Integrating Quantity and Quality: Evidence from Water Rights Trading's Dual Policy Effects on Water-Use Efficiency and Water Environmental Quality

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Abstract

China's water governance confronts concurrent pressures of water scarcity and pollution, yet evidence on whether market-oriented water rights trading (WRT) policies improve water outcomes remains limited. This study examines the dual dimensions of water—quantity and quality—by estimating the causal impacts of WRT pilots on water-use efficiency and water environmental quality. Drawing on both nationally mandated and locally initiated WRT pilots, we compile a panel of 31 provinces spanning 2003 to 2023 and employ a difference-in-differences (DID) design and synthetic control methods (SCM). The analysis yields four key findings:

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(1) the implementation of WRT policy significantly increases water-use efficiency, with an average increase of 25.6%; (2) although DID analyses do not consistently detect national-level effects on water quality, the SCM analyses identify notable improvements in a subset of pilot provinces; (3) further analysis indicates that efficiency improvements are more pronounced in central and northern provinces and in provinces with higher levels of marketization; and (4) the mechanism analysis suggests that efficiency improvements are mainly achieved through optimization of water-use structure, while water quality enhancements are primarily via strengthened governance intensity. By integrating analyses of water efficiency and quality outcomes, this study reframes WRT as a two-dimensional policy instrument, highlighting its potential to reconcile development and environmental goals in water governance.

Keywords: Water rights trading, water-use efficiency, water environmental quality, water markets, policy pilots

Integración de cantidad y calidad: evidencia de los efectos duales de la política de comercio de derechos de agua sobre la eficiencia del uso del agua y la calidad ambiental del agua

Resumen

La gobernanza del agua en China se enfrenta a presiones concurrentes de escasez y contaminación hídrica, pero la evidencia sobre si las políticas de comercio de derechos de agua (WRT) orientadas al mercado mejoran los resultados hídricos sigue siendo limitada. Este estudio examina la doble dimensión del agua (cantidad y calidad) estimando los impactos causales de los proyectos piloto de WRT en la eficiencia del uso del agua y la calidad ambiental del agua. Basándonos en proyectos piloto de WRT tanto exigidos a nivel nacional como iniciados a nivel local, compilamos un panel de 31 provincias que abarcan el período 2003-2023 y empleamos un diseño de diferencias en diferencias (DID) y métodos de control sintéticos (SCM). El análisis arroja cuatro hallazgos clave: (1) la implementación de la política de WRT aumenta significativamente la eficiencia del uso del agua, con un aumento promedio del 25,6%; (2) aunque los análisis DID no detectan de manera consistente efectos a nivel nacional en la calidad del agua, los análisis SCM identifican mejoras notables en un subconjunto de provincias piloto; (3) un análisis más detallado indica que las mejoras de eficiencia son más pronunciadas en las provincias centrales y septentrionales y en las provincias con mayores niveles de mercantilización; y (4) el análisis de mecanismos sugiere que las mejoras en la eficiencia se logran principalmente mediante la optimización de la estructura del uso del agua, mientras que las mejoras en la calidad del agua se logran principalmente mediante el fortalecimiento de la intensidad de la gobernanza. Al integrar los análisis de los resultados de eficiencia y calidad del agua, este estudio replantea la gestión del agua como un instrumento de política bidimensional, destacando su potencial para conciliar los objetivos de desarrollo y ambientales en la gobernanza del agua.

Palabras clave: Comercio de derechos de agua, eficiencia en el uso del agua, calidad ambiental del agua, mercados del agua, políticas piloto

整合量与质：水权交易对用水效率与水环境质量的双重政策影响证据

摘要

中国水治理正同时面临水资源短缺和水环境污染的双重压力，然而，关于市场导向的水权交易（WRT）政策能否改善水治理绩效的经验证据仍然有限。本研究从水资源的量质双重属性出发，评估水权交易试点对水资源利用效率与水环境质量的因果影响。基于国家主导和地方自主发起的水权交易试点，研究构建了覆盖2003至2023年间31个省份的面板数据，并采用双重差分（DID）设计和合成控制法（SCM）进行分析。研究得出四点主要结论：（1）水权交易政策的实施显著提升了水资源利用效率，平均增幅约为25.6%；（2）尽管DID分析未能识别出该政策对水质的全国范围内的影响，但SCM分析发现在部分试点省份中出现明显的水质改善效果；（3）进一步分析表明，用水效率的提升在中部和北部省份以及市场化程度较高的省份中更为显著；（4）机制分析表明，用水效率提升主要通过用水结构的优化实现，而水质改善则主要归因于水治理强度的增强。通过同时考察水权交易政策对用水效率与水质量的影响，研究将水权交易重新界定为一种兼具经济与环境双重功能的政策工具，凸显了其在水治理中统合发展与环境目标的潜力。

关键词：水权交易；用水效率；水环境质量；水市场；政策试点

1. Introduction

Water governance in China is increasingly challenged by the interplay of physical scarcity, deteriorating water quality, and uneven exposure to environmental risks (Dou and Wang 2016; Wang 2017). Existing evidence shows that water pollution compounds the problem of scarcity and exacerbates regional disparities (Ma et al. 2020), highlighting that "quality" is not ancillary to "quantity" but is a co-equal attribute of water resources that shapes allocative outcomes. Addressing these challenges calls for the development of innovative policy tools that are adaptive to dynamic watershed conditions. Water rights trading (WRT), as a market-oriented mechanism (Zhang et al. 2021), provides a potential pathway forward. At its core, WRT establishes property rights that are clearly defined, transferable, and enforceable, thus enabling water to be allocated more efficiently toward higher-valued uses (Matthews 2004; Rosegrant and Binswanger 1994; Vaux Jr. and Howitt 1984). Since the 1980s, various Western countries, including Australia (Bischoff-Mattson and Lynch 2016; Wheeler et al. 2014), Chile (Hearne and Easter 1997), and the United States (Brookshire et al. 2004; Debaere et al. 2014), have implemented WRT. Lessons drawn from these international experiences underscore the potential for WRT to address both water scarcity and pollution (Boretti and Rosa 2019).

Within the context of China, the initiation of WRT can be traced back to the "millennium debate" over the legal and institutional frameworks for managing and utilizing water resources (Wang 2017). In its initial stage, however, WRT lacked a formalized and comprehensive trading system, which limited both its reach and effectiveness (Jia et al. 2016). This began to change in 2014, when the central government launched a series of pilot reforms under top-down national initiatives (Zhang et al. 2021; 2025). In parallel, several local governments initiated bottom-up local pilots, resulting in a staggered rollout across provinces at different times. Implemented in 10 provinces, these pilots have gradually institutionalized key components such as rights confirmation, allocation, and trading mechanisms, laying the foundation for a national water-rights system. The non-simultaneous adoption across provinces provides a quasi-natural experimental setting to evaluate the socioeconomic and environmental effects of WRT—for instance, its influence on rural household income and water-use efficiency (Zhang et al. 2025; 2021; Yan et al. 2024).

Previous literature has underscored the efficiency rationale behind tradable water rights, emphasizing their potential to reallocate water across sectors and regions as a means to mitigate scarcity (Matthews 2004; Vaux Jr. and Howitt 1984). In the Chinese context, recent empirical studies have linked WRT and related reforms to outcomes such as irrigation savings, industrial development, and changes in farmers' behavior. However, these studies tend to conceptualize "policy success" primarily in quantity terms—such as volumes of water saved, gains in productivity, or reported conservation intentions—while paying relatively little attention to the impacts on water environmental quality (Su and Fu 2024; Zhang et al. 2021). Concurrently, modeling research has begun to integrate both quantity and quality, revealing that optimal water allocation is often constrained by water quality considerations. These studies show that pricing and trading rules that ignore pollution dynamics risk misallocating the resource (Martinsen et al. 2019; Ward and Pulido-Velazquez 2008). In response, institutional and market designs have been proposed that reconceptualize water rights as multi-dimensional instruments, combining volumetric entitlements with water quality attributes or compliance obligations. Such frameworks have been advanced for basin-level allocation (Wang et al. 2020) and for "two-dimensional" trading systems that incorporate risk and pollution externalities into pricing mechanisms (Di et al. 2020).

Yet despite these theoretical and modeling contributions, empirical evaluations quantifying the effects of WRT adoption on water quality remain scarce. Moreover, a limitation in prior empirical studies concerns the definition of policy treatment. While some studies code only the seven nationally designated pilots launched in 2014 as adopters (e.g., Zhang et al. 2025; Yan et al. 2024), others take a broader approach, including provinces with only nominal or limited WRT activity (e.g., Zhang et al. 2021). Addressing these gaps, we therefore reconstruct a province-level chronology of WRT pilot implementation and ask: whether, how, and to what extent the WRT adoption affects provincial water-use efficiency and water environmental quality?

