental information disclosure (EID) on transboundary pollution. The sample includes 45 downstream counties from 2001 to 2015. Each observation is a county–year combination. Year_t denotes a dummy variable for year *t*, with Year2007 serving as the reference group. Controls include county-level GDP per capita (lnpgdp), total population (lnpopulation), the proportion of industrial GDP (Ind_gdp), the ratio of government expenditure to GDP (Gov), and interactions between city-level predetermined characteristics and year fixed effects. Standard errors clustered at county level are reported in parentheses. ***, **, and * denotes significance at the 1, 5, and 10 percent levels, respectively.

Table A3. Results of instrumental variable estimation

	EID×Post	Number of w.p. firms	Wastewater emissions	COD emissions
	(1)	(2)	(3)	(4)
EID×Post		5.372*	2.970*	0.021*
		(3.202)	(1.800)	(0.013)
lnVC×Post	0.234***			
	(0.055)			
Kleibergen-Paap rk LM statistic		20.484***	20.484***	20.484***
Kleibergen-Paap rk Wald F statistic		18.187	18.187	18.187
Controls	Y	Y	Y	Y
County FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	675	675	675	675

Notes: This table reports the impact of environmental information disclosure (EID) on transboundary pollution using IV estimation. The sample includes 45 downstream counties from 2001 to 2015. Each observation is a county–year combination. Controls include county-level GDP per capita (lnpgdp), total population (lnpopulation), the proportion of industrial GDP (Ind_gdp), the ratio of government expenditure to GDP (Gov), and interactions between city-level predetermined characteristics and year fixed effects. Standard errors clustered at county level are reported in parentheses. ***, **, and * denotes significance at the 1, 5, and 10 percent levels, respectively.

Table A4. The impact of EID on non-water transboundary pollution

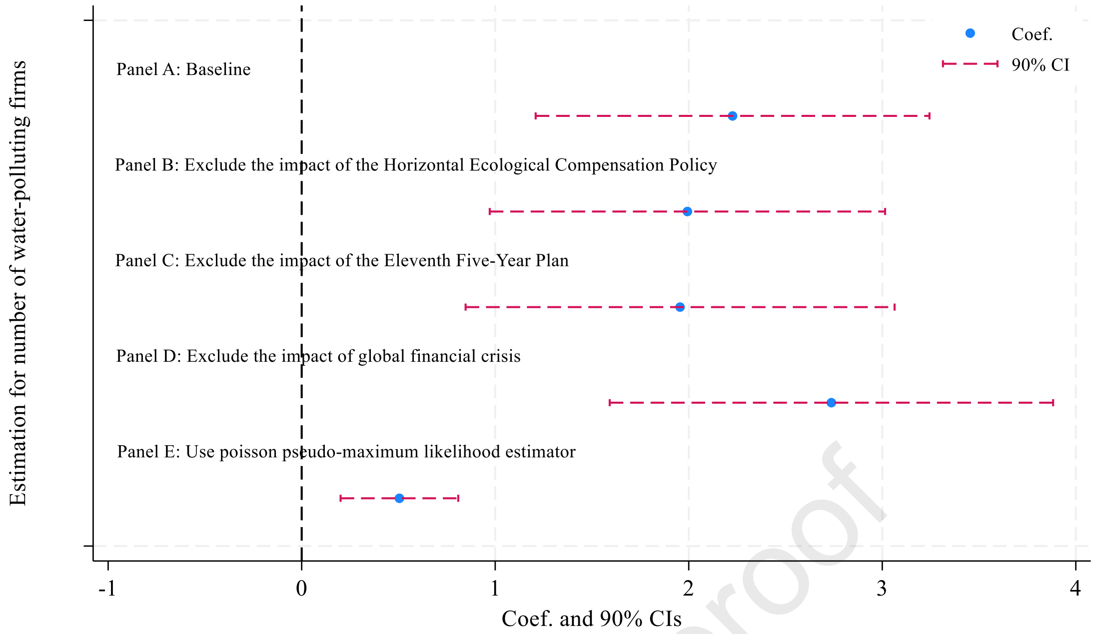
	Number of non-water-polluting firms	
EID	0.123	-0.212
	(0.559)	(0.531)
Controls	N	Y
County FE	Y	Y
Year FE	Y	Y
Observations	675	675
R^2	0.663	0.673

Notes: This table reports the impact of environmental information disclosure (EID) on non-water transboundary pollution using a two-way fixed effects (TWFE) estimator. The sample includes 45 downstream counties from 2001 to 2015. Each observation is a county–year combination. Controls include county-level GDP per capita (lnpgdp), total population (lnpopulation), the proportion of industrial GDP (Ind_gdp), the ratio of government expenditure to GDP (Gov), and interactions between city-level predetermined characteristics and year fixed effects. Standard errors clustered at county level are reported in parentheses. ***, **, and * denotes significance at the 1, 5, and 10 percent levels, respectively.

