El Niño is Coming. Assessing the Impact of Fine-Based Policy on Collective Action in Anticipation of a Drought in Colombia.

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Abstract

This paper examines the effects of announcing and implementing a fine-based water conservation policy in anticipation of a potential extreme weather event on collective action. The policy aimed to reduce excessive residential water use in regions highly susceptible to El Niño-ENSO in Colombia. We analyze the overall effectiveness of the policy and the heterogeneous impacts of different institutional arrangements. Our findings indicate that, on average, the policy reduced residential water demand by approximately 2.6% per month in the targeted areas. Financial penalties did not drive the reductions solely. Users in regions where the government later lifted the policy contributed voluntarily to conservation efforts. According to institutional arrangements for local utilities, state-owned and local-government-operated utilities foster stronger compliance than privately owned utilities. The study shows how pricing mechanisms can stimulate collective action and emphasizes the need for sustained policy enforcement and institutional alignment to support conservation efforts amid climate variability.

Keywords: scarcity prices, collective action, climate variability, pro-environmental behavior, water fines
JEL Classifications: Q21, Q25, Q28, D70

1 Introduction

The hydro-climatic variability associated with the El Niño-Southern Oscillation (ENSO) poses significant challenges to the management of water resources in the tropical Andes, where extreme weather events lead to severe socioeconomic and environmental impacts (UN, 2019; Moura et al., 2019; Poveda et al., 2011). Anomalies in water supply balance and frequent and intense droughts exacerbate water availability issues in multiple sectors, including drinking water, sanitation, irrigation, mining, and hydro-power generation (Vuille, 2013; Bradley et al., 1881). Policymakers face the dual challenge of designing institutions for immediate emergency response and long-term resource planning. Strategies to encourage behavior change among users (Hanak, Lund, 2012) include information-based interventions (Schwarz, Megdal, 2008; Aisbett, Steinhauser, 2014) or scarcity pricing (Olmstead, 2010; Marzano et al., 2018). Although the latter are commonly implemented during drought (Olmstead et al., 2007; Marzano et al., 2018), their effectiveness in promoting collective action at the utility level remains largely underexplored.

We investigate the impact of a water-fine-based policy on collective action in Colombia in anticipation of a potential El Niño-ENSO event. We analyze how the announcement and implementation of this policy influence water usage, considering variations among local institutions that manage water systems. In July 2014, forecasts indicated a high probability of an El Niño-ENSO event, prompting the government to introduce penalties for water consumption exceeding basic needs in drought-prone areas. However, as precipitation improved, the policy was lifted in some regions until a strong El Niño event officially declared a drought season from October 2015 to April 2016. Using a differences-in-differences utility and fixed-effects month regressions, we examine the responses across 534 water utilities in Colombia. We focus on the interaction between local governance structures and user behavior during different policy phases before El Niño-ENSO landed.

We present three main findings. First, the announcement and implementation of the policy effectively promoted water conservation in the targeted regions. On average, the utilities in these areas reduced the usage of residential water by 2. 6% monthly, equivalent to approximately 0.26 cubic meters per user, compared to the areas never targeted during the pre-policy period. These reductions appear to be primarily driven by a combination of financial penalties and voluntary conservation efforts. At the peak of the policy's enforcement, only 0.68% of users were reported as penalized by utilities, suggesting that non-penalized households also contributed to water savings.

Second, the effects of the policy announcement varied depending on the institutional arrangements under which water utilities operate. Our findings indicate that governance structures are crucial in shaping user behavior. Specifically, we observe higher reductions in water consumption in utilities operated by state-owned corporations (SOU), local government offices (LGO), and community-based organizations (CBOs) than in privately owned utilities (POUs), suggesting that institutional factors influence the extent to which conservation measures are adopted.

Third, the policy affected the revenue streams of the utilities, and this impact is different depending on the institutional arrangements in the water utilities. On average, the targeted utilities saw a 6.7% reduction in monthly revenue compared to the non-targeted utilities. However, when examining differences by governance structure, we find a significant increase in revenue in POUs of 6.4% and CBOs of 0.7%. This indicates that the policy in POUs acted mainly as a price signal rather than a conservation measure, with revenue gains stemming from penalty payments instead of reduced consumption below excessive levels. In contrast, state-owned and local government-run utilities (SOUs and LGOs) achieved significant water savings and did not experience significant revenue increases. This suggests that conservation in these systems was driven more by voluntary behavioral responses in users below excessive levels.

This paper contributes to the literature in four domains. First, this study extends the existing literature on water pricing and efficiency in scarcity contexts by providing empirical evidence on how a fine-based conservation policy affects water consumption. Previous research has shown that market-based policies are more cost-effective than command-and-control approaches (Olmstead, Stavins, 2009). Studies indicate that pricing mechanisms help manage extreme weather events (Olmstead, 2014), that rationing policies are less effective than price-based strategies (Brennan et al., 2007), and that price-based policies yield greater welfare gains (Mansur, Olmstead, 2012).

The existing literature largely agrees that water demand is inelastic in response to price changes (Arbués et al., 2003; Marzano et al., 2018). However, market failures and behavioral responses complicate the role of price elasticity in conservation efforts (Olmstead et al., 2007). In this paper, I present evidence that household water conservation behavior is not solely influenced by price increases but also by voluntary contributions in reaction to policy announcements. The results indicate that anticipating drought conditions triggers collective action, reinforcing conservation behaviors beyond direct financial incentives. This underscores the interaction between price signals and social norms in shaping water use behavior.

Second, this study contributes to the literature on property rights and natural resource management, emphasizing the role of institutional arrangements in conservation outcomes. Water governance structures vary beyond the traditional state versus market dichotomy (Ostrom, 2014; Bromley, 1992), and property rights affect cooperation outcomes (Kyriacou, 2010). The findings demonstrate that state-owned utilities (SOUs) and local government-owned utilities (LGUs) were more effective in promoting water savings. In contrast, privately owned utilities (POU) and community-based organizations (CBO) exhibited no significant reductions in consumption. This is the first paper to systematically examine the interaction between pecuniary incentives and institutional structures in the context of water conservation policies.

The findings suggest that collective action is weaker in privately managed utilities because private utilities rely more on pricing signals to indicate scarcity than on fostering cooperative conservation efforts. This raises important questions about how motivation and incentive structures differ between governance models and how private utilities can design complementary mechanisms to encourage conservation. Existing research on water utility privatization has shown mixed results. Although private utilities tend to reduce costs, the impact on efficiency and sustainability is highly context-dependent (Bel, Warner, 2008; Vatn, 2018). In developing countries, evidence suggests that privatization can lead to efficiency gains and welfare improvements, including reductions in infant mortality (Andrés et al., 2007; Cook, 1999; Galiani et al., 2005). However, private utilities often fail to meet sustainability metrics (Lieberherr, Truffer, 2015), and long-term sustainability remains a key challenge, particularly with respect to investment in public infrastructure and the alignment of private incentives with public values (Koppenjan, Enserink, 2009).

Third, this study contributes to the body of research on regulatory efficacy in environmental conservation, highlighting the role of behavioral responses in addition to financial penalties. By documenting reductions in water use among consumers who may not be directly penalized, the study suggests that fines act as behavioral nudges that create awareness and encourage voluntary reductions in resource use. This finding parallels recent work in behavioral economics that suggests that financial penalties can generate broader social signals about resource conservation, motivating even those not directly affected by penalties to change behavior (Pratt, 2023).

The fourth contribution to the paper expands the literature on group size, common-pool resources, and collective action in large social dilemmas. When faced with droughts, the water supply systems are embedded in a social dilemma (Messick, al, 1983; Komorita et al., 1991; Kollock, 1998; Ostrom, 1998). These situations arise when individual interests conflict with collective interests and their outcomes. Olson (1965) logic posits that cooperation is negatively correlated with the size of the group. However, the evidence remains mixed and inconclusive (Ostrom, 1998; Nosenzo et al., 2015; Ge et al., 2019; Chamberlin, 1974; Agrawal, Chhatre, 2006; Zhang, Zhu, 2011; Pecorino, 2015; Rustagi et al., 2010; Esteban, Ray, 2015; Yang et al., 2013; Capraro, Barcelo, 2015). However, the direction depends on the rivalry over the resource (Nosenzo et al., 2015; Chamberlin, 1974). Here, we emphasize how crucial the number of users is in reducing cooperation levels, showing that conservation behaviors are significant in smaller utilities during implementation. Moreover, we provide evidence from a large-scale social dilemma through a quasi-experimental approach.

This paper is structured as follows. Section 2 covers the background on the variability of El Niño-ENSO in Colombia and details the policy intervention, including its implementation and modifications. Section 3 discusses data sources and the empirical strategy for estimating the policy's effects. Section 4 presents the results, starting with static treatment effects from the policy announcement and implementation, followed by the dynamic analysis of heterogeneous effects across water utilities and the mechanisms of behavioral responses. Finally, Section 5 concludes by summarizing contributions, identifying policy lessons, and suggesting future research directions.

2 Background and Context

2.1 Water-sector in Colombia

Colombia, situated in the tropical Andes area, has a large but highly asymmetric water supply. According to IDEAM (2019), the total availability is 64,151 cubic meters per second under normal conditions. However, the distribution of water varies significantly by region: the southern and eastern areas (Amazon and Pacific) hold about 50% of the country's water resources despite having only 4% of the population. In contrast, the northern Caribbean region has roughly 10% of the resources but accounts for 2% of the population. The increasing demand for water from various sectors is a growing concern; in 2016, the total demand reached 37 million cubic meters, with 51% for agricultural production, 21% for hydroelectric generation, and 7. 4% for residential consumption.

The government must ensure access to clean water as a human right[1]. The

[1]The Constitutional Court, in its order T-740 from 2011, established that Water is considered a fundamental right and is defined by the provisions of the Committee on Economic, Social and

water supply systems operate as a regulated monopoly[2]. The Superintendencia de Servicios Públicos (SUPERSERVICIOS in Spanish) inspects, supervises, and regulates water utilities and governmental entities. Municipalities determine the institutional arrangements for providing water and sanitation services, either managing them directly or delegating them to a third party. These decisions depend on local capacity and the political context, although the overarching rules are established nationally.

Superservicios (2014) reported 1424 active water utilities in Colombia. Community-based organizations (CBO) account for 59% of these, utilities managed directly by Local Government Offices (LGOs) represent 13.3%, and State-Owned Utilities (SOU) constitute 6.4%. Private-owned utilities (POU), including public-private partnerships, make up 20%. Different types of utilities exhibit varying performance levels: SOUs and POUs generally operate in larger urban areas, achieve greater population coverage, and demonstrate better financial performance. In contrast, LGOs are found mainly in medium-sized urban areas and often require more resources for investment, with 88% of the municipalities having populations under 10,000 residents. CBOs are typically located in small urban and rural areas, allowing them greater flexibility in establishing operational rules. Although their financial sustainability is in public debate, CBOs play a crucial role in providing water where national and local government capacities are inadequate (Defensoria del Pueblo, 2013).

Residential water rates are regulated by the Water and Sanitation Regulatory Commission (CRA) at the national level. The water rate includes fixed and variable charges per cubic meter. The fixed charge covers administrative costs, while the variable charge addresses operational costs, future investments, and environmental contributions. The scheme aims to achieve the goals of efficiency, fairness, and environmental conservation. To do so, the structure is an increasing block with three tiers: *Basic* (0-20 cubic meters), *Complementary* (20-40 cu-

Cultural Rights, as "the right of everyone to have sufficient, safe, acceptable, physically accessible and affordable water for personal or household use." More details here

[2]According to Law 142 of 1994.

bic meters), and *Luxury* (above 40 cubic meters). The variable charge includes subsidies for low-income groups and contributions from high-income groups as a redistributive measure based on a socioeconomic stratification system.