To answer these questions, we assemble a panel covering 31 mainland provinces from 2003 to 2023, identify both centrally designated and locally initiated WRT pilots, and estimate causal effects using a staggered DID design complemented by province-specific Synthetic Control Methods (SCM) case studies. This mixed-method approach allows us to isolate average policy effects while also detecting province-specific impacts that a single pooled estimator might overlook. The analysis yields four main findings. First, WRT adoption is associated with sizable and statistically robust improvements in water-use efficiency, with an estimated 25.6% increase relative to the counterfactual. Second, the aggregate national effects on water quality are not uniform; the SCM results reveal clear post-adoption quality improvements in a subset of pilot provinces. Third, efficiency gains are more pronounced in central and northern provinces and in provinces with higher marketization. Fourth, the mechanism analysis demonstrates that efficiency improvements stem from the optimization of water-use structures—as WRT reallocates water from agriculture toward higher-value industrial and urban uses—while water-quality gains arise primarily via strengthened governance intensity, reflected in increased capital investment and spending on wastewater treatment facilities.

Taken together, this study makes at least four contributions. First, conceptually, we recast WRT as a two-dimensional policy instrument, in which the object of exchange is inherently composite—encompassing quantity and quality. This framing highlights the need for market transactions to be embedded within regulatory frameworks that align private trading behavior with environmental standards (Martinsen et al. 2019; Z. Wang et al. 2020; Ward and Pulido-Velazquez 2008). Second, empirically, we employ a quasi-experimental design to estimate the causal effects of WRT adoption on both water-use efficiency and ambient water quality, thereby extending a literature that has largely focused on conservation outcomes (Zhang et al. 2021). Third, methodologically, we bridge top-down and bottom-up pilots and exploit staggered rollout of WRT pilots across provinces. By combining DID with SCM methods, we reduce the risk of scope bias and capture province-specific water quality dynamics that would otherwise remain hidden in pooled estimation. Finally, for policy practitioners, our findings suggest that scaling up WRT to meet both efficiency and environmental objectives requires moving beyond a narrowly defined "volume-only" approach toward more integrated designs that account for water quality externalities. Overall, this study contributes to broader debates around the instrument choice versus policy mixes in complex water governance systems (Heikkila 2017; Whitford and Clark 2007).

2. Literature Review and Hypotheses

2.1 Literature Review

WRT is a market-based allocation instrument built on clearly defined, enforceable use rights and transferable entitlements that move scarce water toward higher marginal value uses via price signals (Matthews 2004; Vaux Jr. and Howitt 1984). Water rights, in this context, refer to the legal authorization to access and utilize water (Wurbs Ralph A. 1995). The conceptual foundation of introducing market mechanisms into water allocation has evolved since the 1980s, with the United States, Australia, and Chile pioneering formal markets (Hearne and Easter 1997; Poirier and Schartmueller 2012; Simpson and Ringskog 1997). Water markets have since become institutionalized in these countries—albeit under differing legal doctrines and regulatory frameworks—demonstrating varied institutional paths to tradability (Brookshire et al. 2004; Debaere et al. 2014; Grafton et al. 2011; Hearne and Easter 1997; Wheeler et al. 2014; Zeff Harrison et al. 2019). Doctrinally, legal systems governing water rights generally fall into three broad categories: riparian rights, prior appropriation, and public allocation. China represents the public allocation model, where water rights are granted through administrative permits under a regime of public ownership (Di et al. 2020; Wang Lizhong et al. 2007; Wang 2017).

Beyond allocation volume, the literature increasingly recognizes that water rights encompass both quantity and quality dimensions (Wang et al. 2020; Ward and Pulido-Velázquez 2008). Quantity rights specify the allowable volume of water withdrawals or deliveries, whereas quality constraints determine the usable portion of that volume, depending on ambient pollution levels and regulatory standards. Recent studies have advanced two-dimensional policy designs that jointly allocate withdrawal rights and pollutant discharge allowances within basin-level regimes. These designs frequently incorporate penalty-backed rules that curtail withdrawal entitlements when discharges exceed prescribed caps, thereby internalizing quality externalities into the same decision-making framework that governs volumetric use (Wang et al. 2022; Z. Wang et al. 2020). Basin optimization models that integrate surface and groundwater interactions along with environmental constraints further illustrate how tightening quality standards alters feasible allocations (Martinsen et al. 2019) — such as in the Rio Grande (Ward and Pulido-Velázquez 2008). In China, the shift in water governance from infrastructure-dominated paradigm to a management-focused approach, and the integration of allocation with pollution control, reflects an institutional embrace of these two-dimensional models (Jia et al. 2016).

On the quantity side, the efficiency logic is well established. Clearly specified, transferable rights allow price signals to reveal marginal values, thereby reallocating water from lower- to higher-productivity uses and promoting conservation (Hadjigeorgalis 2009; Lund Jay R. and Israel Morris 1995; Rosegrant and Binswanger 1994; Vaux Jr. and Howitt 1984; Zeff Harrison et al. 2019). A range of modeling studies employing stochastic programming under hydrologic uncertainty, bargaining-based price formation, and risk-averse two-dimensional trading frameworks consistently find robust reallocation and conservation gains (Di et al. 2020; Fu et al. 2016; Schmidt 2007; Tsvetanov and Earnhart 2020; Wang et al. 2022). Empirical evidence from China's WRT pilots supports these theoretical claims. Observed agricultural water savings align with clarified quota allocations and incentive-compatible contractual arrangements (Zhang et al. 2021). Moreover, sector-specific analyses reveal patterns of water transfers from low- to high-value uses, accompanied by improved technologies in irrigation systems and cropping choices (Lv et al. 2021).

By contrast, rigorous causal evaluation of WRT's impacts on water environmental quality remains relatively limited compared to those focusing on quantity outcomes. Although integrated hydrologic-economic models co-optimize withdrawals and pollution abatement—indicating how initial allocations and trading rules can be designed to meet ambient quality standards (Martinsen et al. 2019; Ward and Pulido-Velazquez 2008; Wong and Eheart 1983)—a number of studies suggest that empirical policy assessments still tend to underemphasize quality-related effects (Grantham and Viers 2014; Wang et al. 2020). At the same time, macro-evidence shows that pollution not only exacerbates scarcity but also intensifies regional inequities, underscoring the importance of ensuring that improvements in allocation efficiency do not come at the expense of resource usability (Ma et al. 2020). These concerns point to the need for more targeted empirical assessment of WRT's dual impacts on both water-use efficiency and environmental quality.

2.2 Hypotheses

WRT enhances overall efficiency and encourages the adoption of conservation technologies by establishing well-specified and transferable use rights (Chong and Sunding 2006; Lund Jay R. and Israel Morris 1995; Rosegrant and Binswanger 1994; Zeff Harrison et al. 2019). Evidence from China's pilots is consistent with this logic. Agricultural water saving has been observed in contexts where quotas allocations and transfer rules are perceived as credible (Fu et al. 2016; Zhang et al. 2021). Additionally, dynamic bargaining models and risk-averse formulations suggest that endogenous price and quantity adjustments co-evolve with policy parameters and institutional reliability constraints, thereby preserving incentives while mitigating risk (Di et al. 2020; Wang et al. 2022). Sector-specific studies further demonstrate that trading mechanisms can induce technology adoption and reallocate water to higher-value crops and uses (Lv et al. 2021). Based on these arguments, we propose Hypothesis 1:

H1: The adoption of WRT policy improves water-use efficiency.

When water entitlements are clearly defined and made tradable, price signals can guide the reallocation of water from low-productivity and water-intensive uses toward higher-value sectors, crops, and technologies. Evidence from mature water markets indicates that trading tends to shift water from annual field crops to perennial horticulture, as well as industrial and urban uses. It also promotes the uptake of more efficient irrigation methods and facilitates crop switching (Wheeler et al. 2014; Debaere et al. 2014). This kind of structural adjustment not only improves the marginal productivity of water use but also increases allocative flexibility across time and hydrologic conditions (Young and McColl 2003). In line with these findings, macro-level studies have linked improvements in water productivity to broader transitions toward less water-intensive activities (Debaere and Kurzendoerfer 2015). More recent empirical research from China further confirms this mechanism, showing WRT policies have significantly promoted water transfers from agricultural to industrial sectors, thereby improving the overall efficiency of water use (Yan et al. 2024). Taken together, we argue that WRT contributes to water-use efficiency primarily by reshaping the water-use structure. Accordingly, we propose the Hypothesis 2:

H2: The adoption of WRT policy optimizes water-use structure, thereby improving water-use efficiency.

The environmental effectiveness of WRT depends on whether trading is embedded within regulatory frameworks that explicitly link water use to water quality. Two-dimensional regimes that jointly assign withdrawal and discharge rights, impose real-time, penalty-backed adjustments, and integrate surface-groundwater dynamics align private trading incentives with ambient water quality standards. These institutional features channel water toward cleaner producers or users with lower marginal abatement cost, while discouraging pollution-intensive rebound effects (Karamouz et al. 2010; Martinsen et al. 2019; Wang et al. 2022; Wang et al. 2020; Ward and Pulido-Velazquez 2008; Wong and Eheart 1983). From a Free-Market Environmentalism perspective, environmental externalities can be internalized through market signals—if entitlements are enforceable, and quality is priced appropriately. For example, higher prices for high-quality water and making tradability contingent on meeting environmental standards both create incentives for purification efforts (Delorit and Block 2018). Given that agricultural nonpoint source pollution plays a critical role in determining overall water usability, the co-benefits of WRT depend heavily on whether trading rules account for sectoral externalities. This is especially important in contexts where pollution intensifies water scarcity and regional inequities (Dabrowski et al. 2009; David and Hughes 2024; Grantham and Viers 2014; Ma et al. 2020; Z. Wang et al. 2020). Based on this reasoning, we propose Hypothesis 3:

H3: The adoption of WRT policy improves water environmental quality.