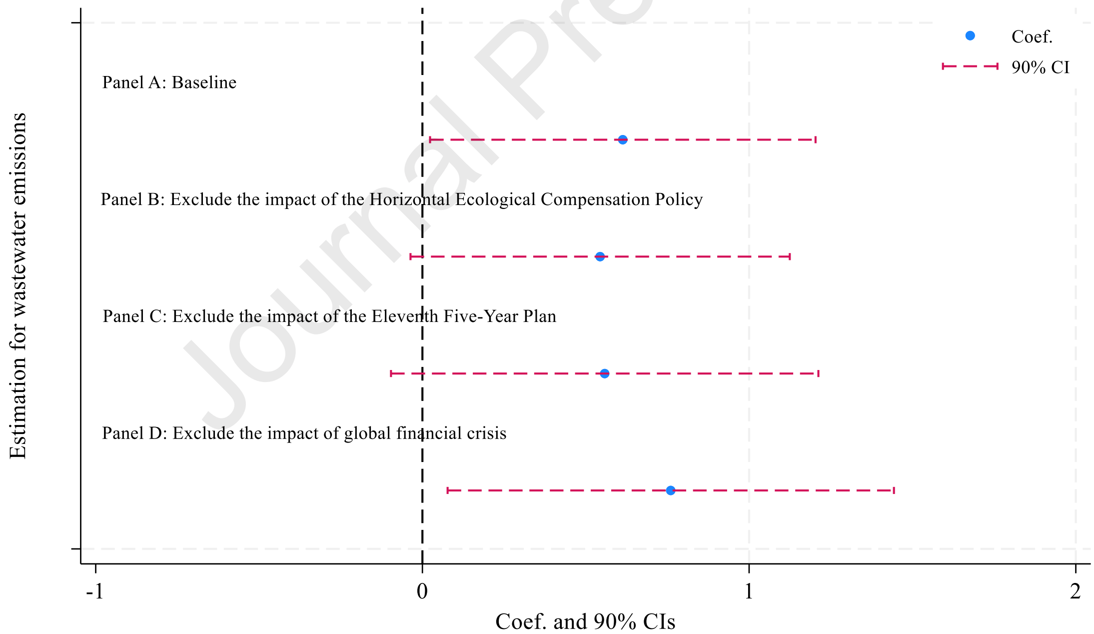
Table A5. Public environmental concern index indicator system

Index	Dimension	Keywords
Public environmental concern	environmental pollutants	sulfur dioxide, carbon dioxide, acid rain, sewage, haze, PM2.5
	environmental awareness	low carbon, environmental protection, environmental protection, clean energy
	environmental perception	pollution, environmental pollution, air quality, green space, greening, global warming, greenhouse effect
	environmental goals	ecological civilization, green ecology, sustainable development
	environmental protection measures	recycling, emission reduction, water saving, decontamination, disposal of sewage

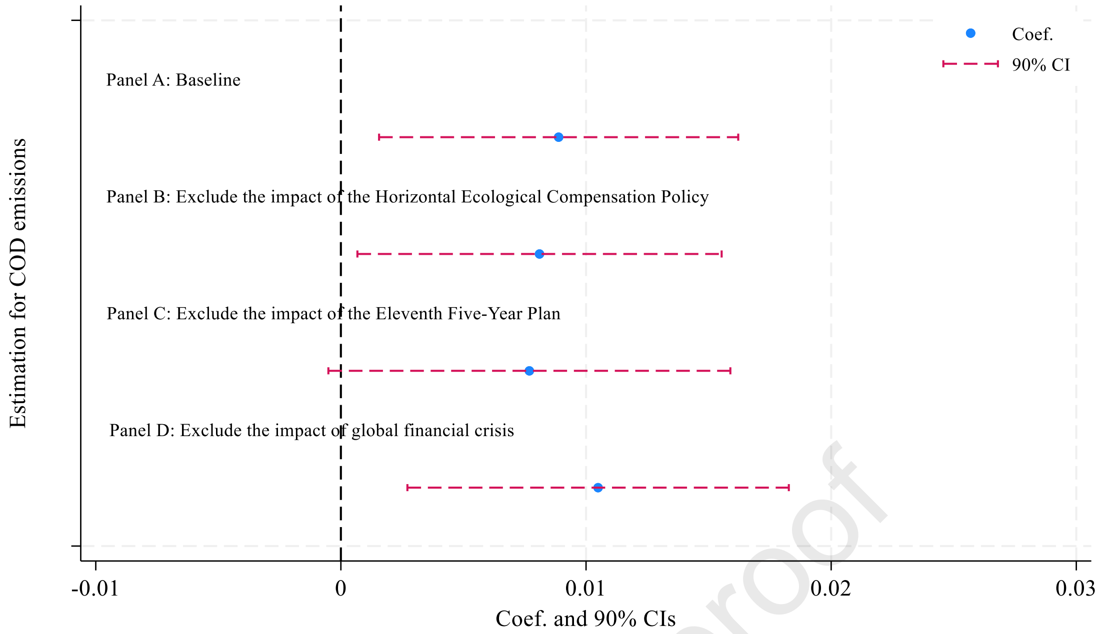
Note: This table shows the indicator system of the public environmental concern Index.