2.2 El Niño-ENSO Evolution in Colombia (2014-2016)

Extreme weather events, such as El Niño and La Niña (Southern Oscillation—ENSO), significantly shape Colombia's hydrological patterns. El Niño brings warm waters to the tropical Pacific, extending drought in northern South America. In contrast, La Niña strengthens trade winds and causes abnormal accumulation of cold water, resulting in excessive rainfall. El Niño influences air currents in Colombia, leading to changes in cloud cover and drier weather throughout the country. However, it does not eliminate the rainy season; instead, it reduces river flow, which can result in water shortages, higher temperatures, and an increased risk of forest fires (Melo et al., 2017a).

The effects of ENSO are closely related to the seasons, strongest from December to February and weakest from March to May; also, changes in rainfall and river flow show that the influence of ENSO travels like waves through the Andes, having a more significant impact in the western Andes and occurring earlier there than in the eastern Andes (Poveda et al., 2011).

In May 2014, the Institute of Hydrology, Meteorology and Environmental Studies (IDEAM) issued alerts urging national agencies to prepare for observed ocean temperature anomalies in the first trimester. The National Disaster Risk Management Unit (UNGRD) provided institutional guidelines and planned actions in anticipation of drought[3]. However, it was not until March 2015 that the National Oceanic and Atmospheric Administration (NOAA) and IDEAM declared that El Niño had entered a weak phase. Later, in August of that year, the condition was upgraded to moderate, and by October, it was classified as strong, persisting until April 2016. See the evolution of the Oceanic Niño Index (ONI) in Figure 1 based on (NOAA (2024)).

[3]The official document can be found here: PNC FEN 2014-2015 Final

El Niño 2015-16 was one of the most severe in recent history, significantly impacting economic activities. The prolonged drought reduced agricultural output by 5%, disrupting the local food supply and causing broader economic implications due to decreased agricultural exports (Melo et al., 2017b). Reduced rainfall also reduced reservoir water levels, adversely affecting hydroelectric power generation by 6.1% (Melo et al., 2017b). This situation led to national calls for energy-saving measures and an increased dependence on expensive and polluting energy sources, such as thermal power plants.

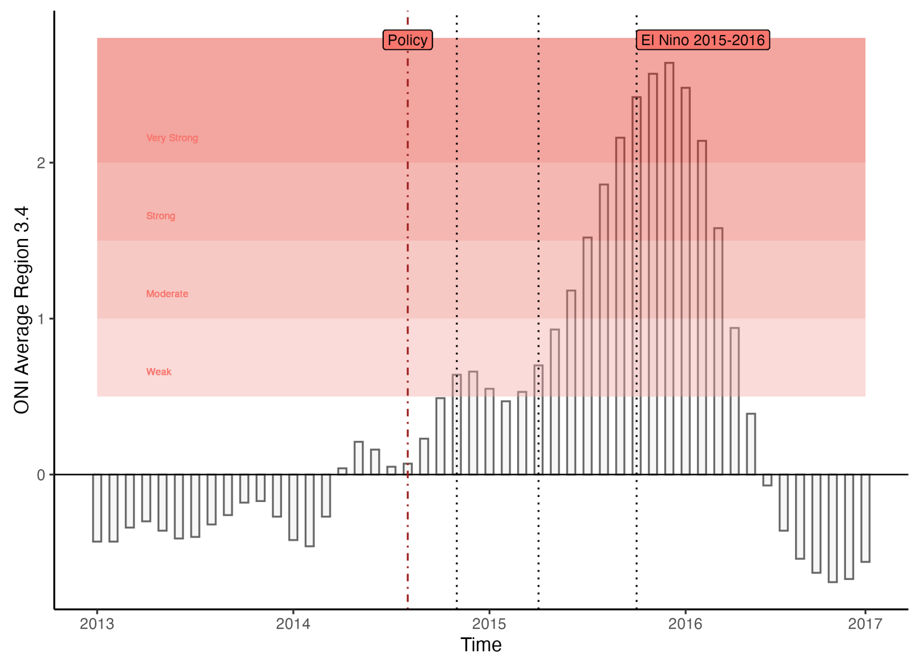
Furthermore, the event exacerbated water scarcity in vulnerable regions, leading to water rationing and increased competition for water resources. 237 municipalities experienced water disruptions, while 296 had rationing periods (Melo et al., 2017a). The event also had public health consequences. The combination of dry conditions and reduced water quality contributed to an increase in respiratory and waterborne diseases. In addition, approximately 19,600 Chikungunya cases and 105,100 Zika cases were reported during that year.

2.3 Fine-based Policy Intervention

In July 2014, the national government announced a plan to address an El Niño-ENSO event that seemed probable. The policy introduced a fine-based system to penalize excessive water use in drought-prone areas and promote collective action in preparation for the weather event. Under this policy, residential water rates increased for households that exceeded certain consumption levels. These levels varied according to the altitude of the municipality: for households above 2,000 meters, the limit was set at 26 cubic meters per month; for those below 1,000 meters, it was 32 cubic meters; and for those between these altitudes, it was 28 cubic meters. Households exceeding these limits had to pay double the usual rate for any additional water used.

The policy specifically targeted areas predicted to be most affected by El Niño. The implementation started in August 2014 and was dynamically adjusted based on the ongoing monitoring of precipitation anomalies. Initially, the policy fo-

Figure 1: Evolution of the Oceanic Niño Index -ONI - Region 3.4



Note. This figure illustrates the Oceanic Niño Index from 1980 to 2019. The shaded areas represent the phases of El Niño according to NOAA. Dotted lines indicate the moments of the policy announcement and subsequent modifications. Authors' calculations using data from http://www.cdc.noaa.gov/enso/.

cused on 12 departments, covering 488 municipalities (Moment 1). In September 2014, 10 departments continued to respond to the alert, impacting 420 municipalities (Moment 2). After seven months, in May 2015, as precipitation began to improve and drought did not take over during its most critical season, the number of targeted areas decreased to three departments and 70 municipalities (Moment 3). Finally, in October of the same year, as El Niño entered a strong phase, the authorities targeted 24 departments until the event ended officially in April 2016.

Figure 2 illustrates the dynamic nature of the policy, showing the targeted areas and the three stages alongside precipitation anomalies by municipality. Notably, the authorities adjusted the policy as precipitation patterns improved. However, the Water and Sanitation Regulatory Commission (CRA) did not respond quickly to El Niño's intensity changes, particularly during its strong phase. The policy was enacted when there was a positive but still low probability of a weak phase (July 2014). Two months later, indicators suggested that a weak phase was imminent, and seven months later, it was officially declared weak. Additionally, most forecasting models generally underestimated the peak intensity of El Niño-ENSO in November 2015, resulting in warmer conditions than anticipated Xue, Kumar (2017).

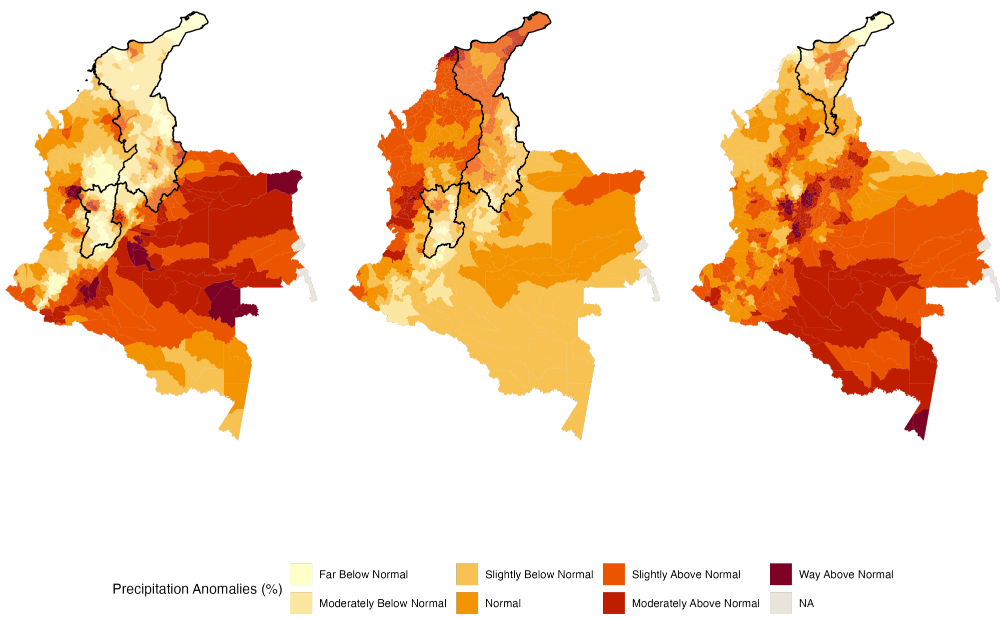
3 Data and Methods

3.1 Data

In this study, we used a panel of water utilities spanning the period before and after the introduction of the fine-based water policy and before the El Niño-ENSO in its strong phase in 2015. We aim to examine the effects of announcing and implementing the policy as a drought preparation measure. To achieve this, we integrate data from multiple spatial and administrative sources at both the utility and municipal levels.

First, we obtain data from the Unified Information System for Utilities(SUI,

Figure 2: Spatial and Temporal Dynamics of the Policy and Associated Precipitation Anomalies



Note. This figure illustrates the relationship between the policy's implementation and the observed precipitation anomalies in municipalities over time. Key moments highlighted include July 2014, September 2014, and April 2015. We calculate precipitation anomalies using data from Muñoz-Sabater et al. (2021), employing the methodology established by IDEAM in Colombia. This parameter measures the percentage deviation of precipitation over a specific period from the historical average value based on 60 years of data.

in Spanish).[4] This system requires that water, electricity and gas utilities report management, operations, finances, and infrastructure information. Our dataset consists of monthly observations from August 2012 to August 2016, covering the announcement, implementation, and subsequent drought period of the policy. The dataset includes key utility-level variables such as residential water consumption, the number and type of users, geographic location, income levels, and administrative and operational costs. Although reporting is mandatory and noncompliance may result in legal consequences, the sample predominantly consists of utilities in major urban and rural centers, reflecting heterogeneity in infrastructure and internet accessibility across water utilities.

Second, we incorporate data from the CEDE Municipality Panel Dataset.[5] This dataset provides monthly and annual observations at the municipal level from 1984 to 2016. We merge these data with key municipal characteristics, including total population, urban population share, rural index, annual income, Unsatisfied Basic Needs Index, municipal area, altitude, and access to water, electricity, and sanitation services. This data set allows us to explore socioeconomic differences between the municipalities targeted by the policy and those that were not.

Finally, we integrate the climatic variables from ERA5-Land (Muñoz-Sabater et al., 2021) to obtain a consistent view of the water and energy cycles at the surface level. This dataset provides monthly averaged reanalysis data from 1950 onward, gridded at a $0.1° \times 0.1°$ latitude-longitude resolution. From this source, we extract monthly temperature and precipitation data, which we aggregate at the municipal level to analyze climate variability and its potential interaction with policy effects.

[4] More information here.
[5] Banco de Datos CEDE - Universidad de los Andes

3.2 Sample Composition

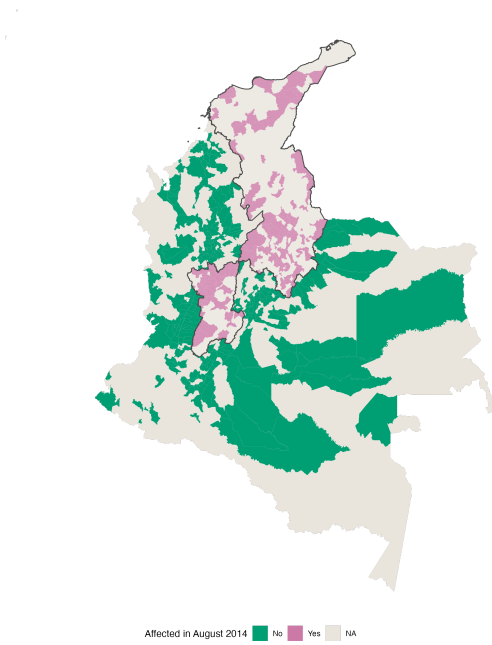
The unit of observation in this study is the water utility. A water utility refers to a group of users connected to the same water network or aqueduct within a specific geographic area and governed by the same rules. However, in some cases, organizations established to operate in one geographic area also operate in different municipalities but under locally defined regulations. To maintain a consistent panel structure, we combine these two levels of observation, the utility and the municipality, treating them as a unique unit of analysis. Our analysis includes 534 water utilities in 464 municipalities (41. 4% of the total) in 29 departments (88% of the total) across the country. Figure 3 illustrates the geographical distribution of the sample, highlighting the municipalities in the sample in both targeted and non-targeted regions as of August 2014.