Theories of property rights and tradable-permit suggests that market-based mechanisms can increase the demand for monitoring, reporting, and sanctions, thereby intensifying governance over both water extraction and pollution (Coase 2013; Ostrom 1990). As a market-based policy instrument, WRT assigns monetary value to water entitlements, encouraging users to reduce both water consumption and pollutant discharge by investing in efficiency improvements and abatement technologies (Stavins 2003). Empirical evidence from China supports this mechanism. The implementation of WRT policies has shown to stimulate green innovation and reduce pollution levels, with stronger effects observed in regions with higher pollution burdens and stronger regulatory capacity. These patterns suggest that WRT may drive governance intensification via improved metering, the development of trading platforms, and the enforcement of binding constraints (Chen et al. 2024). Similar results have been found in other environmental permit systems, such as pollution and carbon trading programs, where emission reductions are more pronounced in jurisdictions with robust legal and regulatory institutions (Tang et al. 2025). Taken together, we propose Hypothesis 4:

H4: The adoption of WRT policy increases the intensity of water pollution governance, thereby improving water environmental quality.

3. Policy Context, Empirical Design, Data, and Variables

3.1 Policy Context

China began experimenting with market-oriented instruments in water governance as early as the 1980s, most notably through the implementation of water-pollutant discharge fee system (Shen and Guna 2018). Building on this foundation, the development of WRT policy unfolded gradually from the early 2000s (Wang 2017). Initial efforts were limited to small-scale, localized experiments—such as the 2000 inter-municipal transfer between Dongyang and Yiwu in Zhejiang and the 2004 guidance on Yellow River main-stem conversion in Inner Mongolia and Ningxia. However, these early pilots were administratively narrow, geographically limited, and short-lived (Jia et al. 2016). A major turning point came on June 30, 2014, when the Ministry of Water Resources officially launched a nationally designated pilot program in seven provincial units: Inner Mongolia, Ningxia, Jiangxi, Henan, Hubei, Guangdong, and Gansu. These provinces were tasked with definition, registration, and facilitating transactions of water use rights. In parallel, a bottom-up trajectory emerged in several provinces that had already begun local experimentation and subsequently formalized these practices through provincial rules. For example, Shaanxi advanced from interim municipal measures in Baoji (2010) to province-wide trading rules by 2017. Shandong issued the Jining pilot plan in 2014 and later introduced provincial guidance to support the establishment of a WRT platform. Hebei initiated province-level registration rules from 2013–2014, followed by agricultural trading measures in 2016. As of 2023, ten of China's 31 provincial-level regions had implemented formal WRT pilots. Figure 1 presents the geographic distribution of these pilots, distinguishing between nationally mandated and locally initiated efforts.

Figure 1. Distribution of WRT Pilots in China

It is worth noting that, prior studies define treatment inconsistently. Some code only the seven nationally designated pilots launched in 2014 as adopters (e.g., Zhang et al. 2025; Yan et al. 2024), while others apply a much broader definition that also includes so-called “provincial pilots” in jurisdictions such as Shandong, Zhejiang, Xinjiang, Fujian, Liaoning, Hebei, Hunan, Shaanxi, Shanxi, Jilin (e.g., Zhang et al. 2021). To avoid both under- and over-coverage, we reconstruct the adoption timeline directly from provincial regulations and official notices and we treat as adopters the seven national pilots plus three provinces that have established province-wide rules and trading platforms.

3.2 Empirical Design

The implementation of WRT pilots across Chinese provinces provides a quasi-natural setting for empirical analysis. While some provinces adopted the program—either through national designation or local initiatives—others did not, resulting in systematic variation in policy exposure over time across regions. By incorporating locally initiated pilots alongside the seven national pilots, we expand the treatment group to ten provinces, thereby capturing the broader and more heterogeneous diffusion of the policy. Based on this refined treatment definition, we employ a DID framework, which is well suited for identifying causal impacts in policy evaluations. By exploiting staggered adoption across provinces, DID enables us to isolate the net effects of WRT pilots while controlling for unobserved, time-invariant heterogeneity and for common shocks that affect all provinces in a given year. Formally, equation (1) specifies the empirical framework:

$$Y_{it} = \alpha + \beta(WRT \times Post)_{it} + \varphi CV_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (1)$$

Where Y_{it} denotes the outcome variable of interest—measured alternately as water-use efficiency or water quality indicators—in province *i* during year *t*. The interaction term $(WRT \times Post)_{it}$ captures the treatment exposure, taking a value of 1 for provinces participating in the WRT pilot during the post-adoption period, and 0 otherwise. The coefficient, β, identifies the average treatment effects of WRT on the outcomes. The control vector CV_{it} includes time-varying covariates such as economic structure, resource endowments, and other confounding determinants of water use or pollution levels. Province fixed effects μ_i account for unobserved, time-invariant differences across provinces, while year fixed effects λ_t absorb common shocks affecting all provinces in a given year. The term ε_{it} represents the idiosyncratic error.

3.3 Data and Variables

Dependent variables. Data on provincial water-use efficiency are drawn from Yan et al. (2024), who estimate efficiency using the Global Non-radical Directional Distance Function (GNDDF) model. This measure captures how effectively water inputs are converted into economic output (i.e., gross domestic product, GDP) while simultaneously considering undesirable outputs such as water pollution. The value of water-use efficiency ranges from 0 to 1, with higher values indicating more efficient and sustainable water use. We obtained the dataset directly from the authors via e-mail correspondence to ensure consistency with their published methodology.

In addition, we evaluate water quality outcomes to capture the dual mandate of WRT. Although many other indicators of water quality—such as biochemical oxygen demand (BOD)—are theoretically available, many were incorporated into routine monitoring only in recent years and therefore lack consistent, long-term coverage at the provincial level. In contrast, DO emissions (10,000 tons) and NH_3-N emissions (10,000 tons) have been systematically recorded for a much longer period and offer full temporal coverage across the study window. We thus use DO and NH_3-N—two widely recognized indicators of surface water quality and pollution load—to measure the changes in water environmental quality. Data for DO and NH_3-N emissions were extracted from the *China Environment Database* available through the EPS platform (https://www.epsnet.com.cn). It is worth noting that all dependent variables used in this study are originally drawn from provincial-level official datasets. We do not rely on real-time data from river basins or monitoring stations.

Policy variable. The key explanatory variable is an interaction term, $(WRT\times Post)_{it}$, capturing a province's exposure to the WRT policy. This variable takes the value of 1 for provinces that adopted WRT pilots—whether through national designation or via locally initiated programs—during the post-adoption period, and 0 otherwise. Provinces that did not adopt WRT at any point during the study period are coded as 0 for all years. Information on pilot adoption was compiled through systematic manual searches of official provincial government websites and policy archives, and cross-verified using the Law Star database (http://law1.law-star.com).

Control variables. To mitigate potential confounding influences on water-related outcomes, we include a set of time-varying control variables, following prior studies (Yan et al. 2024; Zhang et al. 2021). Data for these variables are sourced from the *China Macro-Economic Database* and the *China Environment Database*, both accessed via the EPS platform. These controls capture differences in economic development, resource endowments, and structural characteristics of provincial economies. Specifically, GDP (in billion CNY) reflects the overall scale of economic activity, while per capita water resources (1,000 m^3 per person) proxy for the natural availability of water. To capture sectoral demand, we include agricultural and industrial water use (billion m^3), which differentiate consumption intensity between primary and secondary sectors. Additionally, the GDP shares of primary and secondary industries are included to account for variation in economic structure, as provinces with more industrialized or resource-intensive economies may exhibit distinct patterns of water use and pollution.

In total, the dataset comprises 651 province-year observations spanning the period from 2003 to 2023. Among these, approximately 16.1 percent correspond to years in which provinces implemented WRT pilot. Table 1 summarizes the definitions and descriptive statistics for all variables. On average, water-use efficiency stands at 0.575 on a 0–1 scale, suggesting considerable potential for improvement across provinces. Indicators of water environmental quality display substantial heterogeneity. DO emissions average about 59.8 (10,000 tons), with wide dispersion, while NH_3-N emissions average 5.06 (10,000 tons), likewise reflecting uneven pollution pressures.