(a) Number of water-polluting firms



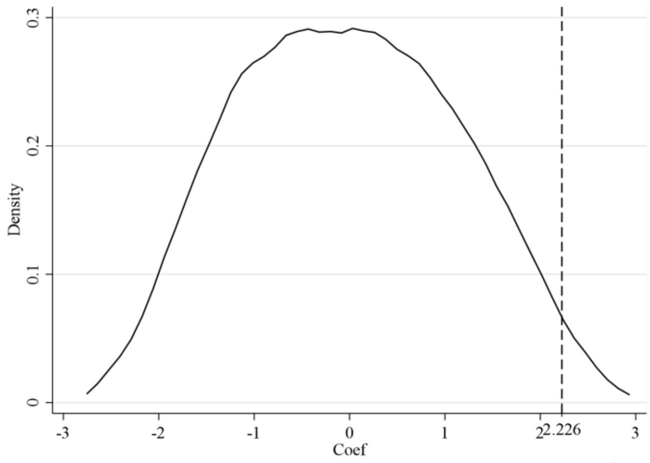
(b) Wastewater emissions



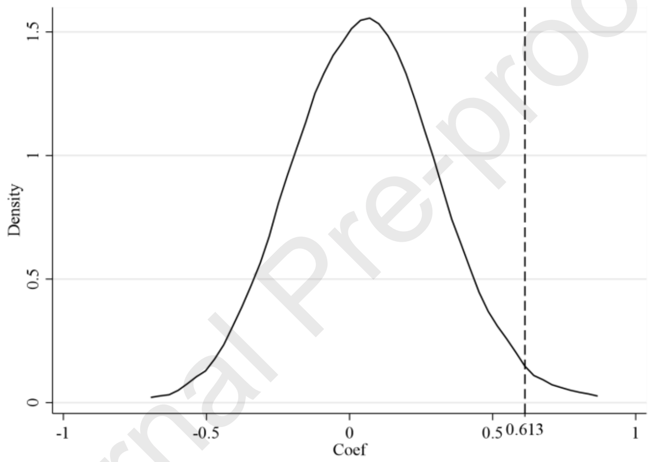
(c) COD emissions

Figure A1. Robust checks: The effects of EID on transboundary pollution in different specifications

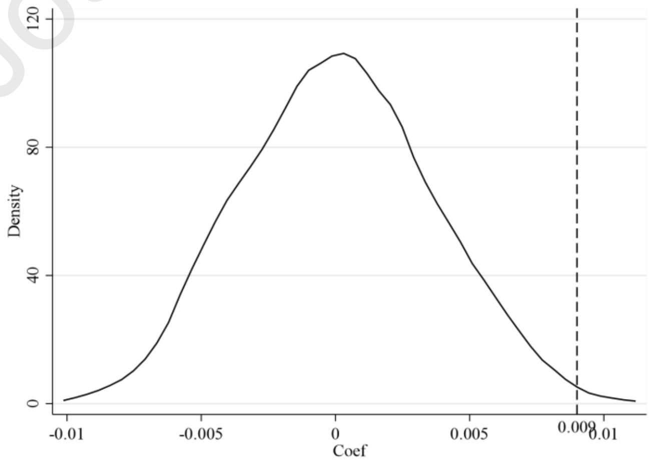
Notes: The sample includes 45 downstream counties from 2001 to 2015. All regressions control for county fixed effects, year fixed effects, county-level controls and interactions between city-level predetermined characteristics and year fixed effects. Panel A presents the baseline results. Panel B additionally controls for the Horizontal Ecological Compensation Policy. Panel C additionally controls for the interaction terms between the target reduction rates of pollutants and year fixed effects. Panel D drop the sample from 2008 and 2009. Panel E, only in figure (a), use poisson pseudo-maximum likelihood estimator. The dashed vertical line represents a regression coefficient of zero. Standard errors are clustered at county level.



(a) Number of water-polluting firms



(b) Wastewater emissions



(c) COD emissions

Figure A2. Placebo Test

Notes: The figure plots the placebo test results conducted with 1000 permutations of the EID and non-EID cities. The sample includes 45 downstream counties from 2001 to 2015. All regressions control for county fixed effects, year fixed effects, county-level controls and interactions between city-level predetermined characteristics and year fixed effects.

Highlights

- China is encountering cross-provincial border water pollution challenges.
- Environmental information disclosure exacerbates transboundary pollution.
- Transboundary pollution arises from firm relocation and the establishment of new firms, rather than from excessive emissions by existing firms.
- The enforcement of environmental penalties is lenient in the downstream counties.

Author Statement

Zengdong Cao: Conceptualization; Data curation; Investigation; Methodology; Project administration; Software; Validation; Visualization; Writing – original draft; Writing – review and editing

Jun Liu: Conceptualization; Formal analysis; Investigation; Resources; Validation; Writing – original draft; writing – review and editing

Drew Woodhouse: Conceptualization; Investigation; Methodology; Project administration; Supervision; Validation; Writing – original draft; Writing – review and editing; Formal analysis