Table 1 reports the descriptive statistics. Before the implementation of the policy, the average monthly water usage per household was 13.73 cubic meters, and the typical number of residential users was 11,500. The sample encompasses a wide range of utilities, from small ones serving 73 users to large ones accommodating approximately 800,000 users. There is significant variation in years of operation, with utilities averaging 18 years, including some more recently established. In addition, 83% of the utilities serve urban areas. Privately owned corporations make up the majority, accounting for 53.4% of the sample, while state-owned corporations, local government offices, and self-organized communities represent equal portions. The sample also exhibits a wide variability in climatic records, with maximum monthly temperatures ranging from 11 ° C to 32 ° C and minimum monthly precipitation of 0.00741 mm to 65.5 mm. In particular, 41% of the urban centers in the sample are below 1,000 meters above sea level, while 38. 6% are located between 1,000 and 2,000 meters.

3.3 Empirical Strategy

We analyze the effects of announcing and implementing a fine-based policy on residential water consumption during the weak phase of the El Niño-ENSO

Figure 3: Location of the sample within Colombia



Note. This Figure shows the geographical location of the sample. In green are municipalities not targeted by the policy in August 2014. We refer to this group as "Never Targeted." Areas in pink are municipalities within the targeted areas by the policy's announcement. The municipalities in grey are not part of the sample because they did not report partially or totally in the reference period.

event. Our analysis addresses two primary research questions. First, we examine the impact of announcing a fine-based policy on collective action as a preparedness measure for a highly probable drought occurrence. Second, we explore how this impact varies depending on the institutional arrangements under which water is supplied and managed. This section introduces the empirical strategy pursued for both questions and discusses the challenges in identifying the causal effect of the policy.

To measure the utility-level effects of the policy, we employ a difference-in-differences (DiD) approach, exploiting exogenous variation in both time and space before the severe phase of the El Niño-ENSO event. We compare average household water usage in utilities in regions targeted by the policy in August 2014 with that in non-targeted areas. The policy was implemented simultaneously across targeted regions, while non-targeted regions remained untreated throughout the study. Although both groups would eventually experience the impacts of the approaching drought at varying intensities, only the targeted regions were expected to adjust their consumption behavior in anticipation of water scarcity, as authorities did not issue conservation mandates in non-targeted areas.

Our main regression is a utility-level fixed-effects model that controls for cyclical seasonal effects. Specifically, we estimate the following specification:

$$Y_{udt} = \alpha_u + \alpha_m + \beta T_{dt} + X'_{ut}\eta + \epsilon_{udt} \tag{1}$$

where, Y_{udt} is the household water usage in a utility u , located in a department d, during the month t . The outcome is transformed by dividing it by the mean of the control group pre-policy times and multiplying it by 100 to ease the interpretation. β is the coefficient of interest where T_{dt} is a binary variable indicating that department d was targeted by the policy at time t. X_{ut} is a vector of time-varying controls at the utility or municipality level. α_u and α_m denote utility-fixed and month-fixed effects, respectively, accounting for time-invariant differences across utilities and seasonal variations. We avoid including month-year fixed effects as they strongly correlate with the policy timing, given that targeted departments started treatment simultaneously and were reversed in two moments for the two groups. We present estimates with linear time trends for robustness. In our estimations, standard errors are bootstrapped at the department level, which aligns with the policy's implementation level, mitigating concerns about autocorrelation given the small number of clusters (29 departments).

Targeted departments experiencing treatment reversals in the latter two policy moments are depicted in Figure 2. These reversals created three distinct treatment groups: Early-Off, utilities that switched off treatment at the moment I; Late-Off, utilities that switched off treatment at the moment II; and Never-Off, utilities that remained under treatment throughout. This heterogeneity complicates our primary estimation, as treatment reversals may mask variation in treatment effects and contaminate the never-targeted group that serves as a counterfactual. We estimate a variation of Equation 1 to address this. The treatment switching model includes binary indicators for utilities in Departments where the policy was lifted as follows:

$$Y_{udt} = \alpha_u + \alpha_m + \beta T_{dt} + \gamma EarlyOff_{d,t>=3} + \delta LateOff_{d,t>=10} + X'_{ut}\eta + \epsilon_{udt} \quad (2)$$

Where $EarlyOff_{dt}$ is a binary indicator of departments that exit the policy from $t >= 3$ or moment I onward and $LateOff_{dt}$ for departments that exit from $t >= 10$ or moment II onward, they allow one to control for and estimate a clean effect of the policy on targeted areas compared to never targeted. γ and δ capture the reversal effects of treatment.

Our approach estimates the change in residential water usage before and after the policy took effect in utilities in targeted regions, relative to changes in never targeted regions. To causally interpret our DiD estimator, our framework must satisfy three main assumptions: (i) Parallel Trends in Baseline Outcomes, (ii) No Anticipation Behavior Before Treatment, and (iii) Homogeneity of Treatment Effects.

The parallel trends in baseline outcomes imply that utilities in targeted and non-targeted regions would have followed the same trends over time without the policy treatment. In our context, any preexisting differences in water usage between targeted and non-targeted utilities before policy implementation must remain stable over time. We provide empirical evidence for this assumption by estimating monthly-based event-study parameters, employing the linear two-way fixed effects model.

$$Y_{udt} = \alpha_u + \alpha_m + \sum_{e=-24, e\neq -1}^{13} \beta_e 1\{T_{dt} = e\} + \gamma EarlyOff f_{d,t>=3} + \delta LateOff f_{d,t>=10} + X'_{ut}\eta + \nu_{udt} \tag{3}$$

Which includes 24 treatment lead indicators (β_e for $e < -1$) and 14 treatment lag indicators (β_e for $e \geq 0$) to estimate the impact of the policy in preparation times. Because our empirical application includes a set of never-targeted regions, we only omit the treatment lead indicators associated with $e = -1$ Borusyak, Jaravel (2018). We include the indicators $EarlyOff f_{d,t>=3}$ and $LateOff f_{d,t>=10}$ for the areas that left treatment. In contrast to the static model Equation 1, which allows only analysis of the average effect of the policy, the dynamic coefficients capture the direct and indirect impact of the policy via lagged indicators. Although selecting treatment lead indicators is related to data availability, we present estimations varying the pre-policy number of treatment lead indicators for robustness analysis.

Although the two-way fixed-effects DiD approach is widely used in many settings, it presents certain limitations. Recent developments highlight issues in staggered treatment settings Borusyak, Jaravel (2018); Goodman-Bacon (2021); Chaisemartin de, D'Haultfœuille (2020); **?**); Callaway, Sant'anna (2021), where negative weighting can bias estimates if treatment effects vary between units and time. However, treatment began simultaneously across units in our setting, making these concerns less relevant. Thus, the estimators by (**?**) and (Callaway, Sant'anna, 2021) -which assume staggered adoption - are not applicable here.

The assumption of no-anticipation behavior before treatment holds if households within a utility do not adjust their behavior before the treatment in anticipation of the forthcoming policy. In other words, the effects of the policy should only emerge after its official announcement and implementation. Since the regulator publicly announced the policy one month before its enforcement, we infer that households in targeted areas were unlikely to foresee its introduction far in advance. In addition, this was the first instance of a policy penalizing excessive water usage, which reduces the likelihood of pre-emptive behavioral adjustments.

However, water utilities may have anticipated potential water shortages due to anomalies in climatic patterns. Although the policy was announced before the actual drought, utilities could have taken additional localized measures to promote conservation among users. Similarly, households could have adjusted their consumption patterns in response to early warnings about reduced water availability. We test for potential differences at pre-policy time on average monthly minimum precipitation and maximum temperature for utilities targeted in August 2014 versus non-targeted utilities. Appendix A reports the monthly estimates. Results indicate that targeted areas did not experience significant differences in precipitation levels. However, we observe a sustained average temperature increase in targeted areas leading to the policy announcement. Since the latter could signal impending drought conditions, it may have triggered anticipatory conservation efforts in some regions. We include monthly precipitation and temperature controls in our regression models and also report estimates without these controls in the robustness section.

Additionally, Table 8 presents standardized mean differences between utilities in targeted and non-targeted areas as of August 2014 (pre-policy period). While differences are statistically significant, they are small in magnitude. Notably, discrepancies appear among Utilities in urban agglomerations, utilities managed by local government offices, municipalities located between 1,000 and 2,000 meters above sea level, municipal area, poverty index, and percentage of households with access to waste collection and sewage services (the last two correlated). Our utility fixed effects specification would control for any bias that could arise from these differences.

Our analysis also tests for potential differences in policy impact across the institutional arrangements under which utilities operate locally. We run separate estimations of Equation 1 by utility types, keeping the controls by temperature and precipitation at the municipality level and utility and season fixed effects. We present separate regressions rather than the pooled sample with interactions, as our goal is to compare targeted utilities to never-treated utilities that operate under the same institutional characteristics.

Furthermore, we analyze heterogeneity in the treatment effects to explore potential mechanisms. The effects at the group level could be mediated by characteristics of the natural resource, social interactions, and institutions (Poteete, Ostrom, 2004). In the resource hypothesis, the rivalry degree plays a crucial role in affecting the direction of the relationship (Nosenzo et al., 2015; Chamberlin, 1974). In addition, the group size, individual appropriation, and scarcity increase resource competition. The social interaction hypothesis relates to reciprocity, trust, and moral motivations (Brekke et al., 2003; Andreoni, 1995; Cárdenas, 2005).

We test for potential differences by group-size of the users in utilities. We augmented our baseline regression model in Equation 1 as follows:

$$Y_{udt} = \alpha_u + \alpha_m + \beta T_{dt} + \sum_{q=2, e\neq -1}^{4} \lambda^q (T_{dt} * Size_{q,u}) + \gamma EarlyOff_{dt} + \delta LateOff_{dt} + X'_{ut}\gamma + \epsilon_{udt} \tag{4}$$

which compares the effects of the policy across quartiles of the distribution of the number of users at pre-policy, $Size_{q,u}$, we use the first quartile as the reference level. The impact of the policy across utility sizes is given by β + λ^q for $q = (1, ..., 4)$.

We also test for potential differences in the policy impact across measures of income heterogeneity for households within utilities as follows:

$$Y_{udt} = \alpha_u + \alpha_m + \beta T_{dt} + \sum_{q=2, e \neq -1}^{4} \lambda^q (T_{dt} * HHI_{q,u}) + \gamma EarlyOff_{dt} + \delta LateOff_{dt} + X'_{ut}\gamma + \epsilon_{udt} \tag{5}$$

where HHI is the Herfindahl-Hirschman index as a measure for income heterogeneity within utilities (see more details in Appendix C), we estimate the treatment effects by quartiles of the distribution of HHI at pre-policy times.

3.4 Hypotheses

In this study, we use residential water usage as a measure of collective action in response to the impending drought. We calculated this by dividing the reported total residential water consumption by the total number of residential users in a given month. While we lack user-level data, reductions in average water usage serve as a proxy for cooperation. Our focus is on users within a local water utility facing drought conditions, positioning their behavior within a large-scale social dilemma framework Messick, al (1983); Komorita et al. (1991); Kollock (1998); Dawes, Messick (2000). In this context, users sharing a common-pool resource must choose between defecting—maximizing their private benefit by maintaining typical water usage—or cooperating by reducing usage to levels that enhance collective benefits, ensuring more water is available to all. The new regulation aims to foster environmental awareness and indirectly encourage users to promote cooperative behavior.