Table 1. Descriptive Statistics

Variables	Definitions	N	Mean	SD	Min	Max
Water Efficiency[a]	Efficiency indices range from 0 to 1	527	0.575	0.229	0.000	1.000
DO Emissions	Dissolved oxygen emissions (10,000 tons)	589	59.800	44.849	0.790	198.250
NH_3-N Emissions[b]	Ammonia nitrogen emissions (10,000 tons)	558	5.057	4.017	0.140	23.089
WRT × Post	Interaction term, measuring net policy effect of WRT pilots.	651	0.161	0.368	0.000	1.000
GDP	Gross Domestic Product (billion CNY)	651	2062.291	2175.335	18.909	13567.320
Per Capita Water	Per capita water resources (1,000 m^3/person)	651	6.641	25.029	0.052	177.175
Agri Water Use	Water used in agriculture (billion m^3)	651	11.955	10.206	0.251	56.360
Indus Water Use	Water used in industry (billion m^3)	651	4.101	4.529	0.034	25.520
Primary Share	Share of primary industry in GDP (%)	651	10.935	5.935	0.200	37.013
Secondary Share	Share of secondary industry in GDP (%)	651	43.868	8.885	14.900	61.500

Note: [a] Water-use efficiency data cover the period 2005–2021; [b] NH_3-N emissions data cover 2004–2023; all other data span 2003–2023.

To contextualize causal estimates, we then visualize the spatial temporal distribution of the two outcomes—water-use efficiency and DO emissions—for the year 2009, 2014, and 2019. We apply within-year quantile breaks to highlight relative differences. As shown in Figure 2, water-use efficiency displays a persistent west–east divide. Higher quantile provinces are clustered on the western plateau (notably Tibet and Qinghai), with some additional clusters in the far south coastal areas (e.g., Guangdong and Hainan). In contrast, lower efficiency levels are concentrated in the central–eastern manufacturing belt, including the North China Plain and the middle–lower Yangtze region. This pattern remains broadly stable across the three time points. In terms of DO emissions, a clear gradient is observed: eastern and coastal provinces repeatedly appear in higher quantiles, whereas provinces in the northwest and plateau regions such as Xinjiang, Gansu, Ningxia, Qinghai and Tibet, tend to fall in the lower quantiles. Importantly, the spatial patterns of water-use efficiency and DO emissions are not colinear. Several plateau provinces combine high water-use efficiency and low DO emissions, while many coastal provinces show higher DO emissions but only moderate levels of water-use efficiency. For brevity, spatial maps of NH_3-N emissions are not shown.

4. Empirical Results

4.1 DID Analysis

4.1.1 Baseline Regression Results

Table 2 reports the estimated effects of the WRT pilot program on water-use efficiency and water quality outcomes. Columns (1) and (2) show the results for water-use efficiency, measured in both absolute levels and logarithmic terms. In both specifications, the estimated coefficients are positive and statistically significant at the 5% level, with magnitudes of 0.082 and 0.228, respectively. In logarithmic terms, this corresponds to roughly a 25.6% $((e^{0.228}-1) \times 100)$ improvement, implying that provinces participating in the pilot program experienced a substantial increase in water-use efficiency. These results lend support to Hypothesis 1 and are consistent with the conclusions of Yan et al. (2024).

Turning to environmental quality outcomes, column (3) shows that WRT pilots have a sizable and positive influence on DO emissions, with a coefficient of 14.649 that is statistically significant at the 5% level. This result suggests that the adoption of WRT improves ecological conditions of water bodies, consistent with expectations that more efficient water allocation may alleviate stress on water ecosystems. However, column (4) reveals that the estimated effect on NH_3-N emissions, while negative, is statistically insignificant. Moreover, the relatively large standard errors across models highlight the imprecision of the estimates, warranting caution when interpreting the magnitude or robustness of the water quality effects.

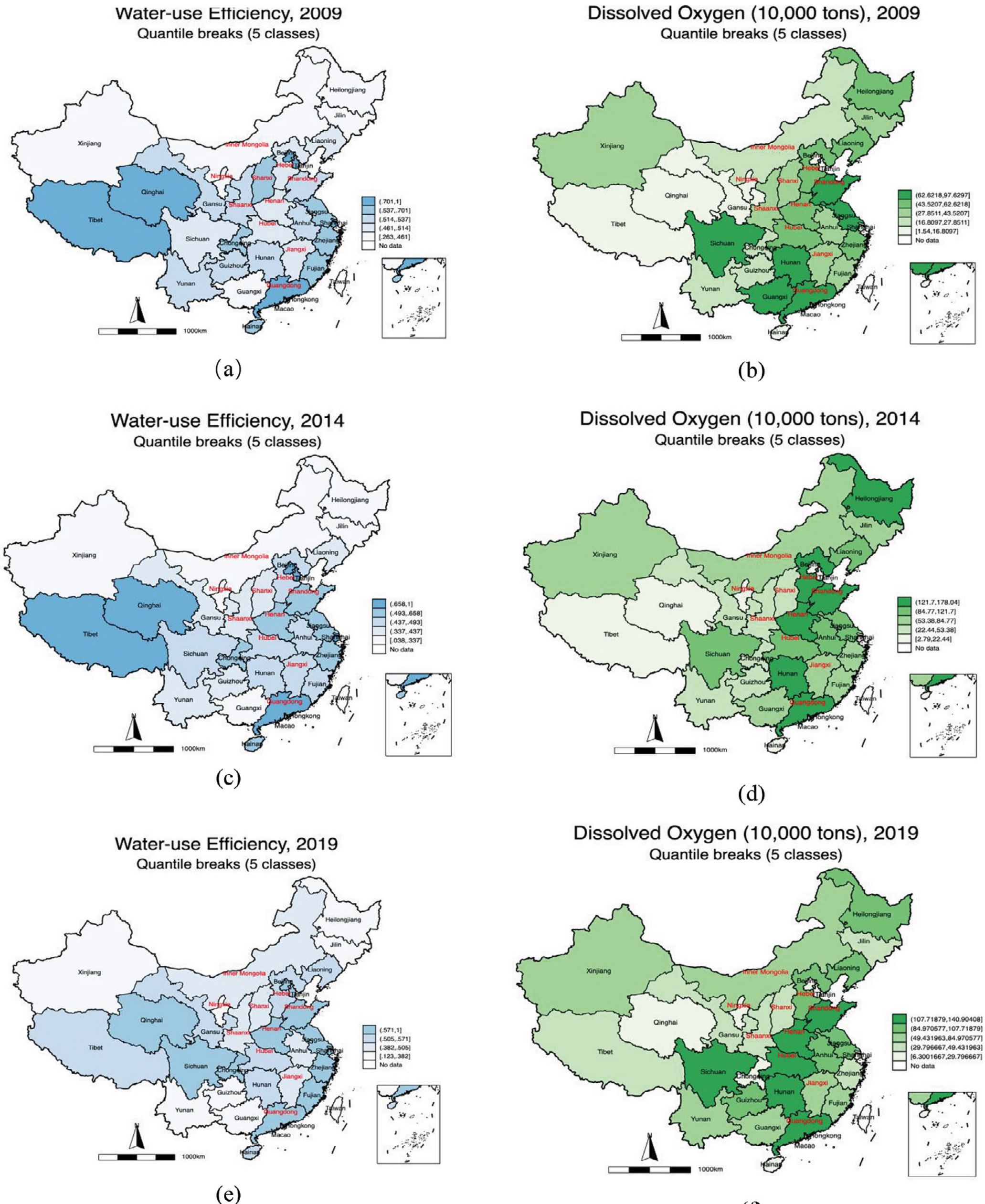


Figure 2. Spatial Distribution of Water-Use Efficiency and DO Emissions in 2009, 2014, and 2019

Note: Pilot provinces are labeled in red text.

Table 2. The Impacts of WRT on water-use efficiency and water quality

VARIABLES	(1) Water Efficiency	(2) Ln (Water Efficiency)	(3) DO Emissions	(4) NH_3-N Emissions
WRT × Post	0.082**	0.228**	14.649**	-0.327
	(0.030)	(0.092)	(5.686)	(0.332)
Ln (GDP)	0.030	0.361	13.953	2.242*
	(0.079)	(0.442)	(17.319)	(1.299)
Ln (Per Capita Water)	0.003	-0.009	3.188	-0.611*
	(0.012)	(0.032)	(4.295)	(0.303)
Ln (Agri Water Use)	-0.147*	-0.477	28.513***	0.066
	(0.073)	(0.289)	(7.804)	(0.401)
Ln (Indus Water Use)	-0.058	-0.128	-1.640	-0.168
	(0.065)	(0.113)	(7.455)	(0.517)
Secondary Share	-0.008**	-0.023	-0.429	0.031
	(0.003)	(0.015)	(0.610)	(0.039)
Primary Share	-0.009	-0.020*	-0.065	0.068
	(0.006)	(0.011)	(1.197)	(0.069)
Province-fixed effects	YES	YES	YES	YES
Year-fixed effects	YES	YES	YES	YES
Constant	1.489**	-0.328	-194.879	-13.421
	(0.665)	(2.768)	(204.900)	(12.267)
Observations	493	493	551	522
Adjusted R-squared	0.912	0.737	0.832	0.866

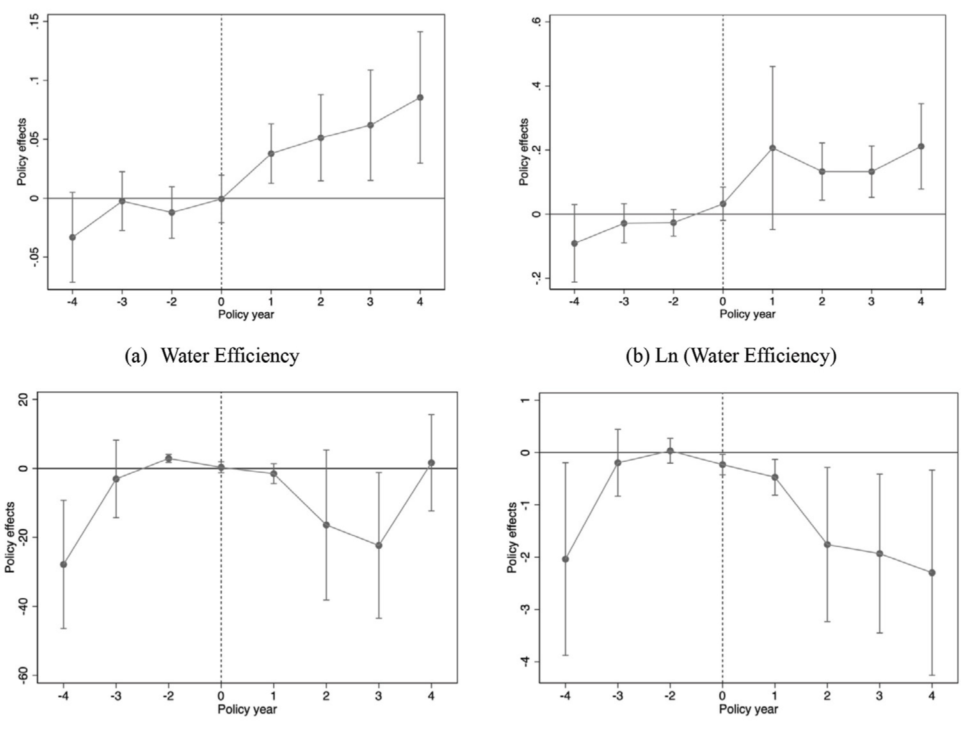
Note: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. "YES" denotes the inclusion of province and year fixed effects; other tables follow the same convention.

4.1.2 Parallel Trend Test

To further validate the credibility of our identification strategy, we assess the parallel-trend assumption that underlies the DID framework. This assumption requires that, in the absence of WRT policy, treated and control provinces would have similar pre-treatment trajectories. If the condition holds, any post-treatment divergence can be more confidently attributed to the implementation of WRT pilots. To test this assumption, we employ an event-study specification that models the dynamic treatment effects over time, relative to the year of WRT adoption. Specifically, the estimation framework is given by equation (2):

In which, T_i^{Start} denotes the first year in which province i initiated a WRT pilot, and the dummy variable $1\{t - T_i^{Start} = \tau\}$ equals 1 if year t is τ periods away from the adoption year, and 0 otherwise. The coefficients δ_τ thus capture the dynamic evolution of treatment effects in event time, where $\tau=-1$ serves as the reference period and is omitted from the regression. All other variable definitions remain consistent with those used in the baseline model.

Figure 3 presents the event-study estimates used to assess the plausibility of the parallel-trend assumption and to illustrate the dynamic effects of WRT pilots on the outcome variables. For water-use efficiency, as shown in panels (a) and (b), the coefficients on pre-treatment leads are near zero and statistically insignificant, suggesting no systematic differences in efficiency trends between treated and untreated provinces prior to policy adoption. This pattern provides supportive evidence for the validity of the DID framework. Following the introduction of WRT, the estimated coefficients turn positive and show a steady increase in magnitude. Notably, efficiency begins to rise in the first policy year, and the log specification in panel (b) reveals a similar upward trajectory, with post-treatment effects becoming statistically distinguishable from zero. These dynamic patterns reinforce the baseline findings and indicate that WRT adoption contributed to sustained improvements in provincial water-use efficiency over time.



(a) Water Efficiency

(b) Ln (Water Efficiency)

(c) DO Emissions

(d) NH_3-N Emissions

Figure 3. Parallel Trend Tests for Policy Effects

The dynamic patterns for water quality are comparatively inconclusive. As shown in panel (c), DO emissions do not exhibit significant differences during the pre-treatment period, yet the post-treatment coefficients vary considerably and are accompanied by wide confidence intervals. A similar pattern is observed for NH_3-N in panel (d). This degree of variability suggests that while WRT may have had some influence on water quality, its observable effects are relatively modest and less statistically robust compared to the more consistent improvements in water-use efficiency.

4.1.3 DID Robustness Check

To address potential concerns about sample selection bias, we complement the baseline DID specification with a propensity score matching (PSM) procedure combined with DID estimation. Specifically, provinces implementing WRT pilots (treatment group) are matched to control provinces based on their pre-treatment characteristics, including all controls from the baseline model, as well as lagged values and trends of the outcome variables. Kernel matching is applied to construct weighted control groups that closely approximate the pre-policy profiles of treated provinces. After matching, DID regressions are re-estimated on the matched sample, both without and with kernel weights.

The results are presented in Table 3. In line with the baseline findings, WRT adoption remains positively associated with improvements in water-use efficiency. In columns (1) and (2), the estimated coefficients for efficiency levels are 0.083 and 0.082, both statistically significant at the 5% level. The log specification in columns (3) and (4) yields similarly positive and significant effects, with estimated coefficients of 0.261 and 0.233, corresponding to an approximate 26-29% increase in efficiency compared to the counterfactual. These estimates reaffirm the robustness of the efficiency gains observed in the main analysis.

For quality outcomes, the evidence remains less definitive. As shown in columns (5) and (6), the estimated coefficients for DO emissions are positive and significant at the 5% level in the unweighted specification. However, the estimates become less precise in the weighted model. Consistent with the baseline analysis, the effects on NH_3-N emissions are not statistically significant; for brevity, the detailed estimates are not reported here.

4.1.4 DID Placebo Test

To further examine the robustness of our baseline findings, we conducted a placebo test. The logic of this test is to repeatedly reassign the WRT treatment status randomly across provinces and re-estimate the DID specification, thereby generating an empirical distribution of placebo coefficients under the null hypothesis. If the estimated treatment effect from the actual data falls in the extreme tail of this simulated distribution, it strengthens the inference that the observed result is unlikely to be due to chance or spurious correlations.

Table 3. DID Robustness Check: PSM-DID Methods

VARIABLES	(1)[a]	(2)[b]	(3) [a]	(4) [b]	(5) [a]	(6) [b]
	Water Efficiency		Ln (Water Efficiency)		DO Emissions	
WRT × Post	0.083**	0.082**	0.261**	0.233**	14.298**	9.848
	(0.030)	(0.039)	(0.111)	(0.112)	(5.740)	(5.804)
Control variables	YES	YES	YES	YES	YES	YES
Province-fixed effects	YES	YES	YES	YES	YES	YES
Year-fixed effects	YES	YES	YES	YES	YES	YES
Constant	2.223***	3.219***	0.651	3.153	-24.642	147.164
	(0.764)	(0.906)	(2.843)	(1.866)	(204.684)	(291.190)
Observations	408	408	408	408	456	456
Adjusted R-squared	0.932	0.922	0.732	0.707	0.838	0.862

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. [a] PSM-DID with control variables on the kernel-matched sample (unweighted); [b] PSM-DID with control variables on the kernel-matched sample (kernel-weighted). To conserve space, coefficients for the control variables are omitted. "YES" indicates inclusion of province and year fixed effects and the full set of controls; the same convention applies to the other tables.

Figure 4 plots the distribution of estimated coefficients from 500 placebo replications for the two water-use efficiency outcomes. In both panels, the placebo estimates cluster closely around zero, while the actual treatment effect (marked by the dashed line) lies well outside the central mass of the simulated distribution. This pattern provides evidence that the observed efficiency improvements in the baseline analysis are unlikely to be driven by random assignment, reinforcing the credibility of the causal interpretation. By contrast, we do not extend the placebo analysis to the water quality outcomes, as the previous estimates for DO and NH_3-N emissions were found unstable and imprecise.