Users may be motivated to respond to the announcement either by increased consumption costs or pro-social/pro-environmental preferences. In the first scenario, the user's response may be influenced by their proximity to excessive use levels. High consumers are more likely to respond to overpricing. In the second scenario, users may be driven by pro-social preferences or the characteristics of the group, such as social contentedness, social image, trust, or reciprocity. Both scenarios are not necessarily exclusive but complementary.

Here, we follow the average user reaction to the policy intervention as a sign of cooperation during the transition from a weak to the strong phase of the weather shock. The estimations provide intent-to-treat estimates, as we are not measuring the direct impact of the fine-based policy on individual users in targeted water systems (since we cannot observe usage at the user level or their deviations from penalized levels). Instead, we infer the average response across groups of users within a utility. An advantage of this approach—beyond its feasibility given the data—is that intent-to-treat estimates capture both the effects on cooperative users and the community-level influences on non-cooperative users.

We expect that, on average, households in targeted areas reduce their usage as the policy is announced and implemented. Scarcity pricing evidence has shown effective reductions in affected populations (Olmstead, 2010, 2014). However, recent evidence points out the existence of non-price channels when households face drought restrictions. Pratt (2023) provides evidence on how financial penalties have non-price effects separate from any punishment avoidance behavior. We explore these implications by providing quantitative evidence supporting the complementary effects of the policy responses.

4 Results

This section presents our empirical findings on the effects of the fine-based policy intervention on household water consumption. We begin by analyzing the overall impact of the policy across all targeted utilities, including those where the policy changed over time. We then explore the dynamic treatment effects, examining how the policy's effectiveness varied with the timing of the El Niño-ENSO event. Next, we assess heterogeneous treatment effects based on institutional arrangements, showing that state-run utilities achieved greater water usage reductions than community-based and private utilities. This finding highlights the crucial role of institutional governance in shaping the effectiveness of conservation policies.

Additionally, we investigate the mechanisms driving the observed collective action response, including the policy's impact on water rates and revenue changes. We also examine how utility characteristics—such as size and income heterogeneity—moderate conservation behaviors. These insights contribute to a deeper understanding of the broader behavioral and economic responses to price-based regulatory interventions in the context of climate variability.

4.1 Effects of the Policy on Collective Action

Table 2 presents the average treatment effects of the fine-based policy intervention on household water usage and utility revenue. The estimates are derived using Equations 1 and 2, which control for temperature, precipitation, utility, and seasonal fixed effects. Columns (1) and (2) report the effects on household water usage, while Columns (3) and (4) focus on changes in utility revenue. The targeted coefficient in Column (1) indicates a 2.69% reduction in water usage in areas where the government implemented the policy. This effect is statistically significant at the 1% level (p=0.000), confirming that the policy had a substantial negative impact on consumption. The effect remains consistent in Column (2), which accounts for policy reversals, showing a slightly larger reduction of 2.83%. The Late-Off group exhibits a 1.99% decrease in water consumption (p=0.002), whereas Early-Off utilities show a 6.26% increase (p=0.000), suggesting that removing the policy increased consumption in those exiting early. These results confirm that the policy effectively reduced water usage, particularly among utilities that remained under regulation for an extended period. However, utilities that exited the policy early saw increased consumption, indicating a potential rebound effect when the government lifted the penalty.

Columns (3) and (4) examine changes in total residential revenue collected by utilities from water consumption. The targeted coefficient in Column (3) indicates a 6.73% decrease in total revenue from water consumption (p=0.000). Considering policy reversals, Column (4) shows an even more considerable 7.50% decrease (p=0.000). Early-Off utilities experienced no statistically significant change in total revenue (p=0.662), while Late-Off utilities saw a 7.56% decline (p=0.000).

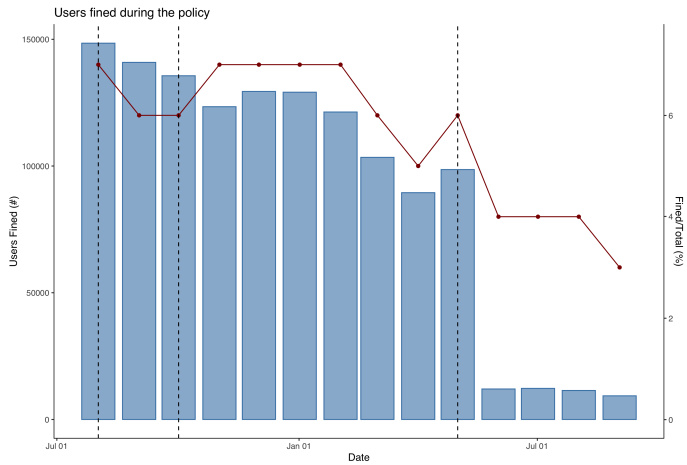
These results suggest the policy's primary effect was a net utility revenue loss. Despite the introduction of penalties, the overall reduction in consumption outweighed any additional revenue generated from fines, leading to a significant drop in total revenue.

The decline in revenue can be attributed to the price elasticity of demand. The significant reduction in water usage led to lower total revenue for utilities, even with penalties imposed on high consumers. It suggests that water demand was more elastic than anticipated, suggesting that users strongly responded to the policy by conserving water instead of merely paying fines. If a considerable number of users reduced their consumption below penalty thresholds, fewer households faced fines, resulting in lower-than-expected revenue from penalties. Conversely, utilities subjected to policy enforcement for a longer duration experienced the most revenue loss, even after the policy was lifted (Late-Off group). In contrast, Early-Off utilities did not experience a significant revenue decline, likely because penalties temporarily increased revenue prior to the lifting of the policy.

Reductions in water consumption align with economic theory regarding price-based water conservation, consistent with previous research (Mansur, Olmstead, 2012; Krause et al., 2003). Households decreased water use to avoid penalties, but voluntary conservation also contributed (Pratt, 2023). Evidence from penalized users indicates that high-consumption households initially adjusted their usage, while spillover effects may have reinforced later reductions. Although our utility-level data do not fully allow us to disentangle the underlying motivations behind reductions in water consumption, we gather insights from reports on penalized users submitted by water utilities to the national regulator.

As shown in Figure 4, the number of penalized users peaked in the first month, impacting up to 7% of households nationwide, before gradually declining to 3% by June 2015. This trend suggests that initial reductions in water consumption were primarily driven by high-consuming users modifying their behavior to avoid financial penalties. Over time, voluntary conservation efforts may have further reinforced these reductions through social spillover effects within com-

Figure 4: Users penalized during the Policy Implementation



Note. This figure displays the number of users penalized under the policy intervention. Blue bars indicate the total number of sanctioned users, while the red line represents the percentage of penalized users relative to the total number of users in targeted systems. Authors' calculations using data from the SUI.

munities or as a broader behavioral response to the policy's signaling of resource scarcity. The combination of compliance with penalties and voluntary conservation shaped the long-term impact of the policy.

The reduction is about $4,920,000 cubicmetersmonthly, aquantityofwaterthatcouldserveapopulati$ users in a month.

4.2 Dynamic Effects of the Policy on Collective Action

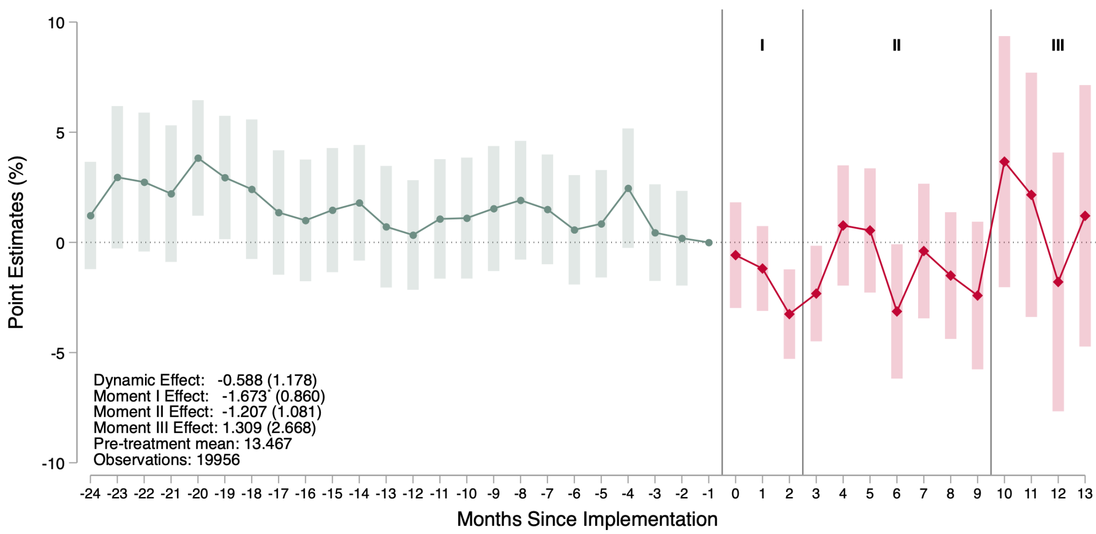
Figure Figure 5 presents the evolution of household water consumption before and after policy implementation. Pre-policy estimates (green line) remain mostly statistically indistinguishable from zero, supporting the assumption of parallel trends. Water consumption in targeted and non-targeted areas exhibited similar trajectories before the government enacted the policy. During Moment I, or the Implementation Phase, a significant reduction in water usage emerges after implementation, with an estimated decline of 1.67% ($p<0.1$). It suggests that the initial behavioral response was primarily driven by high-consuming users adjusting their demand to avoid penalties. At Moment II, or the Partial Reversal moment, the treatment effect weakens over time, with an estimated impact of -1.20% ($p>0.1$). This attenuation implies that some households adapted their consumption permanently while others gradually reverted to previous usage patterns. Finally, at Moment III, or the Full Policy Reversal, the estimated effect becomes statistically insignificant (1.31%, $p>0.1$), indicating that water usage rebounded toward pre-policy levels once the policy was lifted. It aligns with the observed increase in consumption among Early-Off utilities, suggesting that some users resumed higher consumption once the immediate financial disincentive was removed.

The policy's effectiveness in reducing water usage was most substantial during its initial implementation, but diminished over time. This trend coincided with the weak El Niño phase Figure 1, during which behavioral responses to financial penalties were the primary driver of conservation, even though drier conditions had not yet arrived. However, as the region approached a stronger El Niño phase, the worsening drought conditions failed to reinforce the policy effects as expected. The observed pattern poses challenges for this policy, specifically, the ability to predict and anticipate the El Niño conditions. The removal of penalties in some areas contributed to a rebound in consumption, raising concerns about the sustainability of conservation efforts. Although the country activated the early warning system, the timing of the policy seems to have fallen short of its goal to reduce excessive water use over time.

4.3 Effects of the Policy on Collective Action by Institutional Arrangements

This analysis examines how the impact of the policy varies based on the type of water utility management structure. The goal is to evaluate whether different governance models—such as state-owned utilities, local government-run utilities, private corporations, or community-based organizations—affect the effectiveness of the policy in reducing water consumption. Table 3 reports the re-

Figure 5: Dynamic Effects of the Policy Implementation on Residential Water Usage



Note. This figure displays point estimates and confidence intervals at the 95% level of a DiD in Equation 3. It is a utility fixed-effects regression that controls for treatment reversal groups, temperature, precipitation, and seasonal fixed effects. Each dot represents the percentage change in water usage over time, with Moment I starting at the policy's initial implementation, Moment II marking a recalibration, and Moment III a second recalibration. Standard errors are clustered at a combination of Municipality and Department level.

sults. The largest reductions in water consumption are observed in state-owned utilities -4.01% (p=0.000), local government-run utilities -4.30% (p=0.000), and community-based organizations -4.07% (p=0.000). The smallest reduction was noted in private corporations with -1.45% (p=0.004). These results suggest that publicly managed utilities (SOU, LGO) were more effective in enforcing conservation and community-based initiatives. In contrast, privately owned utilities show the weakest response.