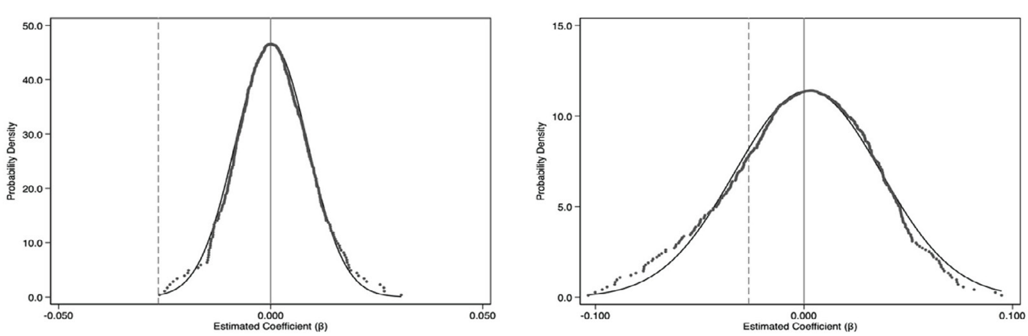


Figure 4. Distribution of Estimated Coefficients

4.2 SCM Analysis

4.2.1 Baseline Results

The preceding DID and PSM-DID analyses yielded unstable and imprecise estimates for water quality outcomes. In particular, the estimated effects on DO and NH_3-N emissions were inconsistent across model specifications, characterized by wide standard errors and limited evidence of parallel pre-trends. These limitations suggest that the DID framework may not adequately capture the treatment effects for environmental outcomes. To address this concern, we apply the SCM analysis to conduct province-level case studies. The SCM approach constructs a weighted combination of untreated provinces that closely approximates the pre-treatment trajectory of a treated province, thereby generating a more credible counterfactual for post-treatment comparison.

Figure 5 presents the results for five pilot provinces where SCM produced valid synthetic controls. For DO emissions, the pre-treatment of the treated province closely match those of their synthetic counterparts in all five cases, lending credibility to the constructed counterfactuals. Notably, Hubei and Gansu exhibit large and sustained improvements in DO levels relative to their synthetic controls. Jiangxi shows a sharp increase immediately following policy implementation, maintaining a persistent lead thereafter. Ningxia records a modest but steady improvement beginning in 2016. In contrast, Shaanxi experiences short-run gains that gradually diminish and converge with the synthetic control by 2016.

In contrast, following WRT adoption, both Gansu and Ningxia show substantial and sustained declines in NH_3-N emissions relative to their synthetic controls, with the gaps continuing to widen through 2020. Hubei experiences a sharp drop around 2016 and thereafter remains slightly below its synthetic counterpart, suggesting a modest improvement. Jiangxi records a decline after 2015 but largely follows its synthetic control, offering limited evidence of treatment effects. Shaanxi, which implemented the policy in 2010, shows an initial rise in emissions followed by convergence and ending slightly below the synthetic control.

In the remaining five pilot provinces, SCM either failed to yield a credible synthetic counterfactual—due to poor pre-treatment fit or unstable donor weights—or produced no consistent post-adoption improvement in either DO or NH_3-N. To conserve space, these cases are not presented. Taken together, the SCM evidence suggests that WRT pilots led to improvements in water quality in a subset of provinces, partially supporting H3.

4.2.2 SCM Robustness Check

To further test robustness, we evaluate the quality of each synthetic control by comparing the root mean squared prediction error (RMSPE) before and after policy adoption. Specifically, we use the post/pre RMSPE ratio to indicate the degree of post-policy divergence relative to pre-treatment fit noise. Ratios close to 1 suggest minimal treatment effect, while larger ratios indicate more

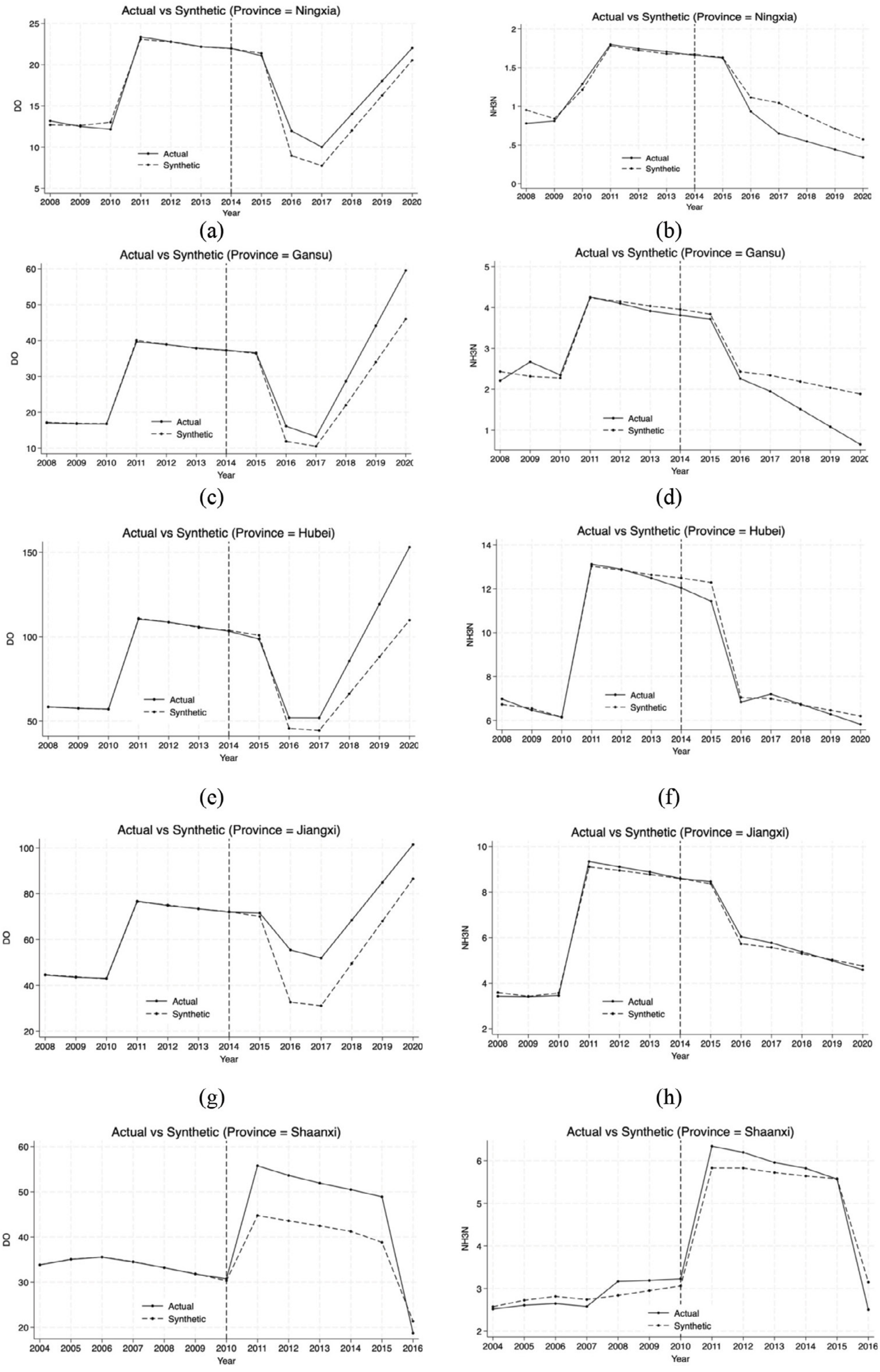


Figure 5. Comparison of Actual and Synthetic Trends for DO and NH_3-N Emissions

substantive impacts. Table 4 presents province-level diagnostics. For DO emissions, the largest effects are observed in Shaanxi, Hubei, Jiangxi, and Gansu; Inner Mongolia and Ningxia show moderate responses, while other pilot provinces exhibit little change. For NH_3-N emissions, pronounced effects are concentrated in Hebei, Henan, and Shandong, with more modest improvements in Gansu, Hubei, and Ningxia, and limited divergence elsewhere.

Table 4. SCM Robustness Check: Pre-/Post-treatment RMSPE and RMSPE Ratio

Province	DO Emission			NH_3-N Emission		
	pre_ RMSPE	post_ RMSPE	RMSPE_ ratio	pre_ RMSPE	post_ RMSPE	RMSPE_ ratio
Hebei	2.009	4.997	2.487	0.113	0.999	8.814
Inner Mongolia	1.168	7.378	6.315	0.320	0.480	1.500
Jiangxi	0.226	16.132	71.512	0.147	0.162	1.102
Shandong	14.855	16.600	1.117	0.180	1.139	6.315
Henan	1.588	0.812	0.512	0.277	1.899	6.855
Hubei	0.248	21.779	87.837	0.130	0.414	3.185
Guangdong	23.233	33.139	1.426	2.378	3.919	1.648
Shaanxi	0.041	8.502	208.609	0.199	0.364	1.831
Gansu	0.190	7.126	37.433	0.181	0.666	3.683
Ningxia	0.421	1.832	4.347	0.080	0.246	3.090

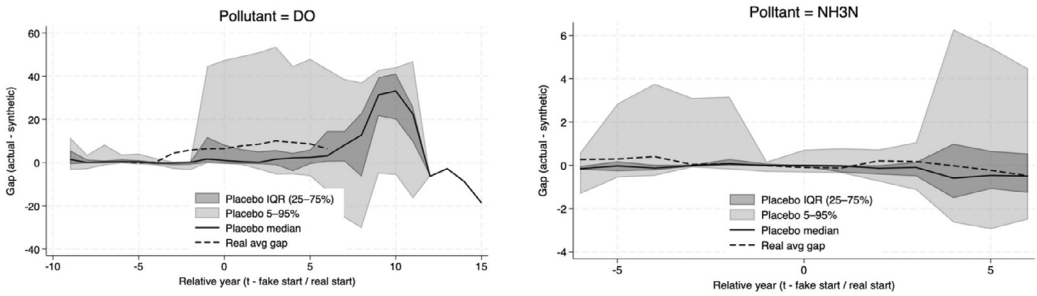
Further, to benchmark the magnitude of each SCM effect against a credible counterfactual, we conduct placebo-in-space tests. For each treated province (referred to as the anchor), we keep its actual adoption year and re-estimate SCM by alternately assigning "pseudo-treatment" to each untreated province. This procedure generates a distribution of post-/pre- RMSPE ratios under the null hypothesis of no treatment effect. The anchor province's actual ratio is then compared against this placebo distribution to calculate a pseudo p-value, along with its position relative to the placebo median (P50) and 95th percentile (P95).

Table 5 shows that, for DO emissions, the post/pre-RMSPE ratios in Jiangxi, Hubei, Shaanxi, and Gansu are highly extreme relative to their placebo distributions ($p \approx 0$), suggesting strong treatment effects. Inner Mongolia's ratio approaches the 5% significance threshold, while the remaining pilots show no discernible divergence from their placebo counterparts. For NH_3-N emissions, pronounced effects are observed in Hebei, Henan, and Shandong ($p \approx 0$), with significant results at the 5% level in Gansu, Hubei, and Ningxia. Other provinces show no notable divergence. These placebo benchmarks align with the SCM plots and reinforce the conclusion that water-quality improvements exist but are heterogeneous across provinces.

Table 5. SCM Robustness Check: Placebo-in-Space Tests (Nplacebo = 21)

Provinces	NO Emission				NH_3-N Emission			
	Treated_ ratio	P50	P95	P_ value	Treated_ ratio	P50	P95	P_ value
Hebei	2.487	2.117	5.156	0.476	8.814	0.965	3.040	0.000
Inner Mongolia	6.315	2.117	5.156	0.048	1.500	0.965	3.040	0.333
Jiangxi	71.512	2.117	5.156	0.000	1.102	0.965	3.040	0.429
Shandong	1.117	2.117	5.156	0.667	6.315	0.965	3.040	0.000
Henan	0.512	2.117	5.156	0.810	6.855	0.965	3.040	0.000
Hubei	87.837	2.117	5.156	0.000	3.185	0.965	3.040	0.048
Guangdong	1.426	2.117	5.156	0.571	1.648	0.965	3.040	0.333
Shaanxi	208.609	5.670	17.531	0.000	1.831	1.98	9.037	0.619
Gansu	37.433	2.117	5.156	0.000	3.683	0.965	3.040	0.048
Ningxia	4.347	2.117	5.156	0.143	3.090	0.965	3.040	0.048

To further probe robustness against concerns of spurious timing, we implement a placebo-in-time analysis within the SCM framework. For each treated province, we re-estimate SCM using a falsified adoption year set just prior to the actual policy start. We then aggregate the resulting placebo gaps across provinces to generate percentile bands—specifically, the median, interquartile, and 5^{th}–95^{th} percentiles. The actual average treatment gap is plotted against these placebo envelopes to assess its deviation from expected random fluctuations. As demonstrated in Figure 6, for DO emissions, the placebo gaps center near zero in the pre-treatment period, while the observed post-policy gap rises above the interquartile range and approaches the upper bound of the placebo envelope in provinces with strong SCM signals. This suggest that the observed effects are unlikely to be artifacts of timing. For NH_3-N emissions, the average gap remains near zero before adoption and declines modestly afterward, dipping toward the lower quantiles around years 3-5 post-treatment. This pattern suggests moderate average reductions, albeit with underlying heterogeneity across provinces.



(a) (b)

Figure 6. SCM Robustness Check: Placebo-in-Time Test

4.3 Heterogeneity Analysis

4.3.1 Heterogeneity Analysis by Geographic Location

While the main analysis centers on the average causal effects of WRT, we also include exploratory heterogeneity analyses to assess whether the estimated effects on water-use efficiency vary across different geographic and market contexts. These analyses are not derived from pre-specified theoretical hypotheses; rather, they serve as supplementary evidence to enrich the interpretation of the baseline results. We begin by examining geographic heterogeneity in the efficiency effects of WRT. Specifically, we re-estimate the DID models based on two commonly used spatial groupings in Chinese policy analysis—East vs. Central (the West omitted because of a lack of treated units) and North vs. South.

The results indicate that the efficiency improvements are more pronounced in the Central and Northern subsamples. In levels, the estimated treatment effects are 0.073 for Central and 0.092 for North, both significant at the 10% level. Although the point estimates for East (0.094) and South (0.038) are also positive, they are statistically insignificant. In log specifications, the coefficients are 0.124 for Central and 0.399 for North, corresponding to approximate improvements of 13.2% and 49.0%, respectively. The South shows a smaller but statistically significant effect of 9.1% (0.087), while East 0.144 remains statistically insignificant.

4.3.2 Heterogeneity Analysis by Marketization Level

To further assess whether the efficiency gains depend on market institutions, we extend the DID model by interacting the treatment variable with an indicator for provinces exhibiting high levels of marketization. This indicator is constructed by following Yang and Zeng (2012). For our study, the coefficient on interaction term identifies the additional effect in provinces with higher marketization levels. All regressions include the baseline set of controls and fixed effects for province and year, with standard errors clustered at the provincial level.

Results reported in Table 7 show that the efficiency effects of WRT are considerably stronger in provinces with higher levels of marketization. In the level specification, the interaction term is estimated at 0.085 ($p < 0.05$). In the log specification, the coefficient rises to 0.227 ($p < 0.01$), implying an efficiency gain of approximately 25.5% (($e^{0.227}-1$) $\times$ 100). Overall, these results suggest that more developed market institutions can significantly amplify the efficiency improvements brought about by WRT policy.

Table 6. Heterogeneity Analysis: East–Central and North–South Comparisons

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Water Efficiency				Ln (Water Efficiency)			
	East	Central	North	South	East	Central	North	South
WRT × Post	0.094	0.073*	0.092*	0.038	0.144	0.124*	0.399*	0.087*
	(0.072)	(0.029)	(0.049)	(0.022)	(0.100)	(0.051)	(0.217)	(0.045)
Control variables	YES	YES	YES	YES	YES	YES	YES	YES
Province-fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
Year-fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
Constant	0.544	3.912*	1.140	1.925	-0.678	4.929	-0.139	2.640
	(1.207)	(1.571)	(0.960)	(1.324)	(1.798)	(2.546)	(2.900)	(2.793)
Observations	136	102	238	238	136	102	238	238
Adjusted R-squared	0.917	0.682	0.913	0.932	0.916	0.749	0.762	0.903

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 7. Heterogeneity Analysis by Marketization Level

VARIABLES	(1)	(2)
	Water Efficiency	Ln (Water Efficiency)
WRT × Post	0.031	0.101
	(0.021)	(0.071)
High_Marketization	-0.045*	-0.207*
	(0.024)	(0.112)
(WRT × Post)× High_Marketization	0.085**	0.227***
	(0.034)	(0.079)
Control variables	YES	YES
Province-fixed effects	YES	YES
Year-fixed effects	YES	YES
Constant	1.450**	-0.590
	(0.633)	(2.761)
Observations	493	493
Adjusted R-squared	0.915	0.745

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

5. Mechanism Analysis

5.1 Water-use Structure

To investigate whether WRT influences water-use efficiency via changing the water allocation patterns, we construct a set of indicators reflecting the provincial water-use structure. Annual data on sectoral water withdrawals are drawn from the EPS China Macroeconomic Database. For each province-year observation, total freshwater withdrawals W_{it} are disaggregated into agricultural A_{it} and industrial I_{it} uses. The rest components, defined as $O_{it} = I_{it} - I_{it} - I_{it}$, primarily reflects residential and ecological water use. Based on these categories, we calculate the sectoral shares of water use across provinces and years:

$$s_{it}^{\text{ag}} = \frac{A_{it}}{W_{it}},\ s_{it}^{\text{ind}} = \frac{I_{it}}{W_{it}},\ s_{it}^{\text{oth}} = \frac{W_{it}-A_{it}-I_{it}}{W_{it}},\ s_{it}^{\text{ag}} + s_{it}^{\text{ind}} + s_{it}^{\text{oth}} = 1, \tag{3}$$

To address measurement noise, we set $O_{it} = 0$ when the residual is slightly negative due to rounding errors, we exclude observations where total freshwater withdrawal $W_{it} \leq 0$, and then renormalize the sectoral shares to ensure they sum to 1. Based on these adjusted values, we calculate the Herfindahl–Hirschman Index (HHI) to capture the concentration of water use across sectors:

$$\text{HHI}_{\text{it}} = \left(s_{it}^{\text{ag}}\right)^2 + \left(s_{it}^{\text{ind}}\right)^2 + \left(s_{it}^{\text{oth}}\right)^2 \in [1/3,\ 1], \tag{4}$$

with $\text{HHI} \in [1/3, 1]$ in a three-sector partition. Higher HHI values indicate a more one-sided structure (greater reliance on a single sector). We then measure diversification using normalized Shannon entropy:

$$H_{it} = -\sum_{k\in\{\text{ag},\text{ind},\text{oth}\}} s_{it}^{k} \ln s_{it}^{k},\ \text{Shannon}_{\text{it}} = H_{it}/\ln 3 \in [0,1], \tag{5}$$

By convention $0 \ln 0 \equiv 0$; in implementation we handle zero shares accordingly. Higher values of Shannon index reflect more balanced water use across agriculture, industry, and other uses. As expected, Shannon and HHI move in opposite directions.