We also assess differences in utility revenues from water consumption. For SOU and LGO, changes in revenue were statistically insignificant, indicating that revenue was not affected despite reductions in consumption. For CBOs, the revenue effects were positive but small by 0.73% (p=0.000), suggesting that penalties slightly increased revenues. Finally, for POUs, revenue increased significantly by 6.41% (p=0.000) despite experiencing the smallest reduction in consumption. These outcomes illustrate that SOU and LGO-managed utilities did not experience substantial revenue growth. This indicates that the policy was more effective at reducing consumption than generating additional revenue, implying that users close to or above the introduced excessive limit changed their consumption. CBO utilities exhibited slight revenue enhancements, potentially due to user contributions or operational flexibility. Conversely, POUs demonstrated the most considerable revenue uplift, regardless of the minimal decrease in water usage observed, which implies that fewer users in the excessive block reduced consumption.

Table 3 also reports the estimated effects of the policy under different institutional arrangements of utilities that exited the policy early and those that exited late. We observe a strong rebound effect in utilities that exit the policy early, with a 7.33% (p=0.000) consumption increase in POUs, while there is no significant effect in CBOs. We find a revenue increase of 33.13% and 1.04%, respectively. This result aligns with the effects observed in the average from targeted utilities. For utilities that exit the policy later, significant reductions occur for LGOs. However, revenues increase by nearly 1% in LGOs and CBOs and about 7.5% for POUs.

These findings contribute to a broader discussion on how property rights arrangements influence users' behavior in water resources. In POUs, property rights are assigned individually—users sign contracts with companies and pay for their consumption as in a market-based transaction. However, this transactional nature may weaken incentives for cooperative behavior, as users may be less aware of the externalities their consumption imposes on others. As Bromley (1992) individuals within a group share expectations but internalize the costs and benefits of their decisions according to the property rights structure in place. Under private ownership, users may perceive water as a purely private good, believing that payment entitles them to consume freely, without considering broader collective concerns. Prior research suggests that prices and private property rights can displace intrinsic motivations to cooperate, undermining conservation efforts (Kyriacou, 2010).

Moreover, evidence suggests that systems under private management perform worse in sustainability outcomes than state-based institutions (Lieberherr, Truffer, 2015). They also face challenges regarding the willingness to invest in public infrastructure and uphold public values, and they are less concerned about long-term sustainability than their counterparts (Koppenjan, Enserink, 2009). In state-run, local government, and community systems, users are not viewed as clients; they also play a role in producing and operating the public good (water systems). These collective property rights could influence contributions or appropriation levels during scarcity. Consequently, it would strengthen compliance.

Another factor influencing households' responses to the policy may be perceptions of system efficiency. According to Superservicios (2014), privately run utilities generally demonstrate higher efficiency in managing financial resources and achieve better coverage rates in their operating areas compared to local government offices or community-based organizations. Users served by these systems may feel less urgency to adhere to conservation measures, perceiving a lower likelihood of water shortages due to the company's effective management of water supply. However, the available data do not enable us to test this hypothesis.

Finally, utility size or the number of users within the water system may introduce additional heterogeneity in responses. Utilities run by LGOs and CBOs are typically smaller than those operated by private corporations. In these contexts, social capital may be crucial in shaping conservation behavior. Smaller communities often exhibit horizontal information flows, reinforcing collective action norms and promoting voluntary cooperation in response to scarcity (Carnap von, 2017). We test for potential differences in impact across utility sizes further in the mechanisms section.

Overall, the findings in this paper indicate that conservation policies must consider governance structures. Market-based mechanisms require complementary interventions, such as behavioral nudges or community incentives, to enhance conservation responses in private utilities in anticipation of weather shocks. Moreover, future policy options could leverage social capital and local engagement. Conservation efforts by households could be improved in smaller, community-driven water systems by reinforcing social norms and peer accountability mechanisms. Finally, stronger regulatory oversight may be necessary in privately run utilities. If revenue gains, rather than conservation, influence utility behavior, adjustments to pricing structures and penalty mechanisms may be required to align economic incentives with environmental objectives.

4.4 Effects of the Policy and Group Features on Collective Action

We examine potential differences in the impact of utility characteristics that may be key to explaining the collective action response. First, we investigate the policy's differential effects on utility size or the number of users. Figure 6a displays the point estimates of the interaction between the targeted utilities and quartiles of the number of users before the policy implementation. We find negative but decreasing treatment effects across quartiles. Small utilities (Q1) show the largest reduction in water usage at -4%, suggesting that the policy was more effective in smaller-scale systems. Medium and large utilities (Q2–Q4) also exhibit reductions, although the effect size is smaller and less significant. The largest utilities (Q4) demonstrate the smallest and most uncertain effect, indicating weaker conservation responses. The confidence intervals are wider for larger utilities, reflecting greater variation in their response to the policy. This may suggest heterogeneous enforcement of penalties or higher behavioral inertia among users in larger systems.

The observed effects of group sizes are in line with what the literature has discussed, which states that cooperation is unsustainable per se in larger groups and requires the use of incentives to produce it. Evidence on the group-size effect on cooperation is mixed Ostrom (2005); Nosenzo et al. (2015); Agrawal, Chhatre (2006); Zhang, Zhu (2011); Kurian (2002); Yang et al. (2013); Barcelo, Capraro (2014); Esteban, Ray (2015). The direction depends on the degree of rivalry within the context of the study Chamberlin (1974). Where the resource presents a high degree of rivalry, cooperation is expected to be negative because of competition for appropriation.

Income heterogeneity is another feature that explains collective action. It may increase the probability that cooperation occurs (Olson, 1965). The logic lies in the existence of subgroups that could gain when cooperation is produced (Oliver et al., 1985). Heckathorn (1993) discusses how cooperation is undermined in more heterogeneous groups. Cardenas, Jaramillo (2007); Cárdenas (2005) discuss that the larger the group size, the less probable it is for cooperation to emerge, and levels of asset inequality can attenuate the observed behavior. We test for differences in the policy effects on collective action by groups of income heterogeneity. We calculate the Herfindahl-Hirschman Index (HHI), a statistical measure of concentration that ranges from 0 to 100, using the share of users within each of the six socioeconomic strata (SES) (More details are in the Appendix). In Colombia, the population is ranked in six levels correlated to income. This measure is particularly salient to the population as a sign of class.

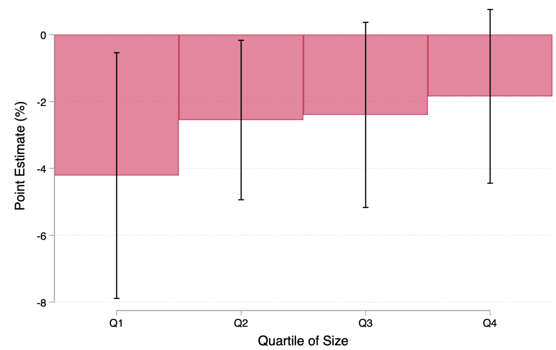
Our index captures how diverse the composition of the population is in terms of income groups. A higher value indicates less income diversity within a water utility. Figure 6a displays the point estimates for the interaction between the targeted utilities and the quartiles of an HHI. The estimated effects suggest that income diversity is not crucial in explaining the observed response to the policy. While reductions in water consumption appear somewhat larger in the lowest HHI quartile (Q1), the overlapping confidence intervals suggest that the differences across quartiles are not statistically significant.

4.5 Robustness

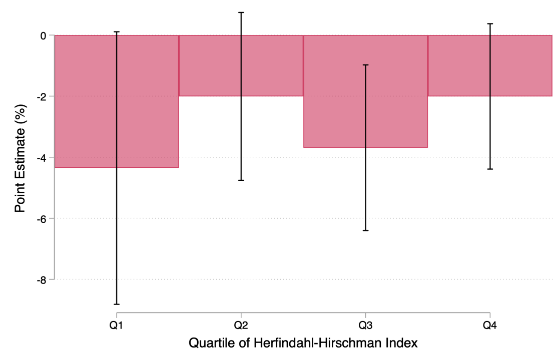
One potential concern in the empirical strategy is the sensitivity of the estimated treatment effects to the length of the pre-policy period used in the analysis. The main specification uses a panel covering 24 months before and 14 months after the policy's implementation. However, to ensure the robustness of our findings, we re-estimate Equations 1 and 2 using a shorter pre-policy period of 14 months. This alternative specification helps assess whether long-term pre-treatment trends drive the estimated effects or the policy's impact remains stable even when a shorter historical reference period is used. Table 4 reports the estimated effects under this revised specification. The findings confirm that the treatment effects remain statistically significant and consistent in their direction with those obtained from the 24-month pre-policy period. However, the magnitude of some coefficients shows slight variation, indicating that longer pre-policy windows may better capture baseline water consumption trends.

A key concern in the analysis is whether strategic reporting behavior by utilities could bias the estimated treatment effects. Since utilities self-report water consumption data to the national information system, they adjusted their records in response to the policy, either to comply with regulations or to optimize revenue collection. To assess this, we examine the reported household water consumption distribution, as shown in Appendix B. The analysis reveals a notable spike in reported consumption at 20 cubic meters per month, particularly in the pre-policy period, with a slightly less pronounced spike post-policy. This threshold corresponds to the boundary between the Basic and Complementary consumption blocks, where households face higher tariff rates. This pattern sug-

Figure 6: Heterogeneous Effects of the Policy on Water Usage by Utility Features



(a) Targeted and Utility Size Quartiles



(b) Targeted and Utility Income Diversity Quartiles

Note. This figure presents the estimated policy impact on water usage across utilities classified into quartiles of two measures: the group size and the group income diversity (Q1 to Q4). The y-axis represents the estimated percentage change in water consumption due to the fine-based policy, while the x-axis represents the quartiles of both measures. The regressions are based on Equation 4, controlling for treatment reversal groups, climatic variables, and utility and seasonal fixed effects. Standard errors are clustered at the municipality and Department level gests that some utilities or households may have adjusted their reported consumption to stay within the lower-cost bracket, raising concerns about data accuracy and potential manipulation. To test the robustness of our estimates against this concern, we re-estimate Equations 1 and 2, excluding all observations where household water consumption equals exactly 20 cubic meters. This approach removes potential distortions caused by bunching at the tariff threshold and allows us to verify whether the policy effects remain stable.

The results, reported in Table 5, show that removing these observations does not significantly alter the estimated effects. Compared to the baseline estimates in Table 2, the coefficients remain consistent in both magnitude and statistical significance. If anything, the original estimates appear to be conservative, suggesting that any reporting bias does not meaningfully alter the study's main conclusions. These findings reassure that the policy's estimated effects on water consumption are not driven by systematic misreporting.

The fine-based policy intervention affected targeted utilities and established artificial policy borders, as shown in Figure 2. This spatial dimension raises the possibility of spillover effects, which could bias the estimated treatment effects depending on how neighboring utilities reacted to the policy. Two potential spillover mechanisms exist. First, utilities near targeted areas may have voluntarily adopted conservation behaviors in anticipation of future regulations or in response to broader conservation messaging. If households in non-targeted but neighboring utilities reduced their consumption, the estimated policy effects could be understated, indicating that the reported results represent a lower bound of the true effect. Alternatively, targeted utilities might have responded by increasing consumption or maintaining prior usage, perceiving that neighboring areas were shouldering the conservation burden. In this scenario, the local policy effects may be smaller or opposite to the intended impact, complicating interpretation.

To investigate these spatial spillovers, we re-estimate Equation 2, incorporating distance buffers from the policy border at Moment I. We define five distance bands ranging from 10 km to 150 km and estimate separate treatment effects for each. Table 6 reports the results. The effect of the policy remains negative and statistically significant across all distance buffers (10km, 25km, 50km, 100km, and 150km). The magnitude of the reduction in water usage is around -3.3% to -3.8%, depending on the buffer distance. This suggests the policy effectively reduced water consumption, even when accounting for potential spillover effects. Early-Off utilities experienced a rebound effect, particularly at longer distances (100-150km), whereas Late-Off utilities demonstrated weaker responses similar to our main estimates.

A potential concern in our main specification is the inclusion of weather variables (temperature and precipitation) as controls. While these factors are crucial for explaining variations in water consumption, their inclusion in a policy impact analysis could introduce biases due to their correlation with the treatment variable. We re-estimate Equation 1 and Equation 2, excluding temperature and precipitation as controls. This approach allows us to assess whether the treatment effect remains stable when not adjusting for weather conditions. Table 7 presents the results. The estimated policy effects on household water consumption remain statistically significant and negative, even after removing temperature and precipitation as controls. This suggests that the observed reductions in water usage are not driven by changes in weather conditions, reinforcing the policy's impact. This strengthens the argument that the policy announcement and financial penalties effectively triggered conservation behaviors regardless of climatic variations.

5 Final Remarks

This study examines the effects of a fine-based water conservation policy implemented in Colombia in response to an anticipated El Niño-ENSO event. By leveraging a dynamic differences-in-differences approach and analyzing data from 534 water utilities across 464 municipalities, we assess how the policy influenced water consumption and whether its effectiveness varied across different institutional arrangements.

Our findings reveal three key insights. First, the policy reduced water consumption, aligning with theoretical expectations that price-based interventions can influence household behavior during drought conditions. However, reductions in water use extended beyond the users who were directly penalized, suggesting that the policy also triggered voluntary conservation efforts. These behavioral spillovers highlight the role of social and psychological mechanisms in reinforcing conservation behaviors beyond strict financial incentives.

Second, the policy's effectiveness varied by utility type, emphasizing the importance of institutional governance in shaping policy outcomes. While state-owned and local government-operated utilities experienced significant reductions in water consumption, privately owned and community-based utilities did not exhibit comparable declines. This indicates that property rights structures and governance models influence how users respond to conservation measures in privately operated utilities, where water access functions as a market transaction and intrinsic motivations to cooperate may be weaker. This reinforces previous findings regarding the relationship between governance models, sustainability, and compliance.

Third, our results suggest that the timing of the policy and perceptions of climate risk affect the effectiveness of conservation interventions. The policy was introduced before the severe 2015-2016 El Niño event, and our analysis indicates that its impact faded as the perceived severity of water scarcity decreased. This finding has important implications for policy design, underscoring the need for timely interventions that align with public risk perceptions to maximize behavioral responses.

Beyond its immediate policy implications, this study contributes to broader discussions on water governance, behavioral responses to conservation policies, and the institutional determinants of sustainability. The results indicate that effective water conservation requires financial deterrents and strategies that leverage social norms, institutional trust, and collective action mechanisms. Policymakers designing conservation interventions should consider how institutional governance structures shape user responses and explore complementary behavioral nudges that reinforce cooperation.

Despite its contributions, this study has some limitations. First, while our analysis identifies heterogeneous policy effects across governance models, our data do not allow us to fully disentangle the specific mechanisms driving voluntary conservation. Future research could incorporate household-level surveys or experimental designs to assess the relative contributions of peer effects, risk perceptions, and social norms in conservation behavior. Second, we do not explicitly measure long-term compliance beyond the policy period, leaving open the question of whether behavioral changes persist once penalties are lifted. Finally, the relationship between system efficiency, perceived reliability, and conservation behavior warrants further investigation, as our findings suggest that users in private utilities may rely more on their provider's infrastructure investments than on their conservation efforts.

Overall, our results emphasize the complexity of water conservation policy design and the importance of considering economic, institutional, and behavioral dimensions. Effective governance in the face of climate variability requires regulatory tools, economic incentives, and behavioral strategies that align with local institutional contexts and user motivations.

References

Agrawal Arun, Chhatre Ashwini. Explaining success on the commons: Community forest governance in the Indian Himalaya // World Dev. 2006. 34, 1. 149–166.

Aisbett Emma, Steinhauser Ralf. Maintaining the Common Pool: Voluntary Water Conservation in Response to Varying Scarcity // Environ. Resour. Econ. 2014. 59, 2. 167–185.

Andreoni J. Cooperation in Public-Goods Experiments: Kindness or Confusion? // Am. Econ. Rev. 1995. 85, 4. 891–904.

Andrés Luis A., Guasch José Luis, Straub Stephane. Does Regulation and Institutional Design Matter for Infrastructure Sector Performance? 2007.

Arbués Fernando, García-Valiñas María Ángeles, Martínez-Espiñeira Roberto. Estimation of residential water demand: A state-of-the-art review // J. Socio. Econ. 2003. 32, 1. 81–102.

Group size effect on cooperation in social dilemmas. // . 2014. 1–17.

Bel Germà, Warner Mildred. Does privatization of solid waste and water services reduce costs? A review of empirical studies // Resour. Conserv. Recycl. 2008. 52, 12. 1337–1348.

Borusyak Kirill, Jaravel Xavier. with an Application to the Estimation of the Marginal Propensity to Consume . 2018.

Bradley Raymond S., Vuille Mathias, Diaz Henry F., Vergara Walter. Threats to Water Supplies in the Tropical Andes // Science (80-.). 1881. 312, 5781. 341–342.

Brekke Kjell Arne, Kverndokk Snorre, Nyborg Karine. An economic model of moral motivation // J. Public Econ. 2003. 87, 9-10. 1967–1983.

Brennan Donna, Tapsuwan Sorada, Ingram Gordon. The welfare costs of urban outdoor water restrictions // Aust. J. Agric. Resour. Econ. 2007. 51, 3. 243–261.

Bromley Daniel W. The commons, common property, and environmental policy // Environ. Resour. Econ. 1992. 2, 1. 1–17.

Callaway Brantly, Sant'anna Pedro H C. Difference-in-Differences with multiple time periods // J. Econom. 2021. 225. 200–230.

Capraro Valerio, Barcelo Hélène. Group size effect on cooperation in one-shot social dilemmas II: Curvilinear effect // PLoS One. 2015. 10, 7. 1–8.

Cárdenas Juan Camilo. Local Commons and Cross-Effects of Population and Inequality on the Local Provision of Environmental Services // Lect. Econ. 2005. 62, 62. 75–121.

Cardenas Juan Camilo, Jaramillo Christian. Cooperation in Large Networks: An Experimental Approach // Search. 2007. 6. 1–46.

Carnap Tillmann von. Irrigation as a Historical Determinant of Social Capital in India? A Large-Scale Survey Analysis // World Dev. 2017. 95. 316–333.

Chaisemartin Clément de, D'Haultfœuille Xavier. Two-Way Fixed Effects Estimators with Heterogeneous Treatment Effects // Am. Econ. Rev. 2020. 110, 9. 2964–2996.

Chamberlin John. Provision of Collective Goods As a Function of Group Size // Am. Polit. Sci. Rev. 1974. 68, 2. 707–716.

Cook P. Privatization and Utility Regulation in Developing Countries: The Lessons So Far // Ann. Public Coop. Econ. 1999. 70, 4. 549–587.

Dawes Robyn M., Messick David M. Social Dilemmas // Int. J. Psychol. 2000. 35, 2. 111–116.

Defensoria del Pueblo . La gestion comunitaria del agua. 2013. 1–128.

Esteban Ray, Ray Debraj. Collective Action and the Group Size Paradox // Am. Polit. Sci. Rev. 2015. 95, 3. 663–672.

Galiani Sebastian, Gertler Paul, Schargrodsky Ernesto. Water for life: The impact of the privatization of water services on child mortality // J. Polit. Econ. 2005. 113, 1. 83–120.

Ge Erhao, Chen Yuan, Wu Jiajia, Mace Ruth. Large-scale cooperation driven by reputation, not fear of divine punishment // R. Soc. Open Sci. 2019. 6, 8. 190991.

Goodman-Bacon Andrew. Difference-in-differences with variation in treatment timing // J. Econom. 2021. 225, 2. 254–277.

Hanak Ellen, Lund Jay R. Adapting California's water management to climate change // Clim. Change. 2012. 111, 1. 17–44.

Heckathorn Douglas D. Collective Action and Group Heterogeneity: Voluntary Provision Versus Selective Incentives // Am. Sociol. Rev. 1993. 58, 3. 329.

IDEAM . Estudio Nacional del Agua 2018. 2019. 452.

Kollock Peter. Social Dilemmas: The Anatomy of Cooperation // Annu. Rev. Sociol. 1998. 24, 1. 183–214.

Komorita S. S., Hilty J. A., Parks C. D. Reciprocity and Cooperation in Social Dilemmas // J. Conflict Resolut. 1991. 35, 3. 494–518.

Koppenjan Joop F.M., Enserink Bert. Public-private partnerships in urban infrastructures: Reconciling private sector participation and sustainability // Public Adm. Rev. 2009. 69, 2. 284–296.

Krause Kate, Chermak Janie M., Brookshire David S. The Demand for Water: Consumer Response to Scarcity // J. Regul. Econ. 2003. 23, 2. 167–191.

Kurian M. People and forests - Communities, institutions and governance. 2002.

Kyriacou a P. Intrinsic Motivation and the Logic of Collective Action: The Impact of Selective Incentives // Am. J. Econ. Sociol. 2010. 69, 2. 823–839.

Lieberherr Eva, Truffer Bernhard. The impact of privatization on sustainability transitions: A comparative analysis of dynamic capabilities in three water utilities // Environ. Innov. Soc. Transitions. 2015. 15. 101–122.

Mansur Erin T., Olmstead Sheila M. The value of scarce water: Measuring the inefficiency of municipal regulations // J. Urban Econ. 2012. 71, 3. 332–346.

Marzano Riccardo, Rougé Charles, Garrone Paola, Grilli Luca, Harou Julien J., Pulido-Velazquez Manuel. Determinants of the price response to residential water tariffs: Meta-analysis and beyond // Environ. Model. Softw. 2018. 101. 236–248.

Melo Sioux, Riveros Leidy, Otalora Germán, Álvarez Andres, Diaz Carolina, Calderon Silvia. Efectos economicos de futuras sequias en colombia estimacion a partir del fenomeno El niño 2015. 2017a. 1–76.

Melo Sioux, Riveros Leidy, Romero German, Álvarez Andres Camilo, Diaz Carolina, Calderon Silvia. Efectos económicos de futuras sequías en Colombia: Estimación a partir del Fenómeno El Niño 2015. Bogotá DC, 2017b. 47.

Messick David M., al Et. Individual adaptations and structural change as solutions to social dilemmas // J. Pers. Soc. Psychol. 1983. 44, 2. 294–309.

Moura Marks Melo, Santos Alexandre Rosa dos, Pezzopane José Eduardo Macedo, Alexandre Rodrigo Sobreira, Silva Samuel Ferreira da, Pimentel Stefania Marques, Andrade Maria Sueliane Santos de, Silva Felipe Gimenes Rodrigues, Branco Elvis Ricardo Figueira, Moreira Taís Rizzo, Silva Rosane Gomes da, Carvalho José Romário de. Relation of El Niño and La Niña phenomena to precipitation, evapotranspiration and temperature in the Amazon basin // Sci. Total Environ. 2019. 651. 1639–1651.

Muñoz-Sabater Joaquín, Dutra Emanuel, Agustí-Panareda Anna, Albergel Clément, Arduini Gabriele, Balsamo Gianpaolo, Boussetta Souhail, Choulga Margarita, Harrigan Shaun, Hersbach Hans, Martens Brecht, Miralles Diego G., Piles Mariá, Rodríguez-Fernández Nemesio J., Zsoter Ervin, Buontempo Carlo, Thépaut Jean Noël. ERA5-Land: A state-of-the-art global reanalysis dataset for land applications // Earth Syst. Sci. Data. 2021. 13, 9. 4349–4383.