Using these measures, Table 8 presents the DID estimates of WRT's impact on water-use structure. For the HHI, the coefficient on *WRT* × *Post* interaction term is negative and statistically significant in both specifications: −0.053 without controls and −0.042 with controls. In contrast, the coefficients for the Shannon index are positive and significant, at 0.068 and 0.053, respectively. These results indicate that WRT pilots reduce concentration by approximately 4-5 percentage points on the normalized 0-1 HHI scale, while increasing water-use diversification by roughly 5 to 7 percentage points on the 0-1 Shannon scale. Taken together, these findings lend support to H2.

Table 8. The Impacts of WRT Pilots on Water-use Structure

VARIABLES	(1)	(2)	(3)	(4)
	Water-use Structure			
	HHI		Shannon	
WRT × Post	-0.053**	-0.042**	0.068**	0.053**
	(0.022)	(0.017)	(0.028)	(0.021)
Control variables		YES		YES
Province-fixed effects	YES	YES	YES	YES
Year-fixed effects	YES	YES	YES	YES
Constant	0.531***	0.973**	0.739***	-0.028
	(0.004)	(0.417)	(0.005)	(0.507)
Observations	609	609	609	609
Adjusted R-squared	0.881	0.926	0.887	0.934

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

5.2 Water Governance Intensity

To explore the mechanism through which WRT contributes to improvements in water environmental quality, we focus on the intensity of water governance. Specifically, we construct two measures to capture this dimension. The first is annual capital investment in industrial wastewater treatment facilities, drawn from the EPS Macroeconomic Database, which reflects the extent to which provinces prioritize infrastructure expansion for pollution control. The second is annual operating expenditure on wastewater treatment facilities, obtained from the EPS Environmental Database, which captures ongoing financial commitments to the operation and maintenance of pollution control systems.

Table 9 reports the results of the mechanism analysis examining how WRT policy influences water environmental quality through strengthened water governance. Across model specifications, the coefficient on the interaction term *WRT* × *Post* is consistently positive and statistically significant. Specifically, WRT pilot implementation is associated with increased capital investment in industrial wastewater treatment facilities. The estimated coefficients for investment are 0.465 without controls and 0.497 with controls, both statistically significant. Similarly, WRT pilots are linked to higher operating expenditures on wastewater treatment, with statistically significant coefficients of 0.334 and 0.328 across specifications.

These results suggest that the implementation of WRT prompts provincial governments to strengthen water pollution control efforts, both by expanding capital investment in wastewater treatment infrastructure and by increasing recurrent operating expenditures to sustain facility operations. Accordingly, the findings provide empirical support for H4.

Table 9. Mechanism Analysis: Water Governance Intensity

VARIABLES	(1)	(2)	(3)	(4)
	Water Governance			
	Ln (Industrial Wastewater Treatment Investment)		Ln (Operating Expenditure on Wastewater Treatment)	
WRT × Post	0.465*	0.497*	0.334**	0.328**
	(0.268)	(0.244)	(0.132)	(0.127)
Control variables		YES		YES
Province-fixed effects	YES	YES	YES	YES
Year-fixed effects	YES	YES	YES	YES
Constant	9.567***	-4.012	11.615***	9.244***
	(0.047)	(4.248)	(0.036)	(2.909)
Observations	598	598	377	377
Adjusted R-squared	0.677	0.686	0.958	0.961

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

6. Discussion and Conclusions

This study set out to evaluate whether China's WRT pilots—launched through a combination of central mandates and local initiatives—have improved water-use efficiency and water environmental quality, and to explore the mechanisms behind any observed effects. The analysis is motivated by the recognition that both scarcity and pollution jointly determine water-related welfare outcomes (Ma et al. 2020), and by a growing body of literature that conceptualizes water rights as multi-dimensional entitlements integrating both quantity and quality dimensions (Martinsen et al. 2019; T. Wang et al. 2022; Z. Wang et al. 2020; Ward and Pulido-Velazquez 2008). Drawing on an extended provincial panel dataset, we employed a DID strategy with event-study diagnostics, supplemented by province-specific SCM analyses. The results reveal that China's WRT pilots have led to notable improvements in both water-use efficiency and water quality. However, these effects are not uniform; rather, they vary across subnational contexts and marketization settings.

In particular, the efficiency results are consistent with the theoretical rationale behind tradable water rights. When withdrawal entitlements are clearly defined, transferable, and enforceable, water prices reveal marginal values, facilitating reallocation from lower- to higher-productivity uses and encouraging both conservation efforts and technological upgrading (Chong and Sunding 2006; Rosegrant and Binswanger 1994; Vaux Jr. and Howitt 1984). Our estimates provide empirical support for H1, indicating that these allocative mechanisms are functioning in practice. In contrast, the environmental outcomes reflect the conditional logic embedded in two-dimensional WRT frameworks. Our mixed findings suggest that WRT can indeed enhance water quality, but the effects are uneven. This pattern resonates with prior evidence indicating that agricultural non-point-source pollution and basin-specific constraints often limited water usability, implying that environmental co-benefits depend critically on the pricing or regulation of runoff and the credibility of enforcement mechanisms (Dabrowski et al. 2009; Grantham and Viers 2014).

Heterogeneity in efficiency effects also yields meaningful insights. We observe more pronounced improvements in the Central and Northern subsamples, as well as in provinces with higher levels of marketization. In contrast, in coastal or more economically diversified areas, the marginal effects of WRT on measured efficiency appear attenuated—potentially due to the availability of alternative water-saving strategies or the presence of pre-existing governance mechanisms.

Furthermore, our mechanism analyses provide a complementary perspective. The findings suggest that water-use efficiency improvements are primarily realized through optimization of water-use structure, with WRT reallocating water from agriculture toward higher-value industrial and other uses. In comparison, improvement in water quality is mainly associated with strengthened governance efforts, as indicated by increased capital investment and recurrent expenditures on wastewater treatment facilities.

Theoretically, these findings contribute to an institutional understanding of water markets. The analysis substantiates the claim that the object of exchange in WRT is inherently composite—encompassing both quantity and quality—and that policy performance should be evaluated along a joint efficiency–environment frontier, rather than on a single dimension (Martinsen et al. 2019; Z. Wang et al. 2020). Moreover, this study suggest that distributional and ecological safeguards—central to ongoing debates in water governance—can be compatible with, and in some cases even strengthened by, well-designed trading institutions, provided that enforcement mechanisms, monitoring systems, and third-party protections are credible (David and Hughes 2024; Whitford and Clark 2007).

Policy implications follow directly from the findings. To enhance the credibility of entitlements, provinces should strengthen registry systems and metering infrastructure and expand market platforms in areas where trading activity remains limited. Most importantly, jurisdictions need to implement two-dimensional designs by linking withdrawal rights to discharge permits and ambient environmental targets. This requires real-time adjustments backed by enforceable penalties, along with clearly defined compliance responsibilities for return flows. Given that nonpoint source pollution often undermines water usability, trading rules should be complemented with instruments that price or cap agricultural runoff, as well as with targeted ecological replenishment measures to maintain instream flows. Considering the observed heterogeneity, policy design should be tailored to local conditions. Provinces in central and northern regions—where water scarcity is more severe and marketization more advanced—may be particularly well-positioned to scale up trading mechanisms. In contrast, coastal and southern provinces might instead focus on tightening water-quality regulations, enhancing monitoring capacity, and aligning market expansion with pollution-abatement capabilities.

Several limitations of this study should be acknowledged. First, the analysis is conducted at the provincial level rather than at hydrologically consistent basin scales, which limits the ability to capture intra-basin water reallocations or spillovers. Future research utilizing watershed-level data could offer a more precise assessment. Second, while event-study diagnostics show balanced pre-trends for water-use efficiency, the less stable pre-trends for water quality outcomes raise concerns about potential policy endogeneity or reverse causality. Although our use of province-level SCM analysis helps to address this, it does not fully resolve this issue. Third, the staggered rollout of WRT pilots may coincide with other policy reforms. While we attempt to isolate cases with clear institutionalization and exclude provinces with major overlaps, some residual policy noise may remain. Finally, while we identify two broad mechanisms at the province level, we lack sector- or plant-level outcome data. Micro-level datasets would allow for a more detailed tracing of heterogeneous impacts and a clearer identification of specific mechanisms.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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