Nosenzo Daniele, Quercia Simone, Sefton Martin. Cooperation in small groups: the effect of group size // Exp. Econ. 2015. 18, 1. 4–14.

Oliver Pamela, Marwell Gerald, Teixeira Ruy. A Theory of the Critical Mass. I. Interdependence, Group Heterogeneity, and the Production of Collective Action // Am. J. Sociol. 1985. 91, 3. 522–556.

Olmstead Sheila M. The economics of managing scarce water resources // Rev. Environ. Econ. Policy. jun 2010. 4, 2. 179–198.

Olmstead Sheila M. Climate change adaptation and water resource management: A review of the literature // Energy Econ. 2014. 46. 500–509.

Olmstead Sheila M., Michael Hanemann W., Stavins Robert N. Water demand under alternative price structures // J. Environ. Econ. Manage. 2007. 54, 2. 181–198.

Olmstead Sheila M., Stavins Robert N. Comparing price and nonprice approaches to urban water conservation // Water Resour. Res. 2009. 45, 4. 1–10.

Olson M. The Logic of Collective Action_ Public Goods and the Theory of Groups. 1965. 5.

Ostrom Elinor. A Behavioral Approach to the Rational Choice Theory of Collective Action // Am. Polit. Sci. Rev. 1998. 92, 1. 1–22.

Ostrom Elinor. Understanding the Diversity of Structured Human Interactions // Underst. Institutional Divers. 2005. 3–31.

Ostrom Elinor. Beyond markets and states: Polycentric governance of complex economic systems // Nobel Lect. Econ. Sci. 2006 - 2010. 2014. 100, 3. 171–176.

Pecorino Paul. Olson's Logic of Collective Action at fifty // Public Choice. 2015. 162, 3-4. 243–262.

Poteete Amy, Ostrom Elinor. Heterogeneity, group size and collective action: the role of institutions in forest management // Dev. Change. 2004. 35, 3. 435–461.

Poveda Germán, Álvarez Diana M., Rueda Óscar A. Hydro-climatic variability over the Andes of Colombia associated with ENSO: A review of climatic processes and their impact on one of the Earth's most important biodiversity hotspots // Clim. Dyn. 2011. 36, 11-12. 2233–2249.

Pratt Bryan. A fine is more than a price: Evidence from drought restrictions // J. Environ. Econ. Manage. 2023. 119, September 2020. 102809.

Rustagi D, Engel S, Kosfeld M. Conditional Cooperation and Costly Monitoring Explain Success in Forest Commons Management // Science (80-.). nov 2010. 330, 6006. 961–965.

Schwarz Andrew, Megdal Sharon B. Conserve to Enhance - Voluntary municipal water conservation to support environmental restoration // J. / Am. Water Work. Assoc. 2008. 100, 1. 42–53.

Superservicios . Informe sectorial Pequeños Prestadores. Bogota, 2014.

UN . UN World Water development report. 88, 5. 2019. 3.

Vatn Arild. Environmental Governance: From Public to Private? // Ecol. Econ. 2018. 148, September 2017. 170–177.

Vuille Mathias. Climate Change and Water Resources in the Tropical Andes, Technical note No. IDB-TN-515. 2013. 29.

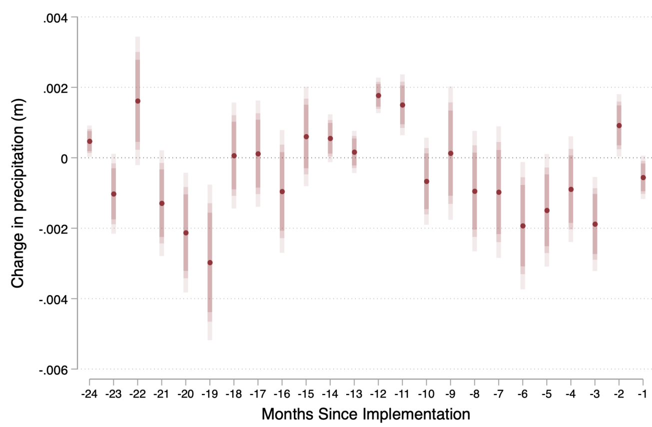
Xue Yan, Kumar Arun. Evolution of the 2015/16 El Niño and historical perspective since 1979 // Sci. China Earth Sci. 2017. 60, 9. 1572–1588.

Yang Wu, Liu Wei, Vina a., Tuanmu M.-N. Mao-Ning, He Guangming, Dietz Thomas, Liu Jianguo, Viña Andrés, Tuanmu M.-N. Mao-Ning, He Guangming, Dietz Thomas, Liu Jianguo, Vina a., Tuanmu M.-N. Mao-Ning, He Guangming, Dietz Thomas, Liu Jianguo, Viña Andrés, Tuanmu M.-N. Mao-Ning, He Guangming, Dietz Thomas, Liu Jianguo. Nonlinear effects of group size on collective action and resource outcomes // Proc. Natl. Acad. Sci. 2013. 110, 27. 10916–10921.

Zhang Xiaoquan Michael, Zhu Feng. Group size and incentives to contribute: A natural experiment at chinese wikipedia // Am. Econ. Rev. 2011. 101, 4. 1601–1615.

A Differences Between Targeted and Non-Targeted Utilities

Figure 7: Average Monthly Minimum Precipitation at Pre-Policy Period (Targeted vs. Non-Targeted)



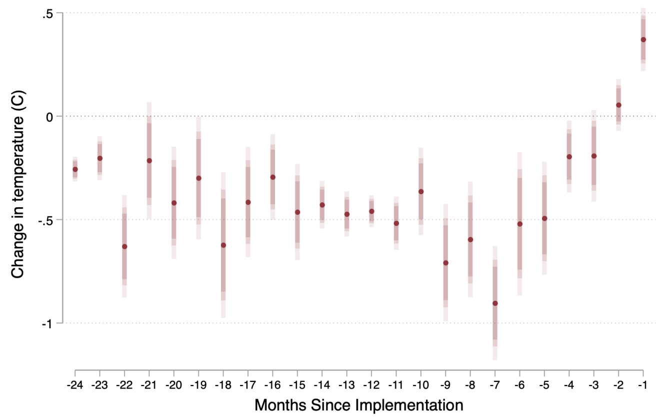
Note. This figure presents point estimates and 95% confidence intervals from a two-way fixed effects regression model of average minimum monthly precipitation comparing utilities located in targeted and non-targeted areas as of August 2014. Standard errors clustered at the municipality and department level.

B Dependent variable: Residential Water usage

C Herfindahl-Hirschman Index (HHI)

We test for potential differences in the policy on residential water usage by income heterogeneity in water utilities. To measure income heterogeneity, we use the distribution of users per socioeconomic stratum as a proxy to calculate the Herfindahl-Hirschman Index (HHI). HH is a statistical measure of concentration that is widely used in social science. A simpler version is as follows:

Figure 8: Average Monthly Maximum Temperature at Pre-Policy Period (Targeted vs. Non-Targeted)

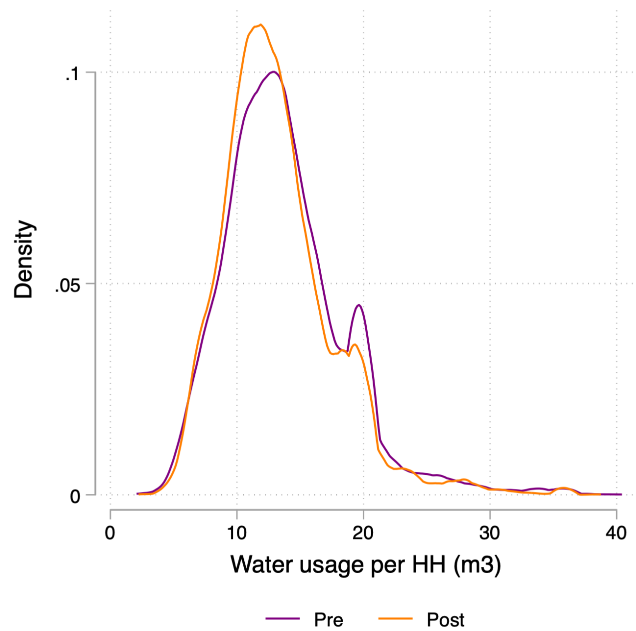


Note. This figure presents point estimates and 95% confidence intervals from a two-way fixed effects regression model of average minimum monthly precipitation comparing utilities located in targeted and non-targeted areas as of August 2014. Standard errors clustered at the municipality and department level.

$$HHI_i = 1 - \sum_{j=1}^{N} s_{j,i}^2 \tag{6}$$

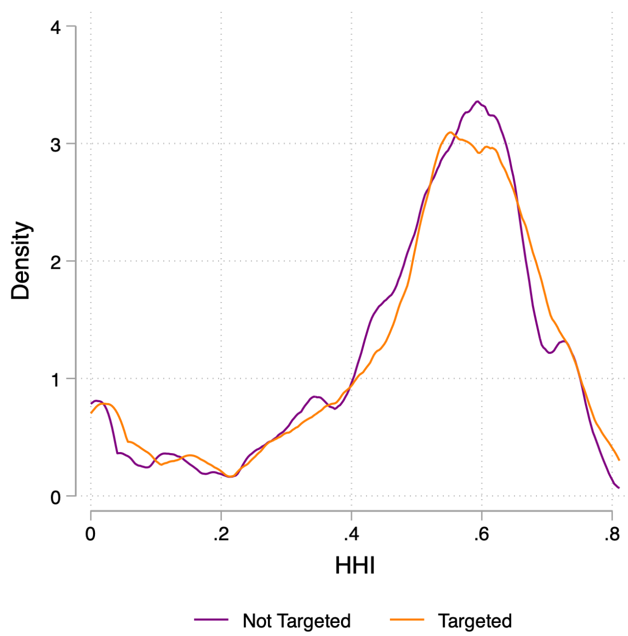
where $s_{j,i}$ is the share of the number of users that belong to an income level j. The values are a measure that ranges from 0 to 1, where 0 (1) implies the lowest (highest) socioeconomic diversity or the probability that two randomly drawn households are from different socioeconomic groups. **??** displays the distribution of the HH index by targeted and not targeted groups by the policy in August 2014.

Figure 9: Distribution of Water Usage Pre and Post Policy



Note. This figure presents the kernel distribution of the water usage per household before and after August 2014 from the full sample of utilities. Authors' estimations using data from 2014 to 2016.

Figure 10: Distribution of the Herfindahl-Hirschman Index



Note. This figure presents the kernel distribution of the Herfindahl-Hirschman Index by groups of exposure to the policy in August 2014. Authors' estimations using data from 2014 to 2016.

Table 1: Descriptive Statistics at Baseline

	Mean	**Std. Dev.**	**Min.**	**Max.**	**Obs.**
Water Uility					
Water Use per HH (m3)	13.72	4.708	4.494	35.93	526
Users (#)	11566.8	56151.0	73	875864	526
Years Operating (#)	18.21	14.77	0	99	523
Serving urban center (1/0)	0.832	0.374	0	1	523
State-Owned (1/0)	0.157	0.364	0	1	534
Local Government (1/0)	0.148	0.355	0	1	534
Community Based (1/0)	0.165	0.371	0	1	534
Private-Owned (1/0)	0.530	0.500	0	1	534
Annual Income (000 USD)	76.33	657.1	0.0403	14234.0	533
Targeted in August 2014	0.393	0.489	0	1	534
Municipality					
Max. Temperature (°C/month)	21.70	4.628	11.25	31.74	534
Min. Precipitation (mm/month)	4.816	7.326	0.00741	65.45	534
Altitude (up to 1000m)	0.410	0.492	0	1	534
Altitude (1000m & 2000m)	0.388	0.488	0	1	534
Altitude (Above 2000m)	0.200	0.401	0	1	534
Urban population (#)	123.5	643.4	0.0950	7760.5	534
Total population (#)	137.2	645.4	1.820	7776.8	534
Rurality Index	0.456	0.257	0.00101	0.983	534
Municipal Area (km2)	935.4	3766.2	15	65674	534
Distance to Main Market (km)	88.33	73.14	0	519.1	534
Multidimensional Poverty Index.	59.24	18.10	14.27	100	534
Infant Mortality Rate (per 1000)	16.29	6.423	6.065	60.90	534
Access to Water (%)	63.78	26.14	2.620	100	534
Access to Waste Collection (%)	51.27	28.54	0	100	534
Access to Sewage (%)	48.00	28.73	0	100	534
Annual Income (000 USD)	27.24	189.0	0.305	2417.1	534

Note. This table reports the descriptive statistics for the panel of water utilities in our sample. It comprises data from variables at the utility and the municipality level.

Table 2: Effect of the Policy on Utilities' Outcomes

	(1) Water Usage	(2) Water Usage	(3) Revenue	(4) Revenue
Targeted	-2.698	-2.829	-6.704	-7.467
	(0.362)	(0.367)	(0.755)	(0.766)
	[0.000]	[0.000]	[0.000]	[0.000]
Off Early		6.259		1.632
		(1.096)		(2.311)
		[0.000]		[0.662]
Off Late		-1.986		-7.532
		(0.591)		(1.232)
		[0.002]		[0.000]
Constant	81.939	81.000	-129.624	-136.964
	(3.629)	(3.678)	(7.625)	(7.730)
Mean pre-policy	13.72	13.72	72156.8	72156.8
Controls	Y	Y	Y	Y
Adjusted r^2	-0.00493	-0.00274	0.880	0.880
Utiltiies	534	534	536	536
Obs.	19956	19956	19921	19921

Note: This table reports the estimated treatment effects from the DiD model presented in Equations 1 and 2. The outcomes are shown in Columns 1 and 2, reflecting the average water consumption per user, adjusted by the mean of the never-targeted group prior to the policy implementation. In Columns 3 and 4, the outcome represents the utilities' revenue from water consumption, also adjusted by the mean of the never-targeted group at pre-policy. All regressions include utility and seasonal fixed effects, with standard errors provided in parentheses. p-values from the wild cluster bootstrap at the Department level are indicated in brackets.

Table 3: Effect of the Policy on Water Usages by Utility Type

	Water Usage				Revenue			
	SOU	LGO	CBO	POU	SOU	LGO	CBO	POU
Targeted	-4.010	-4.304	-4.072	-1.454	1.842	0.109	0.732	6.407
	(0.748)	(0.914)	(1.210)	(0.488)	(13.794)	(0.190)	(0.076)	(0.639)
	[0.000]	[0.000]	[0.000]	[0.004]	[0.401]	[0.108]	[0.000]	[0.000]
Off Early	0.000	0.000	-1.132	7.328	0.000	0.000	1.044	33.129
	(.)	(.)	(4.035)	(1.068)	(.)	(.)	(0.267)	(1.396)
	[.]	[.]	[0.543]	[0.000]	[.]	[.]	[0.003]	[0.000]
Off Late	-2.111	-4.630	-1.029	-0.275	-2.912	0.156	0.812	7.499
	(1.190)	(1.443)	(1.904)	(0.814)	(21.853)	(0.300)	(0.118)	(1.064)
	[0.346]	[0.000]	[0.582]	[0.740]	[0.544]	[0.085]	[0.000]	[0.000]
Constant	76.333	64.001	104.347	84.165	217.320	3.473	0.589	37.127
	(7.207)	(11.336)	(11.084)	(4.850)	(134.736)	(2.373)	(0.699)	(6.323)
Mean Pre-policy	14.10	12.27	14.09	13.90	14.10	12.27	14.09	13.90
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Adjusted r^2	0.00293	-0.00791	0.00372	0.00370	-0.0218	-0.0315	0.0607	0.0490
Utiltiies	82	81	88	283	84	81	88	283
Obs.	3079	2973	3295	10609	3164	2975	3247	10645

Note: This table reports the estimated treatment effects from the DiD model in Equation 3. The outcomes are the average water consumption per user and utility revenue from water consumption, both adjusted by the mean of the never-targeted group at pre-policy. All the regressions include utility and seasonal fixed effects. Standard errors in parentheses. P-values from the wild cluster bootstrap at the Department level are reported in brackets.

Table 4: Effect of the Policy on Utilities' Outcome Alternate Pre-policy Window

	(1) Water Usage	(2) Water Usage	(3) Revenue	(4) Revenue
Targeted	-2.076	-2.186	-4.464	-5.536
	(0.383)	(0.399)	(0.805)	(0.840)
	[0.000]	[0.000]	[0.000]	[0.000]
Off Early		5.449		4.392
		(1.166)		(2.464)
		[0.000]		[0.214]
Off Late		-1.247		-6.374
		(0.606)		(1.273)
		[0.066]		[0.000]
Constant	79.028	78.613	-138.360	-144.258
	(4.187)	(4.234)	(8.874)	(8.975)
Mean pre-policy	13.7	13.7	72156.8	72156.8
Controls	Y	Y	Y	Y
Adjusted r^2	-0.018	-0.016	0.83	0.83
Utiltiies	534	534	536	536
Obs.	13690	13690	13700	13700

Note: This table reports the estimated treatment effects from the DiD model in Equations 1 and 2. The dependent variable is the average water consumption per user adjusted by the mean of the never-targeted group at pre-policy. All the regressions include utility and month-fixed effects. Standard errors in parentheses. P-values from the wild cluster bootstrap at the Department level are reported in brackets.

Table 5: Effect of the Policy on Utilities' Outcomes Addressing Potential Data Manipulation in Reporting

	(1) Water Usage	(2) Water Usage	(3) Revenue	(4) Revenue
Targeted	-2.862	-2.998	-6.866	-7.647
	(0.369)	(0.374)	(0.772)	(0.783)
	[0.000]	[0.000]	[0.000]	[0.000]
Off Early		6.617		1.638
		(1.133)		(2.393)
		[0.000]		[0.679]
Off Late		-2.044		-7.658
		(0.601)		(1.256)
		[0.002]		[0.000]
Constant	81.181	80.152	-130.636	-138.392
	(3.735)	(3.787)	(7.867)	(7.980)
Mean pre-policy	13.7	13.7	72156.8	72156.8
Controls	Y	Y	Y	Y
Adjusted r^2	-0.0046	-0.0023	0.88	0.88
Utiltiies	528	528	530	530
Obs.	19595	19595	19560	19560

Note: This table reports the estimated treatment effects from the DiD model in Equations 1 and 2. The dependent variable is the average water consumption per user adjusted by the mean of the never-targeted group at pre-policy. All the regressions include utility and month-fixed effects. Standard errors in parentheses. P-values from the wild cluster bootstrap at the Department level are reported in brackets.

Table 6: Effect of the Policy on Water Usage Accounting for Potential Spillover Effects

	(1) <10km	(2) <25km	(3) <50km	(4) <100km	(5) <150km
Targeted	-3.303***	-3.058***	-3.817***	-3.448***	-3.277***
	(-4.30)	(-2.63)	(-3.53)	(-3.89)	(-3.76)
Off Early	0	-0.771	-0.686	7.896**	6.244**
	(.)	(-0.51)	(-0.46)	(2.12)	(2.50)
Off Late	2.329	-0.912	-2.665*	-1.954	-2.187*
	(0.67)	(-0.45)	(-1.66)	(-1.47)	(-1.71)
Constant	90.15***	73.91***	80.23***	81.17***	81.74***
	(4.95)	(7.00)	(10.81)	(14.90)	(14.62)
Mean pre-policy	14.1	14.0	13.8	13.6	13.7
Bootstraped SE	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y
Adjusted r^2	0.051	0.037	0.034	0.028	0.025
Utiltiies	51	141	277	457	496
Obs.	1910	5277	10376	17089	18547

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table reports the estimated treatment effects from the DiD model in Equation 1 and Equation 2. The dependent variable is the average water consumption per user adjusted by the mean of the never-targeted group at pre-policy. All the regressions include utility and month-fixed effects. Standard errors in parentheses. P-values from the wild cluster bootstrap at the Department level are reported in brackets.

Table 7: Effect of the Policy on Utility Outcomes No Climate Controls

	(1) <10km	(2) <25km	(3) <50km	(4) <100km	(5) <150km
Targeted	-3.303***	-3.058***	-3.817***	-3.448***	-3.277***
	(-4.30)	(-2.63)	(-3.53)	(-3.89)	(-3.76)
Off Early	0	-0.771	-0.686	7.896**	6.244**
	(.)	(-0.51)	(-0.46)	(2.12)	(2.50)
Off Late	2.329	-0.912	-2.665*	-1.954	-2.187*
	(0.67)	(-0.45)	(-1.66)	(-1.47)	(-1.71)
Constant	90.15***	73.91***	80.23***	81.17***	81.74***
	(4.95)	(7.00)	(10.81)	(14.90)	(14.62)
Mean pre-policy	14.1	14.0	13.8	13.6	13.7
Bootstraped SE	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y
Adjusted r^2	0.051	0.037	0.034	0.028	0.025
Utiltiies	51	141	277	457	496
Obs.	1910	5277	10376	17089	18547

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table reports the estimated treatment effects from the DiD model in Equations 1 and 2. The dependent variable is the average water consumption per user adjusted by the mean of the never-targeted group at pre-policy. All the regressions include utility and month-fixed effects. Standard errors in parentheses. P-values from the wild cluster bootstrap at the Department level are reported in brackets.

Table 8: Differences in Observable Characteristics Between Targeted and Non-Targeted Areas

	Not Targeted		**Targeted**		
	Mean	*Std. Dev.*	*Mean*	*Std. Dev.*	*Std. Diff.*
Water Use per HHs (m3)	13.7	4.62	13.8	4.85	0.018
Users (#)	12516.6	68784.7	10126.3	27689.1	0.046
Years Operating (#)	18.2	14.8	18.2	14.8	0.0015
Serving urban centers? (1/0)	0.79	0.40	0.89	0.31	0.27
State-Owned (1/0)	0.16	0.37	0.15	0.36	0.022
Local Government (1/0)	0.099	0.30	0.22	0.42	0.34
Community Based (1/0)	0.19	0.39	0.12	0.33	0.19
Private-Owned (1/0)	0.55	0.50	0.50	0.50	0.099
Annual Income (000 USD)	91.7	830.9	52.7	185.4	0.065
Max. Temperature (°C/month)	21.5	4.02	22.0	5.43	0.12
Min. Precipitation (mm/month)	4.33	4.43	5.57	10.3	0.16
Altitude (Up to 1000m)	0.43	0.50	0.38	0.49	0.11
Altitude (1000m & 2000m)	0.35	0.48	0.45	0.50	0.20
Altitude (Above 2000m)	0.22	0.41	0.18	0.38	0.10
Urban population (#)	163.8	815.9	61.3	142.8	0.17
Total Population (#)	179.8	817.5	71.5	148.9	0.18
Rurality Index	0.47	0.24	0.44	0.28	0.12
Municipal Area (km2)	1260.0	4786.5	434.5	592.7	0.24
Distance to Main Market (km)	89.2	81.9	86.9	57.2	0.033
Multidimensional Poverty Index.	57.8	19.4	61.5	15.6	0.21
Infant Mortality Rate (per 1000)	16.6	7.10	15.8	5.19	0.12
Access to Water (%)	65.1	25.2	61.7	27.4	0.13
Access to Waste Collection (%)	54.3	28.1	46.6	28.6	0.27
Access to Sewage (%)	50.4	28.2	44.3	29.2	0.21
Annual Income (000 USD)	40.0	241.2	7.60	22.9	0.19

Note: This table reports standardized mean differences in observable characteristics between utilities located in targeted and non-targeted departments as of August 2014. Variables include geographic, demographic, and socioeconomic indicators at the utility and municipality levels.